Asset Prices and Bank Runs

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Abstract

We use a modified Diamond-Dybvig model with an interbank asset market to explore the impact of regional variations in liquidity shocks on asset prices and the stability of the banking system. The model posits banks in two distinct regions, each experiencing offsetting liquidity needs among depositors, thus eliminating aggregate risk. Bankers initially allocate customer deposits between cash and assets. After learning the state of the world, bankers can adjust asset and cash holdings via an interbank asset market to mitigate liquidity or solvency issues. Patient depositors decide whether to run on a bank conditional on asset price realizations and the implications for the liquidity or solvency of their bank. Despite theoretical predictions of no bank runs in the rational expectations equilibrium, our laboratory experiments reveal that bankers frequently over-allocate deposits to cash, thereby inflating asset prices. Also, bank runs remain prevalent in the absence of aggregate risk, highlighting how strategic uncertainty in interbank asset markets can lead to distorted allocation decisions, asset mispricing, and destabilization of the banking sector.

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1 Introduction

Bank runs are frequently associated with volatility in asset prices that induces panic among depositors while worsening the balance sheets of banks (Kindelberger, 1996). Perhaps the best known case is the wave of bank failures following the stock market crash of 1929, where a severe loss of confidence led to panic among depositors, culminating in widespread runs on banks as individuals hurried to withdraw their savings amidst a rapidly deteriorating financial landscape (Friedman and Schwartz, 1963). More recently, in the Great Recession, the failure of Lehman Brothers in the U.S. was linked to its heavy investments in mortgage-backed securities and collateralized debt obligations that suddenly deteriorated in value with the burst of the housing price bubble (Gorton, 2010). Still more recently, a run on Silicon Valley Bank in 2023 was precipitated by rising interest rates in the face of inflationary pressures and that bank's failure to adjust its investments of deposits in long-term bonds, rendering it insolvent (Metrick, 2024). In all of these instances, fire sales of assets by distressed banks led to sharp asset devaluations that further undermined the liquidity and solvency of the distressed banks and made them more susceptible to bank runs.

In the present paper, we inquire about the nature of this linkage between asset prices and bank failures. Our starting point is a modified Allen and Gale (2004a,b) version of the Diamond and Dybvig (1983) workhorse model of bank runs to include an explicit linkage between bank runs and asset prices. In our adaptation of that model, however, there is neither aggregate fundamental uncertainty nor strategic uncertainty among depositors. Accordingly, bank failures should *not occur* in a perfect foresight, rational expectations equilibrium. Yet, in an experimental test of this model we find evidence that strategic uncertainty among *banks*, arising from an interbank asset market, serves as a novel source of stress on both banks and asset markets resulting in overvaluation of the asset relative to theoretical equilibrium values and systematic bank failures.

In the framework advanced here, banks are located in two different regions. Depending on the realized state of the world, banks in those regions face differing short-term liquidity needs. This is because the number of impatient customers, who need to withdraw from their bank early, differ across the two regions. Banks make choices at two stages. In the first stage, banks choose how much of their customer deposits to allocate to assets, keeping the remainder in cash. After making that choice, the state of the world is realized: some banks may find that they have allocated too many deposits to assets to meet immediate withdrawal needs, while others find that they have too much invested in cash. Thus, in the second stage, banks choose to trade on an interbank market: assets in exchange for cash or vice versa. The market clearing asset price is endogenously determined. Depending on the realized asset price, banks may find that they do not have sufficient cash to meet withdrawal needs (are illiquid) or do not have sufficient investments in assets to prevent their patient depositors from withdrawing early (are insolvent). In either case, the bank is declared bankrupt. Whether the bank is found to be illiquid or there is a run due to insolvency is thus entirely endogenously determined by the price of bank assets.

As there is complete information about aggregate fundamentals, a necessary implication of the rational expectations assumption is that banks' optimal choices in each stage of the game should be such that no runs or liquidity problems arise. But this framework ignores the strategic uncertainty and coordination game aspects of the problem that banks actually face when participating in asset markets. Thus, we evaluate this model in a laboratory experiment to better understand the role that strategic uncertainty might actually play.

In our experiment, there is strategic uncertainty among *bankers* in that, according to theory, only aggregate values are determinate in equilibrium, whereas individual choices are not. We consider three environments, or treatments (outlined below). While these treatments all have the same equilibrium predictions for aggregate asset allocation and the market-clearing asset price, their differing designs allow us to challenge whether the equilibrium outcome is indeed invariant to changes in the symmetry of outcomes across regions, and to a higher variance in the number of illiquid depositors, as theory would predict.

In the baseline treatment, idiosyncratic liquidity shocks are symmetric and equiprobable across the two regions. If there is a large number of impatient depositors in one region, then there is a correspondingly smaller number of such depositors in the other region. Thus, in the interbank asset market, banks with a relatively large number of impatient customers (i. e., exceeding their cash holdings) should be sellers of the asset in the interbank market, while banks with a relatively small number of impatient customers should be buyers of the asset in that market. We hypothesize that the symmetric, equiprobable and relatively small liquidity shocks across regions should aid in the planning of asset allocations and market trades so that banks will learn to avoid bankruptcies (illiquidity and/or insolvency) with repeated experience.

In a second, asymmetric treatment, we increase the difficulty of such coordination by changing the probability of the two states of the world. There remains symmetry in the numbers of patient and impatient customers in both states of the world — in a given state, if there are more impatient customers in one region, there are fewer in the other and vice versa — however, there is now a small probability (20%) of a more extreme outcome in which there are many more impatient customers in one region than in the other.

Finally, we consider a high variance treatment. There, the extreme outcomes of the asymmetric treatment are experienced with equal probability across the two regions, but the variance in the number of impatient depositors across the two regions is higher than in the other two treatments (where it is the same).

To preview our findings, we find that subjects have difficulty in achieving the outcomes predicted by theory. Across all three treatments, aggregate cash holdings are too large and the mean market price of the asset is consistently too high (i. e., above their respective predicted equilibrium values). Moreover, subjects thus not only fail to achieve the first-best, they also fail to avoid the no bankruptcy outcome. Bankruptcies are most prevalent in the high variance treatment while there is no difference in bankruptcy between the low variance symmetric and asymmetric treatments.

How can we explain this volatility in a world without aggregate fundamental risks? At the individual level, we find evidence for the use of a cautious allocation strategy by some subjects who allocate the majority of their deposits to cash rather than to assets so as to avoid uncertainties associated with trades in the interbank market in case they need to liquidate asset holdings to meet the liquidity needs of their depositors. At the same time, albeit individual cash holdings are strategic substitutes in theory, other subjects fail to adjust their own cash holdings downwards accordingly. As a consequence, the number of assets potentially available for trade is reduced below theoretical equilibrium levels, resulting in higher than predicted asset prices. The combinations of these strategies appears to be also responsible for the mispricing of assets that we observe across treatments and is greatest in the high variance treatment. Our results suggest that banks' asset allocation decisions play an important role in the level (and volatility) of asset prices, thereby adversely affecting the stability of the financial sector more generally.

The rest of our paper is organized as follows. Section 2 relates our study to the literature. Section 3 lays the theoretical foundations for the experimental design, which is then described in section 4. Section 5 contains the hypotheses that we test in our experiment. Section 6 presents the experimental results, and section 7 offers a summary and some conclusions.

2 Related literature

Our paper is related to two branches in the literature. The first is a theoretical literature linking asset price volatility to instability in the banking sector (for an overview see Allen et al., 2010). Allen and Gale (2004a,b) advance a theory of fundamental bank runs in perfectly competitive environments with banks, asset markets, and aggregate (fundamental) liquidity shocks. Banks in that model are free to choose their modus operandi (i. e., being run-proof or run-prone) and they trade storage for long-term assets on interbank asset markets after the realization of the aggregate liquidity shock. Importantly, if the size of the aggregate liquidity shock converges to zero, their model predicts that there is never any bank failures whilst asset price volatility may still obtain. Building on this framework, Matsuoka (2022) argues that in a two-region model some banks go bankrupt in one region because banks in the other region are hit by a liquidity shock. Bucher et al. (2022) argue that allocations become distorted even in absence of aggregate risks, and the asset market a source of multiplicity of equilibria in the depositing game — provided bank runs can occur as a result of self-fulfilling beliefs on the part of depositors. In contrast to these models, the framework studied in the present paper exhibits neither aggregate fundamental shocks nor coordination failures among bank depositors but regional liquidity shocks that cancel each other out across regions.

The second branch of the literature is a small but growing body of work using experiments to explore behavior in Diamond-Dybvig type bank run games (for a survey see Kiss et al., 2022). A main finding from this literature is that simple, risk sharing deposit contracts do indeed make banks susceptible to coordination failures among bank *depositors* – see, e. g., Garratt and Keister (2009); Arifovic et al. (2013); Arifovic and Jiang (2014); Chakravarty et al. (2014). By contrast, our focus in this paper is on the behavior of the *bankers themselves* who must adapt their portfolio choices to liquidity shocks and face strategic uncertainty when trading in interbank asset markets.[1]

The majority of the experimental literature examines bank depositor behavior. Notable exceptions, and most pertinent to our study, are two recent studies by Davis et al. (2019, 2020) that focus on bankers' decisions in interbank markets. Davis et al. (2019) explore how interbank markets, modeled using double auction markets, serve to manage aggregate liquidity risks arising from regional liquidity shocks that do not offset each other. While these markets display significant price volatility due to heterogeneity in banks' initial investments in illiquid assets, they are shown to facilitate more efficient investments compared to banks self-insuring. Additionally, Davis et al. (2020) investigate the effects of liquidity requirements on interbank lending. They find that these requirements at best only marginally enhance efficiency and stability.

These two studies were designed to test theoretical insights from Allen and Gale (2004a,b), which can be grouped in three hypotheses. First, provided aggregate liquidity demand is stochastic, theory predicts that asset prices are volatile and that banks can occasionally go bust. This is consistent with the experimental findings by Davis et al. (2019). Second, provided aggregate liquidity demand is stochastic, theory predicts that interbank asset markets can deliver a constrained efficient outcome despite asset price volatility and occasional bank failures. This is in line with the experimental findings of Davis et al. (2020). Finally, theory further predicts that if

[1] In prior work (Duffy et al., 2019), we studied determinants of the likelihood of financial contagion in interbank loan markets, but our focus in that paper was on the interbank network structure and the withdrawal decisions of *depositors* and not the choices made by bankers.

aggregate liquidity demand is (asymptotically) *deterministic*, that is, if there is no aggregate risk, then the first-best allocation obtains.

This third insight has not been previously studied and is the main focus of study in this paper. To wit, while aggregate liquidity demand is deterministic, there are regional liquidity shocks that offset each other completely. In a variation of a simplified Allen and Gale (2004a,b) model we first show under which conditions the first-best should still obtain. These conditions necessarily imply that only aggregate cash holdings by banks are determinate, but not an individual bank's choice for they are strategic substitutes. This feature paves the grounds for strategic uncertainty among bankers in their dealings with each other on interbank markets. We design the experiment to match these conditions, thereby studying a form of strategic uncertainty that has not been considered yet — and we obtain evidence that indeed stands in sharp contrast to this third prediction of the theory.

3 A model of interbank asset markets

Consider an economy populated by consumers and banks. There are three dates $t \in \{1,2,3\}$ and two investment opportunities, cash and assets.

Investment opportunities Every dollar put into cash holdings at some date $t \in \{1,2\}$ yields \$1 at the following date $t+1$. By contrast, at date $t=3$ assets generate a deterministic gross return $\$R > \$1$ for each dollar allocated to them at date $t=1$; they do not generate anything at date $t=2$.

Consumers There is a continuum of identical consumers with unit mass, equally distributed across two regions r $\in \{\mathrm{I}, \mathrm{II}\}$. Consumers can hold cash, but cannot hold assets directly. Each is endowed with \$1 at date $t=1$ and nothing thereafter. A consumer is either impatient and values consumption at date $t=2$ or patient and values consumption at date $t=3$. At date $t=2$, everyone learns their own type, which is private information. A share $w \in]0,1[$ of consumers will be impatient whereas the remaining share $1-w$ of consumers will be patient. As of date $t=1$, the shares of impatient and patient consumers are publicly known and the chances for each consumer to be impatient are the same and independent. Therefore, a consumer's probability to be impatient is w and to be patient is $1-w$.

While the aggregate share of impatient consumers is deterministic, the respective shares in the two regions are stochastic and depend on the aggregate state $s \in \{s_1, s_2\}$ of the economy. At date $t = 2$, the state s_1 materializes with probability p, and state s_2 materializes with probability $1-p$. Let w_s^{r} be the share of impatient consumers in region r in state s. To simplify notation, let $\Delta = (1-p)(w_{s_2}^{\mathrm{II}} - w)$. Without loss of generality, we make the simplifying assumption that in state s_1, there are more impatient consumers in region I than in region II, while in state s_2, there are more impatient consumers in region II than in region I.[2] Hence $\Delta > 0$. Note that for a given w, $E(w_s^{\mathrm{r}}) = pw_{s_1}^{\mathrm{r}} + (1-p)w_{s_2}^{\mathrm{r}} = w$ for both $\mathrm{r} \in \{\mathrm{I}, \mathrm{II}\}$ implies $\Delta = p(1-p)\left(w_{s_1}^{\mathrm{I}} - w_{s_2}^{\mathrm{I}}\right) = p(1-p)\left(w_{s_2}^{\mathrm{II}} - w_{s_1}^{\mathrm{II}}\right)$. Note, Δ is thus closely related to $\mathrm{var}(w_s^{\mathrm{r}})$ and can be interpreted as measure of regional liquidity risks.[3]

Let $x_{t,s}^{\mathrm{r}}$ denote what a consumer in region r gets at date t in state s. The consumers' Bernoulli utility function u is twice continuously differentiable with $u' > 0$, $u'' < 0$, and $\lim_{x \to 0} u'(x) = \infty$. Relative risk aversion $k(x) = -xu''(x)/u'(x)$ is supposed to be at least one. Expected utility for consumers in region $\mathrm{r} = \mathrm{I}$ is

$$\begin{aligned} &(pw + \Delta)\, u(x_{2,s_1}^{\mathrm{I}}) + ((1-p)w - \Delta)\, u(x_{2,s_2}^{\mathrm{I}}) \\ &\quad + (p(1-w) - \Delta)\, u(x_{3,s_1}^{\mathrm{I}}) + ((1-p)(1-w) + \Delta)\, u(x_{3,s_2}^{\mathrm{I}}), \end{aligned} \tag{1}$$

and in region $\mathrm{r} = \mathrm{II}$ it is

$$\begin{aligned} &(pw - \Delta)\, u(x_{2,s_1}^{\mathrm{II}}) + ((1-p)w + \Delta)\, u(x_{2,s_2}^{\mathrm{II}}) \\ &\quad + (p(1-w) + \Delta)\, u(x_{3,s_1}^{\mathrm{II}}) + ((1-p)(1-w) - \Delta)\, u(x_{3,s_2}^{\mathrm{II}}). \end{aligned} \tag{2}$$

[2] One interpretation of such regional liquidity shocks is that some depositors withdraw and immediately redeposit with other banks. That way, some banks experience higher net outflows than others.

[3] This interpretation follows since $\mathrm{var}(w_s^{\mathrm{r}}) = p(1-p)\left(w_{s_2}^{\mathrm{r}} - w_{s_1}^{\mathrm{r}}\right)^2$.

Consumers cannot commit to repay loans such that there is no credit market on which consumers can borrow from or lend to each other.

First-best Since there is no risk to the aggregate share of impatient consumers, the optimal risk-sharing obtains if the level of consumption does not depend on region or aggregate state, neither for impatient consumers nor for patient consumers. This can be achieved if the two regions together hold just enough cash to cover the aggregate withdrawals by all impatient consumers; i. e., $y^{\text{fb}} = wd$. Hence, $x^{\text{I}}_{2,s_1} = x^{\text{I}}_{2,s_2} = x^{\text{II}}_{2,s_1} = x^{\text{II}}_{2,s_2} = d$ and $x^{\text{I}}_{3,s_1} = x^{\text{I}}_{3,s_2} = x^{\text{II}}_{3,s_1} = x^{\text{II}}_{3,s_2} = \frac{R(1-wd)}{1-w}$. The distribution of cash holdings across regions is *indeterminate* — all that matters is that the total cash held in aggregate equals wd.

Banks Consider $N = 2K$ banks, with $K \in \mathbb{N}$. One half of the banks, indexed by $n^{\text{I}} \in \{1, \ldots, K\}$, serve consumers in region I. The other half of the banks, indexed by $n^{\text{II}} \in \{K+1, \ldots, 2K\}$, serve consumers in region II. Banks in both regions operate under Bertrand competition. All banks can hold cash as well as assets. Banks potentially differ across regions and within regions with respect to their asset allocation, as this is their choice variable at date $t = 0$.

At date $t = 1$, consumers deposit their endowments in the banks, which allocate those deposits between cash and assets so as to maximize the expected utility of consumers. Let $y_{n^{\text{r}}}$ denote the share of deposits held by bank n^{r} in region r in cash and $1 - y_{n^{\text{r}}}$ the share invested in assets, respectively. In return for their endowments, consumers get a deposit contract from their bank. How the optimal contract can be derived is standard and straight forward. The contract entails that consumers can withdraw at the middle date $t = 2$ if they so wish. Those who withdraw at this date have a claim on the bank of d. They submit their withdrawal requests to the bank and, provided the bank has sufficient means to pay them at least the promised payment d, the bank will pay d to everyone with a withdrawal request submitted at date $t = 2$; everyone who has not submitted a request will equally share the bank's asset values at date $t = 3$. Should the bank not have sufficient means at date $t = 2$, the bank fails. The resources at the disposal of the bank at date $t = 2$ are then equally shared by the consumers who wanted to withdraw early. Those resources consist of the bank's cash holdings and whatever it gets by selling assets on the asset market. Consumers who did not submit a withdrawal request again share the value of the bank's remaining assets and cash at date $t = 3$. The details of the asset market are described next.

Asset market At date $t = 2$, banks can trade in state s assets for cash at a price P_s. The price shows how many units of cash trade for one unit of assets. In equilibrium, prices clear the asset market and arbitrage opportunities do not exist. At date $t = 1$, banks have access to cash and assets at identical costs. At date $t = 2$, the value of assets is (P_{s_1}, P_{s_2}) and the value of cash is $(1, 1)$. For $P_{s_1}, P_{s_2} \geq 1$ with $P_{s_1} + P_{s_2} > 2$, arbitrage opportunities exist. By acquiring assets at date $t = 1$ and selling them at date $t = 2$, banks could realize a profit in at least one state without making a loss in the other state. All banks would then acquire only assets at date $t = 1$, such that there would be no cash, and hence no purchasing power, at date $t = 2$ to buy assets at those prices. Similarly, for $P_{s_1}, P_{s_2} \leq 1$ with $P_{s_1} + P_{s_2} < 2$, arbitrage opportunities also exist. By holding only cash at date $t = 1$ and buying assets at date $t = 2$, banks would make a profit in at least one state without making a loss in the other state. Again, as all banks would hold only cash and none would acquire assets at date $t = 1$, there would be no productive investments to buy at these prices. Therefore, $P_{s_1} < 1 < P_{s_2}$, $P_{s_2} < 1 < P_{s_1}$ or $P_{s_1} = P_{s_2} = 1$. Finally, if $P_s > R$ all banks would sell assets in state s at date $t = 2$. However, as there would be no bank buying them, banks could not sell at this price.

Bank business models The share of consumers who submit a request for early withdrawal in region r in state s is w_s^{r}. A bank n^{r} in region r holds $y_{n^{\mathrm{r}}}$ in reserves and invests $1 - y_{n^{\mathrm{r}}}$ in production. Since $\Delta > 0$, a bank in region I is *run-prone* if it fails in state s_1, and a bank in region II is *run-prone* if it fails in state s_2. It is not optimal that a bank plans to fail in both states. This is because, regardless of the state s, the marginal rate of substitution between consumption when patient and consumption when impatient is equal to one, while the marginal rate of transformation is $R^{-1} < 1$. Accordingly, a bank is run-prone if

$$w_s^{\mathrm{r}} d + (1 - w_s^{\mathrm{r}}) \frac{d}{R/P_s} > y_{n^{\mathrm{r}}} + P_s (1 - y_{n^{\mathrm{r}}}) \tag{3}$$

with $s = s_1$ for $\mathrm{r} = \mathrm{I}$ and $s = s_2$ for $\mathrm{r} = \mathrm{II}$.[4]

A run-prone bank offers consumption bundles satisfying

$$\begin{aligned} x^{\mathrm{r}}_{2,s} &= y_{n^{\mathrm{r}}} + P_s\left(1 - y_{n^{\mathrm{r}}}\right) \\ x^{\mathrm{r}}_{3,s} &= y_{n^{\mathrm{r}}} + P_s\left(1 - y_{n^{\mathrm{r}}}\right), \end{aligned} \tag{4}$$

in state $s = s_1$ if $\mathrm{r} = \mathrm{I}$ and in state $s = s_2$ if $\mathrm{r} = \mathrm{II}$. In the state in which the bank survives, the consumption bundles satisfy

$$\begin{aligned} x^{\mathrm{r}}_{2,s} &= d \\ x^{\mathrm{r}}_{3,s} &= \frac{R}{P_s}\frac{y_{n^{\mathrm{r}}} - w^{\mathrm{r}}_s d + P_s(1 - y_{n^{\mathrm{r}}})}{1 - w^{\mathrm{r}}_s}, \end{aligned} \tag{5}$$

in state $s = s_2$ if $\mathrm{r} = \mathrm{I}$ and in state $s = s_1$ if $\mathrm{r} = \mathrm{II}$. Accordingly, impatient consumers get the promised payment d. Patient consumers share the value of the bank's assets at date $t = 3$. The latter comprises two elements. The first stems from any cash balances net of the amount payable to impatient consumers. If the bank holds any excess cash , $y_{n^{\mathrm{r}}} - w^{\mathrm{r}}_s d \geq 0$, it will use this amount to buy additional units of the asset at date $t = 2$ on the asset market at price P_s. The bank thus buys $(y_{n^{\mathrm{r}}} - w^{\mathrm{r}}_s d)/P_s$ units of assets, which generate R per unit at date $t = 3$. If the bank has a cash deficit, $(y_{n^{\mathrm{r}}} - w^{\mathrm{r}}_s d) \leq 0$, it sells assets to cover the difference; i. e., it gives up $(y_{n^{\mathrm{r}}} - w^{\mathrm{r}}_s d)/P_s$ units of the $(1 - y_{n^{\mathrm{r}}})$ units of assets it has originally acquired. The second element of the payments to patient consumers stems from the units of assets originally acquired $(1 - y_{n^{\mathrm{r}}})$ at date $t = 1$ (net of any sales), which also earn R per unit. The total bank asset value at date $t = 3$ is thus $\frac{R}{P_s}\left(y_{n^{\mathrm{r}}} - w^{\mathrm{r}}_s d + P_s(1 - y_{n^{\mathrm{r}}})\right)$, which is then equally shared among the patient consumers of which there are $1 - w^{\mathrm{r}}_s$.

[4] On the left is the present value of paying exactly d to all impatient consumers and at least d to patient consumers, while on the right is the present value of the bank's total assets. Present values are calculated given that the discount rate is given by the return on the bank's assets held between dates $t = 2$ and $t = 3$.

A bank in region r is *run-proof* if condition (3) does not hold in either state. Accordingly, consumption bundles satisfy

$$\begin{aligned} x^{\mathrm{r}}_{2,s} &= d \\ x^{\mathrm{r}}_{3,s} &= \tfrac{R}{P_s}\tfrac{y_n\mathrm{r} - w^{\mathrm{r}}_s d + P_s(1-y_n\mathrm{r})}{1-w^{\mathrm{r}}_s}, \end{aligned} \tag{6}$$

for both states $s \in \{s_1, s_2\}$.

Equilibrium With a focus on the experiment, we only ask here whether, and under which circumstances, the first-best can be expected as a market equilibrium. As shown above, a necessary condition for attaining the first-best is that consumption does not depend on the state s. This requires that in equilibrium all banks are run-proof and that $u'(d^{\mathrm{r}}) = Ru'(x^{\mathrm{r}}_{3,s})$ regardless of r or s.

We distinguish two cases. The first is $d > 1$.[5] Then, the first-best does not obtain in a market equilibrium. The proof is by contradiction. Consider the first-order condition with respect to d^{r} for banks in region r:

$$wu'(d^{\mathrm{r}}) = \frac{pw+\Delta}{P_{s_1}}Ru'(x^{\mathrm{r}}_{3,s_1}) + \frac{(1-p)w-\Delta}{P_{s_2}}Ru'(x^{\mathrm{r}}_{3,s_2}) \tag{7}$$

For this condition to be equal to the first-order condition associated with the first-best, $u'(d) = Ru'(x^{\mathrm{r}}_{3,s})$, a necessary condition is that prices satisfy

$$\frac{pw+\Delta}{P_{s_1}} + \frac{(1-p)w-\Delta}{P_{s_2}} - w = 0. \tag{8}$$

Consider next the first-order condition with respect to y^{r} for banks in region r:

$$pu'(x^{\mathrm{r}}_{3,s_1})\frac{1-P_{s_1}}{P_{s_1}} + (1-p)u'(x^{\mathrm{r}}_{3,s_2})\frac{1-P_{s_2}}{P_{s_2}} = 0 \tag{9}$$

[5]This holds, e. g., if relative risk aversion is strictly larger than one.

Accordingly, for this to satisfy the first-order condition associated with the first-best (i. e., $u'(x^{\mathrm{r}}_{3,s_1}) = u'(x^{\mathrm{r}}_{3,s_2})$), a necessary condition is that prices satisfy

$$P_{s_2} - \frac{P_{s_1}(1-p)}{P_{s_1} - p} = 0 \tag{10}$$

For $\Delta > 0$, the system of Eqs. (8) and (10) has exactly one solution: $P_{s_1} = P_{s_2} = 1$. Suppose now $P_{s_1} = P_{s_2} = 1$. Eq. (6) then implies $x^{\mathrm{r}}_{3,s} = R\frac{1-w^{\mathrm{r}}_s d}{1-w^{\mathrm{r}}_s}$. Since $\mathrm{d}x^{\mathrm{r}}_{3,s}/\mathrm{d}w^{\mathrm{r}}_s < 0$, consumption by patient consumers is lower in the region with the higher share of impatient consumers than in the region with the lower share of impatient consumers. Since in state s_1, there are more impatient consumers in region I than in region II, while in state s_2, there are more impatient consumers in region II than in region I, consumption by patient consumers is state-dependent. Therefore, while $P_{s_1} = P_{s_2} = 1$ is necessary for state-independent consumption levels, it is not sufficient. Accordingly, markets cannot implement the first-best.

The second case is $d = 1$.[6] It is straight forward to show that $P_{s_1} = P_{s_2} = 1$ and $y = w$ then constitute equilibrium prices and equilibrium aggregate cash holdings, respectively. Accordingly, the first-best indeed obtains in equilibrium. Since $x^{\mathrm{r}}_{3,s}$ does not depend on an individual bank's cash holdings, $y_{n^{\mathrm{r}}}$, they are thus *indeterminate*.

Finally, note that the above findings rest on the notion of consumers and banks behaving both rationally and with perfect foresight. Accordingly, in equilibrium, consumers and banks fully and correctly anticipate for every state the price at which assets are going to be traded.

4 Experimental design

Our experiment closely follows the setup of the model described in the previous section. Specifically we consider the contract where $d = 1$. From the theory this implies that the first-best is feasible, and also that individual bankers' allocation choices are indeterminate. Only aggregate

[6] This holds, e. g., if relative risk aversion is constant and equal to one.

Table 1: Treatment Differences in Regional Liquidity Demands

liquidity shock	$w^{\mathrm{I}}_{s_1}$	$w^{\mathrm{I}}_{s_2}$	$w^{\mathrm{II}}_{s_1}$	$w^{\mathrm{II}}_{s_2}$	p	Δ	w	SD
symmetric	0.68	0.32	0.32	0.68	0.5	0.09	0.5	0.18
asymmetric	0.86	0.41	0.14	0.59	0.2	0.07	0.5	0.18
high variance	0.86	0.14	0.14	0.86	0.5	0.18	0.5	0.36

cash holdings by banks are determinate. This allows us to study the role played by strategic uncertainty in interbank asset markets.

We use a 3×1 between-subjects fractional factorial design. Along one dimension we distinguish between symmetric liquidity shocks and asymmetric liquidity shocks across the two regions holding the variance of those shocks constant. Analyzing asymmetric shocks helps in stress testing the banking system under uneven conditions, which is crucial for understanding how regional disparities may affect overall system stability. Along the other dimension we consider only symmetric shocks across the two regions but between treatments we double the variance of those shocks. Increasing the variance of liquidity shocks provides another type of stress test of whether the banking system is resilient to more severe shocks. We refer to our baseline treatment as the "symmetric" treatment. Our "asymmetric shock" treatment has the same variance as the baseline treatment, but asymmetric liquidity shocks between the two regions. Finally, our "high variance" treatment has symmetric shocks as in the baseline treatment, but a higher variance in those shocks. The parameterizations of these three treatments are shown in Table 1.

4.1 Parametrization

Each bank is represented by one banker, a role taken on by the participants in our experiment. They play for 20 independent rounds. In each round, there are three dates $t \in \{1,2,3\}$, two regions $r \in \{\mathrm{I},\mathrm{II}\}$, and $N = 8$ banks equally distributed across regions. A banker operates in the same region for the entire 20 rounds. Bankers have access to two investment opportunities, cash and assets. Cash earns no interest, providing a one-to-one return while the return on assets to those holding them at maturity (date 3) is $R = 2$ (per unit).

Automated robot players take the role of bank customers. Each bank has 100 such automated customers at date $t = 1$. Each customer deposits one unit of cash in their bank at date 1 in exchange for a claim on the bank with $d = 1$. This is chosen because it allows the first-best allocation. Still at date $t = 1$, but after they have received their deposits, bankers have to decide about their *initial allocation*; i. e., about how many of the 100 units of deposits they wish to invest in assets. Let A denote the volume of those initial investments in assets. The remaining amount, equal to $100 - A$, are held in cash reserves.

While the total share w of impatient customers across both regions is given, the respective regional shares depend on the aggregate state $s \in \{s_1, s_2\}$, which is revealed to participants at the beginning of $t = 2$. Table 1 informs about the parametrization we have used in the experiment. The probabilities of the aggregate state p and $1 - p$ and the measure of regional liquidity risk Δ are such that the total share of impatient customers is $w = 0.5$. The standard deviation of regional liquidity demands $\mathrm{SD} = \sqrt{\mathrm{var}(w_s^{\mathrm{r}})} = 0.18$ in the first two treatments, and $\mathrm{SD} = \sqrt{\mathrm{var}(w_s^{\mathrm{r}})} = 0.36$ in the final treatment. In every session, liquidity shocks are either all symmetric in each round, or they are all asymmetric in each round.

Table 2 shows the respective numbers of impatient and patient bank customers in each region for every state. For example, if a region has 68 impatient customers, each banker in that region will face a withdrawal of at least 68 units of deposits at date $t = 2$, while 32 impatient customers means that they will face a withdrawal of at least 32 units of deposits at date $t = 2$. For later reference we indicate in boldface type the greatest number of impatient customers that can be realized in each region.

Table 2: Number of Impatient and Patient Bank Customers in the 3 Treatments

Note: The greatest number of impatient customers per region is indicated in boldface.

State	Probability	Region I	Region II
s_1	0.5	**68 impatient** 32 patient	32 impatient 68 patient
s_2	0.5	32 impatient 68 patient	**68 impatient** 32 patient

(a) Symmetric Liquidity Shocks

State	Probability	Region I	Region II
s_1	0.2	**86 impatient** 14 patient	14 impatient 86 patient
s_2	0.8	41 impatient 59 patient	**59 impatient** 41 patient

(b) Asymmetric Liquidity Shocks

State	Probability	Region I	Region II
s_1	0.5	**86 impatient** 14 patient	14 impatient 86 patient
s_2	0.5	14 impatient 86 patient	**86 impatient** 14 patient

(c) High Variance Liquidity Shocks

4.2 Asset market

At date $t = 2$, when the state s is revealed and the respective number of their impatient customers known, but before any deposits are actually withdrawn, bankers have to decide whether or not to participate in a centralized market where they can buy or sell assets. If a banker decides to sell assets, then he/she must state the quantity he/she wants to sell (q); and if he/she decides to buy assets, then he/she must state the amount of cash he/she wants to bid (b).

After all banks have stated their trading offers or bids, the asset price is determined by a computer. If no banker makes a cash bid and/or no banker offers to sell assets, there is no trade and hence no market price. Provided the sum of all cash bids and the sum of all assets offered are both strictly positive, the market price is

$$P = \frac{\text{Sum of all cash Bids}}{\text{Sum of all Assets Offered}}$$

Bankers make their choices before they know the actual asset price and trades are settled according to the individual bids and offers. That is, if a banker has bid b units of cash, he/she trades those units of cash in exchange for b/P assets. Accordingly, he/she acquires b/P assets in addition to the assets he/she has already held since $t = 1$ and holds b units less as cash. Conversely, if a banker has offered to sell q assets, he/she trades those assets in exchange for cash. Accordingly, he/she obtains $P \times q$ units of cash in addition to the cash he/she has already held since $t = 1$ and holds q units less as assets. With the above pricing formula, asset prices always clear regardless what price bankers anticipate and, equally importantly, it facilitates the theoretical equilibrium price *provided* bankers anticipate correctly the theoretical equilibrium price.

4.3 Accounting review

Once trades on the asset market have been placed and the market clearing asset price is determined, the computer program conducts an accounting review. A bank is classified as *Liquid* and/or *Solvent*. A banker whose bank is declared *Illiquid* or *Insolvent* or *both*, will be bankrupt.

A bank is considered *Liquid* if it has enough cash on hand to meet the withdrawal demands of its impatient customers at date $t = 2$. A bank is considered *Solvent* if it has enough invested in assets such that patient customers are better off when they withdraw their deposits at date $t = 3$, that is, if the bank is able to offer these customers a payoff greater than or equal to 1.

If the banker has chosen to buy assets, then the bank is liquid if $(100 - A) - b \geq 100 \times w_s^{\mathrm{r}}$. If the banker has chosen to sell assets, then the bank is liquid if $(100 - A) + P \times q \geq 100 \times w_s^{\mathrm{r}}$. If the banker has not traded (either because the banker decided not to participate in the asset Market or because there was no market price), the bank is liquid if $(100 - A) \geq 100 \times w_s^{\mathrm{r}}$.

Similar calculations are made by the computer program with regards to solvency. Provided the banker chose to be a buyer, the bank is thus solvent if $(100-A)-b+2\times(b/P+A)\geq 100$. If the banker chose to be a seller, the bank is solvent if $(100-A)+2\times(A-q)+P\times q\geq 100$. Finally, in the case of no trade, the bank is solvent if $(100-A)+2\times A\geq 100$.

4.4 Guidance and Support

In order to aide participants in making good choices at date $t=2$, we have offered them some further guidance and support. Specifically, when making their trade decisions, we asked bankers to predict whether or not there will be trade on the asset market and, provided they expect any trading, to forecast the asset price. Based on their forecast, their initial allocation between cash and assets, as well as the number of impatient depositors their bank will face, bankers can experiment with different price predictions P^f and quantities of assets to sell (q) or cash to bid (b). For this, we provide a decision screen (Figure 1), where they input their choices and forecast and, given this data, are informed if their bank would be Liquid (Not Liquid) and Solvent (Not Solvent).

4.5 Payoffs

Bankers' Allocation Payoff The payoffs to bankers depend on their own choices at dates $t=1$ and $t=2$ and on the asset price, both directly and indirectly. The indirect effect is because together they determine whether their bank is solvent as well as liquid. Specifically, if the banker has been declared bankrupt, he/she receives an allocation payoff of zero. If the banker has not been declared bankrupt, the allocation payoff is a linear function of the return received by patient customers at date $t=3$ and given by

$$\text{Banker's Allocation Payoff} = \begin{cases} \$10\times\left(\frac{(100-A)-b+2\times(\frac{b}{P}+A)-w_s^r}{100-w_s^r}-1\right) & \text{if banker was a buyer} \\ \$10\times\left(\frac{(100-A)+2\times(A-q)+P\times q-w_s^r}{100-w_s^r}-1\right) & \text{if banker was a seller} \\ \$10\times\left(\frac{(100-A)+2\times A\ -w_s^r}{100-w_s^r}-1\right) & \text{if no trade} \end{cases} \tag{11}$$

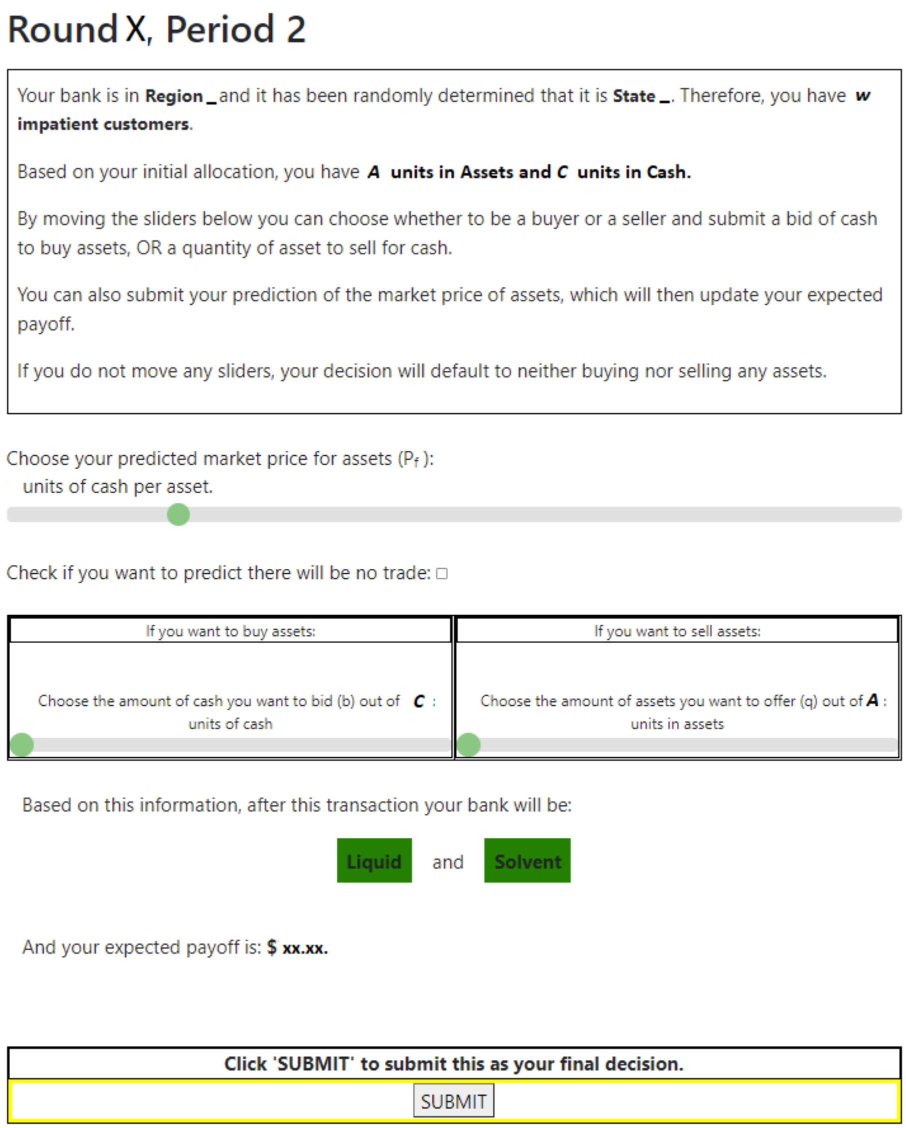


Figure 1: Banker's Decision Screen (variables shown in place of numbers)

Bankers' Prediction Payoff Since bankers' choices at date $t = 2$ crucially depend on the accuracy of their forecast of the market clearing asset price (P^f), we provide incentives to make as accurate a prediction as possible. We do so by introducing a payoff for their price prediction accuracy, which depends on the deviation of their own price forecast, P^f, from the actual market price, P according to

$$\text{Banker's Prediction payoff} = \frac{\$5}{1 + |P^f - P|}. \tag{12}$$

Final Payoffs In order to avoid income and portfolio effects we used a Random Incentive Mechanism. Specifically, at the end of the experiment, 3 rounds are randomly chosen for payment. In 2 of those rounds, each banker gets the payoff earned from their initial allocation and in 1 round, each banker gets the payoff earned from predicting the asset market price. These earnings are added to the $10 participation payment.

4.6 Feedback

At the end of each round in period $t = 3$, each banker learns the market price P, and the amount of assets that they bought or sold, if any. Given the banker's new asset position from asset purchases or cash position from asset sales, an audit review is conducted and bankers are informed as to whether their bank is *Liquid* and *Solvent*. If both are true, then their allocation payoff for the round is positive and equal to (11) depending on whether they were a buyer, a seller or did not engage in trade in the asset market. If they are not liquid or solvent or both, they are declared bankrupt and their allocation payoff is zero for the round. They also learn their price forecast payoff for the round, given by (12). This feedback information not only includes the most recent round outcomes but also includes a scrollable list of all previous round outcomes played up to that point in the study.

4.7 Sequence of Events

The timing of events in the three periods of each round is illustrated in Figure 2. Subjects knew that, in total, 20 three-period rounds would be played and that each three-period round was identical to another in terms of the timing of events and the probabilities of states of the world. In particular, there is no transfer of assets or cash from one round to the next.

4.8 Procedures

The experiment was computerized using the oTree software (Chen et al., 2016). Subjects were undergraduate students at UC Irvine from a variety of different major programs of study. No

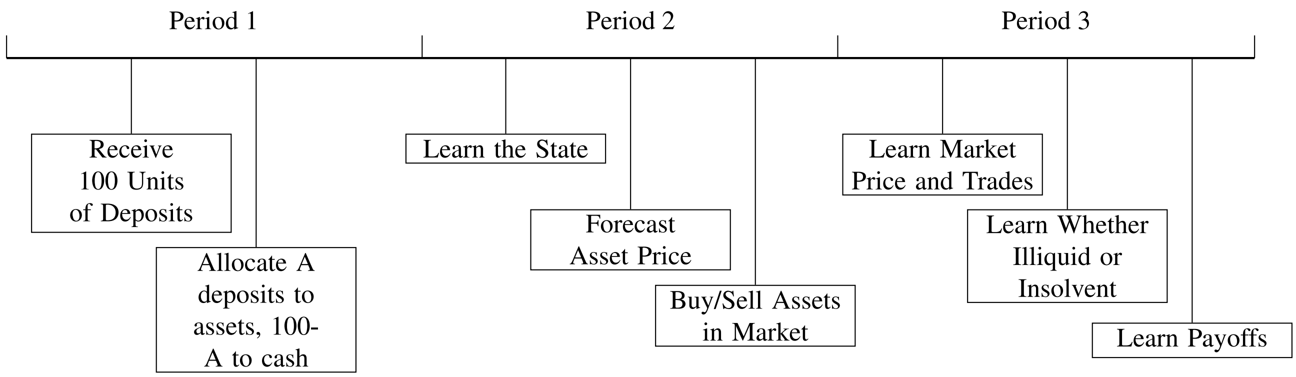


Figure 2: Timing of Events Across the 3 Periods of Each Round

subject had any prior experience with our experimental design and subjects were only allowed to participate in a single session/treatment of our experiment. We obtained 6 observations on choices made by 8-subject cohorts for each of our three treatments. Thus, our study involved a total of 144 subjects (average age = 20.56 years; 56.94% females).

Each experimental session began with subjects being given written instructions that were then read aloud in an effort to make those instructions common knowledge (copies of these written instructions are included in the Appendix A). After the instructions were read, subjects had to answer a number of questions designed to check their comprehension of the instructions (Appendix B). Subjects who made mistakes were instructed as to the correct answers prior to the first round of the game. After completing 20 rounds, subjects were informed as to which round was randomly selected for payment and their payoffs for those rounds. In addition, subjects received a 10 US dollars' participation payment. Between the end of the experiment and the payment phase, a demographic questionnaire was administered. Participants received their payment at the end of the session. Each session was completed within 2 hours and an eight-players cohort participated in each single session. The average payment was 19.680 US Dollars (SD 7.575) in treatment 1; 21.389 US Dollars (SD 9.750) in treatment 2; and 23.058 US Dollars (SD 17.668) in treatment 3.

5 Research Questions

As aggregate fundamentals are not risky and a deposit contract with $d = 1$ thus allows for implementation of the first-best allocation in theory, our main research question is whether subjects in the role of bankers can achieve the first-best or not. According to the model, achievement of the first-best requires from bankers all of the following:

1. Bankers allocate on average 50 units to cash and 50 units to assets in period 1.

2. Bankers correctly predict the price at which assets are going to be traded.

3. Bankers buy/sell assets in period 2 to meet exactly immediate depositor withdrawals.

Furthermore, provided bankers make their choices in accordance with the first-best, the market outcome will necessarily be such that

4. The price of assets in the interbank asset market is 1.

5. There is no bankruptcy, neither due to illiquidity nor due to insolvency.

6. The allocation payoff is $10 and the prediction payoff is $5.

These six model predictions hold for all three of our treatments. In search for supportive evidence for these predictions, we test four hypothesis with our experiment. Our main hypothesis is the following:

Hypothesis 1 *In the baseline symmetric treatment, subjects achieve the first-best allocation; in particular, they avoid bankruptcy in the form of illiquidity as well as insolvency.*

We further test two hypotheses pertaining to differences in the nature of liquidity shocks. As suggested earlier, these are meant to serve as a stress test of the model's prediction that absent any aggregate fundamental risk, the first-best should be attainable and bankruptcy should be avoided.

Hypothesis 2 *Relative to the baseline symmetric shock treatment, there is no change in allocations or prices when we move to the asymmetric shock treatment.*

Table 3: Initial Cash Allocations Across Treatments, Descriptive Statistics

	Obs	Mean	Std. Dev.	Variance	Median	Min	Max	Skewness	Kurtosis
Treatment 1	960	56.391	16.700	278.874	60	0	100	-0.343	3.363
Treatment 2	960	56.892	14.939	223.162	59	0	92	-0.228	3.965
Treatment 3	960	59.964	23.278	541.847	65	0	98	-0.621	2.249

Hypothesis 3 *Holding the symmetry of shocks constant, a doubling of the variance of those shocks as in our high variance treatment results in no change in allocations or prices relative to the baseline symmetric treatment.*

Finally, we posit that agents have rational expectations:

Hypothesis 4 *Bankers can perfectly predict the price at which assets are going to be traded.*

6 Results

In this section, we report on the data from our experiment and address the support for our hypotheses. Our analysis largely follows the order in which bankers make decisions: (1) the allocation of deposits between assets and cash in the first stage of the game, (2) price forecasts, trading decisions and actual market prices in the second stage of the game and (3) the frequency of bankruptcy either owing to liquidity or insolvency or both in the final stage of the game. For all three outcome variables, we begin with an aggregate analysis and then proceed to a more individual-level analysis.

6.1 Allocation of deposits

Table 3 reports aggregate statistics from all three treatments regarding the initial allocation of the 100 units of deposits that each banker received to cash in period 1 of the model; the remaining deposit balance goes toward the acquisition of assets that mature in period 3.

Compared with the prediction of the theory, subjects in all three treatments are found to over-allocate deposits to cash, on average. Alternatively, they underinvest in assets. While the

Table 4: Regression Analysis of Initial Allocations to Cash

	(1) All rounds	(2) First round	(3) Rounds 1-10	(4) Rounds 11-20
Treatment 2	0.501	-2.208	0.288	0.715
	(0.32)	(-0.61)	(0.17)	(0.43)
Treatment 3	3.573*	4.563	4.196**	2.950
	(1.78)	(1.27)	(2.05)	(1.28)
Constant	56.39***	55.69***	56.32***	56.46***
	(40.50)	(21.86)	(37.16)	(38.72)
Observations	360	18	180	180

z statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

cash allocation is predicted to *average* 50% of the 100 units of deposits received by each bank, the actual average allocation of deposits to cash is consistently greater than 50 across all three treatments. For example, in the baseline symmetric treatment, the mean choice is to allocate 56.39 units of deposits to cash.

A panel regression analysis using all 20 rounds of data on initial allocations of deposits to cash and dummies for the two other treatment conditions is reported in specification (1) of Table 4. This specification reveals that relative to the baseline treatment, cash allocations are not statistically different in treatment 2 but are significantly, albeit only somewhat higher in treatment 3 by about 3.6 units ($p < 0.10$). The over-allocation of deposits to cash is found starting from the very first round where the estimated allocations are significantly different from 50 in all three treatments (chi-squared test $p < 0.01$). The over-allocation to cash persists in rounds 1-10 and in rounds 11-20, however in the latter sample, there are no longer any significant differences across treatments in allocations of deposits to cash.

To gain further insight into initial allocations, we look at histograms of the amounts of deposits that subjects allocated to cash in the first period of each round across the three treatments. Figure 3 reveals that across all three treatments, there is a large spike in initial cash allocations at the

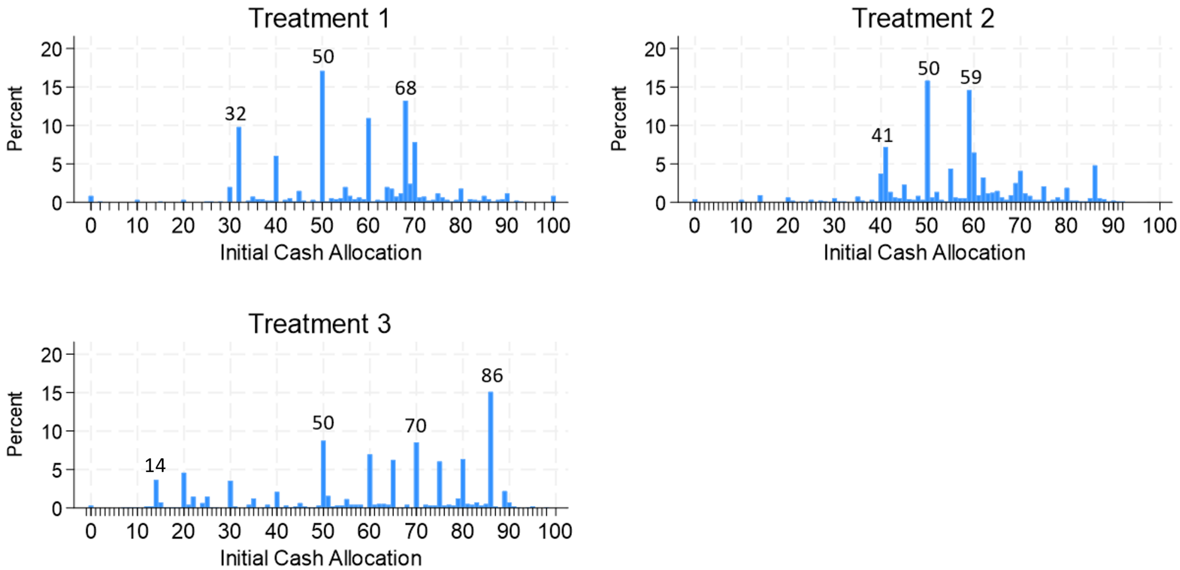


Figure 3: Histograms of Initial Allocations to Cash by Treatment

equilibrium prediction of 50, but in all three treatments, another (and sometimes even larger) spike lies further to the right of 50. In treatment 1, this other spike is the second highest (at 68), in treatment 2 the other spike is also the second highest (at 59) while in treatment 3 the other spike is indeed the highest (at 86). The first number, 68, corresponds to the high-liquidity needs state of the world in the symmetric treatment. The second number, 59, corresponds to the most frequent high liquidity needs state (with an 80% chance) in the asymmetric treatment. The third number, 86, corresponds to the high liquidity needs state in the high variance treatment.[7] Notice further that in addition to spikes above 50, there are also prominent spikes in cash allocations that lie *below* 50, at 32 in Treatment 1, 41 in Treatment 2 and 14 in Treatment 3. These correspond to the low liquidity needs states in each of the three treatments. However, these frequencies are lower than the spikes above 50. Thus, we find evidence that some subjects are trying to guess the state of the world they will face in terms of liquidity needs (the number of impatient depositors) when making initial cash allocations and that there is a bias in favor of the high liquidity needs state. Later on, we will refer to an initial cash allocation equal to the high liquidity needs state as a "salient-safe" allocation.

[7] For reference, see again Table 2 where these high liquidity needs states are indicated in boldface.

The theory allows for *individual* departures of cash and asset positions from 50, but predicts that the average allocation will be 50 for each. However, as we have seen, the actual distributions of initial allocations of deposits to cash are not uniformly centered around 50 but are instead skewed left as is also confirmed by the skewness measures reported on in Table 3. This pattern of cash allocations is rooted in two further observations. First, a sizeable fraction of subjects, 10-15%, are seeking to ensure the liquidity needs of their bank by taking a rather extreme cash position with some bankers holding even more cash than the salient high state liquidity needs; we refer to those subjects as risk-minimizing bankers. Second, the other subject-bankers do not adjust their own individual liquidity holdings sufficiently downward, apparently not even with growing experience in dealing with these risk-minimizing bankers over the course of the 20 rounds of the experiment. The behavior of the risk-minimizing bankers might be viewed as a response to *ambiguity*.[8] It is important to stress, however, that such ambiguity in our setting cannot be about liquidity needs as these are known to take on certain values. It must instead be about the outcome of the asset market in case that asset sales are needed to meet liquidity needs. The lack of adjustment by other bankers, on the other hand, may additionally reflect their own *strategic uncertainty* about the behavior of the risk-minimizing bankers.

6.2 Market prices, forecasts and trading decisions

Recall that after all deposit allocations were made, subjects learned the true state of the world and then had to (1) forecast the market price of assets in the interbank market and (2) decide whether to use some of their cash to bid for units of the asset or offer to sell some of their units of the asset for cash or not to engage in any trade in the interbank asset market. After all bids and offers were posted, the market clearing price was determined by the ratio of the sum of all bids to the sum of all units of the asset offered for sale.

[8] Indeed, Gilboa and Schmeidler (1989) develop a maxmin model of expected utility theory where individuals respond to ambiguous settings by considering the worst-case scenario.

Table 5: Market Asset Prices Across Treatments, Descriptive Statistics

	Obs	Mean	Std. Dev.	Variance	Median	Min	Max	Skewness	Kurtosis
Treatment 1	120	1.288	0.867	0.752	1.057	0.059	6.429	2.309	12.344
Treatment 2	120	2.210	6.261	39.201	1.176	0.102	63.000	8.388	78.957
Treatment 3	120	1.217	0.794	0.630	1.066	0.158	6.059	2.589	14.198

We first consider this market clearing price across treatments and over time. As Table 5 and Figures 4 and 5 reveal, across all three treatments the market price is consistently greater than one and thus greater than theory predicts. Using session-level data, we conducted a Wilcoxon signed-rank test to determine whether the median price in each treatment differed from the theoretical prediction of one. For all treatments, the null hypothesis that the median is not different from the rational expectations equilibrium prediction of 1 can be rejected at a significance level of 0.05.

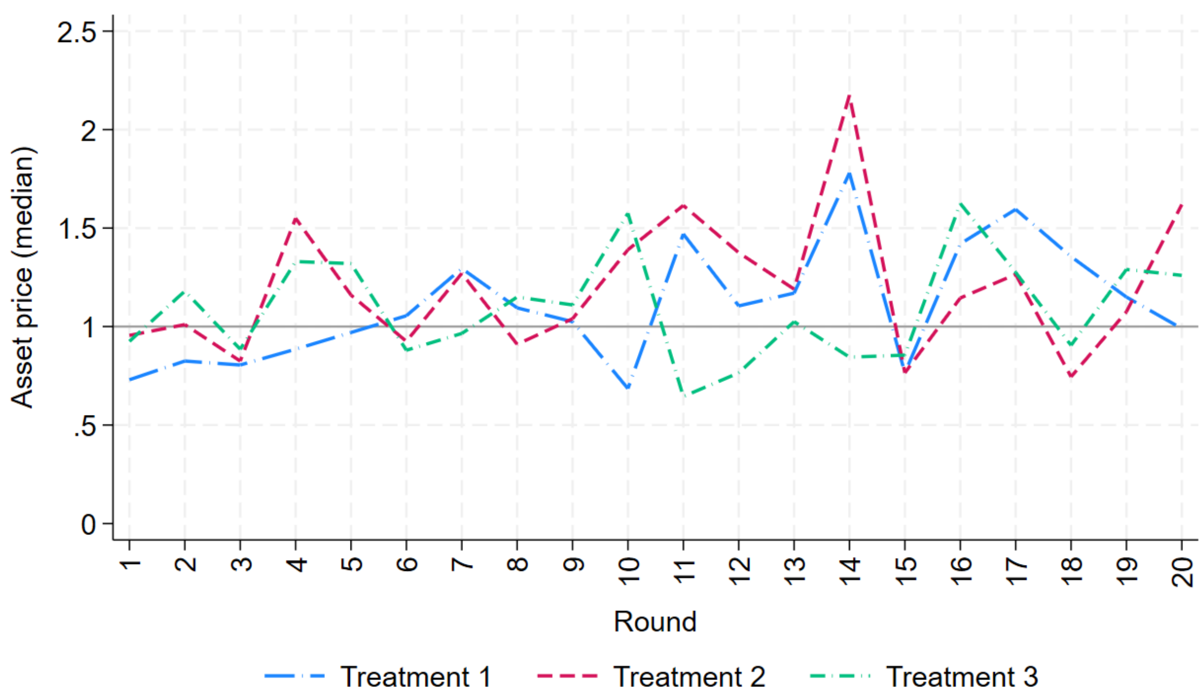


Figure 4: Median Market Price Over Time in Each Treatment

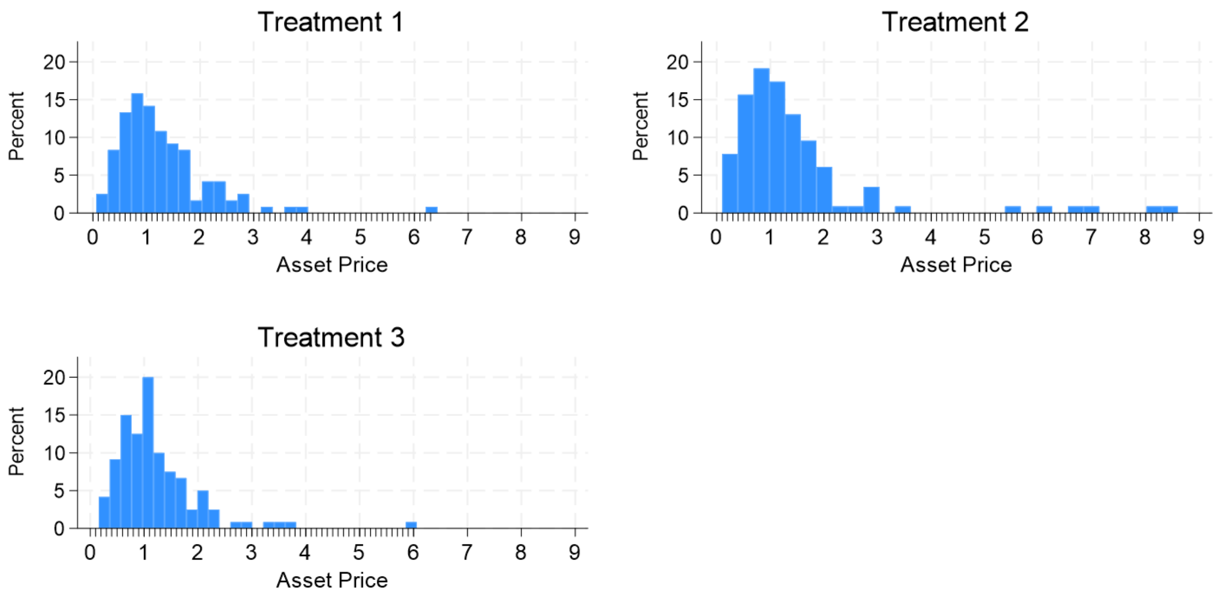


Figure 5: Histograms of Market Prices in Each treatment; Two Outliers Excluded

In the baseline treatment, the asset sells at an average premium of 28.8% over the equilibrium value. A regression analysis of the market price for assets reported in Table 6 reveals that there is no statistical difference in market prices across the three treatments.[9] Overall (specification 1 of the table) prices are significantly different from 1 in all three treatment (p<0.05). In round 1, prices are not significantly different from 1 in any of the treatments (p>0.10). In the first half of the experiment only treatment 3 has prices significantly greater than 1 (p<0.01), while for rounds 11 to 20 prices are significantly greater than 1 in all three treatments (p<0.05). Indeed, the deviation of the asset price from the equilibrium price predicted by theory is a distortion that emerges with experience; the mean price in the baseline treatment round 1 is 1.069 and increases to an average of 1.14 over rounds 1-10 and to 1.44 in rounds 11-20. Interestingly, if we perform the same analysis solely for the first round of each session (where all observations are independent), we cannot reject this null hypothesis.

The overpricing of assets in our experiment is associated with the (aggregate) over-allocation of deposits to cash. The over-allocation to cash results in a scarcity of assets in the interbank

[9]The highest average price obtains in treatment 2, but this is mainly owing to outliers; see Figure 5.

Table 6: Regression analysis of asset prices

	(1) All rounds	(2) First round	(3) Rounds 1-10	(4) Rounds 11-20
Treatment 2	0.938	-0.0201	1.660	0.218
	(1.51)	(-0.05)	(1.45)	(0.81)
Treatment 3	-0.0710	-0.135	0.118	-0.260
	(-0.46)	(-0.31)	(0.82)	(-1.26)
Constant	1.288***	1.069***	1.136***	1.441***
	(9.34)	(3.49)	(10.17)	(7.74)
Observations	357	18	178	179

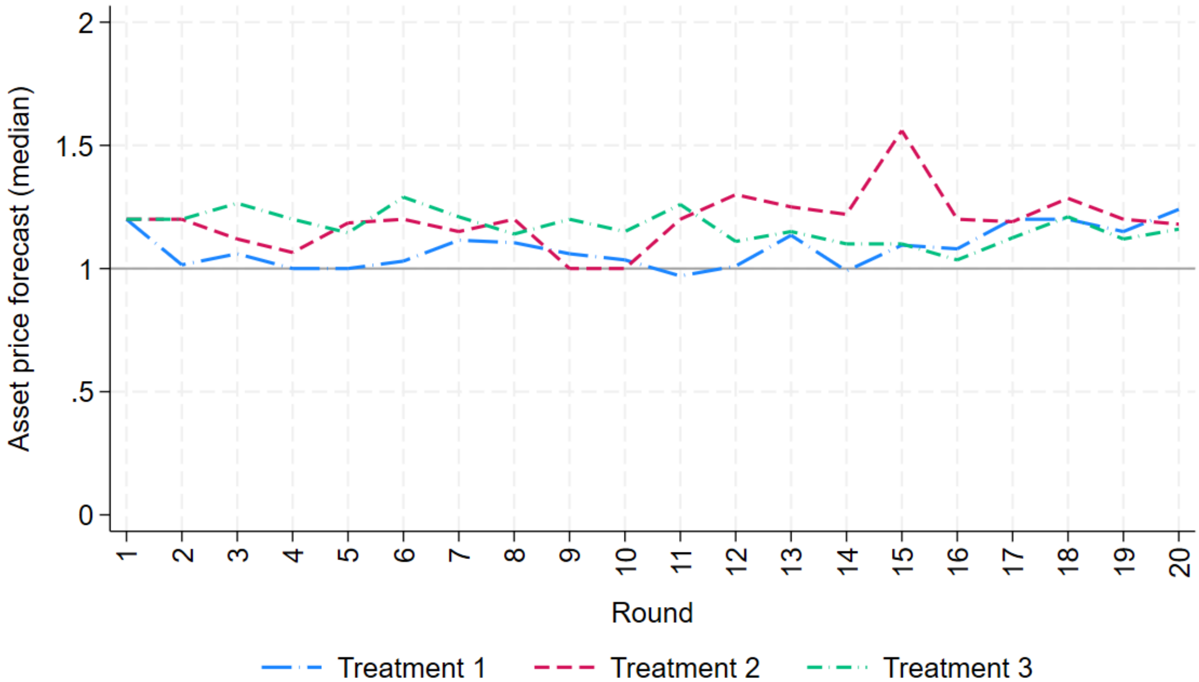
z statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

market and an abundance of cash which works to drive up asset prices across all three experimental treatments.

Interestingly, the persistent overpricing of the asset is to some extent anticipated by the bankers, as revealed by their price forecasts. The top panel of Figure 6 shows median price forecasts over time by treatment while the bottom panel shows median forecast errors (the median difference between the price forecast and actual price) over time by treatment. Recall that subjects were incentivized to correctly forecast these market prices. The median price forecast is generally greater than 1 and the forecast error hovers around zero.

Still, there is considerable variance in these forecasts as is revealed by the histograms for market prices shown in Figure 7. The median forecast errors over all rounds are -0.015, -0.02 and 0.10 for treatments T1, T2 and T3, respectively. Using individual-level data, we conducted a Wilcoxon signed-rank test to determine whether the median forecast error in each treatment differs from zero. For Treatments 1 and 2, there is not enough evidence to reject the null hypothesis that the sample's median is equal to zero (Prob > |z| = 0.1337 and 0.8871, respectively), while for Treatment 3 there is (Prob > |z| = 0.000). Accordingly, we find only mixed support for Hypothesis 4 (i. e., that subjects can perfectly forecast asset prices). Instead, the evidence suggests



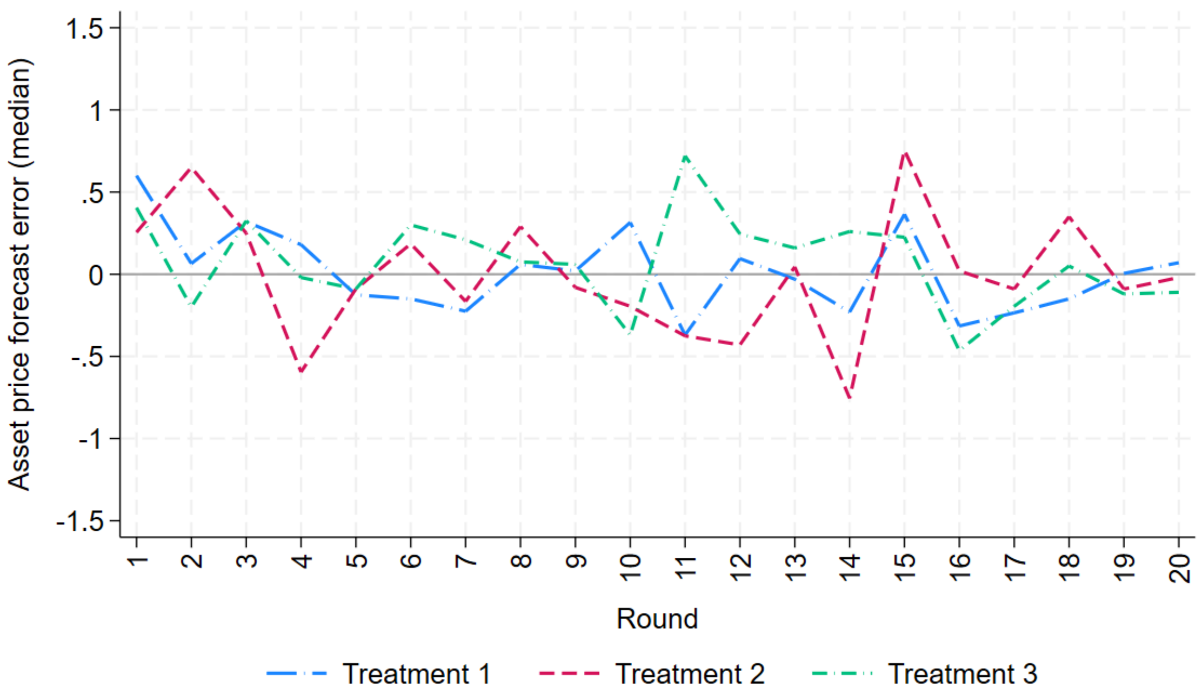


Figure 6: Median Price Forecast (upper panel) and Forecast Error (lower panel) Over Time by Treatment

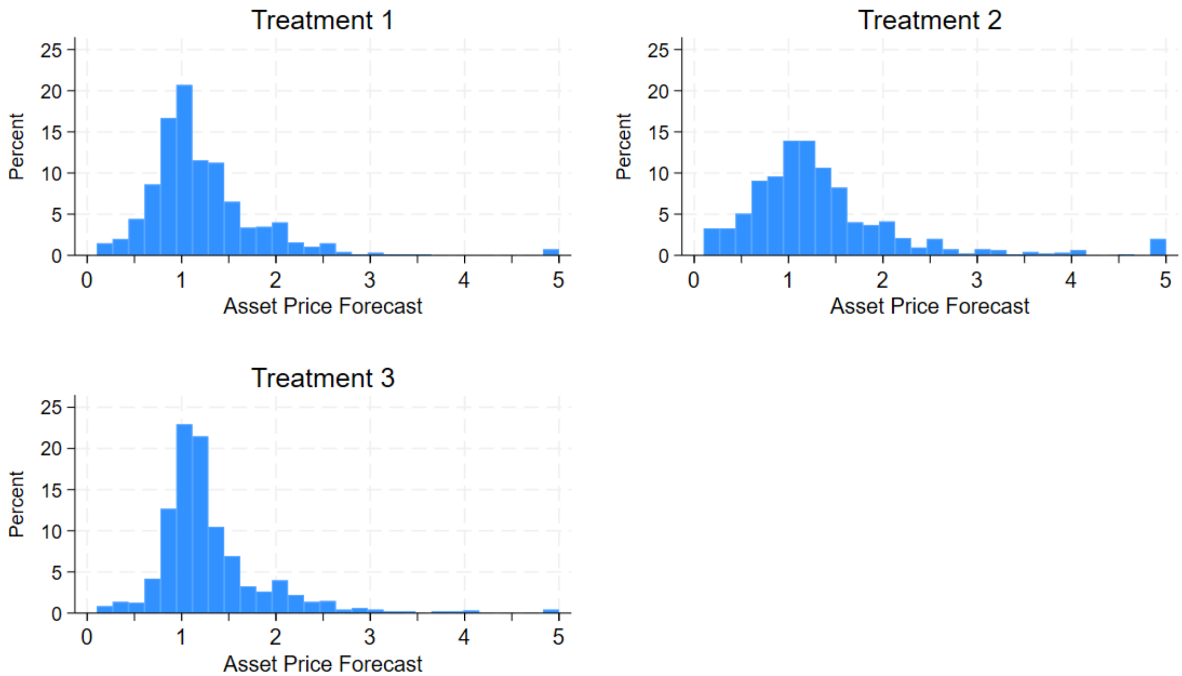


Figure 7: Histograms of Price Forecasts in Each Treatment; Outliers Excluded

that arbitrage opportunities not only exist, but bankers choose to not exploit them and there is a self-fulfilling prophecy aspect to asset prices.

What might cause such behavior? Figure 8 provides some insights by plotting the current period *price forecast* against the prior period's *actual market price* across all three treatments. We observe a small, positive relationship between lagged prices and current price forecasts, indicating that some subjects are adopting trend-following expectation formation strategies. Such behavior can result in a positive feedback loop, wherein expectations of high prices prompt buyers to bid high amounts of cash and sellers to offer few assets, making those expectations self-fulfilling. If enough market participants adopt such trend-following strategies, prices can be sustained at levels that depart from rational expectations for some time. Eventually, prices substantially greater than the fundamental value of the asset will trigger an increase in asset offerings and a fall in asset prices, but thereafter, if there are enough trend-chasing subjects, this same process begins anew.

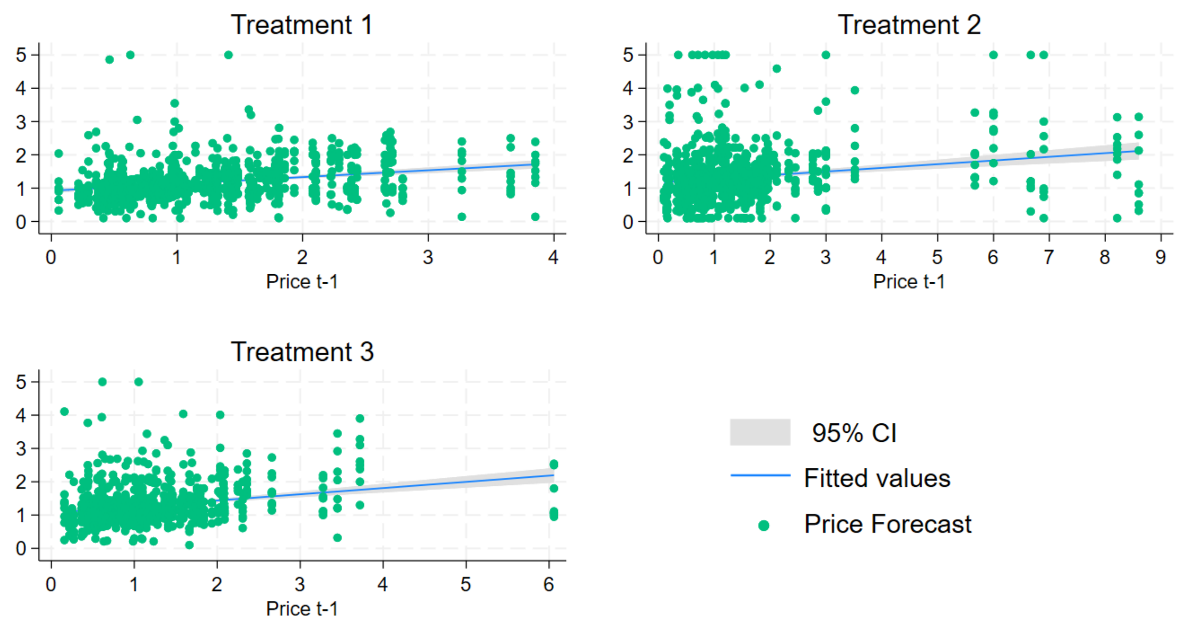


Figure 8: Price Forecasts, Vertical Axis Plotted Against Lagged Prices, Horizontal Axis, by Treatment

Table 7: Trading Volumes Across Treatments, Descriptive Statistics

	Obs	Mean	Std. Dev.	Variance	Median	Min	Max	Skewness	Kurtosis
Treatment 1	120	76.500	31.582	997.395	74.500	14	170	0.433	3.001
Treatment 2	120	65.966	41.328	1708.033	60	1	197	0.815	3.307
Treatment 3	120	123.617	45.861	2103.247	120	34	238	0.518	3.010

In addition to getting market prices and forecasts correct, it is important that the market is sufficiently *liquid*. A simple measure of market liquidity is the volume of trade. Table 7 reports statistics on trading volume in the asset markets of the three treatments. While the volume of trade is indeterminate in the equilibrium of the model, we note that there is a large volume of asset trade in all three treatments suggesting that participants are able to make use of this market to re-balance their portfolios without having a large impact on the price of the asset. The highest trade volume is found in the high variance treatment 3 and the lowest in the asymmetric shock treatment 2.[10]

[10] While we cannot say what trade volume should occur, we can put boundaries on trade volume under assumptions about prices. For example if $P = 1$, then in Treatment 1, trading volume can be anywhere between 0 and 272; in Treatments 2-3 it can be anywhere between 0 and 344.

Table 8: Asset Market Trading Decisions Across Treatments

Trading decision	**Treatment 1**		**Treatment 2**		**Treatment 3**	
	No. Dec.	**Percent**	**No. Dec.**	**Percent**	**No. Dec.**	**Percent**
Buy	440	45.83%	400	41.67%	414	43.12%
No Trade	111	11.56%	148	15.42%	81	8.44%
Sell	409	42.6%	412	42.92%	465	48.44%
Total*	**960**	**100%**	**960**	**100%**	**960**	**100%**

* 20 rounds x 8 players x 6 sessions, respectively.

The liquidity of asset trades and the accuracy of price forecasts are critical to the efficient operation of the interbank asset market. For instance, if a banker needs more cash to cover withdrawal demands, then it is important that he knows that he can sell assets in the interbank market at reasonably stable prices. Further, the banker's forecast matters for the determination of how many assets to offer for sale. A higher price forecast means that fewer assets need to be brought to the market by those bankers who face liquidity needs. Since deposits are over-allocated to cash on average, there will be more cash available to buy assets by bankers who do not face liquidity needs. The result of these price forecasts and asset market decisions is the over-pricing of the asset that we observe.

This explanation is predicated on bankers' making *correct use* of the interbank asset. In particular, it depends on banks playing best responses to their price forecasts and liquidity needs given the realized state of the world in the second stage of the game, and we now turn to such an analysis.

As a first step, Table 8 reports on the trading decisions that subjects made across all rounds of all sessions of each treatment, unconditional on their price forecasts. This table already reveals that there are inefficiencies in the use of the interbank market. In particular, there is a small but sizeable fraction of bankers, between 8 and 15 % who do not or are unable to engage in trade (i. e., they neither buy nor sell assets). As it turns out, these no-trade players are frequently, but not exclusively, the same subjects who choose salient cash allocations in the first stage deposit allocation problem, as Table 9 reveals. In this table we decompose the no trade decisions across the three treatments and relate these to initial cash allocations. A "salient-safe" initial allocation of cash is one that is equal to the high liquidity needs state of the world; e. g., 68 units of cash in treatment 1. A "salient-not safe" allocation is an allocation made to the low liquidity needs

Table 9: No Trade Decisions Across Treatments

Trading Decision	Treatment 1		Treatment 2		Treatment 3	
	Freq.	Percent	Freq.	Percent	Freq.	Percent
No Trade	**111**		**148**		**81**	
Initial allocation was:						
Salient (all)	**88**	**79.28%**	**108**	**72.97%**	**68**	**83.95%**
Salient-safe	49	44.14%	70	47.30%	57	70.37%
Salient-not safe	39	35.14%	38	25.68%	11	13.58%
Non-salient	**23**	**20.72%**	**40**	**27.03%**	**13**	**16.05%**

state of the world; e. g., 32 units of cash in treatment 1. In the event that the state of the world corresponds exactly to the salient liquidity level – safe or not-safe – then there is no need for a banker to engage in trade in the interbank asset market as their liquidity needs are met by their initial cash allocations. Otherwise, of course, they have an incentive to trade. As Table 9 reveals, more than 70% of all no-trade decisions in the interbank asset market can be attributed to subjects who make these types of salient initial cash allocation decisions. Nearly all of these bankers are rationally choosing not to trade given the state of the world and their salient choices. Note however, that 16-20% of no-trade outcomes are for banks that made *non*-salient initial allocation choices. To achieve the first best, these banks would need to have engaged in some amount of trade. This finding suggests that the interbank asset market is not operating as efficiently as needed in order to implement the first best allocation. Nevertheless, among the subjects who do engage in trade, Table 8 reveals that roughly half are buying assets while the other half are selling assets. Overall, we find that 85 to 92 % of subjects *are* using the interbank market to re-balance their portfolios after learning the state of the world. This suggests that most subjects understood the purpose of the interbank market.

Beyond looking at the frequency of buy, sell and no trade outcomes, we now delve deeper and examine whether subjects' trading decisions constitute a best response. Abusing terminology slightly, a trading decision is denoted a *best response* if, given the realised state of the world (the number of impatient depositors), the player's initial allocation of deposits to cash and their price

Table 10: Proportion (%) of Best Responses by Treatment

Best Resp.	Treatment 1 Freq.	Treatment 1 Agg.	Treatment 2 Freq.	Treatment 2 Agg.	Treatment 3 Freq.	Treatment 3 Agg.
Yes	848	**88.33%**	778	**81.04%**	861	**89.69%**
No	112	11.67%	182	18.96%	99	10.31%
Total	960	100%	960	100%	960	100%

forecast, the player places a bid for assets (sells assets) when they should bid (sell) or does not trade when they should not trade. Note that according to this definition, a best response does not require that the chosen bids or offers are equal to the respective optimal quantities; rather it simply means that they are operating on the right side of the market. Table 10 reveals that on average between 80 % and 90 % of subjects were playing best responses to the state of the world, their initial allocation decision and their price forecasts. This indicates that it is not so much the direction of the trading decisions but the respective trading volume that is amplifying distortions in market outcomes.

6.3 Bankruptcies: illiquidity and insolvency

We can now address our most interesting research question: whether bankers are able to avoid bankruptcy in line with Hypothesis 1 in the baseline treatment and Hypotheses 2-3 for the other two treatments.

Following the asset market, trades were automatically executed at the market clearing price according to the subjects' respective bids and offers. Subject's cash and asset balances were updated as the result of any market trades and these updates were reported to subjects so they could understand how their portfolios had changed as the result of any trades at the market price in the interbank market. Finally, an accounting review (conducted by the computer program) was then applied to each bank's post-trade cash and asset position to determine whether banks were (i) (i)lliquid and (ii) (in)solvent. If a bank was either illiquid or insolvent (or both) then it was declared bankrupt.

Table 11: Bankruptcies Across Treatments, Descriptive Statistics

Treatment	Obs	Frequency of	Mean	Std. Dev.	Median	Min	Max
1	**120**	**Bankruptcies**	**0.144**	**0.182**	**0**	**0**	**0.750**
		Illiquid	0.120	0.160	0	0	0.625
		Insolvent	0.039	0.081	0	0	0.375
2	**120**	**Bankruptcies**	**0.144**	**0.183**	**0**	**0**	**0.750**
		Illiquid	0.121	0.165	0	0	0.625
		Insolvent	0.036	0.094	0	0	0.500
3	**120**	**Bankruptcies**	**0.205**	**0.211**	**0**	**0**	**0.625**
		Illiquid	0.175	0.193	0	0	0.625
		Insolvent	0.100	0.153	0	0	0.500

Table 11 reports on mean bankruptcy rates over all rounds of each treatment and disaggregates these bankruptcy frequencies according to whether the source of the bankruptcy was illiquidity or insolvency. Figure 9 shows the mean frequency of bankruptcies *per round* across all three treatments, where again the frequencies are further disaggregated according to whether the bank was bankrupt for any reason (blue), illiquid (red), or insolvent (green). Table 11 and Figure 9 reveals that bankruptcies are fairly common across all 3 treatments, despite the absence of any aggregate risk in our experimental setting. The mean bankruptcy frequency is found to be 14.4% in treatments 1-2 (corresponding to a little more than 1 of 8 banks failing per round on average) and is highest at 20.5% in treatment 3, or a failure rate of about 1.6 out of 8 banks per round on average). A further observation is that across all three treatments, bankruptcies are mainly due to *liquidity problems*, that is, a failure to meet the withdrawal needs of the impatient customers; by contrast, bankruptcies due to insolvencies are comparatively less important. Finally, experience (i. e., repetition) does not seem to reduce the incidence of bankruptcies in any treatment. These findings run counter to our Hypotheses 1 that in the absence of aggregate risk, subjects could avoid bankruptcy.

A regression analysis of whether there are differences by treatment in bankruptcies overall and disaggregated by illiquidity or insolvency reasons for bankruptcy, is reported on in Table 12. The dependent variable in these regressions is binary. In the first specification the dependent variable

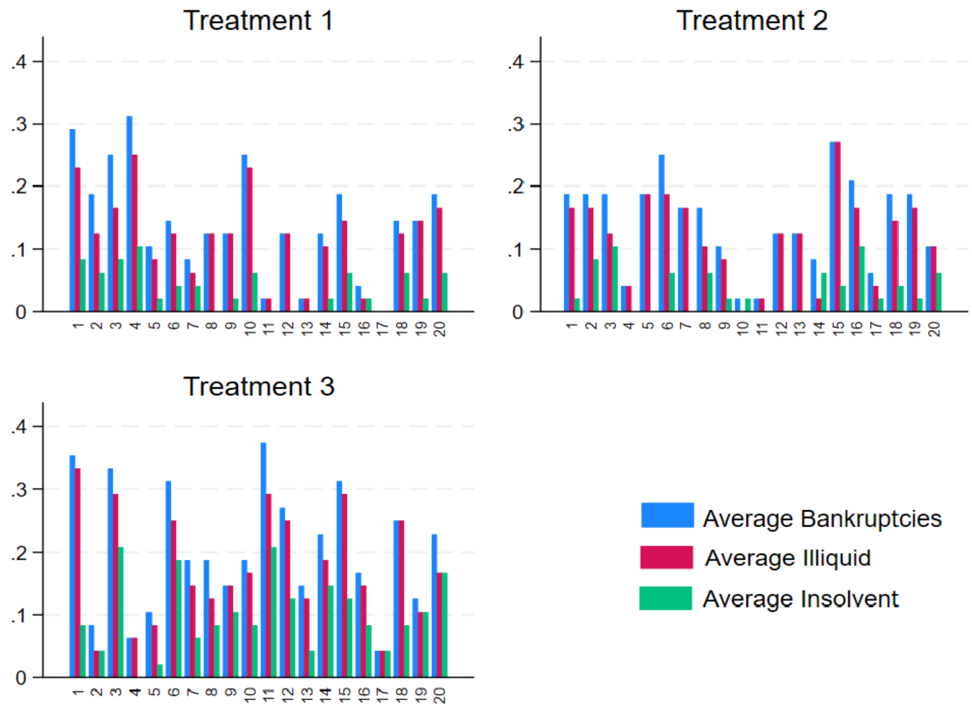


Figure 9: Average Number and Type of Bankruptcies per Round Across Treatments

is equal to 1 if a bank went bankrupt in a round for any reason (illiquidity, insolvency or both) and 0 otherwise. The other two specifications focus on instances where the bankruptcy was due to illiquidity or to insolvency alone. The reported coefficients in Table 12 are the estimated odds ratios. An odds ratio greater than 1 means the outcome becomes more likely with an increase in the explanatory variable, less than 1 means it becomes less likely, and equal to 1 means no effect on the outcome. As Table 12 reveals, the overall odds of bankruptcy are marginally, yet significantly more likely in the high variance treatment 3 as compared with the other two treatments, where the difference in the frequency of insolvencies appear to drive this result. The significance of this treatment effect remains robust if we condition on several potential explanatory variables. First, the variable `dummy_salientsafe` is a dummy variable that is equal to 1 if the banker's initial allocation of deposits to cash was equal to the salient safe amount that is specific to treatment conditions and the banker's region and 0 otherwise.[11] We observe that bankers who made such salient safe

[11]The salient safe allocations of deposits to cash are indicated in boldface in Table 2. As a reminder, for treatment 1, the salient safe allocation was 68 units allocated to cash by banks in both regions; for treatment 2, the salient safe

Table 12: Logit Regressions Involving the Bankruptcy Rate – Odds Ratios

	(1) Bankrupt	(2) Bankrupt	(3) Iliquid	(4) Iliquid	(5) Insolvent	(6) Insolvent
Treatment 2	1.004	1.042	1.008	1.059	0.968	0.971
	(0.02)	(0.17)	(0.03)	(0.19)	(-0.12)	(-0.11)
Treatment 3	1.567*	1.592*	1.590*	1.620*	3.038***	2.988***
	(1.80)	(1.85)	(1.71)	(1.74)	(4.18)	(4.42)
`dummy_salientsafe`		0.107***		0.0110***		0.363**
		(-6.97)		(-4.55)		(-2.46)
GPA		1.010		0.997		1.068
		(0.08)		(-0.03)		(0.38)
Risk Propensity (1-9)		1.068*		1.073**		1.050
		(1.82)		(2.25)		(0.83)
Constant	0.156***	0.121***	0.125***	0.0992***	0.0303***	0.0208***
	(-9.69)	(-3.42)	(-8.96)	(-4.01)	(-18.88)	(-4.25)
Observations	2880	2880	2880	2880	2880	2880

Exponentiated coefficients; z statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

choices were much less likely to experience a bankruptcy.[12] Other potential explanatory variables are subjects' self-reported risk attitudes and GPAs. The regression results in Table 12 reveal that the higher is a subject's willingness to take risks, the greater are the odds that the subject experiences a bankruptcy either due to illiquidity, insolvency or both. By contrast, GPA does not appear to matter for understanding the likelihood of bankruptcy findings. Overall, these findings suggest that a high variance in liquidity needs or a high propensity to take risks are both associated with an increase in the likelihood of a bankruptcy, while salient safe strategies for initial allocations of deposits to cash are associated with a reduced likelihood of bankruptcies.

allocation was 86 units allocated to cash by banks in Region 1 and 59 units allocated to cash by banks in Region 2; for treatment 3, the salient safe allocation was 86 units allocated to cash by banks in both regions.

[12]While this result may not be surprising in the case of bankruptcies due to illiquidity, the salient safe strategy for initial cash allocations also reduces the incidence of bankruptcy due to insolvency.

Table 13: Subject Payoffs, Descriptive Statistics

		Obs.	Mean	Std. Dev.	Variance	Median	Min	Max	Skewness	Kurtosis
Treatment 1	Price forecast	960	3.29	1.04	1.08	3.37	0	5.00	-0.46	2.74
	Allocation	960	8.07	5.29	27.98	8.57	0	52.94	1.13	9.62
Treatment 2	Price forecast	960	2.88	1.29	1.66	3.00	0	5.00	-0.47	2.48
	Allocation	960	8.27	6.48	41.99	8.64	0	69.97	2.78	21.80
Treatment 3	Price forecast	960	3.31	1.02	1.05	3.35	0	5.00	-0.38	2.57
	Allocation	960	8.77	9.38	88.03	7.91	0	72.26	2.40	11.72

6.4 Payoffs

Finally, we consider the payoffs that subjects earned in the experiment. Subjects could earn payoffs in two ways: (1) from the accuracy of their price forecasts and (2) from their portfolio allocations following the interbank market. The payoff earned from final allocations of assets to cash and assets, following trades in the interbank market (referred to as the "allocation payoff") was made equivalent to the payoff that a patient player would earn from depositing their dollar deposit in the subject's bank and waiting to withdraw it in the final period 3. If the bank went bankrupt, then the allocation payoff was 0. In this manner, bankers' payoffs were perfectly aligned with the payoffs earned by patient players. In the first-best equilibrium, no bankruptcies occur and the allocation payoff is predicted to be \$10 per round. The maximum price forecast payoff is \$5 per round.[13]

Table 13 shows statistics on per round payoff earnings over all rounds, disaggregated by the payoff for price forecast accuracy and for final allocation decisions. As Table 13 reveals, payoffs for price forecast accuracy depart from the \$5 maximum. While the median price forecast error was close to zero (see Figure 4) as noted earlier, there was some variance, and the hyperbolic incentive mechanism for price forecasts (12) heavily penalizes differences from the market determined asset price, P. Still, the mean price forecast payoff averages \$3.16 across all treatments (65.2% of the maximum) or a mean absolute forecast deviation of 0.58. Regarding the allocation payoff, Table 13 reveals that the allocation payoff is generally lower than the equilibrium prediction of 10. The

[13]Recall that for the total payoff, we chose two rounds randomly for the allocation payoff and another randomly chosen round for the price forecast payoff. Thus, if subjects were playing according to the equilibrium predictions they could have earned \$25 in addition to the \$10 show-up payment for a 2-hour experiment.

mean allocation payoff is lowest in Treatment 1 and highest in Treatment 3, and the variance in allocation payoffs follows this same pattern.

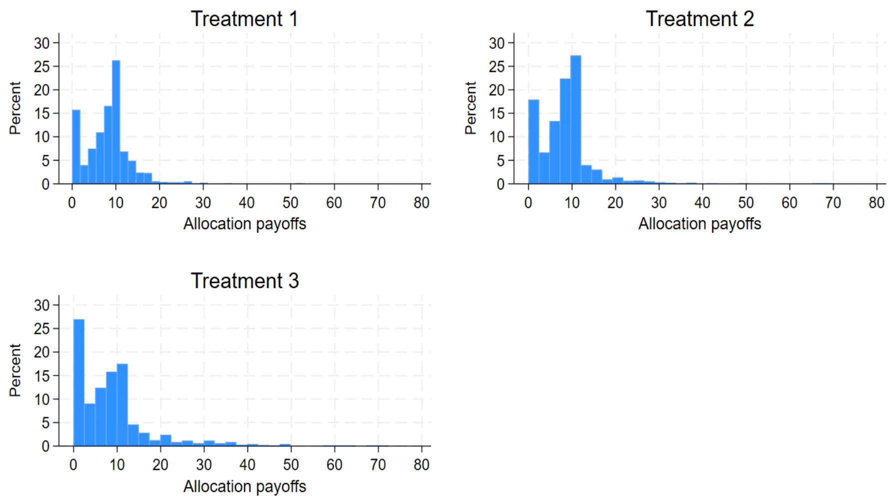


Figure 10: Histograms of Allocation Payoffs Across Treatments

Figure 10 shows histograms of these allocation payoffs and reveals that they are bimodal; there is a spike in the neighborhood of the predicted equilibrium payoff of 10 and another prominent spike at 0, the payoff earned if a bank went bankrupt.

A regression analysis of allocation payoffs reported on in Table 14 confirms the allocation payoff differences across the three treatments. The mean allocation payoff in Treatment 3 is found to be significantly greater than in the baseline treatment 1. The same asset market volatility that bankrupted more banks in treatment 3 compared with the other two treatments also enabled greater payoffs to be earned by those banks that remained liquid and solvent and the gains to these surviving banks outweighed the losses due to bankruptcies, on average. In effect, what we observe is a *market risk premium* that is afforded to those banks who remain liquid and insolvent in the more extreme, high variance liquidity shock environment of Treatment 3. Table 14 further reveals that the significantly higher allocation payoff in treatment 3 is robust to the inclusion of other potential explanatory variables for the allocation payoff. Among these, only a subject's GPA seems

Table 14: Regression Analysis of Allocation Payoffs

	(1) Alloc. Payoff	(2) Alloc. Payoff
Treatment 2	0.203	0.197
	(0.90)	(0.92)
Treatment 3	0.699**	0.713**
	(2.28)	(2.39)
dummy_salientsafe		0.425
		(0.93)
GPA		0.766**
		(2.23)
Risk Propensity (1-9)		-0.116
		(-1.17)
Constant	8.068***	6.037***
	(73.39)	(4.69)
Observations	2880	2880

z statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

to matter, with a higher GPA translating into higher allocation payoffs, on average. Notably, there is no payoff penalty to those who play the salient safe strategy with regard to initial allocations to cash as indicated by the insignificant coefficient on the dummy variable for these players.

Overall, the payoff data confirm our earlier finding that subjects come up short in terms of achieving the first-best allocation and accurately forecasting prices. While there is some support for Hypothesis 2, that asymmetric liquidity shocks do not matter much for payoff outcomes, there is less support for Hypothesis 3 that behavior is invariant in the face of a higher variance to liquidity shocks. Indeed, as we have seen, the high variance treatment leads to greater odds of bankruptcy and greater variance in payoffs compared with the other two treatments.

7 Discussion and Conclusion

We have presented a simple, tractable model linking asset prices to the stability of the banking system based on the contributions by Allen and Gale (2004a,b) to the Diamond and Dybvig (1983) model. We then put our model to an experimental test, where subjects play the role of bankers making portfolio allocation decisions in a first stage and using an interbank market in a second stage in order to rebalance those portfolios once the state of the world regarding liquidity needs is realized. The model is set up in such a manner that 1) there is no aggregate risk, 2) the first-best equilibrium where there are no bank runs is attainable, and 3) only aggregate variables are determinate whereas individual choices are not.

Consequently, there is strategic uncertainty as to the strategies played by individual bankers, about their individual portfolio choices as well as about their trading behavior in asset markets. Both refer to key choices that real bankers face on a daily basis. One consequence of this strategic uncertainty is that some subjects over-allocate deposits to cash as a way of self-insuring against extreme liquidity needs. Indeed, the perfect knowledge that subjects have regarding possible liquidity needs ends up being used by a sizeable fraction of subjects to make safe, high cash allocation choices. As we have seen, this behavior results in mis-pricing of the asset. This mispricing, in turn, means that the first-best equilibrium is consistently not achieved. Perhaps even more surprising, we find that there is a sizeable frequency of bankruptcies even among experienced subjects. Interestingly, most bankruptcies are due to illiquidity rather than to insolvency, even though aggregate cash holdings are too large and the liquidity needs of a bank are perfectly known at the time that the interbank market operates. What is unknown, of course, is the price of assets in terms of cash.

In bank regulation, both liquidity and solvency issues are essential, though their importance may shift based on economic conditions and regulatory objectives. Our results suggest that liquidity regulations may be of first-order importance. Indeed, since the Great Recession, where liquidity shortages were a major issue, regulatory frameworks, such as those outlined by the Basel III regulations have emphasized both solvency and liquidity concerns but have introduced more stringent liquidity requirements through the Liquidity Coverage Ratio (LCR) and the Net Stable Funding

Ratio (NSFR). Such policy measures may perhaps serve as a coordination device for banks, hence reducing strategic uncertainty that may otherwise obtain.

Our results raise further important research questions. First, depositors in our experimental setting are automated robots and their deposit withdrawal decisions were given. How might real depositors change their initial depositing decision if they had a choice between risk-minimizing banks and other banks?[14] Would competition for depositors eventually drive out of the market those banks that behave differently than theory predicts? Second, in our experiment only banks were trading with each other on the asset market. Would allowing other agents (representing, e. g., hedge funds) to trade improve outcomes and lead to greater financial stability? Finally, our bankers were student subjects, and so a natural question is whether our results are externally valid for understanding decision-making in the banking world. We believe that experimental results are largely driven by how agents recognize and respond to incentives and not by the particular subject pool used. Still, it would be of interest to repeat our study with real banking professionals. We leave these and other extensions to future research.

[14]See de Jong (2024) for a first effort to study this question experimentally. In his setting, the risk/return differences between banks are exogenously given while the depositors are subjects who choose which bank to deposit in and whether to withdrawal their deposits early.

References

Allen, Franklin and Douglas Gale, “Financial Fragility, Liquidity, and Asset Prices,” *Journal of the European Economic Association*, 2004, *2* (6), 1015–1048.

_ and _ , “Financial Intermediaries and Markets,” *Econometrica*, 2004, *72* (4), 1023–1061.

_ , Elena Carletti, Jan Pieter Krahnen, and Marcel Tyrell, *Liquidity and crises*, Oxford University Press, 2010.

Arifovic, Jasmina and Janet Hua Jiang, “Do Sunspots Matter? Evidence from an Experimental Study of Bank Runs,” Staff Working Papers 14-12, Bank of Canada 2014.

_ , _ , and Yiping Xu, “Experimental evidence of bank runs as pure coordination failures,” *Journal of Economic Dynamics and Control*, 2013, *37* (12), 2446 – 2465.

Bucher, Monika, Diemo Dietrich, and Mich Tvede, “Bank Stability, Asset Prices, and Liquidity Regulation,” mimeo 2022.

Chakravarty, Surajeet, Miguel A. Fonseca, and Todd R. Kaplan, “An experiment on the causes of bank run contagions,” *European Economic Review*, 2014, *72* (Supplement C), 39 – 51.

Chen, Daniel L, Martin Schonger, and Chris Wickens, “oTree—An open-source platform for laboratory, online, and field experiments,” *Journal of Behavioral and Experimental Finance*, 2016, *9*, 88–97.

Davis, Douglas D., Oleg Korenok, and John P. Lightle, “An experimental examination of interbank markets,” *Experimental Economics*, 2019, *22*, 954–979.

_ , _ , _ , and Edward S. Prescott, “Liquidity requirements and the interbank loan market: An experimental investigation,” *Journal of Monetary Economics*, 2020, *115*, 113–126.

de Jong, Johan, “The initial deposit decision and the occurrence of bank runs,” 2024. Working paper, University of Alicante.

Diamond, Douglas W and Philip H Dybvig, "Bank runs, deposit insurance, and liquidity," *Journal of Political Economy*, 1983, *91* (3), 401–419.

Duffy, John, Aikaterini Karadimitropoulou, and Melanie Parravano, "Financial Contagion in the Laboratory: Does Network Structure Matter?," *Journal of Money, Credit and Banking*, 2019, *51* (5), 1097–1136.

Friedman, Milton and Anna Jacobson Schwartz, *A monetary history of the United States, 1867-1960*, Princeton university press, 1963.

Garratt, Rod and Todd Keister, "Bank runs as coordination failures: An experimental study," *Journal of Economic Behavior & Organization*, 2009, *71* (2), 300 – 317.

Gilboa, Itzhak and David Schmeidler, "Maxmin expected utility with non-unique prior," *Journal of Mathematical Economics*, 1989, *18* (2), 141–153.

Gorton, Gary B, *Slapped by the invisible hand: The panic of 2007*, Oxford University Press, 2010.

Kindelberger, CP, "Manias, Panics and Crashes: a History of Financial," *3 rd edn*, 1996.

Kiss, Hubert J, Ismael Rodriguez-Lara, and Alfonso Rosa-Garcia, "Experimental bank runs," in "Handbook of Experimental Finance," Edward Elgar Publishing, 2022, pp. 347–361.

Matsuoka, Tarishi, "Financial Contagion in a Two-Country Model," *Journal of Money, Credit and Banking*, 2022, *54* (7), 2149–2172.

Metrick, Andrew, "The failure of silicon valley bank and the panic of 2023," *Journal of Economic Perspectives*, 2024, *38* (1), 133–152.

Online Appendix, Not for Publication

A Experimental Instructions

Here we reproduce the written instructions used in the Baseline treatment and the comprehension questions that subjects had to correctly answer before they could participate in the study. The instructions and comprehension questions for the other two treatments are similar.

Experimental Instructions

Introduction

Welcome to this experiment in economic decision-making. Please read these instructions carefully as you, and the other participants, will have to successfully answer some comprehension questions that check your understanding of the material in these instructions before you can proceed on to the experiment.

The experiment consists of 20 rounds. Each round consists of three periods: 1, 2 and 3. Each round is independent of all other rounds; your choices begin anew each round.

For completing this experiment you are guaranteed a participation payment of $10 and you can earn more depending on the decisions that you and other participants make. Specifically, at the end of the experiment your payoffs from 3 rounds, randomly selected, will be added to your participation payment. Since you do not know which rounds will be chosen, you will want to do your best in every round.

Overview

There are 8 participants in your group. You and each of the other 7 participants play the role of *bankers*. Each banker represents a bank that accept deposits from customers in period 1 of each round. The customers are automated robot players as discussed below.

The 8 banks are divided up into two "Regions". One half of the banks service customers in Region I while the other half service customers in Region II. The Region that your bank serves, I or II, will be randomly chosen by the computer program. Your bank will remain in the same Region for the duration of this experiment.

Your payoff in each round depends on the allocations you make of your bank customers' deposits between Cash and Assets in period 1 and on the market price for Assets that will be determined by your choices and the choices of other bankers in period 2. Based on those choices, the computer's accounting review will determine whether your bank is **Liquid** or **Not Liquid** and **Solvent** or **Not Solvent** as explained in detail below. You will want your bank to be declared **Liquid** and **Solvent**, otherwise it will be declared **bankrupt**.

Bankers and the Market for Assets

You and the other bankers make decisions in periods 1 and 2 of each round. At the beginning of period 1, 100 customers, who are all automated robot players, deposit 1 unit of cash in their bank. Therefore, at the beginning of each round, every banker receives 100 units of cash from customers. Then, in the first period, you and each banker must decide how many of its 100 units of cash deposits to invest in assets, the amount A. The asset price in this first period is 1 unit of cash, therefore the remaining amount in cash, C will be equal to $100-A$. You make this allocation decision by moving a slider bar on your computer screen for the amount A of deposits you want to invest in Assets. Note that Asset/Cash amounts are restricted to integer values. You confirm your decision by clicking on a submit button.

Deposits held as Cash earn no interest but are available for you to meet customer withdrawals of deposits in the next period 2. Assets, on the other hand, take time to mature. For each unit of deposits that you allocate to Assets in period 1, there is a payoff of 2 units (a 100% return) in period 3. Assets MUST be held until period 3 in order to earn this return. Moreover, as discussed below, there will be a market among bankers for the buying and selling of Assets in period 2 that all bankers can choose to participate in. Your objective and that of the other bankers is to ensure that your bank remains Liquid and Solvent as explained below while at the same time maximizing the payoff of your customers.

Each bank will face two types of customers: impatient and patient. Impatient customers will always withdraw their deposits in period 2. Patient customers can choose between keeping their deposit in the bank until period 3 (the last period of the round) or withdrawing early in period 2. Therefore, in making their allocation decision, bankers face *two* kinds of uncertainty.

The first concerns the number of customers who are impatient and patient as described in the table below.

State	Region I	Region II
s_1 (prob. 50%)	68 impatient, 32 patient	32 impatient, 68 patient
s_2 (prob. 50%)	32 impatient, 68 patient	68 impatient, 32 patient

As shown in the table, there are two "states", labeled s_1 and s_2, for the number of impatient and patient customers that you and the other 7 bankers will be dealing with depending on their Region. At the start of each new 3-period round, both states are equally likely. You and the other 7 bankers do not learn the state until period 2, but you have to make your allocation of deposits decision in period 1. If you are in Region I (II) and it is state s_1, then your bank will have more (less) impatient customers than banks in Region II (I). Symmetrically, if you are in Region I (II) and it is state s_2, then your bank will have less (more) impatient customers than banks in Region II (I). Specifically, 68 impatient customers means that you will face a withdrawal of at least $w = 68$ units of deposits in period 2, while 32 impatient customers means that you will face a withdrawal of at least $w = 32$ units of deposits in period 2.

The second kind of uncertainty concerns what *patient* customers will choose to do. A patient customer *may wait to withdraw later in period 3* or *choose to withdraw early in period 2 along with impatient customers*. Whether patient customers withdraw later in period 3 or early in period 2 depends on an accounting review of your bank's solvency (as explained below).

Before any period 2 withdrawals are made, you and the other 7 bankers can choose to participate in a centralized market to buy or sell Assets. Each Asset that you sell is exchanged for Cash according to the period 2 market price for Assets, P. Each Asset that you purchase using Cash yields a payoff of 2 if held until period 3. For instance, if given the realized state s_1 or s_2, you find that you have allocated too many deposits to Assets (and too little to Cash) to meet the period 2 Cash withdrawal demands of your impatient customers, then you can *sell* some of your Assets in exchange for Cash deposits. On the other hand, if, given the state, you find that you have allocated too few deposits to Assets (and too much to Cash) to incentivize your patient customers to wait to withdraw their deposits until period 3, then you can use some of your Cash deposits to *buy* Assets from other bankers.

If you choose to be a buyer of Assets then you must decide on the amount of Cash you want to bid, b, for those Assets. Your bid can be any amount from zero up to the amount of Cash you have available (integer values only). If you choose to be a seller of assets, then you choose the quantity q of Assets that you want to sell, which can be any quantity from zero up to the number of Assets that you own (integer values only). After all bankers (participants) have submitted either bids of Cash for Assets or quantities of Assets to sell the period 2 market price of Assets, P, is determined as follows:

$$P = \frac{\text{Sum of all Cash Bid}}{\text{Sum of all Assets Offered}}$$

Thus, the market price is chosen so as to clear the market. If there is no quantity of Assets offered and/or bids of Cash for Assets in the asset market of period 2, then no exchanges take place and there is no market price.

Assuming there *is* a market price P in period 2, then all exchanges take place at that market price, P. If you bid b units of Cash, then, after the market, you will get b/P Assets in addition to any Assets you already hold, but you will have b less Cash. If you sell q Assets, then after the market, you will have $P \times q$ more units of Cash than the Cash allocation you started with, but q fewer Assets.

The decision screen that you and the other bankers see in the period 2 market for Assets is shown in Figure 11.

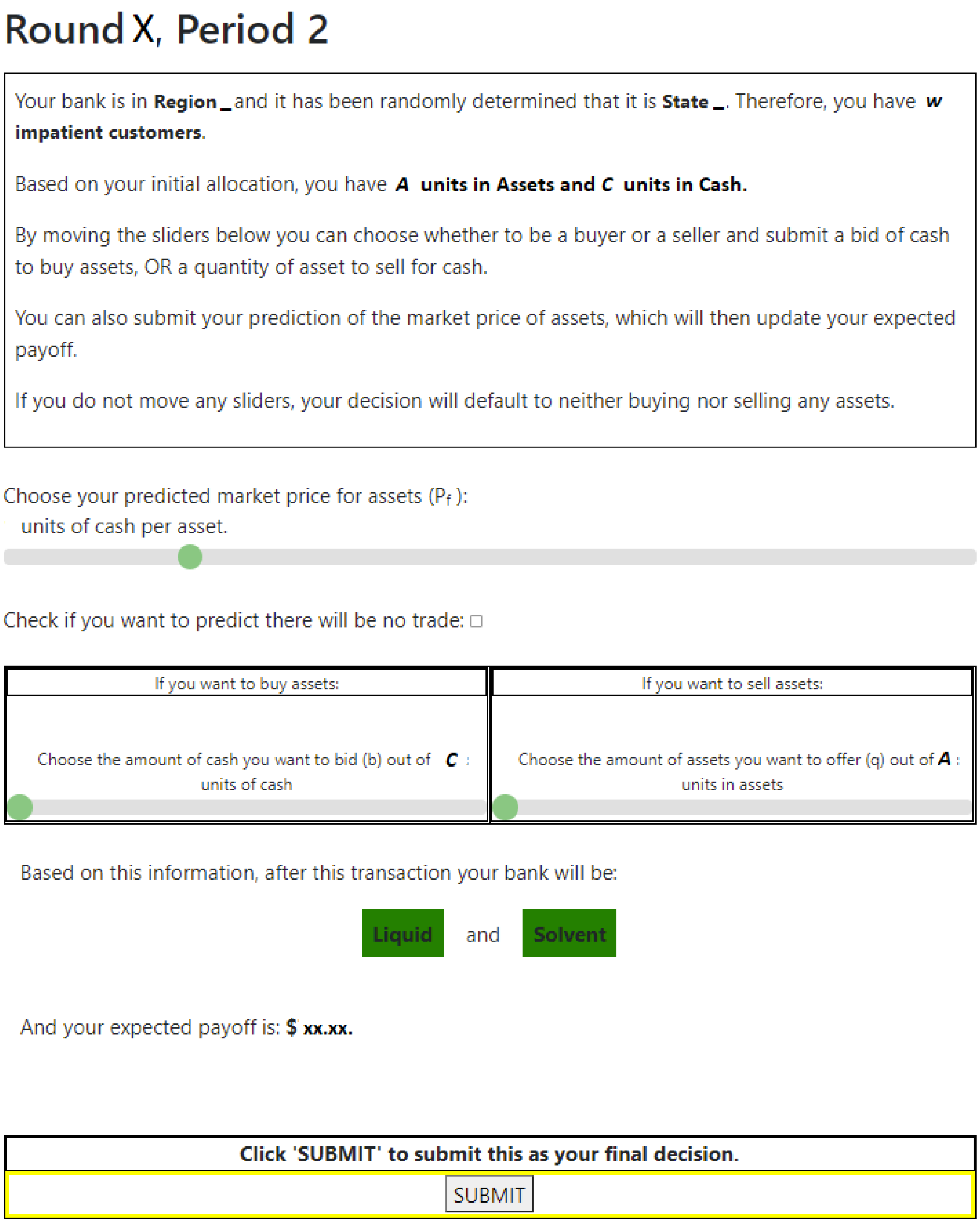


Figure 11: Decision Screen.

At the top of this screen you are informed of the state of the world for this round and the number of impatient customers, w, that your bank will face. You are reminded about how many of your deposits you allocated to assets, A, and to cash, $100-A$ in period 1. Below this information is a slider that you will need to move in order to forecast (or predict) the period 2 market price for assets, P^f, for this round (up to two decimal places). Also, you can experiment with buying or selling assets that mature in period 3, by moving the corresponding sliders, but ultimately, you must choose one role or the other and submit a bid of Cash, b, to buy Assets, or a quantity of Assets, q, to sell for Cash. If you think that no trade will take place, then you can check the corresponding box below the price prediction slider in which case both your bid of Cash, b, and your offer of Assets, q, will automatically be set to zero.

Given your market price prediction P^f, and your bid b, or offer q, the computer program alerts you as to whether your bank may face a liquidity and/or solvency problem and indicates your expected payoff for the round. If you think no trade will take place, the program uses your initial allocation to determine whether your bank may face a liquidity and/or solvency problem.

Your bank is considered *Liquid* if you have enough Cash on hand to meet the withdrawal demands ($w = 32$ or $w = 68$) of your *impatient* customers in period 2. That is if: $(100-A)-b \geq w$, provided you have chosen to be a buyer of Assets, or if $(100-A)+P \times q \geq w$, provided you have chosen to be a seller of Assets, or if $(100-A) \geq w$ provided you have chosen not to trade. Your bank is considered *Solvent* if you have enough invested in Assets to make your *patient* customers willing to wait to withdraw their funds in period 3, that is, if you are able to offer these patient customers a payoff greater than or equal to 1. That is: $(100-A)-b+2\times\left(\frac{b}{P}+A\right) \geq 100$, provided you have chosen to be a buyer, or $(100-A)+2\times(A-q)+P\times q \geq 100$ provided you have chosen to be a seller, or $(100-A)+2\times A \geq 100$ provided you have chosen not to trade.

Based on the above conditions, the box labeled "Liquid" will change to "Not Liquid" if, given your prediction for the market price, P^f and your bid, b, or offer, q, you are unable to meet the withdrawal needs of your bank's impatient customers in period 2. The box labeled "Solvent" will change to "Not Solvent" if, given your prediction for the market price and your bid or offer, your bank's patient customers will not earn a return greater than or equal to 1, and as a result they will withdraw early in period 2 along with the impatient customers. By adjusting your bid or offer and/or your price prediction, P^f, you may be able to make your bank become either "Liquid" or "Solvent" or both, at least in expectation.

Please note that the notifications on your decision screen as to whether or not your bank is Liquid and/or Solvent and your expected payoff rely on your *prediction* of the market price, P^f, and *not* on the actual realization of the market price, P. If your prediction P^f is incorrect, then you could be either Not Liquid or Not Solvent or both, regardless of what was indicated on your decision screen based on your predicted market price, P^f, and your expected payoff could be wrong as well. Therefore, it is very important that you try to accurately predict the actual market price, P. To better incentivize you to accurately predict P, you will earn some payoff each round depending on how close your own price prediction, P^f, is to the *actual* market price, P, where the latter is determined by the actions of all participants. Specifically, your payoff for prediction accuracy is determined by the formula:

$$\text{Prediction payoff} = \frac{\$5}{1+|P^f - P|}.$$

Notice that the maximum payoff you can earn for price prediction accuracy is \$5 and that your prediction payoff decreases the greater is your prediction *error*, equal to the absolute value of the difference $|P^f - P|$ between your prediction, P^f and the actual market price, P; you get the maximum of \$5 only if $P^f = P$. Note that if no trade takes place, you will need to correctly predict this in order to receive the \$5 payoff, otherwise you get \$0 for your price prediction.

Once you have settled on your decisions, click the Submit button to finalize your decision. You can change your decisions anytime *prior* to clicking on the Submit button.

Market Price and the Outcome of a Round

When all 8 bankers have submitted their choices in the asset market, the period 2 market price for the round is determined by the formula given above for P. Depending on the actual realization of the market price, P, you can earn a payoff, provided that you are *both* Liquid and Solvent given the actual market price, P.

Using your holdings of Cash and Assets following the trades in the asset market at price P, if any, the computer program conducts an accounting review of whether or not your bank is both Liquid and Solvent. If your bank is *both* Liquid and Solvent, then you earn a payoff equal to the payoff that a patient customer gets *net* of their initial investment, that is, your bank's period 3 earnings divided by the number of patient customers $(100-w)$, minus 1. This amount is then multiplied by \$10. This payoff depends on whether you participated in the Asset market as a buyer, as a seller or whether you did not participate in the asset market as explained below.

Allocation Payoff:

$$\text{If your bank is } \textit{Liquid} \text{ and } \textit{Solvent} = \begin{cases} \$10 \times \left(\frac{(100-A)-b+2\times(\frac{b}{P}+A)-w}{100-w} - 1\right) & \text{if you were a buyer} \\ \$10 \times \left(\frac{(100-A)+2\times(A-q)+P\times q-w}{100-w} - 1\right) & \text{if you were a seller} \\ \$10 \times \left(\frac{(100-A)+2\times A\ -w}{100-w} - 1\right) & \text{if you did not trade} \end{cases}$$

The expected payoff on the market decision screen uses these same formulas, but it uses your price forecast P^f in place of the actual market price, P; that is why it is important that you accurately predict P. If the computerized accounting review declares that you are $NotLiquid$ and/or $NotSolvent$ for the round, based on the actual market price, then your bank is declared *bankrupt* and you earn an allocation payoff of \$0 for the round.

At the end of the experiment, the computer program randomly chooses 3 rounds for payment. In 2 of those rounds, you get the payoff you earned from your allocation decisions for the round as described above. In 1 round, you get the payoff you earned from predicting the market price P, if any. These earnings will be added to your \$10 participation payment. Finally, you must complete a brief post-study questionnaire. After you complete the questionnaire, you will be paid your total earnings in private.

Summary

Summarizing, the timing of moves in each period is as follows:

Period 1: (a) You receive 100 units of deposits and decide on the amount A of deposits to invest in Assets with a payoff of 2 if held until period 3. The amount $C = 100 - A$ goes to Cash on hand earning no return.

Period 2: (a) You learn the number of impatient customers, w, for your Region and bank.

(b) With knowledge of w and your initial allocation A, you enter a prediction for the market price P^f. You must also decide on the amount of Cash you want to bid to buy Assets or the quantity of Assets you want to sell for Cash in the asset market, if any.

(c) When all 8 bankers have confirmed their choices, the market price P for the round is determined according to the formula:

$$P = \frac{\text{Sum of all Cash Bid}}{\text{Sum of all Assets Offered}}$$

Note that if no trade takes place, there will be no market price.

(d) You and the other 7 bankers are informed of the market price, P.

(e) Considering the number of impatient customers w, the market price P, and your own bank's Cash and Asset positions following trades in the asset market, the computerized accounting review determines whether or not your bank is both Liquid and Solvent.

Period 3: (a) You are informed of the result of the computerized accountancy review, and your **allocation payoff**, as described below:

$$\text{If your bank is } \textit{Liquid} \text{ and } \textit{Solvent} = \begin{cases} \$10 \times \left(\frac{(100-A)-b+2\times(\frac{b}{P}+A)-w}{100-w} - 1\right) & \text{if you were a buyer} \\ \$10 \times \left(\frac{(100-A)+2\times(A-q)+P\times q-w}{100-w} - 1\right) & \text{if you were a seller} \\ \$10 \times \left(\frac{(100-A)+2\times A \;-w}{100-w} - 1\right) & \text{if you did not trade} \end{cases}$$

If your bank is either Not Liquid or Not Solvent, or both, then you earn zero.

(b) You are also informed of the amount you earned based on the accuracy of your price prediction (prediction payoff), maximum $5.

B Comprehension Questions

1. For each of the following statements indicate whether it's true or false:

   - When choosing how many deposit units to invest in assets (in period 1 of each round) you know that is equally likely that your bank will face 68 or 32 impatient customers in period 2 of that round.

     True or False: ____________

   - Impatient customer can decide to withdraw in period 3 together with patient customers.

     True or False: ____________

   - Impatient customer's withdrawal demands in period 2 can be paid with assets that mature in period 3.

     True or False: ____________

   - After learning the number of impatient customers, bankers can participate in a centralized asset market where they can buy or sell assets for cash.

     True or False: ____________

2. Suppose your bank is in Region I and you learn that the number of impatient customers your bank will have this round is 68. How many impatient customers will any of the banks in Region II have in this same round?

   (a) 68

   (b) 32

   (c) 68 or 32

   (d) none of the above

   Your answer: ____________

3. If, after learning the number of your impatient customers you realize that you have ___ of your deposits allocated to Assets to meet period 2 Cash withdrawal demands, then you can ___ Assets in exchange for Cash deposits from other bankers.

   (a) too little; buy

   (b) too little; sell

   (c) too much; buy

   (d) too much; sell

Your answer: _____________

4. If, in a given round, the total amount of Cash bids is 57 and the total quantity of Assets offered is 75, then the market price of Assets, *P*, will be: _______

Your answer: _____________

5. If, in a given round, you bid 24 units of Cash, and after the market exchange takes place *P* turns out to be 1.2, then your bank will have ____ Assets in addition to Assets your bank already had.

Your answer: _____________

6. If, in a given round, you sell 40 Assets, and after the market exchange takes place *P* turns out to be 1.2, then your bank will have _______ units of Cash in addition to the Cash your bank already had.

Your answer: _____________

7. The computerized accountancy review will declare your bank Not Solvent if it determines that after the period 2 asset market, your bank will be unable to:

(a) meet the withdrawal needs of impatient customers in period 2.

(b) meet the withdrawal needs of patient customers in period 2.

(c) pay patient customers at least 1 unit in period 3.

(d) pay patient customers at least 2 units in period 3.

Your answer: ______________

8. Your bank will be declared Not Liquid if, after the period 2 asset market, the bank is unable to:

   (a) meet the withdrawal needs of impatient customers in period 2.

   (b) meet the withdrawal needs of patient customers in period 3.

   (c) pay patient customers at least 1 unit in period 2.

   (d) pay patient customers at least 2 units in period 3.

Your answer: ______________

9. At the end of the experiment, the computer program randomly chooses ________ rounds for payment. In ________ of those rounds, you earn the allocation payoff. In ________ of those rounds, you earn the payoff from prediction accuracy of the market price.

Your answers: ______ ; ______ ; ______

C End of Experiment Questionnaire

The following questionnaire is for research purposes only. Your answers will stay anonymous. Your payment will be prepared while you answer the questionnaire. Thank you for your cooperation!

1. How old are you? [Age]

2. What is your sex? [Male, Female]

3. What is your major field of study?

4. Level of current degree? [Undergraduate, Postgraduate Taught, Postgraduate Research, Other]

5. How do you see yourself: are you a person who is generally willing to take risks, or do you try to avoid taking risks? Scale from 0 to 10, where a 0 means you are “completely unwilling to take risks” and a 10 means you are “very willing to take risks”. You can also use the values in-between to indicate where you fall on the scale.