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Voluntary insurance vs. stabilization funds: An experimental analysis on bank runs

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ABSTRACT

Banking crises have recurrently emphasized the crucial need for establishing effective mechanisms to prevent bank runs, and different organizations are exploring a range of potential measures. With the aim of contributing to this debate, we run a laboratory experiment to study the effectiveness of two untested devices: Stability funds that automatically limit depositors' possibility of withdrawing their assets, and voluntary individual insurance against the risk of default. Depositors start the interaction with a monetary endowment deposited in a bank. They can then withdraw money before and after the bank suffers a liquidity loss. Such a loss can be either permanent or temporary, but its nature will only be discovered at the end of the interaction. The bank defaults if the desired withdrawals exceed its available liquidity. Our results show that the only effective mechanism in reducing bank defaults, compared to the baseline, is the stability fund with high coverage. When groups have a high share of female depositors, there is a significant reduction in the likelihood of bank runs, which can be explained by women's higher propensity to buy insurance. When a critical liquidity signal is issued, indicating a dangerous situation, women's lower propensity to withdraw disappears, bringing it to levels similar to that of men.

1. Introduction

A bank run happens when many customers of a bank withdraw a large amount of money from their deposit accounts at the same time. Bank runs are generally triggered by the belief that the bank might become insolvent, which causes the bank to become illiquid. This can generate a vicious cycle of distrust, leading to more withdrawals and eventually to the potential default of the bank. A systemic financial crisis can arise when bank runs hit many banks concurrently, damaging the whole banking capital of a country. According to Bernanke (1983), the economic losses during the Great Depression were caused directly by bank runs. Even though scholars have different ideas about the role of bank runs in originating financial crises, see Calomiris (2009), the need to adopt measures to prevent and mitigate bank runs is undoubted. These measures involve capital and reserve requirements regulation, central bank as a last resort liquidity provider, government bailout, deposit insurance schemes, and temporary suspension of withdrawals.

After the 2007 financial crisis, several experimental economists tackled the problem of bank runs from different perspectives, providing new elements of analysis. Dufwenberg (2015) presents a short review of the main experimental papers on the subject and an interesting discussion about the role of experimental economics when dealing with banking crises.[1] In particular, he states that "*the key problem* [about the effects of bank runs, A/N], *is lack of data regarding counterfactual circumstances. Lab experiments would seem to have a shot at providing that, as a virtue of the lab is that one can compare treatments. However, the real world may prove too complex to allow direct insights-by-analogy that way. History involved a very complex game, with bank managers, their employees with varying incentives, their customers with their lives and trade-offs and deposit decisions, and government with all its people involved*''. Examining the

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[1] See Kiss et al. (2021) for a more recent review.

[2] In particular, FDIC (2023) states that *the implications of excess deposit insurance on moral hazard, market discipline, and depositors discipline are ambiguous* and that coverage schemes *are unlikely to benefit from a voluntary excess deposit insurance system.*

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experimental literature about bank runs, it is easy to agree with him, and our paper does not elude his criticism. However, Dufwenberg also suggests that experiments can indirectly aid in the understanding of banking crises by evaluating the empirical relevance of ideas circulating in the economic debate. In this respect, following the recent failures of Silicon Valley Bank and Signature Bank in March 2023, which were triggered by runs on uninsured depositors, the Federal Deposit Insurance Corporation (FDIC) introduced the concept of voluntary deposit coverage. Under this system, optional insurance could be provided by the private sector, by the FDIC, or by a combination (for further information, please refer to the reform proposal in FDIC (2023)). There are potential ambiguities in this insurance scheme[2] and FDIC is generally skeptical about its overall benefits. In order to contribute to this debate by investigating the likely effectiveness of alternatives measures, we designed an experiment aimed at test-trying them in the lab. To investigate the effectiveness of voluntary and fee-based insurance as a tool to prevent bank runs, we developed an experimental setup where we test a market based insurance mechanism, which is closer to a bail-in scheme, where depositors spend private money, rather than a classic bail-out mechanism where a third party funds money to pay debts. We are able to corroborate the FDIC's skepticism by demonstrating the existence of misaligned incentives within the voluntary insurance system and its potential to be ineffective or even harmful during bank runs. We also examine the effects of another mechanism: A stabilization fund, in which each depositor contributes proportionally to her share of the deposits. The fund is automatically activated when the bank's liquidity becomes critical and remains active until normal liquidity is restored. Finally, the fund returns to the depositor with interest or the bank defaults and the tokens in the stability fund are lost for the depositor. This mechanism can also resemble a bail-in, as depositors contribute to the stability of the bank with their own money. We compare the results of both treatments with a baseline condition that has no bank-run prevention measures.

The literature on bank run experiments is rich and the model described in the seminal work of Diamond and Dybvig (1983) usually represents the theoretical benchmark. The model admits one good equilibrium, where customers get a profit keeping their money in the bank, and one bad equilibrium, where they suspect that many other customers will withdraw, panicking and withdrawing regardless of their actual liquidity needs. Madiès (2006) is one of the first experimental studies based on the theoretical framework of Diamond and Dybvig (1983). He finds that bank runs occur, but they are usually not total. He is also one of the first to explore partial insurance schemes (75% and 25% deposit coverage), concluding that they do not seem to be able to prevent bank runs. Garratt and Keister (2009) introduce random forced withdrawals that mimic the uncertainty related to adverse macroeconomic conditions, finding that bank runs occur more frequently when this uncertainty is high. Peia and Vranceanu (2019) also find that uncertainty on the actual reimbursement of deposit insurance exert a significant impact on the propensity to withdraw and results in a large number of bank runs. Schotter and Yorulmazer (2009) use a different design, where withdrawals occur sequentially and the bank becomes, at some point, insolvent. They find, in contrast to Madiès (2006), that deposit insurance, even of a limited type, can help to mitigate the severity of bank runs. Kiss et al. (2012) contribute to disentangling the issue by finding that the sequential setup reduces the probability of bank runs and increases the efficacy of deposit insurance (even if full and partial insurance are not significantly different). In a further work, Kiss et al. (2014) find that men and women are equally likely to panic.

Many of the previous papers examine deposit insurance as the primary policy for mitigating financial fragility. However, despite being a key element of modern financial safety nets, deposit insurance also presents shortcomings, like moral hazard (encouraging banks to take on risky portfolios) or size and scope limitations of coverage (see Demirgüç-Kunt and Detragiache (2002) and Demirgüç-Kunt and Huizinga (2004)). Nowadays, several banking systems, particularly in developing countries, do not offer deposit insurance or are not able to claim that the government can guarantee all deposits. Suspension of convertibility of deposits into currency, consisting in a temporary suspension of withdrawals, is perhaps the most frequently discussed alternative. If depositors know that a bank will prevent withdrawals when bank's solvency is undermined, then the threat of suspension may prevent the run, which also means the threat need not be carried out. In the model of Diamond and Dybvig (1983), an appropriate, and quick enough, liquidity suspension policy removes all incentives for depositors to run. However, Ennis and Keister (2009) point out that, after a run has started, a benevolent banking authority would not want to follow through with the suspension because it imposes heavy costs on depositors that definitely need access to their funds. Hence, the complete freeze policy would not be efficient once a run is underway.

The main papers that run experiments on suspension of convertibility are Madiès (2006) and Davis and Reilly (2016). Madiès (2006) includes a "banking holiday" treatment for improving bank stability, finding that, in some situations, a long suspension of deposit availability may reduce panic and improve stability. Davis and Reilly (2016) study the effects of different alternatives in the terms of repayments to depositors following a liquidity suspension, finding that only a tough policy of protecting depositors who maintain their money in the bank, can quite effectively promote stability.

Our framework departs from the classic one of Diamond and Dybvig (1983) for several reasons. First, depositors are aware that an exogenous liquidity shock will hit the bank, independently from their withdrawal decisions. In this sense, we somehow commit to the vision of Calomiris (2009) that bank runs are related to a fundamental shock. Bank runs are seen as a consequence of information regarding the deterioration of bank assets resulting from adverse economic conditions (e.g., Allen and Gale, 1998). Depositors face uncertainty about the permanent or temporary nature of the shock, and have the chance to withdraw before and after its occurrence. Second, as in Schotter and Yorulmazer (2009), subjects' withdrawal decisions are sequential, allowing for first-come first-served rationing mechanisms, and happen in multiple instances. Third, the deposit insurance scheme is voluntary and fee-based, whereas the liquidity suspension is framed as a safety fund to which subjects must contribute in proportion to their deposits. The two instruments are similar because they both entail a payment and provide coverage, but different in the (i) voluntary vs. mandatory nature, (ii) individual vs. collective nature, (iii) non-freezing vs. freezing effect on withdrawals. To the best of our knowledge, we are the first to compare the effects of a private, fee-based, deposit insurance and a liquidity suspension mechanism.[3] In other words, we are comparing an endogenous market mechanism with a precautionary, self-activating external rule.

According to our results, private insurance treatments are not able to prevent bank runs and bankruptcies. We observe a binary behavior, where subjects who purchased the insurance are more likely to leave the money deposited, whereas those who did not purchase it tend to withdraw massively. This evidence seems to indicate that fee-based, voluntary deposit insurances are not effective, or even harmful, as they induce a panic effect on a fraction of the subjects. Costless deposit insurance coverages (see, e.g., Madiès (2006) or Schotter and Yorulmazer (2009)), even if not particularly effective, still appear to be preferable options. We also find that fee-based insurance works better for women, who tend to purchase it more frequently, and therefore to keep money in deposit. However, when the bank seems "closer" to bankruptcy, women tend to increase their withdrawals significantly, getting on a par with men. Our results overall confirm the conjectures presented in FDIC

[3] Kiss et al. (2022) introduced a priority account, allowing depositors to shift part of their deposits. This arrangement insures them, in effect, against bankruptcy, albeit at the cost of forgoing higher interest rate.

(2023) regarding the potential drawbacks of the voluntary insurance scheme.

Madiès (2006) designs the suspension of deposit convertibility as a short or a long suspension of deposit availability, therefore focusing on the timing structure, while Davis and Reilly (2016) explore on terms of repayments to depositors following a liquidity suspension. We focus, instead, on the amount of the stability fund, and on the liquidity conditions that trigger the creation of the fund.[4] Our results show that the amount of the fund is an essential component. In general, the stability funds have no *ex ante* panic-reducing effect, but if the amount of the fund is high enough it has an overall positive impact in reducing bank defaults. This impact is given by a combination of the liquidity constraint effect in limiting withdrawals and the *ex post* panic-reducing effect that appears when the financial fragility of the bank becomes critical.

2. Experimental design and hypotheses

2.1. Design

390 participants were randomly recruited from the pool of university students at the Jaume I University Laboratory of Experimental Economics (Spain), from a variety of different degrees. Students were invited in groups of 60 per session. Each student was randomly assigned to a fixed group made up of five participants, who constitute the depositors of a "bank" in our design. At the beginning of period 1, the bank has 5000 in deposits which it holds as cash. There are 5 depositors each with 1000 deposits and 200 extra cash at home. The bank undergoes a liquidity shock with certainty at the end of period 1. This shock can be interpreted for instance as a committment to extend a loan of 2500 to a counterpart. This loan is illiquid and cannot be repaid until the end of period 3. It also bears credit risk: it may or may not be paid back at the end of period 3 with 50% probability. The interest rate on this loan is 100%. Each participant had three opportunities to ask to withdraw part or all of her deposits from the bank (labeled as periods 1, 2 and 3). The money withdrawn in each period was transferred to the depositor's personal account at no interest and with certainty. The money left in the bank would be kept in a high-yielding cash-like asset. This asset yields 100% return on the funds in the asset at end of period 3, unless the bank had gone bankrupt before, and subject to the following specifications.[5]

In all treatments we introduced two types of uncertainty related with keeping the tokens in the bank account:

- The first type of uncertainty concerned the liquidity loss of 2500 tokens for each bank, which occurred with certainty at the end of period 1. As mentioned above, this loss could be either temporary or permanent. If temporary, the 2500 tokens would be returned to the bank, with 100% interest, at the end of period 3 (e.g., due to the loan repayment). But if the depositors withdrew more than 2500, the bank would not be able to meet its obligations due to the lack of liquidity, and therefore it would be resolved. If the shock was permanent, the 2500 tokens would not be returned (e.g., due to the loan default). Whether the liquidity shock was temporary or permanent was determined after the end of period 3 through the toss of a coin with even probability for the two events to occur. If the loss was not recovered, each agent received a percentage of the final cash balance of the bank (the cash at the end of period 3 multiplied by 2) equal to her share in the total deposits.
- The second type of uncertainty concerned the possibility that the bank would go bankrupt if the depositors' sum of desired withdrawals exceeded the amount of liquidity available in the bank in a certain period. That is, any illiquidity would result immediately into bankruptcy. In this case, a "first come first served" principle would apply, as agents' withdrawal orders were chronologically ranked and sequentially fulfilled until no cash remained in the bank. Accordingly, withdrawals arriving "too late" might be only partially fulfilled or not fulfilled at all. This arrangement simulates the idea of a bank run, with depositors arriving first to queue at the bank having a higher probability that their deposits would be returned than depositors arriving late.

In sum, if the bank did not go bankrupt and recovered the 2500 tokens, an agent would earn an amount equal to twice her deposits at the end of period 3. If the bank did not go bankrupt but the 2500 were not recovered, each agent received a percentage of the final cash balance of the bank (including interests) equal to her share in the total deposits. If the bank went bankrupt, all remaining deposits were lost to the agent.

Four different treatments introduced different mechanisms that modified the baseline interaction just described.

In the **Insurance treatments**, we introduced the option for each agent to buy insurance against a possible bankruptcy of the bank using part or all of the initial 200 cash tokens. Such an insurance purchase could occur only before the first withdrawal decision in period 1. In case the bank went bankrupt in any period and the agent could not recover part of her deposits, she would receive from the insurance at most the amount of cash tokens she had paid as a premium multiplied by a given multiplicative factor. If such a sum exceeded her lost deposits, she could only get her deposits lost when the bank went bankrupt. The cash paid as a premium was never recovered. We stress that this insurance mechanism is in contrast to the standard analysis of mandatory (and costless) government deposit insurance as in the Diamond and Dybvig (1983) model. It can instead be thought of as second-best insurance provided by a private company.

Our design included both a Low and a High Insurance treatments, in which the multiplicative factor that the insurance would pay in case of bankruptcy was equal to either two or three times the tokens spent as a premium, respectively.

In the **Stability Fund treatments**, there was no possibility of insurance, but a fund of X tokens would be automatically created from existing deposits as soon as the bank liquidity went under a given threshold Y. Each agent automatically contributed to this fund in a proportion equal to her share in the total deposits of the bank. Once in place, agents were not allowed to withdraw any amount of their tokens from such a fund until the end of the experiment. Tokens from each depositor allocated to the fund would be recovered with a 100% interest at the end of the experiment if the bank had not gone bankrupt, but would be lost completely in the other case. Note that the stability fund acts as a personalized partial temporary suspension of convertibility for each depositor, but it lasts until the end of the experiment, and the fund's deposits are confiscated by the bank's owners in case of bankruptcy.

Our design included both a High Stability Fund and a Low Stability Fund treatments, which differed on the levels of X and Y. In the Low Stability Fund treatment, X and Y were set at 1000 and 1800, respectively (a fund of 1000 tokens would be created as soon as liquidity went below 1800 tokens). In the High Stability Fund treatment, X and Y were set at 2000 and 2250, respectively (a fund of 2000 tokens would be created as soon as liquidity went below 2250 tokens).

In all treatments, the agents could get, at some point, information about the liquidity state of the bank, as a critical liquidity signal to depositors was issued at the beginning of a period if the cash in the bank had gone under 1800 tokens out of the initial 5000 tokens at the end of the previous period (except in Treatment 4 where the threshold was 2250 tokens).

[4] These combined conditions on the fund share some common elements with the liquidity requirements introduced by Davis et al. (2022).

[5] In order to simplify our framework we consider that any illiquidity of the bank immediately results in the bank's bankruptcy and the depositors losing all their deposits not withdrawn at the moment of bankruptcy.

2.2. Procedures

A post-experiment questionnaire run at the end of each session inquired about participants' gender, field of study and prior attendance of experiments. The percentage of female participants was 46% and the percentage of Business & Economics students was 66%. Regarding experience, 73% of the subjects had previously participated in an economic experiment. Average earnings were 14€ per subject in about 1.5 h. A comprehension test of the instructions was run prior to the real decision task, and we clarified the issues with participants failing to accurately complete the test. Experiments were programmed in zTree (Fischbacher, 2007) and recruitment was done using ORSEE (Greiner, 2015).

2.3. Theoretical analysis

2.3.1. The sub-game perfect Nash equilibria of the game

In this section, we summarize the main results of the theoretical analysis, which are reported in detail in Appendix A. Given the dynamic nature of the game, an equilibrium must be subgame-perfect in all periods. That is, an action must be the optimal response to others' actions in each period of the game. Applying backward induction, we first compute optimal strategies in the final rounds of the game – namely, $r > 1$ – and then compute the optimal response in $r = 1$ that is compatible with the best responses in $r > 1$. This generates the Sub-game Perfect Nash Equilibria (SPNE) of the game.[6]

Lemmas 1 and 2 show that two equilibria exist in the subgame in $r = 2$. In one of them, all agents withdraw their money. In the other, all agents do not withdraw their money. These results are intuitive and are consistent with the Diamond and Dybvig (1983) model. Provided that all other agents do not withdraw their money, not withdrawing money is the dominant individual strategy, and *vice versa*. Lemmas 1 and 2 take into account the possibility of rationing in case of bank runs. Lemma 3 then demonstrates that withdrawing all deposits in $r = 1$ is the SPNE compatible with the sub-game equilibrium of withdrawing all deposits in $r = 2$. In particular, note that if an agent anticipates that other agents will withdraw their deposits in $r = 2$, it is an optimal strategy to withdraw all their deposits in $r = 1$. In this way, the agent can assure the full payment of their withdrawals. Conversely, if they withdraw money in $r = 2$, the possibility that the bank is insolvent may curtail their payoffs. We call NE^{1000} the SPNE in which all agents withdraw their money in $r = 1$. Lemma 4, in turn, demonstrates that not withdrawing any deposit in $r = 1$ is the SPNE compatible with not withdrawing any money in any subsequent period. We call NE^{0} the SPNE in which all agents leave their money in the bank. Finally, Lemma 5 demonstrates that no other SPNE is possible in addition to NE^{1000} and NE^{0} in pure strategies.

2.3.2. Analysis of optimal insurance

Since the insurance decision takes place before the start of the withdrawals, it should be analyzed, once again, through backward induction. In the case of the two SPNE found in Section 2.3.1, it is immediate to show that we should observe no insurance in equilibrium. Let us suppose that the SPNE NE^{1000} holds. Since the agent withdraws all her deposits, it is obvious that there is no point in investing any money in insurance. Likewise, let us suppose that the SPNE NE^{0} holds. Since all other agents are not going to withdraw their deposits in any round, the bank will not go bankrupt. Therefore, it is again irrational to invest any money in insurance.

The above analysis leaves open the issue of equilibrium selection or off-equilibrium paths. In the Appendix A, Appendix A.4.3, we develop a model in which we assume that the agent ignores which equilibria – or off-equilibrium set of actions – other agents are playing. We follow the approach developed in Appendix A.4.1, where an agent assigns a probability P to bankruptcy and $1 - P$ to bank survival. We assume that the agent is considering playing some strategies different from those prescribed by the two SPNEs, thus making insurance possibly profitable. Agents are risk-neutral so that the utility function is the same as that developed for the above analysis, except for having added the amount spent on insurance x_i and having allowed for the payment of the insurance premium in case of bankruptcy. The utility function is laid out in Appendix A.4.1, Eq. (14).

The payoff function depends on the expected value of $\hat{w}_j$. We model this expectation through a two-step uniform distribution function in which the probability mass of P and $1 - P$ is evenly distributed over the intervals associated with bankruptcy - namely, $[2500 - w_i; 4000]$ - and survival - namely, $[0, 2500 - w_i]$, respectively (see Appendix A, Appendix A.4.3, Eq. (21)). This approach permits the determination of a simple relationship that links $E(\hat{w}_j)$ with P and w_i (see Appendix A: Appendix A.4.3, Eq. (23)).

We derive optimality conditions for both x_i and w_i. The optimality condition for an internal maximum for x_i is simply:

$$P > \frac{1}{k} \tag{1}$$

Condition (1) ensures that the expected benefit from buying a unit of insurance - namely, Pk - exceeds the cost - namely, 1.

In the Appendix A, Appendix A.4.4, we use numerical methods to determine the optimal choice on the basis of the above analysis. In our proposed voluntary insurance setting, the fee paid for the insurance and the limited coverage go against effectiveness to prevent withdrawals. Although buying insurance is in some regions the local optimum, this strategy is dominated by the corner solution prescribing to withdraw everything (see case 3 in Appendix A: Appendix A.4.4 and Fig. 4). Hence, the insurance scheme fails to attract risk-neutral agents. In particular, we find that for values of P below a value of approximately 0.24, risk-neutral agents prefer $w_i = 0$. They prefer $w_i = 1000$ for values of P higher than this threshold (see case 4 in Fig. 4).

However, if we consider a utility function characterized by risk aversion and probability weighting (Tversky and Kahneman, 1992), we find that insurance is optimal for a non-negligible interval — albeit never at the maximum possible level of insurance $x = 200$ (see Eq. (24) in Appendix A: Appendix A.4.5).[7] It is for intermediate values of P that risk-averse agents prefer to buy some insurance (see Fig. 5 in Appendix A: Appendix A.4.5). Intuitively, if the probability of bankruptcy is too high, risk-averse agents will prefer to withdraw all the money, thus buying insurance is pointless. If the probability of default is too low, profiting from the insurance indemnity is unlikely, hence agents will prefer not to buy insurance. However, if P lies at intermediate levels, then buying insurance can be seen as part of a "portfolio diversification" strategy whereby risk-averse agents can reduce expected losses in the event the bank goes bankrupt while profiting from the interest of the deposits they have left invested in case it does not. It is also noteworthy that agents characterized by this utility function prefer, for a considerable range of P, to withdraw intermediate levels of their endowment 6.

2.4. Hypotheses

Given the multiplicity of equilibria established in Section 2.3.1, we cannot be *a priori* sure of which of the two equilibria will be selected. Our main assumption is that both mechanisms considered in our design will increase the probability that the payoff-dominant equilibrium NE^{0}

[6] Given the symmetry of $r = 2$ and $r = 3$, we only need to analyze one of these two periods with no loss of generality.

[7] According to our numerical analysis of utility functions characterized by risk aversion but no probability weighting, not insuring turns out to be the optimal strategy. Therefore, probability weighting seems to be necessary for insurance to be optimal in some region of the probability space.

will be selected. We posit that private insurance will help reduce bank runs, as it reduces the variance of the final outcomes and in particular increases the payoff in case of losses. This should make agents *ceteris paribus* more willing to take the risk of leaving a higher share of deposits in the bank. The establishment of the stability fund should also, by construction, limit bank runs, by materially preventing depositors from withdrawing money when bank liquidity is relatively low, but also preemptively, because withdrawing money from the bank increases the likelihood of a deposit freeze. We then posit:

H1: Both the insurance treatments and the stability treatments will reduce withdrawals and bankruptcy rates in comparison with baseline.

We also assume that participants are sensitive to the incentives implicit in the two mechanisms, and that higher insurance indemnity – that is, a higher k – and a higher security threshold for the establishment of the stability fund will result in lower bankruptcy:

H2a: The *Stability High* fund treatment will reduce withdrawals and the bankruptcy rate in comparison with the *Stability Low* treatment.

H2b: The *Insurance High* treatment will reduce withdrawals and the bankruptcy rate in comparison with the *Insurance Low* treatment.

We believe that there are two ways in which a given mechanism can prevent bank runs. Firstly, the existence of a mechanism should *increase* the probability that other depositors will not withdraw money in comparison to the baseline, thus further increasing the subjective incentives to play $w_i = 0$. In other words, the existence of a mechanism should reassure agents that other agents are less likely to withdraw money from the bank, thus making agents more likely to believe that other agents will coordinate on the NE^0 equilibrium rather than the NE^{1000} equilibrium. We call this the "*Panic-Reduction effect*". If mechanisms manage to have a panic-reducing effect, then we expect that withdrawals will be reduced in Period 1 compared to the baseline, because they exert an influence on agents' *ex ante* beliefs and should thus affect agents' initial decisions. Secondly, the stability mechanisms can exert an effect even after Period 1, when the stability fund is actually implemented. We can thus expect that in Stability Fund treatments withdrawals may be reduced in Periods 2 and 3 as well. We call this the "*Fund Stabilisation*" effect. We thus posit:

H3a: According to the *Panic-Reduction* effect, withdrawals in treatment conditions will be significantly lower than in the baseline in Period 1.

H3b: According to the *Fund Stabilisation* effect, withdrawals will be lower in Stability treatments than in other treatments and baseline in Periods 2 and 3.

It is worth stressing that these hypotheses are based on the idea that agents are fully rational and forward-looking and apply backward induction. As stressed in Appendix A.3.1, the SPNE prescribe that withdrawal decisions, if any, should not occur beyond Period 1. Nevertheless, if agents are not forward-looking and follow adaptive, path-dependent, strategies, then H3a will not hold. In particular, agents may decide to follow a "wait-and-see" heuristic, conditioned on withdrawing more or less money when the signal communicating low liquidity is observed. If that is the case, then we should observe a significant amount of withdrawals even in Periods 2 and 3. We then formulate these hypotheses:

H4a: According to the hypotheses of full rationality and forward-looking expectations, no withdrawals will occur after period 1.

A weaker version of this hypothesis, assuming that some agents follow path-dependent heuristics, is:

H4b: If some agents follow path-dependent heuristics, but if forward -looking behavior prevails in the population, the amount of withdrawals will be significantly higher in Period 1 than in subsequent periods.

Table 1
Outcomes per treatment.

Treatment	N Bankrupt	N Survive	% Bankrupt	N Total
Baseline	10	6	62	16
Insurance low	13	3	81	16
Insurance high	11	4	73	15
Stability low	10	6	62	16
Stability high	5	10	33	15

3. Results

3.1. Descriptive statistics

Overall, 62.8% banks (49 out of 78) went bankrupt (Table 1). Hence, in spite of not withdrawing money from the bank being a payoff-dominant SPNE of the game, the majority of participants opted to play the risk-dominant equilibrium of withdrawing money from the bank (Appendix A.3.1). This result is in line with other experiments on bank runs, and more generally on coordination games, showing that individuals often fail to coordinate on the payoff-dominant equilibrium (Section 1). H1 appears to be violated for all treatments except *Stability High*, as the bankruptcy rate is actually higher in both *Insurance Low* (81%) and *Insurance High* (73%) treatments than baseline (62%), while it is the same in *Stability Low* (62%) and baseline. Conversely, the bankruptcy rate is nearly half in the *Stability High* (33%) treatment compared to baseline. We also notice that the *Insurance High* treatment performs marginally better than the *Insurance Low* treatment, while the difference between *Stability High* and *Stability Low* is larger, consistently with both H2a and H2b.

The share of defaulted banks across treatments and periods is shown in the top panel of Fig. 1. None of the implemented mechanisms is capable of reducing withdrawals in comparison to baseline in Period 1. Hence, no *Panic-Reduction effect* seems to be at work (see H3a). It is only in Periods 2 and 3 that the bankruptcy rate in the *Stability High* treatment appears to be systematically lower than in baseline. All other treatments appear to follow a similar pattern as the baseline, with the exception of the *Insurance Low* treatment, in which bankruptcies appear systematically higher than the baseline since Period 1.

3.2. Econometric analysis of treatment effects

We test our hypotheses through a linear regression model with the dichotomous variable *Bankruptcy* as the dependent variable.[8] The covariates include dummy variables identifying treatments and controls for group-level gender and age means. Standard errors are robust to heteroscedasticity.[9] Unless, otherwise stated, we refer to the model with demographic controls. Only the *Stability High* Treatment significantly reduces bankruptcies as compared to the baseline ($p = 0.080$, see in Table 2: Model 2). Omitting demographic controls, the null that the coefficient for *Stability High* is equal to zero drops out of the border with statistical significance at conventional levels ($p = 0.105$; see Table 2, model 1). The null that the coefficient is equal to zero is not rejected for *Stability Low* ($p = 0.70$), *Insurance High* ($p = 0.57$) and *Insurance Low* ($p = 0.18$, see Table 3). While the sign of the coefficient is negative for *Stability High*, it is positive in all other cases, in accordance with

[8] The data obtained for this article and scripts used for its analysis can be accessed online at: https://osf.io/9ynhg/?view_only=662dfe95a2504ec1b2b4e7bc23efa8b4.

[9] Gomila (2021) suggest that linear regression is generally the best strategy to estimate causal effects of treatments on binary outcomes. Alternative Bayesian data analysis tools exist, such as those used by Shrivastava et al. (2019), however we decided to stick to the classical approach in this article.

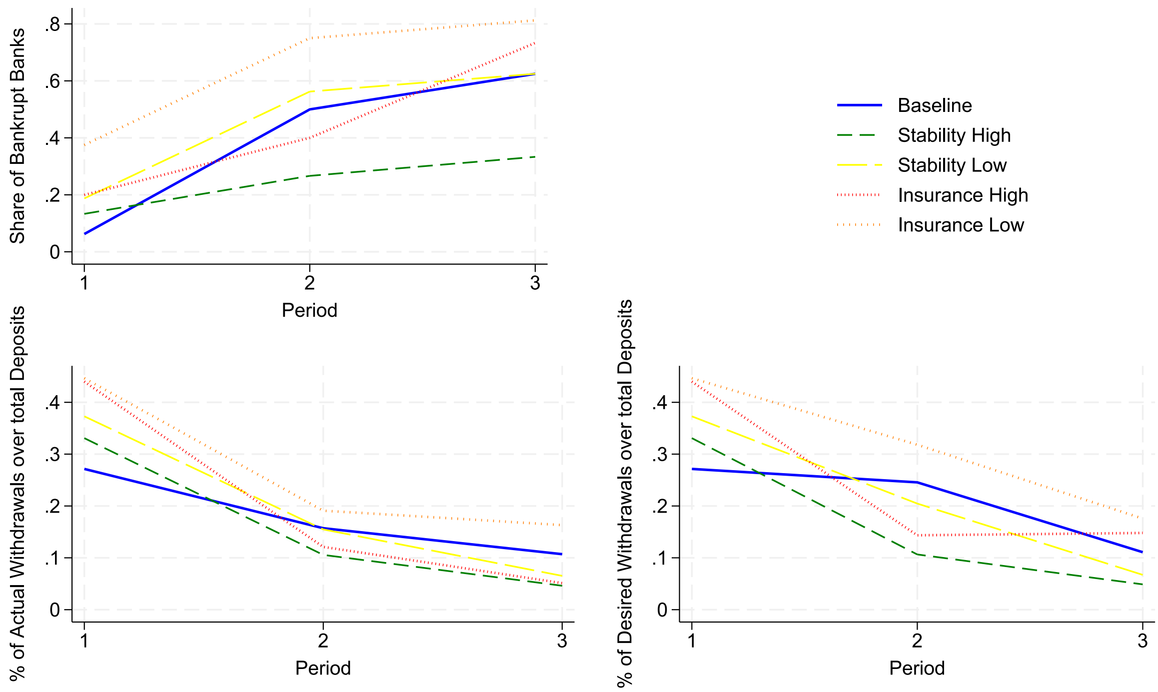

Fig. 1. Top: Share of bankrupt banks at the end of each period by treatment and period. Bankruptcies at the end of period 1 are due to the combined effect of withdrawals and the shock (see Section 2.1). Bottom: Actual (left) and desired (right) withdrawals over total deposits.

Table 2
Regression on Bankruptcy.

Dep. var.: Bankruptcy				
	(1)	(2)	(3)	(4)
Baseline			−0.188	−0.228
			(0.161)	(0.169)
Insurance low	0.188	0.228		
	(0.161)	(0.169)		
Insurance high	0.108	0.098	−0.079	−0.130
	(0.172)	(0.170)	(0.155)	(0.151)
Stability low	0.000	0.071	−0.188	−0.157
	(0.177)	(0.182)	(0.161)	(0.159)
Stability high	−0.292	−0.311*	−0.479***	−0.539***
	(0.177)	(0.174)	(0.161)	(0.150)
Age		0.010		0.010
		(0.016)		(0.016)
Gender		−0.675**		−0.675**
		(0.256)		(0.256)
Constant	0.625***	0.675	0.813***	0.903**
	(0.125)	(0.477)	(0.101)	(0.410)
Observations	78	78	78	78
R^2	0.111	0.186	0.111	0.186

The Table reports coefficients from regression on Bankruptcy. Robust standard errors are shown between parentheses, and the significance of the coefficients is flagged following the usual convention: *p < 0.1; **p < 0.05; ***p < 0.01.

Table 3
Pairwise tests of treatment effects on Bankruptcy.

BANKRUPTCY		Baseline	Insurance low	Insurance high	Stability low
Insurance low	Coefficient	0.228			
	Std. Err.	(0.17)			
	P-value	*0.18*			
Insurance high	Coefficient	0.098	−0.130		
	Std. Err.	(0.17)	(0.15)		
	P-value	*0.57*	*0.39*		
Stability low	Coefficient	0.071	−0.156	−0.027	
	Std. Err.	(0.18)	(0.16)	(0.17)	
	P-value	*0.70*	*0.33*	*0.87*	
Stability high	Coefficient	−0.31*	−0.538***	−0.409**	−0.381**
	Std. Err.	(0.17)	(0.15)	(0.16)	(0.17)
	P-value	*0.080*	*0.001*	*0.015*	*0.026*

The Table reports coefficients, std. err., and P-values for Wald tests on the equality of the treatment coefficients in the column entry and the row entry. Tests have been run on the regression in Table 2, column 2. A positive (negative) value for the coefficient means that banckruptcy is on average higher (lower) in the row-entry treatment than in the column-entry treatment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the descriptive analysis (Section 3.1).[10] Non-parametric tests return qualitatively similar results.[11]

We conclude:

Result 1: The *Stability High* treatment is the only treatment reducing bankruptcy rates in comparison to baseline, but only at weak levels of significance. *Stability Low* achieves the same bankruptcy rate as baseline, while the two *Insurance* treatments perform worse than baseline, albeit at statistically insignificant levels.

Performing pairwise Wald tests on the equality of pairs of Treatment coefficients, we also find that the coefficient for *Stability High Treatment* is significantly lower than the coefficients for *Stability Low Treatment* ($\beta = -0.381,\ SE = 0.17\ p = 0.026$), *Insurance High* ($\beta = -0.409,\ SE = 0.16\ p = 0.015$), and *Insurance Low* ($\beta = -0.538,\ SE = 0.15\ p = 0.001$; Table 3). No other pair of coefficients is significantly different from each other. This is, in particular, the case for the difference in the coefficients between the two Insurance treatments, thus contradicting H2a ($\beta = -0.130,\ SE = 0.15\ p = 0.39$; see Table 3).

We thus conclude:

Result 2a: Consistently with H2a, the *Stability High* treatment significantly reduces the bankruptcy rate in comparison with the *Stability Low* treatment. It also reduces bankruptcy with respect to both *Insurance* treatments.

[10] R-squares in our regression are low. Schotter and Yorulmazer (2009) calculate R-squares and pseudo R-squares in their experimental study and they also obtain low values, ranging from 0.02 to 0.4.

[11] A chi-squared test yields a p-value of 0.104 for the null of equality of distribution between Baseline and *Stability High*.

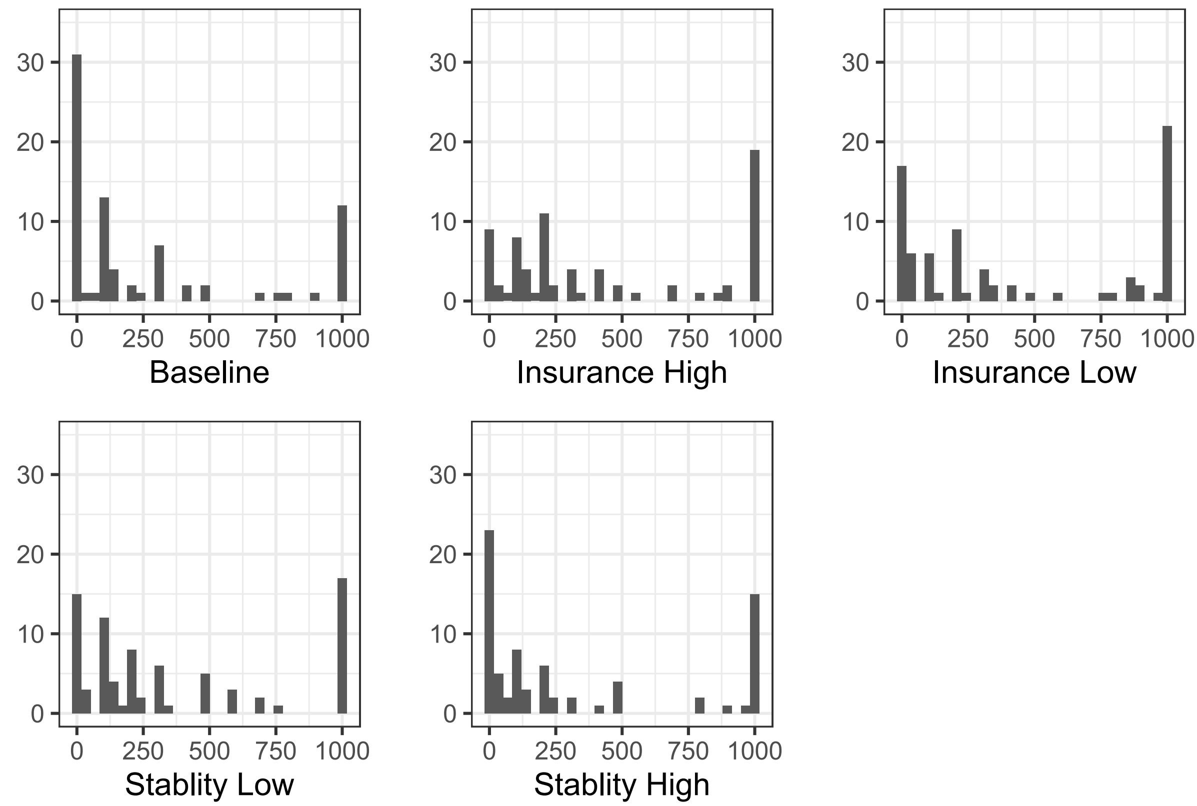

Fig. 2. Distribution of withdrawals in the first period by treatment.

Result 2b: No difference emerges between the two Insurance treatments, thus contradicting H2b.

3.3. Analysis of evolution of withdrawals

We now investigate in more detail the mechanisms underlying the treatment differences in bankruptcy rates, examining the patterns of withdrawals over periods across treatments.

H3a posits that both the stability and the insurance mechanisms would have had a Panic-Reduction effect in Period 1, in particular even before the Stability mechanism could be set in place. Fig. 2 shows the histograms of withdrawals in the first period for the different treatments. It is evident that in no treatment withdrawals in Period 1 were lower than in baseline. In fact, the modal value of withdrawals is zero tokens only for baseline and for the *Stability High* treatment. The modal value is 1.000 tokens for all other treatments.

Using OLS estimators with demographic controls, we find that withdrawals in the baseline in Period 1 were significantly lower than in *Insurance Low* ($p = 0.002$), *Insurance High* ($p = 0.018$) and *Stability Low* ($p = 0.019$). The only treatment in which withdrawals do not differ from the baseline in Period 1 is the *Stability High* treatment ($p = 0.44$). The sign of the coefficient is positive and the point estimates range from 43 extra tokens withdrawn in *Stability High* compared to the baseline (out of a total of 1000 tokens), up to 183 extra tokens withdrawn in *Insurance Low* compared to the baseline (Table 4, column2). Results are qualitatively similar omitting demographic controls (Table 4, column 1). Coefficients of pairs of treatments are not significantly different from each other, except for all pairs involving *Stability High*. In particular, withdrawals in *Stability High* are significantly lower than in *Insurance Low* ($\beta = -139.8$, $SE = 51.9$ $p = 0.009$), *Insurance High* ($\beta = -117.5$, $SE = 64.3$ $p = 0.072$), and *Stability Low* ($\beta = -86.2$, $SE = 50.5$ $p = 0.092$). See Table 5.

We conclude:

Table 4
Regression on actual withdrawals.

Dep. var.: Actual withdrawals	Period1		Periods 2&3	
	(1)	(2)	(3)	(4)
Insurance low	175.00***	183.46***	−18.13	−20.37
	(64.60)	(57.42)	(27.34)	(28.01)
Insurance high	168.50**	161.08**	−42.41*	−41.36*
	(67.47)	(66.59)	(23.42)	(23.14)
Stability low	101.43*	129.83**	−32.05	−32.82
	(55.85)	(53.91)	(23.78)	(24.35)
Stability high	59.45	43.59	−53.02**	−51.44**
	(58.05)	(55.82)	(21.83)	(21.31)
Age		0.18		0.60
		(5.35)		(2.08)
Woman		−322.24***		30.18
		(86.05)		(35.51)
Constant	271.50***	412.11**	97.20***	68.68
	(43.35)	(150.65)	(19.95)	(58.33)
Observations	78	78	63	63
R^2	0.137	0.256	0.120	0.131

The Table reports coefficients from regression on withdrawals in different periods. Robust standard errors are shown between parentheses, and the significance of the coefficients is flagged following the usual convention: *p < 0.1; **p < 0.05; ***p < 0.01.

Result 3a: We find no evidence of a *Panic-Reduction* effect in Period 1 for any treatment. In fact, withdrawals in Period 1 were significantly higher in *Insurance* and *Stability Low* treatments than in baseline. Only in *Stability High* were withdrawals not significantly different from the baseline.

Given that the *Panic-Reduction* effect does not receive support in Period 1, the overall greater efficacy of the *Stability High* treatment than baseline is likely driven by the *Fund Stabilisation* effect. The bottom panel in Fig. 1 contrasts desired and actual withdrawals over periods. The desired withdrawals are the amount that participants would like to withdraw, whereas the actual ones are the amount that they finally

Table 5
Pairwise tests of treatment effects on Withdrawals — Period 1.

Withdrawals Period 1		Baseline	Insurance low	Insurance high	Stability low
Insurance low	Coefficient	183.46***			
	Std. Err.	(57.41)			
	P-value	*0.002*			
Insurance high	Coefficient	161.08**	−22.38		
	Std. Err.	(66.39)	(65.82)		
	P-value	*0.018*	*0.74*		
Stability low	Coefficient	129.83**	−53.63	−31.25	
	Std. Err.	(53.9)	(54.06)	(63.33)	
	P-value	*0.019*	*0.33*	*0.62*	
Stability high	Coefficient	43.59	−139.88***	−117.49*	−86.24*
	Std. Err.	(55.82)	(51.94)	(64.3)	(50.46)
	P-value	*0.44*	*0.009*	*0.072*	*0.092*

The Table reports coefficients, std. err., and P-values for Wald tests on the equality of the treatment coefficients in the column entry and the row entry. Tests have been run on the regression in Table 4, column 2. A positive (negative) value for the coefficient means that withdrawals were on average higher (lower) in the row-entry treatment than in the column-entry treatment. For instance, the negative value for the coefficient in the Baseline/Insurance Low cell indicates that the coefficient for the Baseline was lower than in the Insurance Low treatment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

manage to withdraw. By construction, desired and actual withdrawals coincide in Period 1.

Out of 42.1% total withdrawals occurring in the Stability High treatment, 33.1% occurred in Period 1 and the remaining 9.0% occurred in subsequent periods, while in Baseline these frequencies were 40.9%, 27.5%, 13.7%.

Econometric analysis supports the relevance of a *Fund Stabilisation* effect for the Stability High treatment, as withdrawals in Periods 2 and 3 are significantly lower than in the corresponding periods in baseline, ($p = 0.019$;), while the difference was not significant in the Stability Low treatment ($p = 0.18$; see Table 8). The coefficients do not appear particularly large, ranging from 51.4 fewer tokens in *Stability High* than the baseline to 20.3 fewer tokens in *Insurance Low* than the baseline.

It also has to be noted that only 10% of the depositors who wanted to withdraw some money when the Stabilization mechanism was in place did actually express a desire to withdraw the maximum amount that they were allowed to. Desired withdrawals, for instance, are significantly lower in the Stability treatments than in the Insurance ones, as can be seen in Table 7. Thus, in addition to the purely mechanic effect of limiting withdrawals, we cannot rule out that the stabilization mechanism also induced some "panic-reduction" effects on depositors from Period 2. It is possible that becoming aware that they will not be able to recover their whole deposits by withdrawing, because of the implemented partial freeze, depositors with some frozen deposits have higher incentives to contribute to the stability of the bank by not withdrawing the rest. Alternatively, it could be that only after seeing the mechanism in operation depositors felt reassured about the safety of their deposits, thus leaving them in the bank. It is difficult to precisely quantify this effect.

We conclude:

Result 3b: We find evidence of a *Fund Stabilisation* effect in the *Stability High* treatment, but not in the *Stability Low* treatment.

H4 concerns the theoretical prediction that all withdrawals should take place in Period 1. It is indeed the case that the largest percentage of withdrawals occur in Period 1, but a non-negligible amount of withdrawals also takes place afterwards. To assess H4, we consider the withdrawal rate, that is, the ratio of withdrawal and available deposits. Since Deposits are generally lower in Periods 2 and 3 compared to Period 1, a comparison of absolute withdrawals would arbitrarily inflate the amount withdrawn in Period 1.

H4a that withdrawals are nil is rejected for both Period 2 and Period 3 (two-tailed t-test: $P < 0.001$). Nonetheless, the weaker version H4b seems to be supported. In each individual treatment, the hypothesis that withdrawals in Period 1 are equal to withdrawals in Periods 2 and 3 considered together is rejected at P < 0.001 in a two-tailed t-test.

We conclude:

Result 4: The theoretical prediction that no withdrawal should occur after period 1 (H4a) is rejected. The hypothesis that withdrawals are significantly larger in Period 1 than subsequent periods (H4b) is however not rejected.

3.4. Withdrawal patterns in the insurance treatment

The lack of effectiveness of the Insurance treatment in reducing bankruptcy went against our main hypothesis. In this section, we seek to better understand why this was the case.

The underlying idea behind this mechanism is that depositors who buy insurance should be less likely to withdraw their money knowing that they will recover a part of their saving in case of bankruptcy.

For this mechanism to be effective, it should be the case that the higher depositors' insurance, the lower the money withdrawn. Conversely, had investors somehow misunderstood the payoffs associated with the insurance mechanism, they may have at the same time insured their saving *and* withdrawn large sums of money in order to cause the bank to go bankrupt and thus receive the payment from the insurance.

Overall, we find a strong and significant negative correlation between amount insured and amount withdrawn ($r(153) = -0.38$, $p < 0.001$; see Fig. 3), confirming that the mechanism went in the expected direction and that participants who did buy insurance correctly understood its underlying incentives. That is, people buying insurance were more willing to leave their money in the bank. As found out in the numerical analysis of optimal insurance, this should be the case for risk-averse individuals who believe that the probability of bankruptcy is intermediate (see Appendix A: Appendix A.4.5 and Figs. 5 and 6).

To further analyze the impact of insurance, we divide the population into two groups: those who did not buy insurance ("No insurance buyer") and those who bought a positive level of insurance ("Positive insurance buyer"). We focus on the first period of interaction, because this is the period in which we can observe whether the treatment had any panic-reduction effect. Our analysis shows that the group comprising positive insurance buyers tended to withdraw less than in the baseline (18 tokens on average; Table 6, column 1), but the difference with baseline is statistically insignificant ($\beta = -18.6$, $SE = 49.0$; $p = 0.71$). Conversely, uninsured participants withdrew a staggering 457 tokens more than baseline and 476 more than Insurance buyers, the difference being strongly significant in both cases ($t = 6.93$, $p < 0.001$ for pairwise test with Baseline; $t = 8.09$ $p < 0.001$ for pairwise test with Insurance Buyers).[12]

Groups in which average levels of insurance were higher tended to have lower probability of bankruptcy, as there is a negative correlation between bankruptcy and amount insured ($r = -0.30$, $p = 0.096$). However, in a regression controlling for treatment and demographic effects, amount insured had an insignificant effect ($p = 0.18$).

We conclude that the introduction of insurance had no significant effect in reducing withdrawals among those buying insurance, while it had a panic-inducing effect in those not buying insurance. As a result, this treatment recorded the highest bankruptcy rate in our experiment. Our results support the idea in FDIC (2023) that depositors who opt into an excess deposit insurance system are likely to have different characteristics than those who do not opt in. Furthermore, our study demonstrates how these differences in characteristics and incentives can lead to poor outcomes.

[12] These results are robust to identifying groups in terms of buying insurance above and below the median-not reported; available upon request. They are also robust to controlling for demographic variables. See Analyses output.

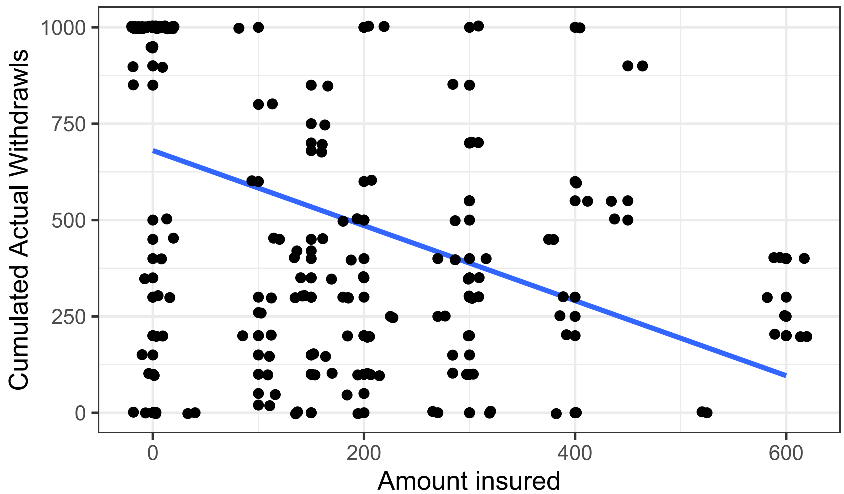

Fig. 3. Cumulated withdrawals by insured amount.

Table 6
Insurance.

	Dependent variable: Withdrawals		
	Both insurance treatments	Insurance high treatment	Insurance low treatment
Positive insurance buyer	−18.60	−20.50	−16.38
	(49.02)	(53.10)	(60.34)
No insurance buyer	457.53***	546.50***	397.42***
	(66.01)	(80.41)	(82.88)
Constant	271.50***	271.50***	271.50***
	(40.62)	(40.76)	(40.74)
Observations	235	155	160
R^2	0.27	0.28	0.18

The Table reports coefficients from regression on period 1 withdrawals in the insurance treatments compared to the baseline treatment (constant). Robust standard errors are shown between parentheses, and the significance of the coefficients is flagged following the usual convention: *p < 0.1; **p < 0.05; ***p < 0.01.

3.5. Additional results

3.5.1. Announcement effects

We study whether the announcement that the bank liquidity had gone below the safety threshold prompted people to withdraw more or less money from Period 2. In general, we do not find any significant effect for this variable ($\beta = -0.006$, $SE = 0.041$, $p = 0.875$), see in Table 9. However, we notice a relevant effect of the announcement on women, in line with Dijk (2017). More details are to be found in the next Section 3.5.2.

3.5.2. Gender effects

It is well-known that women tend to be both more risk-averse and more pro-social than men, e.g., Eckel and Grossman (2002), Charness and Gneezy (2012) and Eagly (2009). It is then interesting to study gender effects in the setting of our experiment, where both risk aversion and pro-sociality affect individual choices. It may be argued that more risk-averse individuals should withdraw more because all the money withdrawn transfers with certainty to one's own final payoffs, while all the money left deposited in the bank is exposed to the risk of the bank defaulting. On the other hand, more pro-social individuals can be expected to leave more of their money deposited in the bank. The reason is that withdrawing money creates a negative externality on all

Table 7
Regression on desired withdrawals.

Dep. var.: Desired withdrawals	Period1		Periods 2&3	
	(1)	(2)	(3)	(4)
Insurance low	175.00***	183.46***	−7.47	8.20
	(64.60)	(57.42)	(41.98)	(42.53)
Insurance high	168.50**	161.08**	−73.83*	−75.05**
	(67.47)	(66.34)	(38.39)	(37.14)
Stability low	101.43*	129.83**	−65.73*	−59.78
	(55.85)	(53.91)	(37.58)	(37.79)
Stability high	59.45	43.59	−117.48***	−114.86***
	(58.05)	(55.82)	(35.61)	(35.68)
Age		0.18		5.27
		(5.35)		(3.70)
Woman		−322.24***		−46.45
		(86.04)		(44.84)
Constant	271.50***	412.11***	163.33***	58.46
	(43.14)	(150.65)	(34.46)	(103.17)
Observations	78	78	63	63
R^2	0.137	0.256	0.245	0.284

The Table reports coefficients from regression on desired withdrawals in different periods. Robust standard errors are shown between parentheses, and the significance of the coefficients is flagged following the usual convention: *p < 0.1; **p < 0.05; ***p < 0.01.

Table 8
Pairwise tests of treatment effects on Withdrawals — Periods 2 & 3.

Withdrawals periods 2–3		Baseline	Insurance low	Insurance high	Stability low
Insurance low	Coefficient	−20.37			
	Std. Err.	(28.01)			
	P-value	*0.47*			
Insurance high	Coefficient	−41.36*	−20.99		
	Std. Err.	(23.14)	(22.52)		
	P-value	*0.079*	*0.36*		
Stability low	Coefficient	−32.82	−12.5	8.54	
	Std. Err.	(24.34)	(23.00)	(19.11)	
	P-value	*0.18*	*0.59*	*0.66*	
Stability high	Coefficient	−51.44**	−31.1	−10.1	−18.62
	Std. Err.	(21.31)	(20.54)	(16.37)	(16.98)
	P-value	*0.019*	*0.14*	*0.54*	*0.28*

The Table reports coefficients, std. err., and P-values for Wald tests on the equality of the treatment coefficients in the column entry and the row entry. Tests have been run on the regression in Table 4, column 4. A positive (negative) value for the coefficient means that withdrawals were on average higher (lower) in the row-entry treatment than in the column-entry treatment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9
Desired withdrawals over withdrawable deposits.

	Dependent variable: Desired withdrawals over withdrawable deposits		
	Insurance treatments	Non-insurance treatments	All treatments
Critical liquidity signal	−0.152* (0.777)	0.076* (0.042)	0.006 (0.041)
Woman	−0.280** (0.111)	−0.076 (0.050)	−0.163*** (0.046)
Signal * Woman	0.189** (0.075)	0.116** (0.050)	0.154*** (0.042)
Insured	−0.399*** (0.062)		−0.122*** (0.045)
Insured * Woman	0.087 (0.147)		−0.025 (0.062)
Period	−0.037 (0.035)	−0.104*** (0.014)	−0.099*** (0.015)
Constant	0.810*** (0.056)	0.463*** (0.040)	0.574*** (0.037)
Observations	300	519	819
Clusters	31	47	78
Wald	139.24***	60.87***	100.31***

The Table reports coefficients from regression on desired withdrawals over withdrawable deposits in different treatments. Robust standard errors are shown between parentheses, and the significance of the coefficients is flagged following the usual convention: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

others, by increasing the probability of default and thus the probability of collective monetary losses.[13]

In contrast to Kiss et al. (2014), we find a gender effect in our experiment, as groups with a higher share of women tend to default with *lower* probability ($\beta = -0.675$, $SE = 0.269$ $p = 0.0145$; Table 2). According to our estimates, a group composed exclusively of women would be about 68% less likely to cause a bank default than a group including exclusively men. The reason of this discrepancy with respect to the previous literature is due to the presence of the fee-based insurance among our treatments. Indeed, the gender effect is very strong in the two insurance treatments, whereas it disappears when excluding them. Women's lower propensity to withdraw is actually related to their higher propensity to buy the insurance. In fact, women tend to take out insurance more frequently then men,[14] and they have, therefore, less motivation to withdraw money from the bank. Results concerning desired withdrawals, discussed in Section 3.4, show indeed that insurance holders have higher propensity to keep money in deposits. In the end, our suggested way to disentangle our evidence of a gender effect is the following: women's higher propensity to get insured, which most likely derives from a higher risk aversion, allows them to avoid withdrawals, as they are in a safer (insured) condition with respect to men, who are mostly uninsured. This interpretation is also supported by the interaction term in Table 9, showing that, given the level of insurance, women do not withdraw less then men.

We also find that women tend to withdraw much less than men in the first period but this effect disappears in the subsequent periods. This might be related to the result of Dijk (2017), who finds that women are significantly more likely to withdraw than men when induced with fear. In our case, subjects become aware of bank's financial fragility between period one and period two, when a critical liquidity signal is transmitted. If we conjecture that this liquidity signal produces a sort of "fear" effect on subjects, which seems reasonable, then our results are in line with Dijk (2017). The interaction term between the critical liquidity signal and gender (*signal_woman*) in Table 9 confirms that the transmission of the signal significantly increases women's desired withdrawals, bringing their propensity to withdraw on a level with men.

4. Discussion and concluding remarks

We analyzed the behavior of depositors in a bank under liquidity stress with the aim of investigating the emergence of bank runs under different conditions. A liquidity shock hit each bank at the end of Period 1 and could be recovered by the bank at the end of period 3 with 50% probability. If the loss was not recovered, each agent received a percentage of the final cash balance of the bank equal to her share in the total deposits. The agents had some information about the liquidity state of the bank, as a warning signal to depositors was sent at the beginning of a period if bank's liquidity dropped under a critical level. Our design included an *insurance treatment* and a *stability fund treatment* with the aim of reducing bank runs and defaults, both characterized by two sub-treatments: *high* insurance (fund) vs. *low* insurance (fund).

In the *Insurance* treatment, each subject can choose to buy the insurance policy at the beginning of the session. This feature is important as it distinguishes our design from the more classic case of a deposit guarantee scheme, which is addressed in the literature (Madiès, 2006; Schotter and Yorulmazer, 2009; Kiss et al., 2012). The rationale for our design choice is to reproduce a market based insurance mechanism, similar to a bail-in, where depositors decide to spend money to be used in the case of bank's default. In the bail-out scheme, money typically comes from outside the system (e.g., generic taxpayers' money), making the two cases quite different both from a financial and from a psychological point of view. Results in the literature show that deposit insurance can be effective in preventing bank runs if some conditions are fulfilled. First of all, the insurance should be high enough to achieve the desired aim, as described by Madiès (2006) and Schotter and Yorulmazer (2009), even if the insurance amount becomes less relevant when depositors' decisions are observable (Kiss et al., 2012). Peia and Vranceanu (2019) show that strategic uncertainty about deposit coverage can result in a high probability of runs if depositors fear that the insurance scheme cannot cover all deposits.

Our study confirms that low coverage levels are ineffective but also shows that fee-based voluntary insurance brings about a dual behavior of depositors, which undermines also the benefit of a higher coverage. Depositors not buying the insurance, who are 46% in the case of low coverage and 34% in the case of high coverage, have a much higher probability of withdrawing with respect to insurance buyers. These uninsured depositors have little motivation to keep money in the bank, as they are not protected. It may be observed that also in the baseline treatment, where insurance and funds are not active, no protection is provided to depositors, and they withdraw much less. However, in the fee-based insurance case, uninsured depositors know that other depositors may have purchased the insurance, and they are therefore aware of being less protected. This "awareness of fragility" with respect to others probably stimulates their massive withdrawals, leading to higher bankruptcies. This potential effect deserves further study to determine whether it is relevant in this kind of situation. It is also worth noting that the average spending for the insurance is moderate. Insurance buyers pay 28% of their available 200 tokens for the low coverage policy, which just raises to 34% in the case of high coverage. This seems to be consistent with our numerical analysis of risk-averse agents, for which spending only a part of their endowment available for insurance and withdrawing part of their deposits turn out to be the optimal actions. When groups have a high share of female depositors, there is a significant reduction in the likelihood of bank runs, which can

[13] For instance, Yamagishi et al. (2013) find that elicited pro-sociality impacts consistently on the behavior in coordination games, such as the prisoner's dilemma.

[14] The percentage of women who purchase the insurance is 76% in the low coverage treatment (against 33% of the men, $p = 0.0001$ in a two-sample test of proportions) and 87,5% in the high coverage treatment (against 51% of the men, $p = 0.001$).

be explained by women's higher propensity to buy insurance. When a critical liquidity signal is issued, indicating a dangerous situation, women's lower propensity to withdraw disappears, bringing it to levels similar to that of men. Our results provide greater depth and help to clarify the ambiguity surrounding depositor discipline in the case of voluntary insurance, as evoked by the FDIC (2023) report. All in all, the market-based insurance implemented in our treatments is not only useless in preventing bank runs and defaults, but even harmful, producing uncoordinated and adverse behaviors.

In the *stability fund treatments*, part of the deposits are automatically transferred to an emergency fund (high or low) when the liquidity of the bank goes under a critical level. Depositors cannot withdraw any token from the fund, but they may recover it with a 100% interest rate if the bank does not default; they lose everything otherwise, contributing to bail-in the bankrupt bank. Madiès (2006) is the first to study a mechanism of suspension of convertibility in the experimental setting, finding that short suspensions are more effective than long ones. We focus instead on the amount of the fund, which strongly drives our results, as only the high version of the fund turns to be mildly effective in reducing bankruptcies. We identify two main processes that may drive the efficiency of the fund. The first one is related to the balance sheet mechanical effect of restricting the possibility to withdraw, while the second depends on the psychological panic-reduction effect. We find that less than 10% of depositors, in the fund treatments, withdraw the maximum amount of tokens that is allowed by the fund liquidity restrictions, or, in other words, less that 10% are restrained by the liquidity constraint of the fund. This suggests that the mechanical process is not the only cause of the significantly lower withdrawals observed in the high stability fund treatment and a psychological effect might be at work. There is room for future research to further disentangle these two effects. Moreover, the restrained depositors are less (6.1%) in the high fund treatment than in the low fund treatment (9.2%), despite the lower availability of withdrawable deposits, signaling that the high fund treatment might reassure individuals about potential future bankruptcies. We do not observe *ex-ante* treatment effects on subjects' propensity to withdraw, but after the first period, when the liquidity suspension becomes active, the fund treatments (especially the high fund one) reduce the amount of withdrawals. In the case of the high fund treatment, this results in a lower likelihood of bankruptcy in comparison to the baseline and all other treatments.

CRediT authorship contribution statement

Iván Barreda-Tarrazona: Writing – review & editing, Writing – original draft, Software, Project administration, Methodology, Data curation, Conceptualization. **Gianluca Grimalda:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Andrea Teglio:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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Appendix A. Theoretical background

A.1. The dynamic nature of the game

Our game is dynamic, as players have three chances to withdraw money from the bank. The choice faced in Round 1 differs from the choices in subsequent rounds, because the bank has no liquidity issues in Round 1, thus there is no risk of default. At the beginning of Round 2, however, a liquidity shock of 2500 tokens hits the bank. In Rounds 2 and 3, then, the bank may go bankrupt if total withdrawals exceed the total cash. Players do not receive any feedback on others' individual choices. Rather, they receive a warning signal if cash goes below a threshold level. In this section, we analyze the sub-game perfect Nash equilibria (SPNE) of the game. We first provide the Nash equilibria (NE) of the game in Round 2 or Round 3 - which are strategically identical-as if they were one-shot games. We then analyze the game in Round 1 taking into account what would have been the players best-response in the subsequent rounds, thus obtaining the overall SPNE. The SPNE prescribe players to either withdraw all their deposits, or to leave all their deposits in the bank in Round 1, and stay put in subsequent rounds. Clearly this multiplicity of equilibria leaves open the problem of equilibrium selection. We offer some insights into the strategies that participants may use, taking into account the prior that agents may have on others' behavior and their degree of risk aversion.

A.2. The best responses in rounds 2 and 3

We first analyze players' best responses in $r = 2, 3$, where r stands for round. To simplify the notation we assume that the sub-game is played as a one-shot game, rather than as a derivation from the sub-game played in Round 1. Making the dependence between the subgames explicit would require an unduly complex notation.

Since Rounds 2 and 3 are strategically equivalent, we can, with no loss of generality, consider them as a single game. We define the strategy space for each individual i as $W_i = [0, 1000]$[15] and call the strategy space for all individuals other than i the cartesian product of W_j for $j \neq i$-namely, $\underline{W}_j = \times_{j\neq i} W_j$. We define $w_i \in W_i$ the sum of the intended withdrawals in Round 2 and 3 by individual i, while $\underline{w}_j \in \underline{W}_j$ is the vector of withdrawals by all other agents in Round 2 and 3. $\left(w_i, \underline{w}_j\right) \in W_i \times \underline{W}_j$ is a vector of strategies for the five players involved in a game. Moreover, we define $\hat{w}_j = \sum_{j\neq i} w_j$ the sum of withdrawals by agents other than i in $r = 2, 3$. The payoff for agent i is conditional on three events:

1. The bank goes bankrupt, which happens when $w_i + \hat{w}_j > 2500$, given an exogenous shock of 2500 at the beginning of Round 2.
2. The bank does not go bankrupt, but does not recover the liquidity shock. This happens with probability $q = 1/2$ when $w_i + \hat{w}_j \leq 2500$.
3. The bank does not go bankrupt and recovers the liquidity shock. This happens with probability $1 - q = 1/2$ when $w_i + \hat{w}_j \leq 2500$.

The payoff function for agent i in $r = 2, 3$ is thus equal to:

$$V_r\left(w_i, \underline{w}_j\right) = \begin{cases} \widetilde{w_i} & if\ w_i + \hat{w}_j > 2500 \\ w_i + q\left[2(2500 - w_i - \hat{w}_j)s_{ij}\right] & \\ \quad + (1-q)\left[2(1000 - w_i)\right] & if\ w_i + \hat{w}_j \leq 2500 \end{cases} \tag{2}$$

where:

$$s_{ij} = \frac{1000 - w_i}{5000 - w_i - \hat{w}_j} \tag{3}$$

[15] If we considered this game to come after the game played in Round 1, we would have to modify the strategy space in the following way: $W_{it} = [0, 1000 - \sum_{k=1}^{t-1} w_{ik}]$, $t = 1, 2, 3$.

$$\widetilde{w_i} = \begin{cases} w_i & if\ \forall j \neq i : t_i < t_j \cap w_i \leq 2500 - \hat{w}_j \\ \theta w_i & otherwise \end{cases} \tag{4}$$

$\widetilde{w_i}$ is the payoff to agent i if there is a bank run. If the time that agent i takes to withdraw-that is, t_i- is less than the time taken by all other agents t_j, and if there is enough liquidity in the bank – namely, if $w_i \leq 2500 - \hat{w}_j$– then agent i can withdraw her desired amount and w_i is her payoff. In all other cases, agent i's actual payoff will be a portion of w_i, with $\theta \in [0, 1]$. Therefore, if $w_i + \hat{w}_j > 2500$, then the bank goes bankrupt, the deposits and interests are lost, hence the profit is equal to $\widetilde{w_i}$.

If $w_i + \hat{w}_j \leq 2500$, then the bank does not go bankrupt. Agent i's payoff depends on whether the bank recovers the loss of 2500 tokens or not. If the loss is temporary, the bank is fully solvent at the end of Round 3, so agent i's profit is equal to the amount withdrawn w_i plus the deposits $(1000 - w_i)$ multiplied by two. This event occurs with probability $(1 - q)$. If the loss is permanent, then the bank will be insolvent. Agent i will only recover a share s_{ij} of the total cash held in the bank, where s_{ij} is equal to the ratio between agent i's deposits and total deposits. This share of deposits yields interests and thus it is multiplied by two. The final payoff in this case adds the amount withdrawn w_i to the share of deposits and interests.

We first demonstrate the following Lemma:

Lemma 1. *Withdrawing all the money is the only best response in Rounds 2, 3 in the region $\hat{w}_j > 2500$.*

Proof of Lemma 1. Let us suppose that the desired withdrawals by all other agents other than i falls in the region $\hat{w}_j > 2500$. This means that the bank will go bankrupt with probability 1. Agent i's payoff is then defined by expression (4). For every $\theta > 0$, (4) is maximized by $w_i = 1000$. If $\theta = 0$, which can only be the case if $r > 1$, player i is indifferent among all withdrawal claims, and thus $w_i = 1000$ is still a best response to other agents' strategies, albeit weakly. □

Intuitively, if all other agents intend to withdraw all their money, then the bank will go bankrupt with probability 1. Hence, agent i's best response is also to attempt to withdraw as much money as she can, because all money left in the bank will be lost.

We then demonstrate that the following Lemma holds:

Lemma 2. *Not withdrawing any money is the only best response in Rounds 2, 3 in the region $\hat{w}_j \leq 2500$.*

Proof of Lemma 2. Let us suppose that $\hat{w}_j \leq 2500$ and $r > 1$. The functional form of (2) depends on whether w_i brings the bank in default-namely, $\hat{w}_j \leq 2500 < w_i + \hat{w}_j$, or not-namely, $w_i + \hat{w}_j \leq 2500$. Choosing a w_i such that: $\hat{w}_j \leq 2500 < w_i + \hat{w}_j$ is not profitable for the agent because this would make the bank default and the following inequality holds:

$$\begin{aligned} V\left(w_i, \underline{w}_j \mid w_i + \hat{w}_j \leq 2500\right) &= w_i + \frac{1}{2}\left[2(2500 - w_i)s_{ij}\right] \\ &\quad + \frac{1}{2}\left[2(1000 - w_i)\right] \\ &> 1000 \geq \theta w_i = V\left(w_i, \underline{w}_j \mid \hat{w}_j \right. \\ &\quad \left. \leq 2500 < w_i + \hat{w}_j\right) \end{aligned} \tag{5}$$

As for the region where $w_i + \hat{w}_j \leq 2500$, we compute the derivative of (2). After some algebra, this derivative boils down to:

$$\frac{\partial V\left(w_i, \underline{w}_j \mid w_i + \hat{w}_j \leq 2500\right)}{\partial w_i} = 2q\left(1 - s_{ij}\right)\left(1 - a_{ij}\right) - 1 \tag{6}$$

where:

$$a_{ij} = \frac{2500 - \left(w_i + \hat{w}_j\right)}{5000 - \left(w_i + \hat{w}_j\right)} \tag{7}$$

Since $w_i \in (0, 1000)$ and $w_j \in (0, 2500 - w_i)$, the following inequality constraints are satisfied: $q = \frac{1}{2}$, $0 \leq s_{ij} \leq \frac{2}{5}$, and $0 \leq a_{ij} \leq \frac{1}{2}$. Hence, expression (6) is always negative. This means that $w_i = 0$ is always a best response in the region. □

The intuition is that if other agents' withdrawals will not cause the bank to go bankrupt, then leaving money deposited will bear interest at a 50% rate in expected value (if $q = 0.5$), while withdrawing money will not yield any interest. A player will thus maximize her payoffs by not withdrawing any money.

A.3. The sub-game perfect Nash equilibria of the game

The analysis of Appendix A.2 shows that the only strategies sustainable in an SPNE involve players either keeping all their money in the bank or withdrawing all the money in the bank in Rounds 2 and 3. This makes the analysis of the SPNE in $r = 1$ simple. First we note that the payoff function from the standpoint of $r = 1$ is slightly, but importantly, different than from the standpoint of $r = 2, 3$. The payoff function in $r = 1$ is equal to:

$$V_1\left(w_i, \underline{w}_j\right) = \begin{cases} w_i & if\ w_i + \hat{w}_j > 2500 \\ w_i + q\left[2(2500 - w_i - \hat{w}_j)s_{ij}\right] & \\ \quad + (1-q)\left[2(1000 - w_i)\right] & if\ w_i + \hat{w}_j \leq 2500 \end{cases} \tag{8}$$

where s_{ij} is defined in (3), and all other variables are as defined in Appendix A.2. The only difference between (8) and (2) concerns the payoff in the region where $w_i + \hat{w}_j > 2500$. While in (2) the agent suffers the risk of not being able to withdraw her desired amount, in $r = 1$ the bank is solvent hence each player is ensured the possibility to withdraw all the money they wish. In other words, $\theta = 1$ when $r = 1$.

We now prove that there are two SNPE in the game, one in which all agents withdraw all their deposit in $r = 1$ and another on in which all agents leave all their money in the bank in $r = 1$ as well as in the subsequent periods.

We begin demonstrating:

Lemma 3. *Withdrawing all the money in Round 1 is a SPNE of the game.*

Proof of Lemma 3. If all other agents withdraw money in $r = 1$, then it follows straightforwardly from (8) that the optimal strategy is $w_i = 1000$. Given that this action in $r = 1$ exhausts the strategy space for $r > 1$, this strategy is also trivially a best response in $r > 1$. Given the symmetry of the game, the above reasoning holds for all other agents, hence the vector $\left(w_i = 1000, \underline{w}_j = \underline{1000}\right)$ is an SPNE of the game. □

The intuition of this Lemma is as follows. If all agents other than j intend to withdraw $\left(\underline{w}_j = \underline{1000}\right)$ in $r = 1$, then the bank will go bankrupt with probability 1 in $r = 2$. Hence, agent i's best response is to withdraw money in $r = 1$. Delaying money withdrawal to the next period would imply the loss of the entire deposits, because of the negative liquidity shock. Given the symmetry of the game, this reasoning also holds for other agents, hence $\left(w_i = 1000, \underline{w}_j = \underline{1000}\right)$ is a SPNE of the game. We define it:

$$NE^{1000} := \left(w_i = 1000, \underline{w}_j = \underline{1000}\right) \tag{9}$$

Lemma 4. *Not withdrawing any money throughout the three rounds is an SPNE of the game.*

Proof of Lemma 4. Suppose that other agents do not withdraw any money throughout the three rounds. According to Lemma 2, $w_i = 0$ is the only optimal best response for $r > 1$. When $r = 1$, the payoff function (8) is identical to (2). Hence, the derivative is given by (6), which is maximized for $w_i = 0$. Given the symmetry of payoffs among agents, the above reasoning holds for all other agents, hence the vector $\left(w_i = 0, \underline{w}_j = \underline{0}\right)$ is an SPNE of the game. □

The intuition is the same as that given for Lemma 2. Given the symmetry of the game, the best response for each agent when others do not withdraw money is not to withdraw money. Trivially, this strategy is sub-game perfect because we showed that not withdrawing money in $r > 1$ is the best response to other players not withdrawing money. Hence $\left(w_i = 0, \underline{w}_j = \underline{0}\right)$ is an SPNE of the game. We call this equilibrium:

$$NE^0 := \left(w_i = 0, \underline{w}_j = \underline{0}\right) \tag{10}$$

Lemma 5. *No SPNE other than NE^{1000} and NE^0 exists in pure strategies.*

Proof of Lemma 5. According to Lemmas 1 and 2, an agent's only best response in $r > 1$ is either $w_i = 1000$ if $\hat{w}_j > 2500$ and in particular $\underline{w}_j = \underline{1000}$. Or it is $w_i = 0$ if $\hat{w}_j \leq 2500$ and in particular $\underline{w}_j = \underline{0}$. An equilibrium that was different from NE^{1000} or NE^0 would be one in which the player switched from $w_i = 1000$ in $r = 1$ to $w_i = 0$ when $r > 1$ and $\underline{w}_j = \underline{0}$, but this is not a feasible strategy. Or it would be one in which the player switched from $w_i = 0$ in $r = 1$ to $w_i = 1000$ when $r > 1$ and $\underline{w}_j = \underline{1000}$. But this latter strategy is strictly dominated by the strategy whereby $w_i = 1000$ in $r = 1$ for all $\theta < 1$, because, according to (2) and (8) the payoff in this case is w_i for withdrawing in $r = 1$ and θw_i for withdrawing in $r > 1$. If $\theta = 1$, then the payoffs from withdrawing in $r = 1$ and $r > 1$ are the same. But since it must be true for at least two agents that $\theta < 1$, then the outcome where some agents switch from $w_i = 0$ in $r = 1$ to $w_i = 1000$ when $r > 1$ while $\underline{w}_j = \underline{1000}$ cannot be a SPNE. □

Intuitively, Lemma 5 follows from Lemmas 1 and 2 and the consideration that any strategy where an agent switched from $w_i = 0$ in $r = 1$ to $w_i = 1000$ when $r > 1$ is sub-optimal for at least some players. The reason is that the bank is not solvent in $r = \{2, 3\}$ but is solvent in $r = 1$, hence payoffs must be higher by withdrawing money in $r = 1$. In other words, if an agent wants to withdraw money, it is optimal to withdraw in $r = 1$ rather than in $r > 1$, because in $r = 1$ the agent is sure to get all the money withdrawn, while in $r > 1$ the agent runs the risk of the bank being insolvent.

A.3.1. Payoff-dominance and risk-dominance of the equilibria

We can further analyze the SPNE in terms of their payoff dominance and risk dominance. NE^0 guarantees an expected payoff of 1500, while NE^{1000} yields a sure payoff of 1000. NE^0 is then payoff-dominant over NE^{1000} for risk-neutral agents. However, NE^{1000} is the risk-dominant equilibrium. This may be shown computing the risk factor for the two SPNE.[16]:

$$R = log\left[\frac{V\left(1000, \underline{1000}\right) - V\left(0, \underline{1000}\right)}{V\left(0, \underline{0}\right) - V\left(1000, \underline{0}\right)}\right] = log\left[\frac{1000 - 0}{1500 - 1000}\right] > 1$$

The idea behind the above formula is that the deviation losses are higher for NE^{1000} than NE^0. Intuitively, an agent has higher incentives to stick with NE^{1000}than with NE^0 if she is uncertain over how other agents will act. Let us assume that a player is uncertain over which SPNE the other agents will play. Let us call Z the probability that others will play $\underline{w}_j = \underline{0}$ and $(1 - Z)$ the probability that others will play $\underline{w}_j = \underline{1000}$, where $\underline{w}_j$ is the vector of strategies played by all other agents except for $i \neq j$. The expected payoff by playing $w_i = 0$ is then:

$$\begin{aligned} E\left[V(0, Z)\right] &= ZV\left(0, \underline{0}\right) + (1 - Z)V\left(0, \underline{1000}\right) \\ &= 1500Z \end{aligned} \tag{11}$$

The expected payoff by playing $w_i = 1000$ is instead:

$$\begin{aligned} E\left[V(1000, Z)\right] &= ZV\left(1000, \underline{0}\right) + (1 - Z)V\left(1000, \underline{1000}\right) \\ &= 1000 \end{aligned} \tag{12}$$

Therefore, $E\left[V(0, Z)\right] > E\left[V(1000, Z)\right]$ if and only if:

$$Z > \hat{Z} = \frac{2}{3} \tag{13}$$

$\hat{Z}$ is also called the risk factor associated with NE^{1000}. The fact that $\hat{Z} > \frac{1}{2}$ entails that if an agent is uncertain over which strategy others will play, she should preferentially play NE^{1000} rather than NE^0. In other words, the basin of attraction of NE^{1000} is larger than the basin of attraction of NE^0, hence NE^{1000} should be more frequently selected when players are uncertain over others' strategies.

So far, we have implicitly assumed that agents were risk neutral. But it is well-known that a large number of individuals are risk-averse in the gains domain (Rieger et al., 2015). It is clear that risk-averse players will, *ceteris paribus*, derive more utility from playing $w_i = 1000$ than $w_i = 0$, because the former guarantees a certain payoff of 1000 (see (12)), while the latter guarantees a random payoff given by (11). This adds an extra incentive for risk-averse players to play $w_i = 1000$ over $w_i = 0$. We further analyze the impact of risk aversion in Appendix A.4.5.

A.4. Optimal insurance

In this section, we set up an off-equilibrium-path theoretical model that investigates the optimal level of insurance, which we then analyze through numerical methods.

A.4.1. Set up for off-equilibrium solutions

As argued in the main text, we should observe no insurance for the two SPNEs in pure strategies found in Appendix A.3. To model optimal choice off the equilibrium path, we assume that the agent ignores which of the two SPNEs, or of any other outcome, will be played.

Upon introducing the possibility of insurance, the payoff function is as follows:

$$\begin{aligned} V_1\left(w_i, \underline{w}_j, x_i\right) &= 200 \\ &+P\left[w_i + min\left\{kx_i, 1000 - w_i\right\}\right] \\ +(1-P)&\left\{w_i + q\left\{2\left[2500 - w_i - E\left(\hat{w}_j\right)\right]s_{ij}\right\}\right. \\ &\left. + (1-q)\left[2(1000 - w_i)\right]\right\} - x_i \end{aligned} \tag{14}$$

The first term of (14) is the expected payoff if the bank goes bankrupt. P is the subjective probability that the bank will go bankrupt. We assume that each agent has a probability distribution over other agents' withdrawals $\hat{w}_j$ (see Appendix A.4.3 for its modeling). Since $\hat{w}_j$ is a real number over the interval $[0, 4000]$, the probability distribution over its realization can be represented as a density function $f\left(\hat{w}_j\right)$ defined over $[0, 4000]$, with $F\left(\hat{w}_j\right) = \int_0^{\hat{w}_j} f\left(\hat{w}_j\right) d\hat{w}_j$ being the cumulated probability. Given this density function, the probability of bankruptcy will then be defined as: $P = Prob\left(w_i + \hat{w}_j > 2500\right) = \int_{2500-w_i}^{4000} f\left(\hat{w}_j\right) d\hat{w}_j$. $E\left(\hat{w}_j\right)$ is the expected value of $\hat{w}_j$ over the relevant interval. In the case of bankruptcy, thus, the agent's payoff will equal the amount that she manages to withdraw, plus the insurance indemnity, which yields $min\left\{kx_i, 1000 - w_i\right\}$, $k = \{2, 3\}$, where x_i is the amount insured. If the bank does not go bankrupt, which occurs with probability $1 - P$, the agent will gain the associated expected payoff, already determined in Eq. (8). In either event, the agent will pay the premium x_i, which is then subtracted from payoff in (14).

[16] An alternative approach to evaluate the risk dominance is through applying the formula by Harsanyi and Selten (1988).

A.4.2. First order conditions for off-equilibrium solutions

Let us first of all find the optimal condition for the amount insured. It is clear that a rational agent will choose x_i in relation to her planned w_i. It would make no sense, in particular, to insure at a level of x_i such that the premium paid in case of bankruptcy exceeds the amount of deposits held in the bank. For instance, if the agent held 200 tokens in the bank, it would be irrational to insure more than $200/k$. We then assume that the following condition holds for any value $1000 - w_i \leq 200k$, $200k$ being the highest possible premium that can be obtained from insurance:

$$kx_i = 1000 - w_i \tag{15}$$

This condition ensures that the amount insured is just enough to recover the losses in case of bankruptcy. Moreover, differentiating (14) with respect to x_i yields the following simple condition:

$$\frac{\partial V_1\left(w_i, \underline{w}_j, x_i\right)}{\partial x_i} = Pk - 1 \tag{16}$$

(16) yields a simple "bang–bang" solution for an internal optimum such that the agent insures the full amount given by (15) iff:

$$P > \frac{1}{k} \tag{17}$$

If (17) is violated, $x_i = 0$. Intuitively, the subjective probability of bankruptcy must be high enough to make insurance attractive. Provided that insurance is attractive, a risk-neutral agent will then insure the maximum possible amount. A corollary of (17) is that we should expect higher insurance in the Insurance High condition than in the Insurance Low condition, because insurance is then profitable for a larger set of values of P.

After having established the optimality condition for x_i, we can now examine the ramifications for the optimal choice of w_i. We assume that both (17) and (15) hold. We must distinguish across four different cases.

(1) $P > \frac{1}{k}$ and $1000 - w_i \leq 200k$

In this region, it is always profitable to insure the highest possible amount and the amount of withdrawals exceeds the maximum amount that can be insured. The first term of (14) equals zero so that the FOC, after some simplifications, is:

$$\frac{\partial V_1}{\partial w_i} = -\left[(1000 - w_i)(5000 - w_i - E\left(\hat{w}_j\right)) + (2500 - w_i - E\left(\hat{w}_j\right))(E\left(\hat{w}_j\right) - 4000)\right] \geq 0 \tag{18}$$

where we have used the following derivative for s_{ij}:

$$\frac{\partial s_{ij}}{\partial w_i} = -\frac{4000 - E\left(\hat{w}_j\right)}{\left(5000 - w_i - E\left(\hat{w}_j\right)\right)^2} \tag{19}$$

We note that, on the basis of the probability distribution specification as of Appendix A.4.1, it is the case that $\partial P/\partial w_i = f\left(2500 - \hat{w}_j\right)$. However, for most "regular" density functions, such as in particular a uniform density, this value is negligible with respect to the other terms of (18). To simplify computations, we will then assume that $\partial P/\partial w_i = 0$. Intuitively, the probability that the agent will cause bankruptcy by withdrawing an additional token is virtually zero. We note that at $w_i = 1000$, $sign\left(\partial V_1/\partial w_i\right) = sign\left(E\left(\hat{w}_j\right) - 1500\right)$. In particular, if $E\left(\hat{w}_j\right)$, that is, if no bankruptcy is expected to occur, $\frac{\partial V_1}{\partial w_i} < 0$, hence it will be profitable for the individual to reduce withdrawals, thus ensuring an internal solution for w_i. We will check for the feasibility of this condition below.

(2) $P < \frac{1}{k}$ and $1000 - w_i \leq 200k$

In this case, it is never profitable to buy insurance. Hence, the first term of (14) is now positive and the first derivative equals:

$$\frac{\partial V_1}{\partial w_i} = P + (1 - P)\left(\frac{1}{5000 - w_i - E\left(\hat{w}_j\right)}\right)^2 \cdot \left[-(1000 - w_i)(5000 - w_i - E\left(\hat{w}_j\right)) + (2500 - w_i - E\left(\hat{w}_j\right))(E\left(\hat{w}_j\right)_j - 4000)\right] \geq 0 \tag{20}$$

(3) $P > \frac{1}{k}$ and $1000 - w_i > 200k$

In this region, it is optimal to buy insurance, but the amount deposited exceeds the insurable amount. This implies that, at the margin, an extra unit of money being withdrawn will not increase the premium received in case of bankruptcy. Hence, the FOC is the same as in (20).

(4) $P < \frac{1}{k}$ and $1000 - w_i > 200k$

In this region, it is not optimal to buy insurance. Hence, the FOC is the same as in (20).

A.4.3. Assumptions on the distribution of others' withdrawals

We now proceed with assuming a specific functional form for $f\left(\hat{w}_j\right)$, the density function for others' withdrawals. We assume that the distribution of $f\left(\hat{w}_j\right)$ has the following form, which is conditional on the probability of bankruptcy P:

$$f\left(\hat{w}_j\right) = \begin{cases} \frac{1-P}{2500-w_i} & \hat{w}_j < 2500 - w_i \\ \frac{P}{1500+w_i} & 2500 - w_i \leq \hat{w}_j < 4000 \end{cases} \tag{21}$$

(21) assumes that the probability distribution *conditional* on survival by the bank is a uniform distribution in which the probability mass $(1 - P)$ is spread evenly over the interval associated with survival, that is, $[0; 2500 - w_i]$. Likewise, the probability distribution *conditional* on bankruptcy is a uniform distribution in which the probability mass P is spread evenly over the interval associated with bankruptcy, that is, $[2500 - w_i; 4000]$. In other words, this distribution takes as given the subjective probability P of bankruptcy and "adjusts" the density function to be compatible with such a "prior" under the condition that the probability masses P and $1 - P$ are uniformly distributed over the relevant intervals.

This specification enables us to find a simple specification for $E\left(\hat{w}_j\right)$:

$$E\left(\hat{w}_j\right) = \int_0^{2500-w_i} \left(\frac{1-P}{2500-w_i}\right)\hat{w}_j d\hat{w}_j + \int_{2500-w_i}^{4000}\left(\frac{P}{1500+w_i}\right)\hat{w}_j d\hat{w}_j$$
$$= \left|\left(\frac{1-P}{2500-w_i}\right)\frac{\left(\hat{w}_j\right)^2}{2}\right|_0^{2500-w_i} + \left|\left(\frac{P}{1500+w_i}\right)\frac{\left(\hat{w}_j\right)^2}{2}\right|_{2500-w_i}^{4000}$$
$$= \left(\frac{1-P}{2}\right)\left(2500 - w_i\right) + \left(\frac{P}{1500+w_i}\right)\left(6500 - w_i\right)\left(1500 + w_i\right) \tag{22}$$

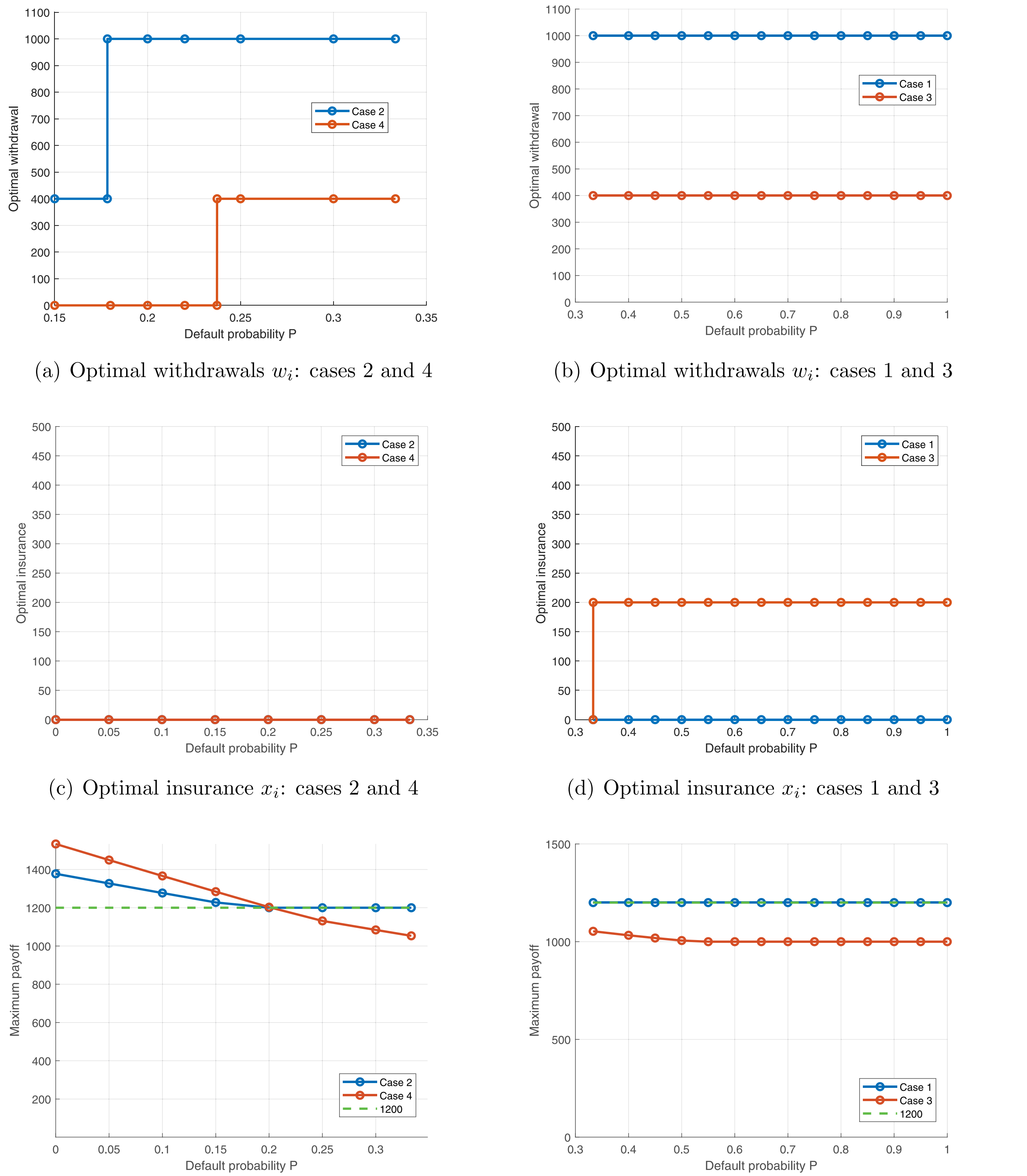
After simplifying, we obtain the expression of $E\left(\hat{w}_j\right)$ given distribution (21):

$$E\left(\hat{w}_j\right) = 1250 + 2000P - \frac{w_i}{2} \tag{23}$$

A.4.4. Numerical analysis of optimal insurance with a risk-neutral utility function

We provide a numerical analysis that calculates, for various values of P, the maximum payoff based on the choice of withdrawals and on the choice of the amount to be insured. Moreover, the payoff of the internal optimum needs to be compared with the outside option of 1200. That is the payoff that the agent obtains if she withdraws all the money not investing in insurance.

The procedure we use is as follows. For each $P \in \mathcal{P}$, we compute a two-dimensional payoff matrix, according to Eq. (14), containing all possible combinations of withdrawals ($w_i \in \mathcal{W}$) and insurance amounts ($x_i \in \mathcal{X}$), where $\mathcal{P}$, $\mathcal{X}$, $\mathcal{W}$ are the numerical sets defining the variables range. Subsequently, from each of these matrices, we extract the maximum payoff and the corresponding pair (w_i, x_i) that generated it. Consistently with Appendix A.4.3, we assume that agent



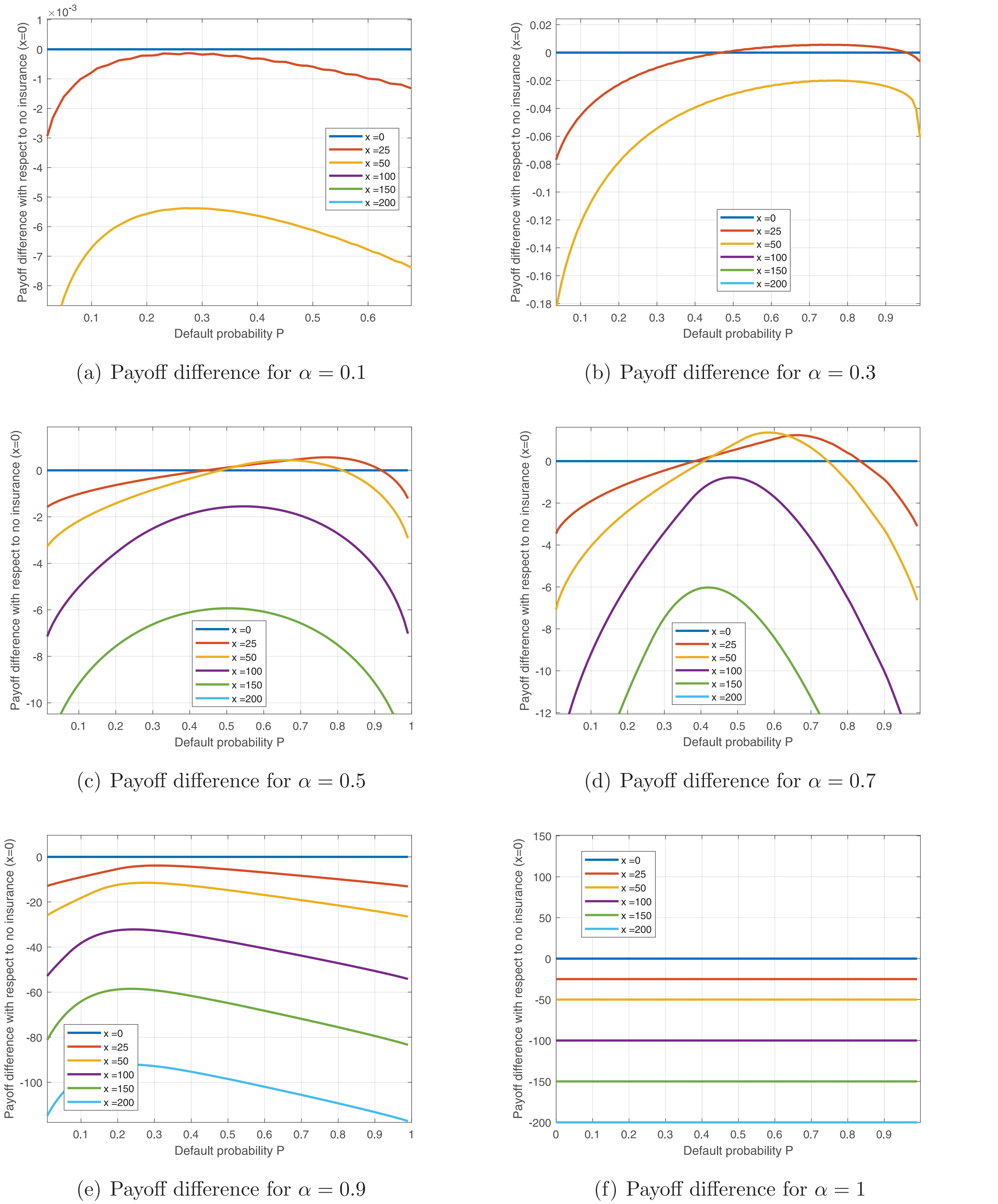
(a) Optimal withdrawals w_i: cases 2 and 4
(b) Optimal withdrawals w_i: cases 1 and 3
(c) Optimal insurance x_i: cases 2 and 4
(d) Optimal insurance x_i: cases 1 and 3
(e) Maximum payoff: cases 2 and 4
(f) Maximum payoff: cases 1 and 3

Fig. 4. Optimal behavior as a function of bankruptcy probability P. In sub-plot (c) the two cases are overlapped.

i, conditional on the probability of bankruptcy P, expects $\hat{w}_j$ according to Eq. (23). The insurance parameter k is set to 3. Qualitatively similar results are obtained for $k = 2$. Results for $k = 3$ are depicted in Fig. 4.

We analyze in turn the four regions identified above:

1. $P \geq \frac{1}{k}$ and $1000 - 200k \leq w_i$
   In this region, the optimality conditions for an internal solution are such that $x_i = 200$. As found out in Appendix A.4.2, a sufficient condition for an internal optimum for w_i is that $sign\,(\partial V_1/\partial w_i) = sign\left(E\left(\hat{w}_j\right) - 1500\right)$. However, after plugging in the expression for $E\left(\hat{w}_j\right)$ determined in (23), we find that the sign of this expression is positive over the region $P > 3/8$. This entails that $w_i = 1000$ must be a local maximum over this region. This result also emerges in the numerical analysis reported in Fig. 4, panel (b). The associated payoff is 1200 (see panel (f)). As a consequence, the strategy $x_i = 200$ is dominated by $x_i = 0$

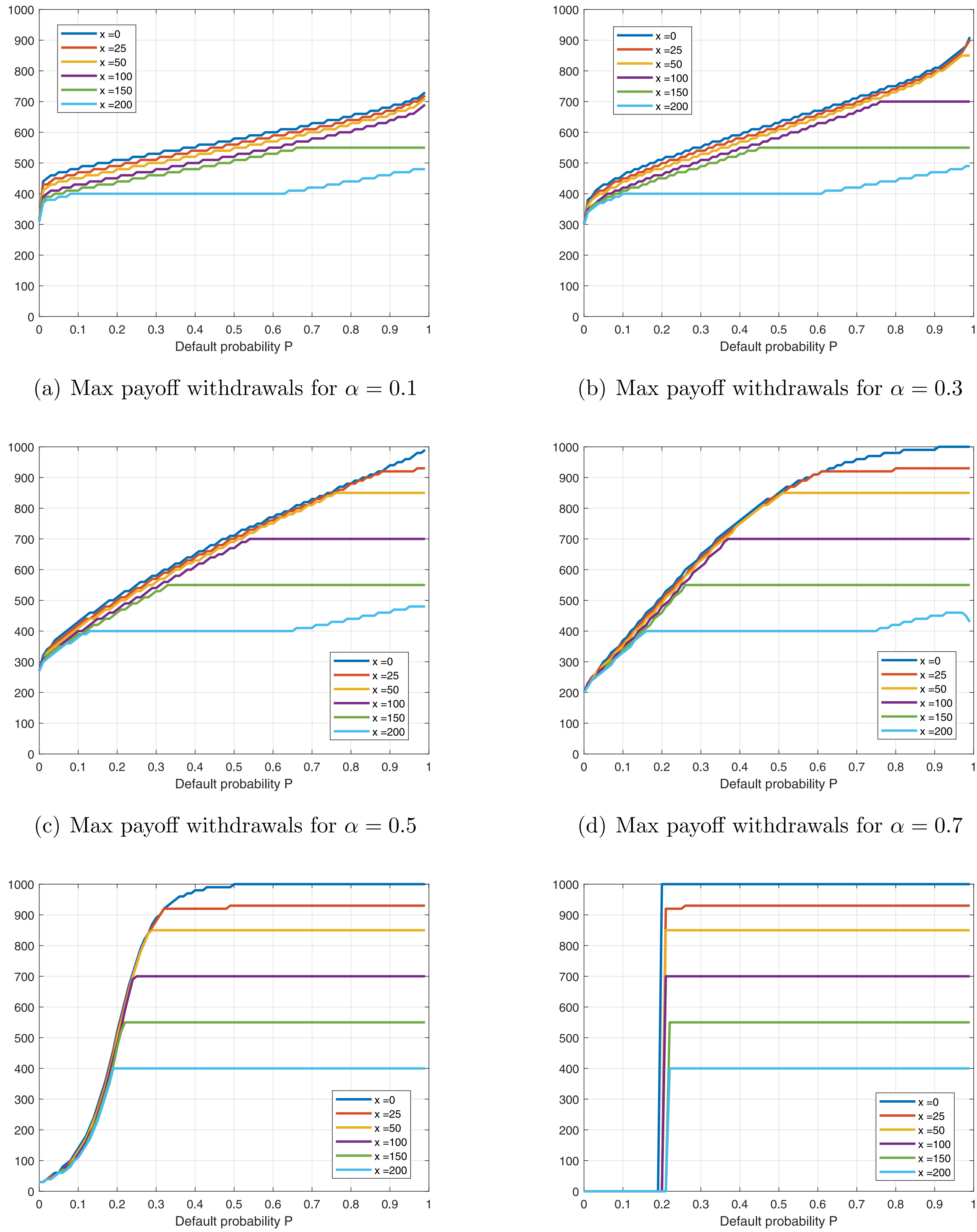


(a) Payoff difference for $\alpha = 0.1$
(b) Payoff difference for $\alpha = 0.3$
(c) Payoff difference for $\alpha = 0.5$
(d) Payoff difference for $\alpha = 0.7$
(e) Payoff difference for $\alpha = 0.9$
(f) Payoff difference for $\alpha = 1$

Fig. 5. Difference in maximum payoff for a given value of insurance x compared to the scenario with no insurance ($x = 0$). For lower α, certain ranges of P show higher payoffs with insurance.

(Fig. 4, panel (d)). In the region $1/3 < P < 3/8$ the numerical analysis does not identify an optimum internal to the interval.

2. $P < \frac{1}{k}$ and $1000 - 200k \leq w_i$
In this region, the theoretical analysis finds that insurance is not profitable and the numerical analysis, accordingly, finds $x_i = 0$ as the optimal strategy (Fig. 4, panel (c)). As for the optimal $w_i = 0$, the numerical analysis finds that for low values of P - that is for values lower approximately 0.2 -, agents prefer to withdraw the minimum possible in the region - $w_i = 400$ for $k = 3$. Conversely, for relatively high values of P, agents find it optimal to withdraw the full amount $w_i = 1000$ (Fig. 4, panel (a)). It is noteworthy that for values $P < 0.2$, the expected payoffs exceed the outside option 1200 (Fig. 4, panel (e)).



(a) Max payoff withdrawals for $\alpha = 0.1$

(b) Max payoff withdrawals for $\alpha = 0.3$

(c) Max payoff withdrawals for $\alpha = 0.5$

(d) Max payoff withdrawals for $\alpha = 0.7$

(e) Max payoff withdrawals for $\alpha = 0.9$

(f) Max payoff withdrawals for $\alpha = 1$

Fig. 6. Withdrawals corresponding to maximum payoff as a function of default probability, for different values of insurance x.

3. $P \geq \frac{1}{k}$ and $w_i < 1000 - 200k$
Consistently with the theoretical analysis, in this region the optimal internal solution is full insurance, namely $x_i = 200$. An optimal withdrawal of $w_i = 400$ is associated with this strategy (Fig. 4, panel (b) and (d)). Nonetheless, the associated expected payoff is only 1000 (Fig. 4, panel (f)), which is dominated by the outside option of 1200.
4. $P < \frac{1}{k}$ and $w_i < 1000 - 200k$
In analogy with case 2 above, the numerical analysis reveals a preferred strategy of withdrawing nothing for relatively low values of P and withdrawing the highest possible amount for relatively high values of P in the region.

On the basis of the analysis, we conclude that, for risk-neutral agents, insurance is never optimal. Risk-neutral agents will choose $w_i = 0$ for relatively low values of P (estimated to be around 0,2 in our numerical analysis) and will choose $w_i = 1000$ for relatively high values of P.

A.4.5. Numerical analysis of risk aversion with probability weighting

In this section, we explore the case of individuals characterized by risk aversion and probability weighting. In accordance with the seminal model of prospect theory by Tversky and Kahneman (1992), we posit the following utility function:

$$V_r\left(w_i, \underline{w}_j, x_i\right) = (200 - x)^\alpha + P^\alpha \cdot (wi + \min(k \cdot x, 1000 - wi))^\alpha + (1-P)^\alpha \cdot (wi)^\alpha + ((1-P)\cdot q)^\alpha \cdot (2 \cdot (2500 - wi - \underline{w}_j) \cdot s)^\alpha + ((1-P)\cdot(1-q))^\alpha \cdot (2 \cdot (1000 - wi))^\alpha \quad (24)$$

The probability weighting captures individuals' propensity not to weight outcomes by their objective probabilities but rather by transformed probabilities or decision weights. In line with experimental evidence, this weighting function overweights low probabilities and underweights high probabilities (Barberis, 2013). The expected value of others' withdrawal is again given by Eq. (23).

Similarly to the previous section, we calculate the combinations (w_i, x_i) that yield the maximum payoff for various values of P. Fig. 5 displays the results in the form of the difference between the maximum payoff achievable with different levels of insurance (x_i) and the one achieved with no insurance. We perform this analysis for a set of values of α, where $\alpha = 1$ is the case of risk neutrality and $\alpha < 0$ denotes risk aversion (the lower α, the higher risk aversion). In accordance with what found in the previous section, $x_i = 0$ is always optimal for $\alpha = 1$; $x_i = 0$ is also optimal for $\alpha = 0.9$. However, for lower values of α, getting insured becomes the optimal decision for an intermediate range of bankruptcy probability P. Interestingly, the relationship between α and the propensity to buy insurance appears to be non-linear, because for extremely low values of α – in particular $\alpha = 0.1$ – the choice of $x_i = 0$ comes back as the dominant strategy. The intuition for this result is that when risk aversion is extremely high, the option of withdrawing all money and not insuring against losses is dominant. For intermediate levels of risk aversion, conversely, individuals prefer to keep some money in the bank with the protection of the insurance scheme.

Fig. 6 shows, for different risk aversions, the amount of withdrawals that maximizes the payoff of Eq. (24), as a function of bankruptcy probability P. For values of α lower than 1, transition from no (or limited) withdrawal to full (or close to full) withdrawal are smoother.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbef.2024.100909.

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