# Experimental Evidence of Bank Runs as Pure Coordination Failures*

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**Abstract**

This paper investigates whether bank runs can occur as a result of pure coordination failures through controlled laboratory experiments. The finding is that miscoordination-based bank runs can be observed when the coordination parameter, defined as the amount of coordination among late withdrawers that is required for them to receive a higher payoff than early withdrawers, is high enough. In particular, when the coordination parameter is below (above) a certain value, the experimental economies stay close to or converge to the non-run (run) equilibrium. When the coordination parameter lies between the two threshold values, the outcomes of the experimental economies vary widely and are hard to predict. The behavior of human subjects in the laboratory can be accounted for by a version of the evolutionary learning algorithm.

JEL Categories: D83, G20

Keywords: Bank Runs, Experimental Studies, Evolutionary Algorithm, Coordination Games

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# 1 Introduction

A bank run is the situation in which a large number of depositors, fearing that their bank will be unable to repay their deposits, simultaneously try to withdraw their funds even in the absence of liquidity needs. Bank runs were frequently observed in the United States before the establishment of the Federal Deposit Insurance Corporation in 1933. The enactment of the deposit insurance program has greatly reduced the incidence of bank runs. However, a new wave of bank runs has occurred across the world during the recent financial turmoil. Examples include the runs on Northern Rock in September 2007, on Bear Stearns in March 2008, on Wamu in September 2008, on IndyMac in July 2008, and on Busan II Savings Bank in February 2011.

The theoretical literature on bank runs is largely built on the seminal paper by Diamond and Dybvig (1983) (hereafter DD). The bank is modelled as a liquidity insurance provider that pools depositors' resources to invest in profitable illiquid long-term assets, and at the same time, issues short-term demand deposits to meet the liquidity need of depositors. The term mismatch between the bank's assets and liabilities opens the gate to bank runs.

There are, broadly speaking, two opposing views about the cause of bank runs. The first view (represented by DD) is that bank runs are the result of pure coordination failures. The bank run model in DD has two symmetric self-fulfilling Nash equilibria. In one equilibrium, depositors choose to withdraw early only when they need the liquidity. In the other equilibrium, in fear that the bank will not be able to repay them, all depositors run to the bank to withdraw money irrespective of their liquidity needs. The run forces the bank to liquidate its long-term investment at fire-sale prices and makes the initial fear a self-fulfilling prophecy. As a result, even banks with healthy assets may be subject to bank runs. The competing view (represented by Allen and Gale, 1998) is that bank runs are caused by adverse information about the quality of the bank's assets.

To empirically test the competing theories of bank runs is challenging. Real-world bank runs tend to involve various factors and this makes it difficult to conclude whether the bank run is due to miscoordination or the deterioration of the quality of the bank's assets. There are some attempts to empirically test the source of bank runs, nonetheless with mixed results. For example, Gorton (1988), Allen and Gale (1998) and Schumacher (2000) show that bank runs have historically been strongly correlated with deteriorating economic fundamentals which erode away the value of the bank's assets. In contrast, Boyd et al. (2001) conclude that bank runs may often be the outcome of coordination failures.

An experimental approach has the advantage that it is easier to control different factors that may cause bank runs in the laboratory. In this paper, our goal is to study whether bank runs can occur as a result of pure coordination failures, and if yes, under what conditions. To do this, we fix the rate of return of the bank's long-term asset throughout the experiments to rule out the deterioration of the quality of the bank's assets as the source of bank runs. We also fix the short-term interest rate (promised to early withdrawers) for 10 rounds before it changes. This allows subjects to interact with each other in a stable environment where they can focus on their coordination choice. The short-term interest rate affects what we call the *coordination parameter*, which measures the amount of coordination (the fraction of depositors to choose to withdraw late) that is required to generate enough complementarity among late withdrawers so that they earn higher payoff than early withdrawers. Our main finding is that bank runs can occur as the result of miscoordination if the required amount of coordination is high enough. More specifically, when the coordination parameter is below (above) a critical value, the experimental economies stay close to or converge to the non-run (run) equilibrium within the 10 periods when the coordination parameter is fixed. When the coordination parameter lies between the two critical values, the outcomes of the experimental economies vary widely and are hard to predict.

There have been several previous studies of bank runs in controlled laboratory environments. Garrat and Keister (2009) study how depositors' withdrawing decisions are affected by uncertainty about the aggregate liquidity demand and by the number of opportunities subjects have to withdraw. Schotter and Yorulmazer (2009) investigate bank runs in a dynamic context and examine the factors that affect the speed of withdrawals, including the number of opportunities to withdraw and the existence of insiders. Klos and Sträter (2010) test the prediction of the global game theory in the context of bank runs and focus on the effect of the existence of noisy private information about the quality of the bank's long-term assets.[1] Madiès (2006) studies the DD model of bank runs with an emphasis on the effectiveness of alternative ways to prevent bank runs including suspension of payments and deposit insurance. Our focus is to find the situations in which bank runs occur as

[1] The theoretical foundation of the experiments is the global game theory of bank runs by Morris and Shin (2000) and Goldstein and Pauzner (2005). The paper also tries to use the level-$k$ approach to explain the experimental data.

pure coordination failures.

More generally, the paper is also related to experimental studies of coordination games. Under the demand deposit contract, depositors in essence play an entry game, or a binary choice (to enter or not to enter) game of complete information with strategic complementarity. The payoff to entry exceeds that to non-entry only if the number of entrants exceeds a threshold. The game involves two symmetric Nash equilibria: in one equilibrium, everyone chooses not to enter and earns a low payoff; in the other, all players coordinate on entry and receive a high payoff. There has been a long tradition of studying coordination games with multiple equilibria in controlled laboratory environments. Much discussion centers around how the selection of different equilibria is affected by payoff parameters. For example, Van Huyck et al. (1990, 1991) study the effect of the number of players. Battalio et al. (2001) and Cabrale et al. (2007) investigate the effect of the payoff difference between the two Nash equilibria of an entry game. Heinemann et al. (2004) and Duffy and Ochs (2010) (hereafter DO) study how individual strategies respond to a continually changing payoff relevant variable that affects both the payoff difference and the coordination requirement. Heinemann et al. (2009) investigate how individual strategies change with respect to the payoff difference between the two Nash equilibria, and how that relationship is affected by the coordination requirement.[2]

In this paper, we intend to investigate whether bank runs can occur as a result of pure coordination failures. To effectively achieve the goal, we create an environment where subjects can focus solely on coordinating their action choices by minimizing the variation in the experimental environment. We fix the number of subjects and the payoff difference between the two Nash equilibria. All payoff-relevant variables are also fixed for a period of time (the long-term rate is fixed throughout the experiments to rule out the deterioration of the bank's asset as the source of bank runs; the short-term rate or the coordination parameter is fixed for 10 rounds before it changes) so

[2] The main focus in DO and Heinemann et al. (2004, 2009) is the study of the global game theory of entry games in the laboratory. According to the theory, when agents receive noisy (but precise enough) signals about a random payoff relevant variable, there is a unique solution where agents play a threshold strategy choosing to enter if and only if their signals exceed a critical value. HNO (2004) carry out experiments with two information treatments: one with public information about the economic fundamental and one with noisy private signals about the fundamental. They find that in both cases, individual behavior exhibits the same pattern, although the threshold values to enter may differ. DO improve upon the experimental methodology in HNO (2004) by introducing a within-subject design, and investigate dynamic entry games. The main purpose of HNO (2009) is to measure strategic uncertainty when agents have common information about payoff relevant variables.

that players can interact in a stable environment. We study the coordination behavior with 7 different values of the coordination parameter. The setup allows us to systematically investigate how subjects coordinate and interact and how the performance of the aggregate economy (the number of early or late withdrawals) evolves in response to the coordination requirement. It also enables us to find a stronger learning effect for intermediate coordination requirement, a result that is not captured by other experimental studies of coordination games. In our paper, the stronger learning effect is evidenced by the observation that for intermediate coordination requirement, it takes time for the experimental to reach the equilibrium as subjects adjust their choices in response to the results in previous rounds. In contrast, when the coordination parameter takes extreme values, the experimental economies arrive at the equilibrium almost instantly and tend to stay there across the whole 10 rounds.

The paper proceeds as follows. Section two outlines the model that underlies the experimental studies. Section three describes the experimental design. Section 4 presents and discusses the experimental results. In section five, we use the evolutionary algorithm to explain the experimental results. Section six concludes and discusses future work.

## 2 The Theoretical Framework

The theoretical framework that underlies our experimental studies is the DD model of bank runs. There are three dates indexed by 0, 1, and 2. There are $D$ *ex ante* identical agents in the economy. At date 0 (the planning period), each agent is endowed with 1 unit of good and faces a liquidity shock that determines his/her preferences over goods at date 1 and date 2. The liquidity shock is realized at the beginning of date 1. Among the $D$ agents, $N$ of them become patient agents who are indifferent between consumption at date 1 and date 2, and the rest become impatient agents who care only about consumption at date 1. Realization of the liquidity shock is private information. Preferences are described by

$$U(c_1, c_2) = \begin{cases} u(c_1) & \text{for impatient consumers,} \\ u(c_1 + c_2) & \text{for patient consumers,} \end{cases}$$

where $c_1$ and $c_2$ denote the consumption at date 1 and date 2, respectively. The function $u(\cdot)$ satisfies $u'' < 0 < u'$, $\lim_{c\to\infty} u'(c) = 0$ and $\lim_{c\to 0} u'(c) = \infty$. The relative risk aversion coefficient $-cu''(c)/u'(c) > 1$ everywhere. There is a productive technology that transforms 1 unit of date 0 output into 1 unit of date 1 output or $R > 1$ units of date 2 output.

At the socially optimal allocation, impatient agents consume only at date 1 and patient agents consume only at date 2. Let $c_i$ and $c_p$ denote the consumption by impatient consumers and patient consumers, respectively. The optimal allocation is characterized by $1 < c_i^*(N/D, R, u) < c_p^*(N/D, R, u) < R$. A bank, by offering demand deposit contracts, can support the optimal risk-sharing allocation. The contract requires agents to deposit their endowment with the bank at date 0. In return, agents receive a bank security which can be used to demand consumption at either date 1 or 2. The bank pays $r^* = c_i^* > 1$ to agents who demand consumption at date 1 until it runs out of money or bankrupts. There is a sequential service constraint (SSC): in the case of bankruptcy, only those who are early in line receive payment. Resources left after paying early withdrawers generate a rate of return $R > r^*$ and the proceeds are shared by all late withdrawers at date 2. Let $c_e$ and $c_\ell$ are the payoffs to early and late withdrawers, respectively. Use $z$ to denote the number of depositors who choose to withdraw late. Let $\hat{z} = D/r$ be the minimum number of late withdrawals that prevents bankruptcy. The deposit contract can be described by

$$c_e = \begin{cases} r^*, \ \text{if } z \geq \hat{z}, \\ r \text{ with probability } \frac{D-\hat{z}}{D-z}, \text{ and } 0 \text{ with probability } \frac{\hat{z}-z}{D-z}, \text{ if } z \leq \hat{z}; \end{cases}$$

$$c_\ell = \begin{cases} \frac{D-r^*(D-z)}{z}R, \ \text{if } z \geq \hat{z}, \\ 0, \ \text{if } z \leq \hat{z} \end{cases}$$

For the experiments, we keep the important features of the DD model. To facilitate the experimental design, we modify the original model along three dimensions. First, in the original model, there are both patient and impatient agents. Impatient agents always withdraw early and only patient agents are "strategic" players. Here we will focus on "strategic" players so we let $D = N$.[3] Second, instead of calculating the optimal short-term interest rate, $r^*(N/D, R, u)$, we simply set $r$

[3] Madiès (2006) adopts the same arrangement in this regard.

to be a value that is greater than 1.[4] This allows us to study how the coordination parameter affects the pattern of bank runs (as will be clear in the next section, there is a one-on-one correspondence between $r$ and the coordination parameter). Third, we abstract from SSC for simplification and assume instead that when the bank does not have enough money to pay every early withdrawer $r$, it divides the available resource evenly among all depositors who demand consumption. The SSC is not essential for the existence of multiple equilibria; the fact that $r > 1$ is sufficient to generate a payoff externality and panic-based runs. The payoff function that we use for the experiments can be represented as:

$$c_e = \min\left\{r, \frac{N}{N-z}\right\}; \quad (1)$$

$$c_\ell = \max\left\{0, \frac{N - r(N-z)}{z}R\right\}. \quad (2)$$

The coordination game characterized by the above payoff structure has two symmetric Nash equilibria. In the run equilibrium, every depositor chooses to run on the bank and withdraws early expecting others to do the same. As a result, $z = 0$ and everybody receives a payoff of 1. In the non-run equilibrium, every depositor chooses to wait expecting others to do the same. In this equilibrium, $z = N$ and everybody receives a payoff of $R$. The payoff difference between the two equilibria is $R - 1$.

## 3 Experimental Design

Our main objective is to test the DD model and examine whether or not bank runs can be the result of pure coordination failures. To fulfill the purpose, we adopt the following measures while designing the experiments. First, in contrast to earlier experimental literature on coordination games, which adopts context-free phrasing, we phrase the task explicitly as a decision about when to withdraw money from the bank. The specific banking context makes it easier for subjects to

[4] For optimal contracting in the DD framework, please refer to Green and Lin (2000, 2003), Andolfatto, Nosal and Wallace (2007), Andolfatto and Nosal (2008), and Ennis and Keister (2009a, 2009b, 2010). The first few papers show that the multiple equilibria result goes away if more complicated contingent contracts – as compared with the simple demand deposit contracts in DD – are used. The three papers by Ennis and Keister show that the multiple equilibrium result is restored if the banking authority cannot commit to not intervene in the event of a crisis, or the consumption needs of agents are correlated.

comprehend the task they are required to perform and makes the payoff structure more intuitive to understand. Second, to rule out the possibility that bank runs are caused by weak performance of the bank's long-term portfolio, we fix the rate of return of the long-term investment, $R$, throughout the experiment. Third, to create an environment with minimal change in economic parameters so that we can single out the role of miscoordination, we fix the second payoff relevant variable, the short-term interest rate, $r$, for a period of time (10 rounds) before it changes. During that period, subjects play exactly the same game, which makes it easier for them to focus solely on performing the coordination task implied by that game. The setup also allows us to observe how subjects interact with each other and how the aggregate economy evolves in each situation characterized by a different level of coordination requirement.

The change of the short-term interest rate, $r$, induces a change in the coordination parameter (denoted as $\eta$) while leaving the payoff difference between the two Nash equilibria fixed at $R-1$. The coordination parameter measures the amount of coordination that is required for agents who choose to withdraw late to receive a higher payoff than early withdrawers. We can calculate the value of the coordination parameter through two steps. First, solve the value of $z$, the number of depositors who choose to withdraw late, that equalizes the payoffs to early and late withdrawers:

$$r = \frac{N-(N-z)r}{z}R;$$

and denote it by $z^*$. Thus, $z^*$ is given by:

$$z^* = \frac{R(r-1)}{r(R-1)}N.$$

Second, divide $z^*$ by $N$ to get $\eta$, the fraction of depositors who withdraw at the second date, that equalizes the payoffs to early and late withdrawers:

$$\eta = \frac{z^*}{N} = \frac{R(r-1)}{r(R-1)}.$$

To systematically study the effect of the coordination parameter, we try 8 different values of $r$, or equivalently, $\eta$, in each session of experiment.

For each session of experiment, we enroll 10 subjects from graduate and upper level undergraduate economics classes. The program used to conduct the experiments is written in z-Tree (Fischbacher, 2007). During the experiments, subjects are each assigned a computer terminal through which they can input their decisions to withdraw early or late (see the Appendix for the experimental instructions). Communication among subjects is not allowed during the experiments.

Each experimental session consists of 8 phases. Each phase is characterized by a different $r$, or equivalently, $\eta$. Each phase lasts for 10 periods or rounds (see table 1). Throughout the experiments, $R$ is fixed at 2. Every subject begins each period with 1 experimental dollar ($ED$) in the bank and then makes a decision to withdraw or to leave money in the bank. Payoff tables for all 8 phases are provided to list the payoff that an individual will receive if he/she chooses to withdraw early or to leave money in the bank given that $n = 1 \sim 9$ of the other 9 subjects choose to withdraw early. The payoff tables help to reduce the calculation burden of the subjects so that they can focus on playing the coordination game. Once all subjects make their decisions, the total number of late withdrawers is calculated. Subjects' payoffs are then determined by equations (1) and (2). At the end of each round, subjects are presented with the history of their own actions, payoffs, and cumulative payoffs for the current period and all previous periods. A reminder is broadcast on the subjects' computer screens each time $r$ is changed. The first 10 periods (phase 0) are for trial purposes so that the subjects can familiarize themselves with the task to be performed. Subjects are paid only for the 7 formal phases. After the experiment, the total payoff that each subject earns is converted from $EDs$ into cash.

A total of 8 experimental sessions are conducted. For robustness check, we run experiments at different places and with different ordering of the coordination parameter. The experiments are run at three locations: Simon Fraser University (SFU), Burnaby, Canada; University of Manitoba (UofM), Winnipeg, Canada; and University of International Business and Economics (UIBE), Beijing, China. Among the 8 sessions of experiments, 4 have the coordination parameter increasing over time and 4 have it decreasing. The conversion rate used to pay subjects is 1 $ED = 0.2\ CAD$ at SFU and UofM, and 1 $ED = 0.8\ RMB$ at UIBE. The conversion rates from $ED$ to local currency are set such that participants on average earn about 1.5 times as much as they earn as tutors. All experiments are run in English. To ensure that the subjects in Beijing have sufficient English reading and listening skills, we restrict our subject pool to those who have passed the College English Test Grade IV, a standardized national English language test for college students in China. We also ensure that the subjects understand the experimental instructions by giving them 10 trial periods and several opportunities to ask questions before the formal experiments begin.

## 4 Experimental Results

In this section, we present and discuss the experimental results. Figure 1 plots the path of $z$, the number of late withdrawals, for the 8 sessions of experiments. Table 2 lists the starting, terminal, and mean values of the number of late withdrawals (denoted as $S$, $T$, and $M$ respectively) for each phase marked by a different value of $\eta$. To characterize the performance of the experimental economies, we define 8 performance categories: very close to the non-run equilibrium (NN), fairly close to the non-run equilibrium (FN), converging to the non-run equilibrium (CN), moderate high coordination (H), very close to the run equilibrium (RR), fairly close to the run equilibrium (FR), converging to the run equilibrium (CR) and moderate low coordination (L). The detailed definitions of the performance categories are provided in table 3. Table 4 categorizes the performance of the 8 sessions of experiments. In SFU1, UIBE1, UIBE3, and UofM1, $\eta$ increases from 0.1 to 0.9; in SFU2, UIBE2, UIBE4, and UofM2, $\eta$ decreases from 0.9 to 0.1. Three observations stand out.

*Finding* 1. *There is more coordination at late withdrawal when a lower amount of coordination is required.*

Note (in figure 1) the downward trend in the 4 experiments (left panel) with increasing $\eta$ and the upward trend in the 4 experiments (right panel) with decreasing $\eta$. As shown in table 2, the average number of late withdrawals tends to decrease with $\eta$.

*Finding* 2. *When the required amount of coordination is low (high), all experimental economies stay close or converge to the non-run (run) equilibrium. The experimental economies perform very differently when $\eta$ is equal to* 0.7.

As shown in table 4, when coordination is easy (when $\eta$ is 0.1, 0.2, 0.3, and 0.5), the economy stays very (or fairly) close to or converges to the non-run equilibrium; when coordination is difficult (when $\eta$ is 0.8 and 0.9), the economy stays very (or fairly) close to or converges to the run equilibrium. When $\eta \leq 0.5$, all economies are marked by NN, FN or CN. When $\eta \geq 0.8$, all economies are marked by RR, FR or CR. When $\eta = 0.7$, the experimental results are very different across the 8 sessions. UIBE1 starts with 6 subjects who coordinate on late withdrawals. This number proceeds up to 8 and then back to 6. This session is marked by "H". SFU1 begins with a high level of coordination with 8 subjects withdrawing late at first, but the number of late withdrawals goes down to 2. UIBE3 and UofM1 start with 7 subjects who coordinate on late withdrawals, but the number of late withdrawals eventually goes down to 0. These three sessions are marked by "CR". UIBE2, UIBE4, and UofM2 begin with very low coordination and stay there; they are marked by "RR". SFU2 starts with 6 subjects who coordinate on late withdrawal. This number goes up to 8. This session is marked by "CN".

The results of the experimental economies exhibit a threshold phenomenon: bank runs are frequently observed when coordination requirement is high enough (when $\eta \geq 0.8$) while they disappear when coordination requirement is low (when $\eta \leq 0.5$). Bank runs may occur or not when $\eta$ takes an intermediate value between 0.5 and 0.8, for example, 0.7.

*Finding 3. There is a stronger intra-phase learning effect for intermediate values of $\eta$.*

The experimental results show that the learning process is also affected by the coordination parameter. As seen in table 4, for intermediate values of $\eta$ (0.5, 0.7, and 0.8), it takes time for some economies to reach the equilibria as subjects learn from previous rounds and change their actions. For example, when $\eta$ is 0.5, two sessions are marked by "CN" (please refer to table 3 for definition of the performance categories); when $\eta$ is 0.7, four sessions are marked by either "CN" or "CR"; when $\eta$ is 0.8, three sessions are marked by "CR". When $\eta$ takes extreme values ( 0.1, 0.2, 0.3, and 0.9), the learning effect is weak: most agents keep their initial choices and the experimental economies reach either the run or the non-run equilibrium almost instantly. When $\eta$ is 0.1, 0.2, or 0.3, all sessions are marked by "NN"; when $\eta$ is 0.9, 7 sessions are marked by "RR" or "FR".

To ensure that the experimental results are robust, we try different ordering of the coordination parameter and run the experiment in two countries. A quick examination of figure 1 and table 4 shows that the experimental results are robust to the change of ordering of $\eta$ and locations. The three main findings are universally observed irrespective of the ordering of $\eta$ and the location of the experiments. In all 8 sessions, there is downward trend in the average number of late withdrawals as $\eta$ increases. The learning effect is stronger for intermediate values of $\eta$. As for the occurrence of bank runs, all 8 sessions exhibit the threshold phenomenon. When $\eta = 0.1$, 0.2, and 0.3, all sessions stay close to the non-run equilibrium and are marked by "NN" in table 4. When $\eta = 0.5$, all sessions settle down to the non-run equilibrium (marked by "NN", "FN" or "CN"). When $\eta = 0.8$ and 0.9, all sessions settle down to the run equilibrium (marked by "RR" or "CR"). When $\eta = 0.7$, for the increasing order, we have 1 session with moderate high coordination (marked by "H" and conducted in China) and 3 sessions marked by settling down to the run equilibrium (marked by "CR"). When $\eta$ takes the decreasing order, we have 1 session settling down to non-run equilibrium (marked by "CN" and conducted in Canada) and 3 sessions staying close to the run equilibrium (marked by "RR").[5]

The experimental results show that bank runs tend to occur when coordination requirement is high and vice versa. This threshold phenomenon reminds the audience easily of the threshold results in Heinemann et al. (2004, 2009) and DO (2010). All three papers find that individual subjects tend to play a threshold strategy in response to a changing payoff relevant variable. Using the notations of our paper $(c_e, c_\ell, z, z^*)$, we can rewrite the payoff function adopted in Heinemann et al. (2004, 2009) and DO as

$$c_e = \bar{x};\ c_\ell = \begin{cases} \bar{y} \text{ if } z \geq z^*(\bar{y}) \\ 0 \text{ if } z < z^*(\bar{y}) \end{cases}$$

where $z^{*\prime}(\bar{y}) \leq 0$ (upper bars on $x$ and $y$ mark that the payoffs to non-entry and successful entry

[5] To statistically investigate the ordering (country) effect, we separate the 8 sessions into two groups according to the ordering of $\eta$ (country), and run the Wilcoxon rank sum test on the staring, terminal, and mean value of the number of late withdrawals. The tests suggest there is no significant country effect. The ordering does affect the statistics for some $\eta$ values (when $\eta = 0.2$, 0.7, and 0.9) through interphase learning. When $\eta$ is 0.9, the starting, terminal, and mean values of the number of late withdrawers are significantly lower when $\eta$ descends over time. When the experiment starts with $\eta = 0.9$, subjects have no experience in playing with high $\eta$ and they try withdrawing late more often. When $\eta$ takes the increasing order, subjects have already accumulated some experience in playing with high $\eta$ (when $\eta$ was 0.8) before they play with $\eta = 0.9$ so they withdraw late less often. Similarly, when $\eta$ is 0.2 and follows an increasing order, subjects only have 10 periods' experience with very easy coordination when $\eta$ was 0.1. When $\eta$ decreases over time, more experience in playing with relatively easy coordination has been accumulated (when $\eta$ was 0.5 and 0.3) before the phase with $\eta = 0.2$, so subjects choose withdrawing late more often. As a result, for $\eta = 0.2$, the starting and mean values of $z$ are higher in sessions with decreasing $\eta$. When $\eta = 0.7$, the initial number of late withdrawals tends to be higher in sessions with increasing $\eta$. This fact can again be explained by an interphase learning effect: subjects tend to coordinate more (at late withdrawal) after they have observed more coordination in the past.

are independent of the number of entrants).[6] In Heinemann et al. (2004) and DO, the changing payoff relevant variable is $\bar{y}$ and the result is that most subjects choose to enter if $\bar{y}$ is high enough. In Heinemann et al. (2009), $\bar{x}$ changes and the finding is that most subjects decide to enter if $\bar{x}$ is low enough.

In Heinemann et al. (2004, 2009), in each round, subjects are presented a table of 10 situations each characterized by a different value of $\bar{y}$ or $\bar{x}$, and choose whether to enter or not under each situation. In DO, $\bar{y}$ changes in every round.[7] As a result, subjects have to consider many games all the time. For example, in Heinemann et al. (2004, 2009), subjects have to play 10 different games in the same round. This may make it difficult for subjects to focus on each single game. Juxtaposing 10 games together may also be conducive to the adoption of threshold strategies. To study whether bank runs can occur as a result of pure coordination failures, we try to minimize the change in the environment to make it easier for the subjects to focus solely on coordinating their action choices. For this purpose, we fix all payoff parameters for a period of 10 rounds. During the period, players play the same game and interact in a stable environment.

The experimental design in our paper also facilitates a systematic investigation of the effect of the coordination parameter. In Heinemann et al. (2004) and DO, the change of $\bar{y}$ induces a change in both the payoff difference, $\bar{y}-\bar{x}$, and the coordination parameter, $z^*(\bar{y})$, which makes it difficult to disentangle the effects of the two factors. Heinemann et al. (2009) fix $\bar{y}$ and study how individual choices depend on $\bar{x}$ (which changes the payoff difference between the two equilibria) and how this relationship is affected by the level of coordination requirement.[8] In our paper, $R$ is fixed and $r$ only changes the coordination parameter, $\eta$, while leaving the payoff difference fixed at $R-1$. As a result, we can be more confident that the different outcomes in different phases of the experimental economies are due to the change in the coordination parameter. Repeating the same game with the same coordination requirement also allows us to catch its effect on the learning process. As stated in finding 3, we find that the learning effect is stronger for intermediate coordination requirement. This result has not been captured by other experimental studies of coordination games. For example,

[6] In our experiments, $c_e$ and $c_\ell$ depend on the number of entrants, or late withdrawers.

[7] DO also try to directly elicit the threshold strategy through the within subject design by asking subjects to choose a threshold before revealing $\bar{y}$ in each round.

[8] They try three levels of coordination requirement ($z^* = 1/3, 2/3$ and 1) and find that the threshold with respect to $\bar{x}$ increases when $z^*$ decreases.

Van Huyck et al. (1991) find that the initial coordination behavior well predicts the final outcomes in repeated coordination games. Heinemann et al. (2004) and Klos and Sträter (2010) find the value of the thresholds adopted by individual subjects changes little across time. Citing the result of weak learning effect in previous studies, Heinemann et al. (2009) study non-repeated games and focus solely on the initial coordination behavior.

Finally, we would like to comment on the value of the threshold of bank runs exhibited in our experiments. As mentioned in finding 2, bank runs are frequent events when $\eta \geq 0.8$ while they disappear when $\eta \leq 0.5$. When $\eta = 0.7$, we observe huge variation across different sessions. Since we do not try all values between 0.5 and 0.8, we cannot determine the exact value(s) of the threshold for the occurrence of bank runs. However, we can conclude the threshold is larger than 0.5 and less than 0.8. This is consistent with the results in Heinemann et al. (2004) that the threshold chosen by subjects seems to be the best response to the belief that each other player chooses to enter with probability of $0.6 \sim 0.7$, and that equilibria with coordination requirement higher than 0.8 are never observed.

## 5 The Evolutionary Learning Algorithm

The evolutionary algorithm (Young, 1993 and Kandori et al., 1993) has been introduced as an equilibrium selection mechanism into many rational expectation models with multiple equilibria and have greatly contributed to the understanding of these models. Temzelides (1997) applies the evolutionary algorithm to a repeated version of the DD model.[9] The algorithm has two main components. The first is myopic best response with inertia. Myopic best response means that when agents react to the environment, they respond by choosing the strategy that performed better in the previous period. In the context of the DD model, the myopic best response is to withdraw early if the number of late withdrawers in the previous period, $z_{t-1}$, is $\leq z^*$, and to withdraw late otherwise. There is inertia in the sense that not all agents react instantaneously to the environment. The second component is experimentation, during which agents change their strategies at random

[9] One may question the appropriateness of using learning or evolutionary algorithms for bank runs since bank runs are nowadays rare events (due to the existence of explicit or implicit deposit insurance). However, there are some historical episodes of frequent bank runs. For example, the 1932-33 banking panic in the United States was so severe that it induced president Roosevelt to enact the federal deposit insurance program. A wave of runs on financial firms has also been observed during the recent financial crisis.

with probability $\delta$. In the context of the DD model, experimentation involves flipping strategies from early to late withdrawal or vice versa.

In the standard version of the evolutionary algorithm, the probabilities of engaging in best response and experimentation are governed by some exogenous process. For example, in the algorithm used in Temzelides (1997), agents always play myopic best response, and the probability of experimentation is fixed and iid across subjects and time. Temzelides (1997) proves that as the probability of experimentation approaches zero, the economy stays at the non-run equilibrium with probability one if and only if it is risk dominant, or when $\eta < 0.5$. In other words, Temzelides (1997) predicts $\eta = 0.5$ as the watershed for the occurrence of bank runs. Our experimental results, however, suggest a higher threshold: when $\eta = 0.5$, all 8 experimental economies stay close or converge to the non-run equilibrium and only when $\eta = 0.7$ do we observe huge variation across different sessions. As mentioned at the end of last section, Heinemann et al. (2004) also suggest a higher threshold than 0.5 (their estimate is between 0.6 and 0.7). To resolve the discrepancy between the results in Temzelides (1997) and the experimental studies, we modify the learning algorithm in Temzelides (1997). In particular, we allow individual strategies to depend on their information sets.

First, instead of assuming that agents always play best response, we let the decision be based on whether they can infer what the "best response" was, i.e., whether $z_{t-1} > z^*$. Those who do not have the information play "inertia". During the experiments, subjects who withdrew late in the previous period (*late withdrawers*) can always infer what the best response was. If they had payoff higher than $r$, they can infer that $z_{t-1} > z^*$ and that withdrawing late was the better strategy. They infer that the reverse is true if their payoff was less than $r$. Subjects who chose to withdraw early in the previous period (*early withdrawers*) may or may not be able to infer whether $z_{t-1} > z^*$ depending on their payoffs in the past period. They can infer that $z_{t-1} < z^*$ and that withdrawing early was the best response if they received less than $r$. If their payoff was higher than $r$, they do not have enough information to tell whether $z_{t-1} > z^*$ and as a result, play inertia and keep the same strategy as before.

Second, after best response with inertia, agents experiment by flipping their strategies with some probabilities. The rate of experimentation depends on their information sets. During the experiments, subjects know $r$ and thus $\eta$ all the time. They can also try to infer $z_{t-1}$, the number of late withdrawals in the previous period, by looking at their individual payoffs and the payoff tables (see the experimental instructions in the Appendix). Remember that $\eta$ measures how difficult the coordination task is. The number of late withdrawals in the previous period shows how the group coordinated in the past. Both $\eta$ and $z_{t-1}$ may influence a subject's belief about what other subjects will do in the next period, which in turn may affect the subject's strategy choice. For those who cannot infer the exact value of $z_{t-1}$ (*uninformed subjects*), the rate of experimentation depends only on $\eta$. For those who can infer the exact value of $z_{t-1}$ (*informed subjects*), the rate of experimentation depends on both $\eta$ and $z_{t-1}$. Early withdrawers can infer the value of $z_{t-1}$ only when they were paid less than $r$ in the previous period. Late withdrawers can infer $z_{t-1}$ only when they received positive payoffs in the previous period.

In the following, we first run logit regressions to estimate the probability of experimentation from the experimental data. The estimated probabilities are then used to simulate time paths of the number of late withdrawals. Finally, we compare the simulation outcomes with the results from experiments with human subjects.

Note that as a result of the myopic best response play with inertia, only informed late withdrawers (who received payoffs higher than $r$) choose to withdraw late. All other agents (early withdrawers and uninformed late withdrawers) choose to withdraw early. Therefore, we run three logit regressions: one for the probability of flipping from early to late withdrawal for informed agents (denoted as $\delta^i_{e\ell}$), one for the probability of changing in the same direction for uninformed agents (denoted as $\delta^u_{e\ell}$), and one for the probability of changing in the reverse direction (denoted as $\delta_{\ell e}$). There are 8 experimental sessions, each session has 10 players and 7 phases, each phase is run for 10 periods generating 9 observations for each player if the initial actions are taken as given. The total number of observations is given by $8 \times 10 \times 7 \times 9 = 5040$. Table 5 lists the number of observations for each of the three logit regressions. The number and rate of observed experimentation are also listed.

According to feedback from subjects, the difference between $z_{t-1}$ and $z^*$ played an important role in determining the probability that subjects experiment with a strategy, even though they know that the other strategy gave a higher payoff in the previous period. In view of this, we use the term

$(z_{t-1} - z^*)$ as the regressor to estimate $\delta^i_{e\ell}$ and $\delta_{\ell e}$, the experimentation rates for informed agents. Note that $z^* = \eta N$ so $z^*$ contains information about $\eta$. The expected sign of $(z_{t-1} - z^*)$ is positive in the case of $\delta^i_{e\ell}$, meaning that agents are more likely to change strategies to late withdrawal as $z_{t-1}$ moves closer to $z^*$ from below. The expected sign of $(z_{t-1} - z^*)$ is negative for $\delta_{\ell e}$, meaning that the probability of experimentation from late to early withdrawal increases as $z_{t-1}$ moves closer to $z^*$ from above. For uninformed agents, we use $\eta$ as the regressor. In the estimation of $\delta^u_{e\ell}$, the expected sign of $\eta$ is negative, meaning that uninformed subjects are less likely to flip strategy from early to late withdrawal as coordination becomes more difficult.

The first logit regression investigates the rate at which informed agents change strategy from early to late withdrawal. The rate $\delta^i_{e\ell}$ is modelled as

$$\text{logit }(\delta^i_{e\ell}) = log\left(\frac{\delta^i_{e\ell}}{1-\delta^i_{e\ell}}\right) = \alpha_0 + \alpha_1(z_{t-1} - z^*).$$

The regression result is presented in table 6. The coefficient of $(z_{t-1} - z^*)$ is very significant (the $p$-value is 0) and has the expected sign. The probability of experimentation from early to late withdrawal for informed subjects increases as $z_{t-1}$ moves closer to $z^*$ from below. This fact means that even though informed subjects know withdrawing early was the better strategy (which gives payoff $r$) in the previous period, they may be willing to try withdrawing late, hoping that a better coordination will occur in the next period and that they can receive a higher payoff than $r$. The estimated probability of experimentation from early to late withdrawal is

$$\delta^i_{e\ell}(z_{t-1}, \eta) = \frac{1}{1 + e^{-0.74-0.51(z_{t-1}-z^*)}}. \tag{3}$$

The second logit regression examines the rate of experimentation from early to late withdrawal for uninformed agents. The experimentation rate $\delta^u_{e\ell}$ depends only on $\eta$ and is modelled as

$$\text{logit }(\delta^u_{e\ell}) = log\left(\frac{\delta^u_{e\ell}}{1-\delta^u_{e\ell}}\right) = \beta_0 + \beta_1\eta.$$

The result of the regression is presented in table 7. The coefficient of $\eta$ is significantly negative (the $p$-value is 0) meaning that uninformed agents are less likely to change from early to late withdrawal if $\eta$ is higher, or as coordination becomes more difficult. The estimated probability of experimentation from early to late withdrawal is given by

$$\delta^u_{e\ell}(\eta) = \frac{1}{1 + e^{-1.03+2.74\,\eta}}. \quad (4)$$

The third logit regression estimates the rate of experimentation from late to early withdrawal. As mentioned earlier, those who choose to withdraw late as a result of myopic best response with inertia are late withdrawers who are informed about $z_{t-1}$. The term $(z_{t-1} - z^*)$ is used as the regressor to estimate $\delta_{\ell e}$:

$$\text{logit } (\delta_{\ell e}) = log\left(\frac{\delta_{\ell e}}{1 - \delta_{\ell e}}\right) = \gamma_0 + \gamma_1(z_{t-1} - z^*).$$

Table 8 shows the regression result. The coefficient of $(z_{t-1} - z^*)$ is negative and significant (the $p$-value is 0) meaning that subjects are less likely to change actions from late to early withdrawal if $(z_{t-1} - z^*)$ increases or the number of late withdrawals in the previous period moves further above $z^*$. The expected experimentation rate from late to early withdrawal is given by

$$\hat{\delta}_{\ell e}(z_{t-1}, \eta) = \frac{1}{1 + e^{3.04+0.24(z_{t-1}-z^*)}}. \quad (5)$$

We now apply the modified evolutionary algorithm and use the estimated probability of experimentation to simulate the path of the number of late withdrawals. We use the same model parameters that were used in experiments with subjects: there are 10 simulation subjects, 7 phases or values of $\eta$, and 10 rounds in each phase. Each simulation adopts the starting values (S) in one of the 8 experimental sessions.

In the following, we illustrate the simulation process using the starting values of SFU1. The starting values of $z$ in the 7 phases are respectively 10, 9, 10, 10, 8, 2 and 1. In each phase, strategies in the first round are set to match the starting value of $z$. For example, in phase 1, the simulation economy starts with all 10 agents withdrawing late so that $z$ is equal to 10 in the first round. From round 2 on, each simulation agent updates its strategy according to the rules of the modified evolutionary algorithm. First, the agent plays best myopic response with inertia updating strategy if it can infer whether or not $z_{t-1} > z^*$. Second, after the myopic best response with inertia, the agent experiments by flipping strategies. The probability of experimentation depends on the agent's information set and is calculated from equation (3), (4) or (5). For example, if the agent chooses early withdrawal as the strategy after the myopic best response play and knows the value of $z_{t-1}$, the probability of changing strategy to late withdrawal is given by $\delta^i_{e\ell}(z_{t-1}, \eta)$. After each agent's strategy is determined, we calculate the number of late withdrawals. Each simulation is run for 70 periods, generating 70 values of $z$.

We run 100 simulations for each set of starting values. In table 9, we list the minimum, maximum, and average (across the 100 simulations) of the terminal (T) and mean value (M) of $z$ for each phase or $\eta$. For example, the 100 simulations using SFU1 starting values generate the following result. For $\eta = 0.1$, the minimum, maximum, and average value of the 100 terminal values are 9, 10, and 9.9, respectively. Table 10 lists the frequencies at which the simulated economies fall into each of the 8 performance categories: "NN", "FN", "CN", "H", "RR", "FR", "CR", and "L" as defined in table 3. An investigation of tables 9 and 10 shows that the modified evolutionary algorithm captures the main features of the experimental data. For instance, the economies stay close to or converge to the non-run equilibrium when $\eta$ is small. For $\eta = 0.1$, 0.2 and 0.3, all simulated economies stay close to the non-run equilibrium, spending 100% of the time at "NN" or "FN". When $\eta = 0.5$, all economies spend more than 98% of the time at "NN", "FN" or "CN" (and very occasionally at "H"). When $\eta = 0.8$ and 0.9, all simulated economies spend more than 99% of the time at "RR", "FR" or "CR" (and very occasionally at "L"). When $\eta = 0.7$, as in the actual experiments, the simulated economies produce very different results, spending a positive amount of time in each of the 8 performance categories. We also provide a plot of a sample simulated time path of $z$ in figure 2, which looks very similar to the time path of $z$ from experiments with subjects. Compared with the standard evolutionary algorithm in Temzelides (1997), the modified algorithm replicates the experimental data more closely, and successfully captures 0.7 as the watershed for coordination.

## 6 Conclusion

In this paper, we take an experimental approach to studying the possibility and conditions under which bank runs occur purely as a result of coordination failures. To do that, we enroll human subjects to act as depositors and play a repeated version of the game defined by a demand deposit contract. We fix the rate of return of the bank's long-term investments to rule out the deterioration of the bank's assets as the source of bank runs. The only variation in the experiments is that the coordination parameter, which measures the amount of coordination that is required for late withdrawers to receive a higher payoff than early withdrawers, changes every 10 periods. We find that bank runs can happen as the result of pure coordination failures, but only when the required coordination is high enough. In particular, bank runs are frequently (rarely) observed if the coordination parameter is $\geq 0.8$ ($\leq 0.5$). When the coordination parameter is in the middle (for example, 0.7), the performance of the experimental economies becomes unpredictable. At the same time, there is a stronger learning effect for intermediate coordination requirement.

In order to capture the observed features of the experimental data, we use an evolutionary algorithm with myopic best response with inertia and experimentation. We modify the standard algorithm as in Temzelides (1997) to make the probabilities of playing best response and experimentation depend on the subjects' information sets: the coordination parameter and possibly the history of the number of late withdrawals. The modified algorithm is able to replicate the main features of the experimental results.

Finally, DD originally attribute banks runs to the realization of a sunspot variable. In this paper, we do not pursue the sunspot explanation. Instead, we study whether bank runs can occur as a result of pure coordination failures in the absence of a sunspot variable. Sunspot behavior, especially in the context of a model with equilibria that can be Pareto ranked such as the bank run model, is rarely observed in controlled experiments with human subjects. Duffy and Fisher (2005) and Fehr et al. (2011) have provided direct evidence of sunspots in the laboratory. However, the payoff structure is such that the multiple equilibria are not Pareto rankable or are Pareto equivalent. Most recently, Arifovic et al. (2011) generate some initial experimental evidence of sunspot behavior when the payoff structure is associated with multiple equilibria that can be Pareto ranked. One important finding is that training with respect to the sunspot variable during the practice period is crucial for the observation of sunspot behavior in later periods.[10] The experimental results in our paper suggest that the level of coordination requirement may also be an important factor that affects the occurrence of sunspot behavior. In the experiments, there is little ambiguity when the coordination parameter is $\leq 0.5$ or $\geq 0.8$, but a huge variation in performance when the coordination is equal to 0.7. This seems to suggest that sunspot behavior is more likely to be observed when the coordination parameter lies between 0.5 and 0.8. We intend to pursue the studies in the future to test directly the sunspot-based theory of bank runs, and at the same time, provide more experimental evidence about sunspot behavior in games with multiple equilibria that can be Pareto-ranked.

[10] The training is achieved by building a correlation between the realization of the sunspot variable and the aggregate outcome. The process is determined by the experimenter and is not known to the subjects.

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**Table 1: Parameters Used in the Experiment**

| Phase | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| $r$ | 1.43 | 1.05 | 1.11 | 1.18 | 1.33 | 1.54 | 1.67 | 1.82 |
| $\eta$ | 0.60 | 0.10 | 0.20 | 0.30 | 0.50 | 0.70 | 0.80 | 0.90 |
| Period (increasing $\eta$) | -9-0 | 1-10 | 11-20 | 21-30 | 31-40 | 41-50 | 51-60 | 61-70 |
| Period (decreasing $\eta$) | -9-0 | 61-70 | 51-60 | 41-50 | 31-40 | 21-30 | 11-20 | 1-10 |

**Table 2: Mean, Starting and Terminal Value of the Number of Late Withdrawals**

| | 0.1 | | | 0.2 | | | 0.3 | | | 0.5 | | | 0.7 | | | 0.8 | | | 0.9 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | S | T | M | S | T | M | S | T | M | S | T | M | S | T | M | S | T | M | S | T | M |
| SFU1 | 10 | 9 | 9.8 | 9 | 9 | 9.7 | 10 | 9 | 9.7 | 10 | 9 | 9.6 | 8 | 2 | 1.1 | 2 | 0 | 3.1 | 1 | 0 | 0.2 |
| UIBE1 | 10 | 10 | 10 | 9 | 10 | 9.9 | 10 | 9 | 9.7 | 8 | 10 | 9.3 | 6 | 6 | 1.2 | 2 | 0 | 7.5 | 1 | 0 | 0.2 |
| UIBE3 | 9 | 10 | 9.8 | 8 | 10 | 9.5 | 10 | 10 | 10 | 9 | 10 | 9.6 | 7 | 0 | 0.4 | 3 | 0 | 2.1 | 0 | 0 | 0 |
| UofM1 | 8 | 10 | 9.7 | 10 | 10 | 9.9 | 9 | 10 | 9.8 | 9 | 10 | 9.9 | 7 | 0 | 0.7 | 1 | 0 | 2.2 | 0 | 0 | 0.1 |
| SFU2 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 9.8 | 6 | 9 | 1.9 | 6 | 0 | 7.9 | 4 | 2 | 2.2 |
| UIBE2 | 10 | 10 | 10 | 10 | 10 | 9.9 | 8 | 10 | 9.7 | 4 | 8 | 7.2 | 1 | 0 | 0.5 | 1 | 0 | 0.4 | 1 | 1 | 0.6 |
| UIBE4 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 6 | 9 | 8.7 | 0 | 0 | 0.7 | 2 | 0 | 0.5 | 1 | 0 | 0.5 |
| UofM2 | 10 | 9 | 9.7 | 10 | 10 | 10 | 8 | 9 | 9.6 | 4 | 9 | 7.8 | 1 | 0 | 0.6 | 1 | 1 | 1 | 3 | 3 | 2 |

**Table 3: Performance Classification**

| Category | Label | Criterion |
|---|---|---|
| Very close to the non-run equilibrium | NN | $\text{M} \geq 9$ |
| Fairly close to the non-run equilibrium | FN | $8 \leq \text{M} < 9$ |
| Converging to the non-run equilibrium | CN | $5 < \text{M} < 8$ and $\text{T} \geq 8$ |
| Moderate high coordination | H | $5 < \text{M} < 8$ and $\text{T} < 8$ |
| Very close to the run equilibrium | RR | $\text{M} \leq 1$ |
| Fairly close to the run equilibrium | FR | $1 < \text{M} \leq 2$ |
| Converging to the run equilibrium | CR | $2 < \text{M} < 5$ and $\text{T} \leq 2$ |
| Moderate low coordination | L | $2 < \text{M} < 5$ and $\text{T} > 2$ |

**Table 4: Performance of the Experimental Economies**

| $\eta$ | 0.1 | 0.2 | 0.3 | 0.5 | 0.7 | 0.8 | 0.9 |
|---|---|---|---|---|---|---|---|
| SFU1 | NN | NN | NN | NN | CR | CR | RR |
| UIBE1 | NN | NN | NN | NN | H | CR | RR |
| UIBE3 | NN | NN | NN | NN | CR | RR | RR |
| UofM1 | NN | NN | NN | NN | CR | RR | RR |
| SFU2 | NN | NN | NN | NN | CN | CR | CR |
| UIBE2 | NN | NN | NN | CN | RR | RR | RR |
| UIBE4 | NN | NN | NN | FN | RR | RR | RR |
| UofM2 | NN | NN | NN | CN | RR | RR | FR |

**Table 5: Observations for Logit Regression and Overall Experimentation Rates**

| | | Number of Obs. | Number of Experimentation | Experimentation Rate (%) |
|---|---|---|---|---|
| $s_b = e$ | Informed | 1824 | 149 | 8.17 |
| | Uninformed | 336 | 108 | 32.1 |
| $s_b = \ell$ | Informed | 2880 | 31 | 1.08 |

**Table 6: Logit Regression of Experimentation from Early to Late Withdrawal (Informed Subjects)**

| Experimentation from Early to Late Withdrawal | Coefficient | Standard Error. | $t$-statistic | $p$-value |
|---|---|---|---|---|
| $z_{t-1} - z^*$ | 0.51 | 0.04 | 13.93 | 0.00 |
| Constant | 0.74 | 0.22 | 3.30 | 0.00 |

**Table 7: Logit Regression of Experimentation from Early to Late Withdrawal (Uninformed Subjects)**

| Experimentation from Early to Late Withdrawal | Coefficient | Standard Error. | $t$-statistic | $p$-value |
|---|---|---|---|---|
| $\eta$ | -2.74 | 0.62 | -4.43 | 0.00 |
| Constant | 1.03 | 0.41 | 2.49 | 0.01 |

**Table 8: Logit Regression of Experimentation from Late to Early Withdrawal**

| Experimentation from Late to Early Withdrawal | Coefficient | Standard Error. | $t$-statistic | $p$-value |
|---|---|---|---|---|
| $z_{t-1}-z^*$ | -0.24 | 0.07 | -3.40 | 0.00 |
| Constant | -3.04 | 0.04 | -7.10 | 0.00 |

**Table 9: Starting, Terminal and Mean Value of the Number of Late Withdrawals in Simulated Economies**

| | | 0.1 | | | 0.2 | | | 0.3 | | | 0.5 | | | 0.7 | | | 0.8 | | | 0.9 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | S | T | M | S | T | M | S | T | M | S | T | M | S | T | M | S | T | M | S | T | M |
| | Min | | 9 | 9.5 | | 9 | 9.1 | | 8 | 9.2 | | 7 | 8.6 | | 0 | 1.8 | | 0 | 0.2 | | 0 | 0.1 |
| SFU1 | Max | 10 | 10 | 10 | 9 | 10 | 9.9 | 10 | 10 | 10 | 10 | 10 | 10 | 8 | 10 | 9.8 | 2 | 5 | 2.8 | 1 | 3 | 1.1 |
| | Ave | | 9.9 | 9.9 | | 9.9 | 9.7 | | 9.8 | 9.8 | | 9.7 | 9.7 | | 6.5 | 7.5 | | 0.5 | 0.9 | | 0.3 | 0.4 |
| | Min | | 9 | 9.5 | | 9 | 9.1 | | 8 | 9.2 | | 7 | 7.9 | | 0 | 1 | | 0 | 0.2 | | 0 | 0.1 |
| UIBE1 | Max | 10 | 10 | 10 | 9 | 10 | 9.9 | 10 | 10 | 10 | 8 | 10 | 9.8 | 6 | 10 | 9 | 2 | 5 | 2.8 | 1 | 3 | 1.1 |
| | Ave | | 9.9 | 9.9 | | 9.9 | 9.7 | | 9.8 | 9.8 | | 9.6 | 9.2 | | 1.9 | 3 | | 0.5 | 0.9 | | 0.3 | 0.4 |
| | Min | | 9 | 9.4 | | 9 | 8.7 | | 8 | 9.2 | | 7 | 8.3 | | 0 | 1.5 | | 0 | 0.3 | | 0 | 0 |
| UIBE3 | Max | 9 | 10 | 9.9 | 8 | 10 | 9.8 | 10 | 10 | 10 | 9 | 10 | 9.9 | 7 | 10 | 9.2 | 3 | 5 | 2.9 | 0 | 3 | 1 |
| | Ave | | 9.9 | 9.8 | | 9.9 | 9.6 | | 9.8 | 9.8 | | 9.7 | 9.5 | | 2.1 | 3.6 | | 0.5 | 1.1 | | 0.3 | 0.3 |
| | Min | | 9 | 9.2 | | 9 | 9.4 | | 8 | 8.8 | | 7 | 8.3 | | 0 | 1.5 | | 0 | 0.1 | | 0 | 0 |
| UofM1 | Max | 8 | 10 | 9.8 | 10 | 10 | 10 | 9 | 10 | 9.9 | 9 | 10 | 9.9 | 7 | 10 | 9.2 | 1 | 5 | 2.4 | 0 | 3 | 1 |
| | Ave | | 9.9 | 9.6 | | 9.9 | 9.9 | | 9.8 | 9.7 | | 9.7 | 9.5 | | 2.1 | 3.6 | | 0.5 | 0.7 | | 0.3 | 0.3 |
| | Min | | 9 | 9.5 | | 9 | 9.4 | | 8 | 9.2 | | 7 | 8.6 | | 0 | 1 | | 0 | 0.7 | | 0 | 0.4 |
| SFU2 | Max | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 6 | 10 | 9 | 6 | 5 | 3.6 | 4 | 3 | 1.7 |
| | Ave | | 9.9 | 9.9 | | 9.9 | 9.9 | | 9.8 | 9.8 | | 9.7 | 9.7 | | 1.9 | 3 | | 0.5 | 1.7 | | 0.3 | 0.9 |
| | Min | | 9 | 9.5 | | 9 | 9.4 | | 8 | 8.8 | | 7 | 3 | | 0 | 0.2 | | 0 | 0.1 | | 0 | 0.1 |
| UIBE2 | Max | 10 | 10 | 10 | 10 | 10 | 10 | 8 | 10 | 9.8 | 4 | 10 | 9.1 | 1 | 10 | 7.4 | 1 | 5 | 2.4 | 1 | 3 | 1.1 |
| | Ave | | 9.9 | 9.9 | | 9.9 | 9.9 | | 9.8 | 9.5 | | 9.5 | 7.5 | | 1.6 | 1.3 | | 0.5 | 0.7 | | 0.3 | 0.4 |
| | Min | | 9 | 9.5 | | 9 | 9.4 | | 8 | 9.2 | | 7 | 7 | | 0 | 0.1 | | 0 | 0.2 | | 0 | 0.1 |
| UIBE4 | Max | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 10 | 6 | 10 | 9.6 | 0 | 6 | 3 | 2 | 5 | 2.8 | 1 | 3 | 1.1 |
| | Ave | | 9.9 | 9.9 | | 9.9 | 9.9 | | 9.8 | 9.8 | | 9.6 | 8.7 | | 1.5 | 1.1 | | 0.5 | 0.9 | | 0.3 | 0.4 |
| | Min | | 9 | 9.5 | | 9 | 9.4 | | 8 | 8.8 | | 7 | 3 | | 0 | 0.2 | | 0 | 0.1 | | 0 | 0.3 |
| UofM2 | Max | 10 | 10 | 10 | 10 | 10 | 10 | 8 | 10 | 9.8 | 4 | 10 | 9.1 | 1 | 10 | 7.4 | 1 | 5 | 2.4 | 3 | 3 | 1.5 |
| | Ave | | 9.9 | 9.9 | | 9.9 | 9.9 | | 9.8 | 9.5 | | 9.5 | 7.5 | | 1.6 | 1.3 | | 0.5 | 0.7 | | 0.3 | 0.7 |

**Table 10: Performance of Simulated Economies**

| | | 0.1 | 0.2 | 0.3 | 0.5 | 0.7 | 0.8 | 0.9 | | | 0.1 | 0.2 | 0.3 | 0.5 | 0.7 | 0.8 | 0.9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | NN | 100 | 100 | 100 | 98 | 41 | | | | NN | 100 | 100 | 100 | 98 | 1 | | |
| | FN | | | | 2 | 26 | | | | FN | | | | 2 | 3 | | |
| | CN | | | | | | | | | CN | | | | | 2 | | |
| SFU1 | H | | | | | 10 | | | SFU2 | H | | | | | 3 | | |
| | RR | | | | | | 75 | 99 | | RR | | | | | 1 | 85 | 100 |
| | FR | | | | | 1 | 21 | 1 | | FR | | | | | 25 | 13 | |
| | CR | | | | | 19 | 4 | | | CR | | | | | 53 | 2 | |
| | L | | | | | 3 | | | | L | | | | | 12 | | |
| | NN | 100 | 100 | 100 | 70 | 1 | | | | NN | 100 | 100 | 97 | 3 | | | |
| | FN | | | | 29 | 3 | | | | FN | | | 3 | 36 | | | |
| | CN | | | | 1 | 2 | | | | CN | | | | 59 | 1 | | |
| UIBE1 | H | | | | | 3 | | | UIBE2 | H | | | | 1 | | | |
| | RR | | | | | 1 | 75 | 99 | | RR | | | | | 42 | 85 | 99 |
| | FR | | | | | 25 | 21 | 1 | | FR | | | | | 42 | 13 | 1 |
| | CR | | | | | 53 | 4 | | | CR | | | | | 6 | 2 | |
| | L | | | | | 12 | | | | L | | | | | 9 | | |
| | NN | 100 | 99 | 100 | 90 | 3 | | | | NN | 100 | 100 | 100 | 29 | | | |
| | FN | | 1 | | 10 | 6 | | | | FN | | | | 65 | | | |
| | CN | | | | | | | | | CN | | | | 5 | | | |
| UIBE3 | H | | | | | 6 | | | UIBE4 | H | | | | 1 | | | |
| | RR | | | | | | 63 | 100 | | RR | | | | | 61 | 75 | 99 |
| | FR | | | | | 11 | 30 | | | FR | | | | | 29 | 21 | 1 |
| | CR | | | | | 60 | 6 | | | CR | | | | | 6 | 4 | |
| | L | | | | | 14 | 1 | | | L | | | | | 4 | | |
| | NN | 100 | 100 | 98 | 90 | 3 | | | | NN | 100 | 100 | 97 | 3 | | | |
| | FN | | | 2 | 10 | 6 | | | | FN | | | 3 | 36 | | | |
| | CN | | | | | | | | | CN | | | | 59 | 1 | | |
| UofM1 | H | | | | | 6 | | | UofM2 | H | | | | 1 | | | |
| | RR | | | | | | 85 | 100 | | RR | | | | | 42 | 85 | 90 |
| | FR | | | | | 11 | 13 | | | FR | | | | | 42 | 13 | 10 |
| | CR | | | | | 60 | 2 | | | CR | | | | | 6 | 2 | |
| | L | | | | | 14 | | | | L | | | | | 9 | | |

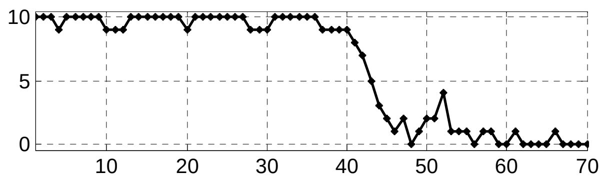



Figure 1: Experimental Results

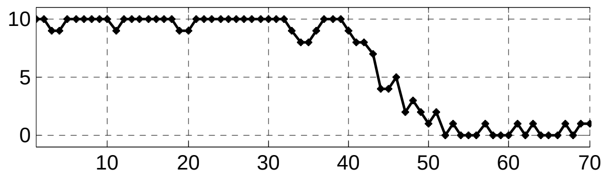



Figure 2: Sample Simulated Path of Number of Late Withdrawals

**Appendix**

**Experimental Instructions - Increasing Order of the Coordination Parameter**

This experiment has been designed to study decision-making behavior in groups. During today's session, you will earn income in an experimental currency called experimental dollars or for short $ED$. At the end of the session, the currency will be converted into dollars. 1 $ED$ corresponds to 0.2 dollars. You will be paid in cash. The participants may earn different amounts of money in this experiments because each participant's earnings are based partly on his/her decisions and partly on the decisions of the other group members. If you follow the instructions carefully and make good decisions, you may earn a considerable amount of money. Therefore, it is important that you do your best.

Please read these instructions carefully. You will be required to complete a quiz, in order to demonstrate that you have a complete and accurate understanding of these instructions. After you have completed the quiz, the administrator will check your answers and discuss with you any questions that have been answered incorrectly.

**Description of the task**

You and 9 **other people** (there are 10 of you altogether) each have 1 $ED$ deposited in an experimental bank. You must decide whether to withdraw your 1 $ED$ or leave it deposited in the bank. The bank promises to pay $r > 1$ $EDs$ to each withdrawer. The money that remains in the bank will earn interest rate $R > r$. At the end, the bank will divide what it has evenly among people who choose to leave money in the bank. Note that if too many people desire to withdraw, the bank may not be able to fulfill the promise to pay $r$ to each withdrawer (remember that $r > 1$). In that case, the bank will divide the 10 $EDs$ evenly among the withdrawers and those who choose to wait will get nothing.

Your payoffs depend on your own decision and the decisions of the other 9 people in the group. Specifically, how much you receive if you make a withdrawal request or how much you earn by leaving money deposited depends on how many people in the group place withdrawing requests.

Let $e$ be the number of people who request withdrawals.

The payoff (in $ED$) to those who withdraw will be:

$$\min\{r, \tfrac{10}{e}\} \text{ or the minimum of } r \text{ and } \tfrac{10}{e}.$$

The payoff (in $ED$) to those who leave money in the bank will be:

$$\max\{0, \tfrac{10-er}{10-e}R\} \text{ or the maximum of 0 and } \tfrac{10-er}{10-e}R.$$

In the experiment, $R$ will be fixed at 2.0. There are 8 values of $r$: 1.43, 1.05, 1.11, 1.18, 1.33, 1.54, 1.67 and 1.82. To facilitate your decision, the payoff tables $0 \sim 7$ list the payoffs if $n$ **of the other** 9 **subjects** request to withdraw ($n$ is unknown at the time when you make the withdrawing decision – it can be any integer from 1 to 9 – and you have to guess it) for each of the 8 situations. Table 0 will be used for practice, and table $1 \sim 7$ will be used for the formal experiment. Let's look at two examples:

*Example* 1. Use table 0 where $r = 1.43$. Suppose that 3 other subjects request withdrawals. Your payoff will be 1.43 if you request to withdraw (the number of withdrawing requests $e$ will be $3 + 1 = 4$, and your payoff is $\min\{r = 1.43, \frac{10}{e} = \frac{10}{4} = 2.5\} = 1.43$). If you choose to leave money in the bank, your payoff will be 1.63 (the number of withdrawing requests $e = 3$, and your payoff is $\max\{0, \frac{10-er}{10-e}R = \frac{10-3\times1.43}{10-3}2.0 = 1.63\} = 1.63$).

*Example* 2. Use table 7 where $r = 1.82$. Suppose that 6 of other subjects request withdrawals. Your payoff from withdrawing will be $\min\{1.82, \frac{10}{e} = \frac{10}{7} = 1.43\} = 1.43$ and your payoff for leaving money in the bank will be $\max\{0, \frac{10-6\times1.82}{10-6}2.0 = -0.46\} = 0$.

Now let us take a closer look at the tables. Note the following features of tables:

- The payoff to withdrawing is more stable, it is fixed at $r$ for most of the time and is bounded below by 1.
- The payoff to leaving money in the bank is more volatile. When $n$ – the number of other people requesting withdrawals – is small, leaving money in the bank offers higher payoff than withdrawing. The opposite happens when $n$ is large enough. For your convenience, bold face is used to identify the threshold value of $n$ at which withdrawing starts to pay equal to or higher than leaving money in the bank.
- The threshold values of $n$ varies from table to table. The general pattern is that it is smaller when $r$ is bigger.

**Note** that you are not allowed to ask people what they will do and you will not be informed about the other people's decisions. You must guess what other people will do – how many of the other 9 people will withdraw – and act accordingly.

**Procedure**

You will perform the task described above for 70 times. Each time is called a period. Each period is completely separate; i.e., you start each period with 1 in the experimental bank. You will keep the money you earn in every period. At the end of each round, the computer screen will show you your decision and payment for that period. Information about earlier periods and your cumulative payment is also provided.

Note that the payment scheme changes every 10 periods, so please use the **correct** payoff table:

Table 1 for period 1-10,

Table 2 for period 11-20,

Table 3 for period 21-30,

Table 4 for period 31-40,

Table 5 for period 41-50,

Table 6 for period 51-60, and

Table 7 for period 61-70.

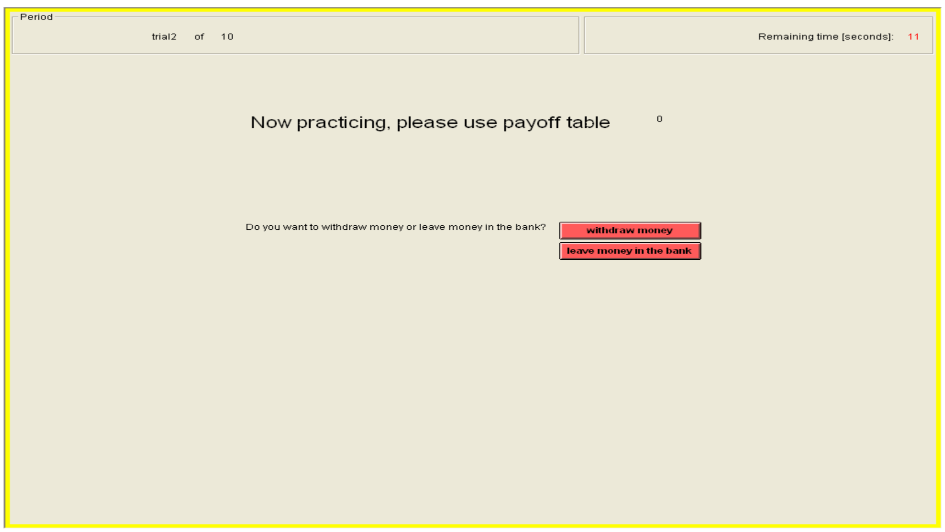
You will be reminded when you need to change to a new table; pay attention to the message.

Beside the 70 paid periods, you will also be given 10 practice periods get familiar with your task. You will not be paid for the practice periods. Please use table 0 for practice. After the practice periods, you will have a chance to ask more questions before the experiment formally starts. You will be paid for each formal period.

**Computer instructions**

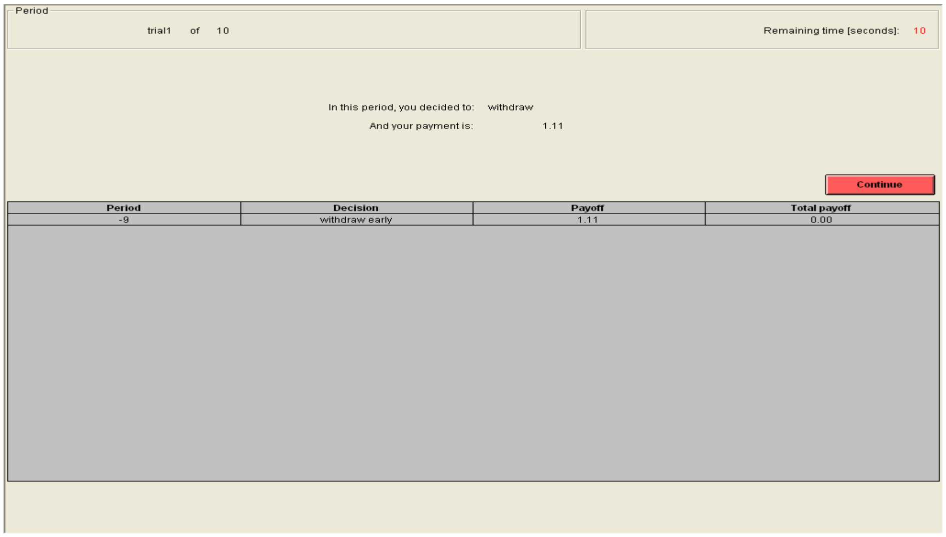
You will see three types of screens: the decision screen, the payoff screen and the waiting screen.

Your withdrawing decisions will be made on the decision screen as shown below. You can choose to withdraw money or leave money in the bank by pressing one of the two buttons. **Note** that your decision will be final once you press the buttons, so be careful when you make the move. The header provides information about what period you are in and the time remaining to make a decision. After the time limit is reached, you will be given a flashing reminder 'please reach a decision!'. The screen also shows which table you should look at.




The Decision Screen

After all subjects input their decisions, a payoff screen will appear as shown below. You will see your decision and payoff in the current period. The history of your decisions and payoffs as well as your cumulative payoff are also provided. After finishing reading the information, push the 'continue' button to go to the next period. You will have 30 seconds to review the information before a new period starts.




The Payoff Screen

You may see a waiting screen following the decision or payoff screens – this means that other people are still making decisions or reading the information, and you will need to wait until they finish to go to the next step.


The Waiting Screen

**Payment**

At the end of the entire experiment, the supervisor will pay you in cash. Your earnings in dollars will be:

$$\text{total payoff in } ED \times 0.2.$$

**Table 0 (for practice): payoff if n of other 9 subjects withdraw**

$r = 1.43$

| n | payoff if withdraw | payoff if leave money in the bank |
|---|---|---|
| 0 | 1.43 | 2.00 |
| 1 | 1.43 | 1.90 |
| 2 | 1.43 | 1.79 |
| 3 | 1.43 | 1.63 |
| 4 | 1.43 | 1.43 |
| 5 | 1.43 | 1.14 |
| 6 | 1.43 | 0.71 |
| 7 | 1.25 | 0.00 |
| 8 | 1.11 | 0.00 |
| 9 | 1.00 | 0.00 |

**Table 1: payoff if n of other 9 subjects withdraw**

$r = 1.05$

| n | payoff if withdraw | payoff if leave money in the bank |
|---|---|---|
| 0 | 1.05 | 2.00 |
| 1 | 1.05 | 1.99 |
| 2 | 1.05 | 1.98 |
| 3 | 1.05 | 1.96 |
| 4 | 1.05 | 1.93 |
| 5 | 1.05 | 1.90 |
| 6 | 1.05 | 1.85 |
| 7 | 1.05 | 1.77 |
| 8 | 1.05 | 1.60 |
| 9 | 1.00 | 1.10 |

**Table 2: payoff if n of other 9 subjects withdraw**

$r = 1.11$

| n | payoff if withdraw | payoff if leave money in the bank |
|---|---|---|
| 0 | 1.11 | 2.00 |
| 1 | 1.11 | 1.98 |
| 2 | 1.11 | 1.94 |
| 3 | 1.11 | 1.91 |
| 4 | 1.11 | 1.85 |
| 5 | 1.11 | 1.78 |
| 6 | 1.11 | 1.67 |
| 7 | 1.11 | 1.49 |
| 8 | 1.11 | 1.12 |
| 9 | 1.00 | 0.02 |

**Table 3: payoff if n of other 9 subjects withdraw**

$r = 1.18$

| n | payoff if withdraw | payoff if leave money in the bank |
|---|---|---|
| 0 | 1.18 | 2.00 |
| 1 | 1.18 | 1.96 |
| 2 | 1.18 | 1.91 |
| 3 | 1.18 | 1.85 |
| 4 | 1.18 | 1.76 |
| 5 | 1.18 | 1.64 |
| 6 | 1.18 | 1.46 |
| 7 | 1.18 | 1.16 |
| 8 | 1.11 | 0.56 |
| 9 | 1.00 | 0.00 |

**Table 4: payoff if n of other 9 subjects withdraw**

$r = 1.33$

| n | payoff if withdraw | payoff if leave money in the bank |
|---|---|---|
| 0 | 1.33 | 2.00 |
| 1 | 1.33 | 1.93 |
| 2 | 1.33 | 1.84 |
| 3 | 1.33 | 1.72 |
| 4 | 1.33 | 1.56 |
| 5 | 1.33 | 1.34 |
| 6 | 1.33 | 1.01 |
| 7 | 1.25 | 0.46 |
| 8 | 1.11 | 0.00 |
| 9 | 1.00 | 0.00 |

**Table 5: payoff if n of other 9 subjects withdraw**

$r = 1.54$

| n | payoff if withdraw | payoff if leave money in the bank |
|---|---|---|
| 0 | 1.54 | 2.00 |
| 1 | 1.54 | 1.88 |
| 2 | 1.54 | 1.73 |
| 3 | 1.54 | 1.54 |
| 4 | 1.54 | 1.28 |
| 5 | 1.54 | 0.92 |
| 6 | 1.43 | 0.38 |
| 7 | 1.25 | 0.00 |
| 8 | 1.11 | 0.00 |
| 9 | 1.00 | 0.00 |

**Table 6: payoff if n of other 9 subjects withdraw**

$r = 1.67$

| n | payoff if withdraw | payoff if leave money in the bank |
|---|---|---|
| 0 | 1.67 | 2.00 |
| 1 | 1.67 | 1.85 |
| 2 | 1.67 | 1.67 |
| 3 | 1.67 | 1.43 |
| 4 | 1.67 | 1.11 |
| 5 | 1.67 | 0.66 |
| 6 | 1.43 | 0.00 |
| 7 | 1.25 | 0.00 |
| 8 | 1.11 | 0.00 |
| 9 | 1.00 | 0.00 |

**Table 7: payoff if n of other 9 subjects withdraw**

$r = 1.82$

| n | payoff if withdraw | payoff if leave money in the bank |
|---|---|---|
| 0 | 1.82 | 2.00 |
| 1 | 1.82 | 1.82 |
| 2 | 1.82 | 1.59 |
| 3 | 1.82 | 1.30 |
| 4 | 1.82 | 0.91 |
| 5 | 1.67 | 0.36 |
| 6 | 1.43 | 0.00 |
| 7 | 1.25 | 0.00 |
| 8 | 1.11 | 0.00 |
| 9 | 1.00 | 0.00 |