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Abstract

Informal risk sharing enables individuals to smooth consumption when access to formal insurance is limited. While previous studies have examined the roles of income correlation and initial income inequality, little is known about how differences in individual risk exposure affect voluntary risk sharing. We investigate this question using a laboratory experiment based on an indefinitely repeated risk-sharing game. Subjects are randomly assigned to either homogeneous income risk, in which both members of a pair face the same level of risk, or heterogeneous income risk, in which one subject faces high income risk and the other faces low income risk. The benchmark repeated-game model predicts that transfers should be highest under homogeneous high income risk and lower, but comparable, under homogeneous low income risk and heterogeneous income risk. Consistent with this prediction, transfers are higher when both subjects face high income risk than when both face low income risk. However, subjects facing heterogeneous income risk exhibit a higher incidence of positive transfers than those in the homogeneous-risk configurations. Although average transfers under heterogeneous income risk lie between those observed under homogeneous high and homogeneous low income risk, they are considerably closer to the former than the latter. These findings provide the first experimental evidence that heterogeneous income risk does not undermine voluntary risk sharing and may instead encourage greater participation in reciprocal transfer arrangements.

Keywords: risk sharing; heterogeneous risk; cooperation; infinitely repeated games, economic experiment

JEL classifications: D81, C91, C73, O17

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1 Introduction

Individuals are frequently exposed to income shocks arising from sources such as weather fluctuations, health conditions, and market uncertainty. In economies with well-functioning financial and insurance markets, individuals can smooth consumption through formal insurance contracts or access to credit. In many developing settings, however, formal insurance is unavailable, making informal risk-sharing arrangements an important mechanism for coping with adverse shocks. Under these arrangements, individuals voluntarily transfer resources to others experiencing negative income shocks with the expectation that similar assistance will be provided when they themselves experience a loss. Because these agreements are voluntary rather than contractually enforceable, their sustainability depends critically on repeated interactions and the prospect of future cooperation. Understanding the conditions under which informal risk-sharing agreements emerge and are sustained therefore remains a central question in development economics and behavioral economics.

A large empirical literature documents the importance of informal risk sharing in developing countries. Evidence from India (Townsend, 1994; Ligon, Thomas and Worrall, 2002), the Philippines (Fafchamps and Lund, 2003; Fafchamps and Gubert, 2007), Tanzania (De Weerdt and Dercon, 2006; De Weerdt and Fafchamps, 2007), Kenya (Jack and Suri, 2014), and Malawi (Fitzsimons, Malde and Vera-Hernández, 2018) shows that households rely on reciprocal transfers and social networks to smooth consumption following idiosyncratic income shocks, although risk sharing is generally incomplete. Motivated by these findings, a growing theoretical literature studies informal insurance under limited commitment, demonstrating how self-enforcing agreements can sustain consumption smoothing despite the absence of formal contracts (Genicot and Ray, 2003). Together, these studies establish informal risk sharing as an important institution in environments where formal insurance markets function imperfectly.

A complementary experimental literature investigates the strategic foundations of informal risk sharing under controlled environments. A seminal study by Charness and Genicot (2009) models informal risk sharing as an indefinitely repeated game in which two individuals experience perfectly negatively correlated income shocks. They demonstrate that repeated interactions can sustain voluntary transfers and show that cooperation is stronger when subjects begin with identical initial incomes than when initial incomes differ, suggesting that perceived similarity or group identity promotes cooperation. More recently, Jindapon, Sujarittanonta and Viriyavipart (2026) investigate how the correlation of income shocks affects informal risk sharing. They find that transfer behavior depends not only on strategic incentives but also on the pattern of income realizations, with more frequent common income outcomes strengthening cooperation through perceived similarity or group identity. These studies demonstrate that characteristics of the economic environment influence informal risk-sharing behavior through both strategic incentives and social considerations.

Despite these advances, one important feature of real-world informal risk-sharing environments has received little attention. Individuals participating in informal risk-sharing arrangements rarely face identical income risks. Farmers within the same village cultivate different crops with different exposure to weather and price fluctuations, workers differ in employment stability, and households face different health risks. Consequently, informal risk-sharing networks typically consist of individuals with heterogeneous income risk rather than identical risk exposure. Yet, to our knowledge, no laboratory experiment has been specifically designed to examine how heterogeneous income risk affects voluntary risk sharing across interacting individuals.[1]

Whether heterogeneous income risk promotes or hinders cooperation is theoretically ambiguous. On the one hand, differences in risk exposure may weaken perceived similarity between interacting individuals, reducing group identity and the willingness to cooperate. It may also create asymmetric incentives to contribute to reciprocal arrangements. On the other hand, individuals facing greater income risk have stronger incentives to maintain cooperative relationships because they benefit more from future transfers. Consequently, individuals may be more willing to sustain an informal risk-sharing relationship when paired with someone facing greater income risk. Which of these opposing forces dominates is

[1]Lin, Liu and Meng (2014) and Lin, Meng and Weng (2020) investigate the interaction between formal and informal insurance in laboratory experiments. In their setting, differences in risk exposure arise endogenously through insurance choices rather than exogenously through heterogeneous underlying risks.

ultimately an empirical question.

To address this question, we extend the experimental framework of Charness and Genicot (2009) by introducing heterogeneity in individual income risk while holding constant expected income, the correlation of income shocks, and the continuation probability. Subjects are randomly assigned either to a homogeneous-risk environment, in which both members of a pair face the same level of income risk, or to a heterogeneous-risk environment, in which one subject faces high income risk and the other faces low income risk. The high-risk environment is constructed as a mean-preserving spread of the low-risk environment, allowing us to isolate the effect of heterogeneous income risk from differences in expected income and other features of the strategic environment.

The benchmark repeated-game model predicts that transfers should be highest when both subjects face high income risk because maintaining a cooperative relationship yields the greatest future benefit in this environment. It further predicts comparable transfer levels under homogeneous low income risk and heterogeneous income risk. An alternative prediction arises from the literature on perceived similarity and group identity. If individuals are more willing to cooperate with partners who face similar economic circumstances, homogeneous risk profiles should generate stronger cooperation than heterogeneous risk profiles regardless of the underlying level of income risk.

The experimental evidence supports some theoretical predictions while departing from others. Consistent with the benchmark model, transfers are higher when both subjects face high income risk than when both face low income risk. However, subjects facing heterogeneous income risk are significantly more likely to make positive transfers than subjects facing homogeneous income risk. Although transfers conditional on making a positive transfer are smaller than under homogeneous high risk, the higher participation rate results in average transfers under heterogeneous income risk that are comparable to those observed under homogeneous high risk and substantially larger than those under homogeneous low risk. Moreover, post-transfer income allocations remain close to the efficient benchmark despite the asymmetry in risk exposure. These findings suggest that heterogeneous income risk does not undermine cooperation and, in several important dimensions, is associated with a greater willingness to participate in voluntary risk sharing.

Our findings contribute to several strands of the literature. First, we extend the experimental literature on informal risk sharing by providing the first controlled evidence on how heterogeneous income risk affects voluntary risk sharing while holding expected income and the correlation of income shocks constant. Second, our findings complement the extensive empirical, field experimental, and lab-in-the-field literature demonstrating the importance of informal risk sharing in developing economies. Field experiments show that information, commitment, and formal insurance arrangements influence informal risk sharing (Barr and Genicot, 2008; Berg, Blake and Morsink, 2022), while lab-in-the-field experiments demonstrate that trust, social ties, and network position strengthen cooperation in environments without formal enforcement (Attanasio et al., 2012; Chandrasekhar, Kinnan and Larreguy, 2018; Islam et al., 2020). Our results identify heterogeneous income risk as another important feature of the economic environment shaping cooperative behavior. Finally, our findings contribute to the broader literature on the mechanisms underlying informal risk sharing. Previous research highlights the importance of social networks (Bramoullé and Kranton, 2007; Ambrus, Mobius and Szeidl, 2014; Ambrus and Elliott, 2021; Ambrus, Gao and Milám, 2022), the interaction between formal and informal insurance (Lin, Meng and Weng, 2020; Will et al., 2021; Berg, Blake and Morsink, 2022), and other-regarding preferences and distributional concerns (Barbet, Bourlès and Rouchier, 2020; Kritikos and Bolle, 2001; Charness and Rabin, 2002; Engelmann and Strobel, 2004). Our evidence suggests that heterogeneous income risk itself is an important determinant of cooperation and that transfers from low-income subjects reflect behavioral considerations beyond the benchmark repeated-game framework.

2 Theory

Consider a game with two players, 1 and 2, who interact with each other infinitely repeatedly. In each period of interaction, the state of the world is either 1 or 2. For $i = 1, 2$ and $t = 1, 2, ...$, Player i's income in period t, denoted by $W_{i,t}$, is a state-dependent random variable. We assume that $W_{1,t} = G_1$ and $W_{2,t} = B_2$ in state 1, $W_{1,t} = B_1$ and $W_{2,t} = G_2$ in state 2, and $G_i > B_i \geq 0$ for $i = 1, 2$. Thus, Player i has a higher income in state i than in state i' where $i, i' = 1, 2$ and $i \neq i'$. In other words, state 1 is the "good" state for Player 1 and the "bad" state for Player 2, while state 2 is the "good" state for Player 2 and the "bad" state for Player 1. We let S_t denote the state variable in period t and $\pi_i \in (0, 1)$ denote the probability that $S_t = i$ for $i = 1, 2$ and all $t = 1, 2, ...$

There are two stages in each period. In Stage 1, both players are informed about the state of the world and each other's income for the period. In Stage 2, each simultaneously transfers a portion of their income to the other player. Given that $w_{i,t}$ is the realized value of $W_{i,t}$, we let $x_{i,t} \in [0, w_{i,t}]$ denote the amount that Player i transfers to Player j in Period t.

2.1 Grim-Trigger Strategy

Consider the following risk-sharing strategy. "Player 1 transfers $x_1 > 0$ to Player 2 whenever $S_t = 1$ and Player 2 transfers $x_2 > 0$ to Player 1 whenever $S_t = 2$. For $i, i' = 1, 2$ and $i \neq i'$, if $S_{t-1} = i'$ and $x_{i',t-1} \neq x_{i'}$, then $x_{i,\tau} = 0$ for all $\tau \geq t$." This is a grim-trigger strategy profile in which Player i shares part of their income with Player i' in State i.

We assume that all players have the same utility function u and discount factor $\delta \in (0, 1)$. Under expected utility theory, we let $U_i(x_i, x_{i'})$ denote Player i's expected utility in each period under a risk-sharing agreement such that Player i transfers x_i to Player i' in State i and receives $x_{i'}$ from Player i' in State i' for $i, i' = 1, 2$ and $i \neq i'$. Thus,

$$U_i(x_i, x_{i'}) = \pi_i \cdot u(G_i - x_i) + (1 - \pi_i) \cdot u(B_i + x_{i'}) \tag{1}$$

and $U_i(0, 0) = \pi_i \cdot u(G_i) + (1 - \pi_i) \cdot u(B_i)$ is Player i's expected utility in autarky.

The informal risk-sharing agreement (x_1, x_2) is sustainable under such a grim-trigger strategy if it satisfies the following individual sustainability (IS) constraint for $i = 1, 2$:[2]

$$u(G_i - x_i) + \frac{\delta}{(1 - \delta)} \cdot [\rho \cdot U(x_i, x_{i'}) + (1 - \rho) \cdot U_i(0, 0)] \geq u(G_i) + \frac{\delta}{(1 - \delta)} \cdot U_i(0, 0) \tag{2}$$

[2]This condition is called implementability constraint in Coate and Ravallion (1993) and sustainability constraint in Ligon, Thomas and Worrall (2002)

which can be re-written as

$$\frac{\delta}{1-\delta} \geq \frac{[u(G_i) - u(G_i - x_i)]}{\rho[U_i(x_i, x_{i'}) - U_i(0,0)]} \tag{3}$$

or

$$\delta \geq \frac{[u(G_i) - u(G_i - x_i)]}{[u(G_i) - u(G_i - x_i)] + \rho[U_i(x_i, x_{i'}) - U_i(0,0)]} \tag{4}$$

to represent the minimum value of δ that supports the grim-trigger strategy in equilibrium in the right-hand side of (4). In addition, by defining $D(x_i, x_{i'}) := U_i(x_i, x_{i'}) - U_i(0,0)$, we can re-write the IS constraint in (2) as

$$D(x_i, x_{i'}) \geq \frac{(1-\delta)}{\delta\rho} \cdot [u(G_i) - u(G_i - x_i)] > 0. \tag{5}$$

To participate in such a risk-sharing agreement, the individual rationality (IR) constraint for $i = 1, 2$ is given by

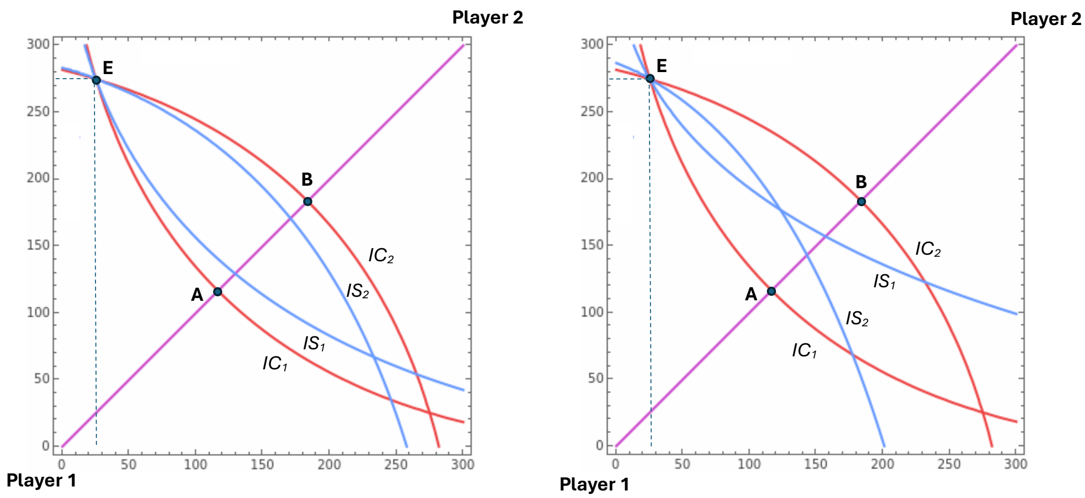
$$D(x_i, x_{i'}) \geq 0. \tag{6}$$

Given the two constraints in (5) and (6), we find that, for Player i, IS is stronger than IR because IS implies IR for all $\delta, \rho \in (0, 1]$. The two constraints coincide when δ converges to 1.

2.2 Numerical Examples

To illustrate the individual sustainability (IS) constraint and the individual rationality (IR) constraint, we use a set of parameters used in our experiment.[3] Suppose that $G_1 = G_2 = 275$, $B_1 = B_2 = 25$, and $\pi_1 = \pi_2 = 0.5$. That is, in State 1 (i.e., the good state for Player 1), Player 1's income is 275 and Player 2's income is 25, while in State 2 (i.e., the good state for Player 2), Player 1's income is 25 and Player 2's income is 275. We illustrate both players' state dependent income in an Edgeworth Box in Figure 1 with State-1 income

[3]We use a mixed design for the experiment with two between-subjects factors (homogeneous risks and heterogeneous risks) and two within-subjects factors (high risk and low risk). The numerical example discussed in this section is from the homogeneous-risk treatment where both players are in a high-risk situation.



(a) $\delta = 0.9$ (b) $\delta = 0.7$

Figure 1: IS and IR constraints for Players 1 and 2 when both have high risk.

on the vertical axis and State-2 income on the horizontal axis. Point E represents the initial endowment for the two players. We assume that both players' utility function is given by $u(w) = w^{0.5}$ and let IC_1 and IC_2 be Player 1's and Player 2's indifference curves that include the initial endowment. In each panel of Figure 1, the area between the two indifference curves satisfies both players' IR constraints in (6) and the 45-degree line is the contract curve representing all the efficient allocations. Thus, in this symmetric situation, all of the risk-free allocations (on the 45-degree line) are efficient because they are on the contract curve, and the AB segment of the contract curve is the core of the situation because they are also individually rational for both players.

In each panel of Figure 1, the IS_1 and IS_2 curves include all the allocations such that the IS constraint of each player in (2) holds with equality. Thus, the area between the two curves satisfies both players' IS constraints. We assume that $\delta = 0.9$ in Panel (a), and $\delta = 0.7$ in Panel (b). We find that a perfect risk-sharing agreement (which is also efficient) is sustainable when $\delta = 0.9$ but not sustainable when $\delta = 0.7$.

2.3 Parameters in the Experiment

In the experiment, subjects face one of two income-risk situations: High Risk (H) or Low Risk (L). Each situation has two equally likely income realizations, denoted as the good and bad states. Under the high-risk situation, income equals 275 in the good state and 25 in the bad state. Under the low-risk situation, income equals 225 in the good state and 75 in the bad state. Thus, both situations generate the same expected income of 150 experimental units, while the high-risk situation is a mean-preserving spread of the low-risk situation.

Let $R_i \in \{H, L\}$ denote Player i's risk situation and $R_1 R_2$ denote the risk situation profile of the two-player group. The four possible profiles are LL, HH, LH, and HL, where the first (second) letter denotes Player 1's (Player 2's) assigned risk situation. Table 1 summarizes the resulting state-dependent incomes under each profile. Throughout the paper, these labels are used to distinguish the different treatment conditions implemented in the laboratory experiment.

Table 1: State-Dependent Income under Each Risk Profile

		Risk Profile			
State	Player	HH	LL	LH	HL
1	1	275	225	225	275
	2	25	75	25	75
2	1	25	75	75	25
	2	275	225	275	225

3 Design, Hypotheses, and Procedures

3.1 Experimental Design

The laboratory experiment closely follows the theoretical environment described in Section 2.3. Subjects face the same income-risk situations and state-dependent income realizations summarized in Table 1, allowing the theoretical predictions to be tested directly in a controlled setting. To isolate the effect of heterogeneous income risk on informal risk sharing, all treatments share the same expected income, income correlation, continuation probability, and institutional environment. They differ only in the distribution of risk exposure across subjects.

The experiment consists of a repeated two-player informal risk-sharing game with an infinite-horizon structure. The interaction is divided into five independent segments. At the beginning of each segment, subjects are randomly matched into pairs and randomly assigned one of two identities, Red or Blue. These identities remain fixed throughout the segment but are randomly reassigned after rematching in subsequent segments. Subjects are informed that the experiment consists of five segments, each consisting of an uncertain number of periods. At the end of each period, the segment continues with probability 0.9 and ends with probability 0.1, implying a per-period discount factor of $\delta = 0.9$. Once a segment ends, subjects are randomly rematched with another subject whom they have not previously encountered. For implementation purposes, two predetermined continuation sequences were used, generating between 45 and 54 periods per subject over the course of the experiment.[4] Subjects were not informed of the predetermined continuation sequences and therefore could not anticipate the realized length of a particular segment.

Within each segment, each subject is assigned either Situation L (Low Risk) or Situation H (High Risk). In Situation L, subjects receive an initial income of 225 experimental units and face a 50% probability of losing 150 units. In Situation H, subjects receive an initial income of 275 experimental units and face a 50% probability of losing 250 units. Although the two situations differ in risk exposure, they generate the same expected income of 150 experimental units.

The assignment of risk situations is determined by the treatment condition. In the Symmetric treatment, both subjects are assigned the same risk situation, resulting in either an LL or HH pairing. In the Asymmetric treatment, one subject is assigned Situation L and the other Situation H, resulting in either an LH or HL pairing. Risk situations remain fixed throughout the segment and are publicly known by both subjects.

Each period consists of two stages. In Stage 1, both subjects first receive the initial

[4] Sequence 1: [8, 3, 10, 5, 19]; Sequence 2: [11, 1, 27, 4, 11].

income associated with their assigned risk situation. The computer then randomly selects one of the two identities, Red or Blue. The subject whose identity matches the selected color incurs the income loss associated with his or her assigned situation, while the other subject retains the full initial income. Consequently, each period produces one subject with a good outcome (G) and one subject with a bad outcome (B), generating perfectly negatively correlated income realizations in every treatment.

In Stage 2, both subjects observe their own and their counterpart's realized incomes before simultaneously and privately deciding how much of their realized income to transfer to the other subject. Subjects may transfer any portion of their realized income. Accordingly, the maximum feasible transfer equals 225 (275) experimental units following a good outcome and 75 (25) experimental units following a bad outcome in Situations L (H), respectively. Beginning in Period 2 of each segment, subjects also observe the complete history of transfers made by both members of the pair in all previous periods within the segment.

3.2 Hypotheses

The theoretical model generates four testable hypotheses under the assumptions that individuals are risk averse and maximize their own expected utility. Consider a pair in which Player i and Player j are assigned risk situations Ri and Rj where $R_i \in \{H, L\}$, respectively. We let $T_{R_iR_j}$ denote the average transfer amount from Player i to Player j in state i, i.e., when Player i is in Good state and Player j is in Bad state. Figure 2 summarizes the theoretical predictions for transfers from the player in the Good state across the four risk configurations. The equalities and inequalities indicate the pairwise rankings implied by the benchmark repeated-game model.

$$
\begin{array}{ccc}
\textbf{Symmetric} & & \textbf{Asymmetric} \\
T_{LL} & = & T_{LH} \\
\wedge & & \parallel \\
T_{HH} & > & T_{HL}
\end{array}
$$

Figure 2: Theoretical predictions for transfers from the player in the Good state

Hypothesis 1:

$$T_{HH} > T_{LL}.$$

Within the homogeneous treatment, both individuals face identical risk exposure. When both players face larger risks, each has a stronger incentive to engage in risk sharing against potential losses, leading to a larger transfer from the player who is in Good state.

Hypothesis 2:

$$T_{HL} = T_{LH}$$

Within the heterogeneous treatment, one individual faces a larger risk while the other faces a smaller risk. Under the self-interest assumption, we anticipate that cooperation will be sustained when both players reciprocate each other by making the same amount of transfer when one is in Good state. A player would not have an incentive to make a transfer to their counterpart larger than the transfer from their counterpart.

Hypothesis 3:

$$T_{LL} = T_{LH}$$

Under the self-interest assumption, the low-risk player's sustainability constraint depends only on their own risk exposure, the equilibrium transfer is unaffected by whether the counterpart faces high or low risk.

Hypothesis 4:

$$T_{HH} > T_{HL}.$$

A high-risk player has a stronger incentive to engage in risk sharing than a low-risk player. Thus, high-risk players anticipate a larger transfer from the counterpart who is also facing high risk than from a low-risk counterpart.

Collectively, the model predicts

$$T_{HH} > T_{HL} = T_{LH} = T_{LL}.$$

Thus, the benchmark repeated-game model predicts that equilibrium transfers are highest when both players face high risk, whereas the remaining three risk configurations yield the same equilibrium transfer amount.

3.3 Experimental Procedures

The experiment was conducted at The University of Alabama's TIDE Lab with an IRB review exemption granted by the University's Institutional Review Board (IRB Protocol #24-04-7572). The experiment was programmed using oTree (Chen, Schonger and Wickens, 2016). All subjects were undergraduate students at the University of Alabama, and each subject participated in only one experimental session.

A total of eight experimental sessions were conducted, involving 128 subjects. Four sessions (64 subjects) were assigned to the Symmetric treatment and four sessions (64 subjects) to the Asymmetric treatment. Each session consisted of three parts. In Part 1, subjects participated in the repeated informal risk-sharing game described earlier. In Part 2, individual risk preferences were elicited using a task similar to Gneezy and Potters (1997). Subjects received an endowment of 50 experimental units and decided how much to invest in a risky asset that paid 2.5 times the invested amount with probability 0.5 and zero otherwise. Higher investment levels therefore indicate lower risk aversion. In Part 3, subjects completed a short questionnaire collecting demographic information and responses to questions about the experiment.

Before each part, the experimenter read the instructions aloud, and subjects could refer to the written instructions throughout the experiment. Appendix B reproduces the complete experimental instructions, while Appendix C presents screenshots of the instruction screens and decision interface. Earnings from one randomly selected period of the repeated game were combined with earnings from the risk-elicitation task. Experimental earnings were converted at a rate of 10 experimental units per U.S. dollar. Subjects also received a show-up fee of $7.50. Average total earnings were $27.18, for a session that lasted approximately 60 minutes.

Table 2 reports the realized distribution of risk profiles across all segments and periods. Because subjects were rematched with a counterpart and risk situations were randomly reassigned at the beginning of each segment, the realized frequencies of LL, HH, LH, and HL profiles differ slightly from their theoretical proportions. Overall, the realized distribution closely matches the intended experimental design.

Table 2: Realized Frequencies of Risk Profiles

	HH	LL	LH	HL	Total
Number of segments	140	180	160	160	640
	(21.0%)	(28.1%)	(25.0%)	(25.0%)	
Number of periods	1,314	1,854	1,584	1,584	6,336
	(20.7%)	(29.3%)	(25.0%)	(25.0%)	

Subject characteristics are well balanced across the symmetric and asymmetric treatments. The proportion of male subjects was 0.42 in the Symmetric treatment and 0.36 in the Asymmetric treatment. The average age was 21.48 and 20.69 years, respectively. The mean investment in the risk-preference task was also nearly identical across treatments (28.05 versus 28.22). None of these differences is statistically significant based on two-sample tests of equality of means, suggesting that the treatment groups are well balanced. Thus, differences in transfer behavior are unlikely to be driven by systematic differences in observable subject characteristics.

4 Main Results

4.1 Descriptive Results

We begin by examining descriptive evidence on transfer behavior across the four risk profiles. Table 3 reports summary statistics for transfers made in the high-income (Good) state, the low-income (Bad) state, and net transfers, defined as transfers made in the high-income state minus those made in the low-income state. Together, these statistics provide an initial comparison of transfer behavior across the four risk profiles before turning to the regression analysis.

Several patterns emerge from the data. First, transfer behavior differs substantially across risk profiles. Average transfers are highest in the HH profile (54.39 experimental units), followed by the heterogeneous profiles LH (47.13) and HL (46.11), while transfers are considerably lower in the LL profile (24.98). Expressed relative to initial income, subjects in the heterogeneous profiles transfer 20.95 and 16.77 percent of their initial income, respectively, compared with 19.78 percent in HH and only 11.10 percent in LL. Thus, average transfers under heterogeneous income risk are much closer to those observed when both subjects face high income risk than when both face low income risk.

The decomposition of average transfers into the extensive and intensive margins provides additional insight. Subjects facing heterogeneous income risk are substantially more likely to make a positive transfer than subjects in the homogeneous treatments. The probability of making a positive transfer is 76.24 percent in LH and 73.78 percent in HL, compared with 68.95 percent in HH and 65.70 percent in LL. In contrast, conditional on making a positive transfer, average transfers are largest in HH (78.88), followed by the heterogeneous profiles (61.82 and 62.49), and smallest in LL (38.02). This pattern suggests that the main behavioral difference under heterogeneous income risk operates at the extensive margin: subjects are more likely to engage in risk sharing, while the amount transferred conditional on transferring is lower than under homogeneous high risk. The larger conditional transfers observed in HH are also consistent with the fact that achieving a similar degree of income equalization requires larger transfers when both subjects face high income risk.

Table 3: Transfer Behavior across Risk Profiles and Income States

	Symmetric		Asymmetric	
Risk Profile	HH	LL	LH	HL
Good-State Transfers				
Average Transfer	54.39	24.98	47.13	46.11
	(2.27)	(0.98)	(1.53)	(1.65)
Average Transfer | Transfer > 0	78.88	38.02	61.82	62.49
	(2.57)	(1.19)	(1.62)	(1.77)
Positive Transfer (%)	68.95	65.70	76.24	73.78
	(1.81)	(1.56)	(1.48)	(1.60)
% of Initial Income	19.78	11.10	20.95	16.77
	(0.83)	(0.44)	(0.68)	(0.60)
No. of Observations	657	927	825	759
Bad-State Transfers				
Average Transfer	2.14	3.66	2.49	1.99
	(0.21)	(0.30)	(0.29)	(0.17)
Average Transfer | Transfer > 0	9.30	11.88	11.90	8.18
	(0.62)	(0.76)	(1.10)	(0.50)
Positive Transfer (%)	22.98	30.85	20.95	24.36
	(1.64)	(1.52)	(1.48)	(1.50)
% of Initial Income	8.55	4.89	3.32	7.97
	(0.08)	(0.13)	(0.13)	(0.06)
No. of Observations	657	927	759	825
Net Transfers (Good-State – Bad-State Transfers)				
Average Net Transfer	52.25	21.31	45.14	43.62
	(2.26)	(0.99)	(1.55)	(1.64)
Average Net Transfer | Net Transfer > 0	78.12	38.58	61.85	61.05
	(2.55)	(1.19)	(1.64)	(1.78)
Positive Net Transfer (%)	67.58	58.68	73.58	72.07
	(1.83)	(1.62)	(1.54)	(1.63)
% of First-Best Net Transfer	0.418	0.284	0.451	0.436
	(0.018)	(0.013)	(0.015)	(0.016)
No. of Observations	657	927	825	759

Note: Standard errors are reported in parentheses.

Although the benchmark model predicts that transfers should originate only from the high-income subject, Table 3 shows that transfers from the low-income state are relatively common. Between 21 and 31 percent of low-income observations involve a positive transfer, although the average amounts are small, ranging from 1.99 to 3.66 experimental units. Conditional on making a positive transfer, subjects transfer between 8 and 12 experimental units on average. These transfers therefore represent a modest but systematic departure from the benchmark equilibrium and suggest that some subjects voluntarily transfer resources even after experiencing an unfavorable income realization.

The final panel reports net transfers, which account for transfers made in both income states and therefore provide a more comprehensive measure of realized risk sharing. Average net transfers again exhibit the same ordering observed in the Good state, with HH generating the largest net transfers (52.25), followed closely by LH (45.14) and HL (43.62), while LL remains substantially lower (21.31). Similarly, the probability of achieving the first-best transfer is highest in the heterogeneous profiles (45.1 and 43.6 percent), slightly exceeding HH (41.8 percent) and considerably higher than LL (28.4 percent). Thus, despite the asymmetry in individual risk exposure, subjects in the heterogeneous treatment frequently choose transfers that are close to the efficient benchmark. Overall, the descriptive evidence indicates that heterogeneous income risk does not undermine voluntary risk sharing. Instead, subjects facing heterogeneous income risk participate in risk sharing more frequently than subjects facing homogeneous income risk, leading to average net transfers and levels of efficiency that are comparable to those observed when both subjects face high income risk.

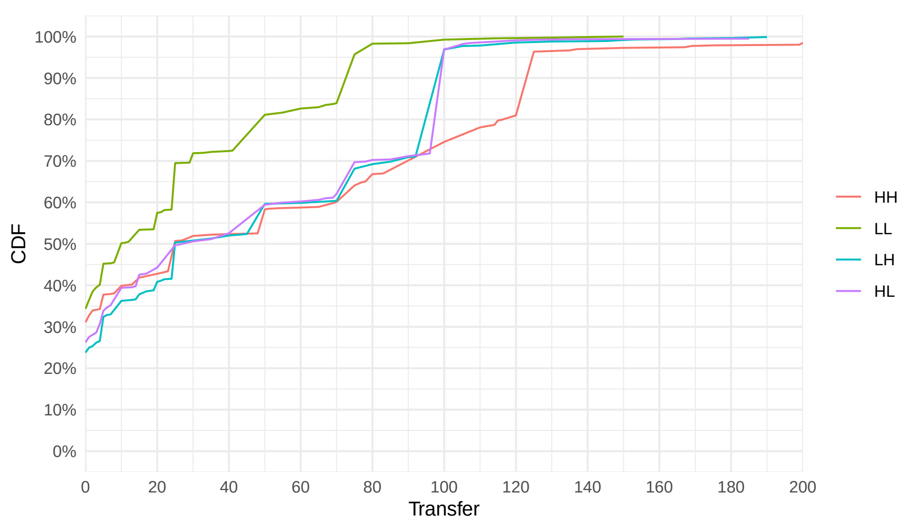


Figure 3: Cumulative Distribution of Transfers in the High-Income State by Risk Profile

Figure 3 complements the summary statistics by presenting the cumulative distribution of transfers made in the high-income state. The figure confirms that transfer behavior differs systematically across risk profiles. Transfers are smallest under the homogeneous low-risk profile (LL), largest under the homogeneous high-risk profile (HH), while the two heterogeneous profiles (LH and HL) lie between these two benchmarks and are nearly identical to one another throughout the distribution.

The descriptive patterns reported in Table 3 are robust to alternative samples. Appendix Table A.1 shows that the qualitative findings remain unchanged when the analysis is restricted to Period 1. Appendix Figure A.1 further shows that the treatment differences in transfer behavior remain broadly stable over time.

4.2 Transfer Amounts and Income States

Table 4 reports random-effects Tobit estimates of transfer amounts separately for the symmetric and asymmetric treatments. Columns (1) and (2) present estimates for the symmetric treatment, while columns (3) and (4) present estimates for the asymmetric treatment. Columns (2) and (4) additionally control for individual characteristics, including investment in the risk-preference task and gender. All specifications include segment and period controls. Because transfers are bounded below at zero, the dependent variable is estimated using a Tobit model with left-censoring at zero.

The results for the symmetric treatment show a clear relationship between the income state and transfer behavior. The coefficient on the *Good State* indicator is positive and statistically significant in both columns (1) and (2), at 49.805 ($p < 0.01$) and 49.163 ($p < 0.01$), respectively. This indicates that subjects transfer substantially more when they are in the Good state than when they are in the Bad state. The coefficient on *High Risk* is negative and statistically significant in both specifications, at -15.010 and -12.961 ($p < 0.01$), while the interaction between *Good State* and *High Risk* is positive and statistically significant, at 46.921 and 46.768 ($p < 0.01$). Taken jointly, these estimates indicate that the difference between transfers in the Good and Bad states is substantially larger under high risk. Thus, when risk is symmetric, subjects make relatively large transfers when they receive the high income associated with the Good state and relatively small transfers when they receive the low income associated with the Bad state, with this state-contingent transfer pattern being stronger under high risk. The close similarity of the estimates across the two specifications

Table 4: Random-effects Tobit Estimates given Symmetric and Asymmetric Risks

	(1) Symmetric	(2) Symmetric	(3) Asymmetric	(4) Asymmetric
Good State (G)	49.805^{***}	49.163^{***}	89.846^{***}	90.338^{***}
	(2.351)	(2.342)	(2.818)	(2.833)
High Risk (H)	-15.010^{***}	-12.961^{***}	4.388	6.782^{**}
	(3.014)	(2.966)	(3.141)	(3.091)
G × H	46.921^{***}	46.768^{***}	-9.583^{***}	-10.493^{***}
	(3.660)	(3.638)	(3.711)	(3.722)
Investment		-0.532^{***}		-0.678^{***}
		(0.094)		(0.103)
Female		12.807^{***}		7.499^{***}
		(2.570)		(2.902)
Segment	-1.621^{***}	-1.716^{***}	-0.328	-0.325
	(0.607)	(0.601)	(0.614)	(0.615)
Period	-0.422^{***}	-0.377^{***}	-0.753^{***}	-0.783^{***}
	(0.137)	(0.135)	(0.142)	(0.141)
Constant	-35.094^{***}	-25.484^{***}	-34.221^{***}	-26.336^{***}
	(3.245)	(4.250)	(3.455)	(4.399)
Observations	3168	3168	3168	3168

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors are reported in parentheses.

Notes: The dependent variable is the transfer amount. All models are estimated using random-effects Tobit specifications with left-censoring at zero. Models (1)–(2) report estimates for the symmetric treatment, and Models (3)–(4) for the asymmetric treatment. Models (2) and (4) additionally control for individual investment and gender. All specifications include segment and period controls. *Good State* indicates that the subject receives the high income in the current state, and *High Risk* indicates that the subject faces the high-risk income profile. The omitted category is the Bad state under the low-risk profile.

indicates that these main patterns are not sensitive to the inclusion of individual-level controls.

The estimates for the asymmetric treatment display a somewhat different pattern. The coefficient on *Good State* is large and positive in both columns (3) and (4), at 89.846 and 90.338 ($p < 0.01$), respectively. The coefficient on *High Risk* is positive but considerably smaller, at 4.388 in column (3) and 6.782 ($p < 0.05$) in column (4), while the interaction between *Good State* and *High Risk* is negative and statistically significant in both specifications, at -9.583 and -10.493 ($p < 0.01$), respectively. These coefficients should again be interpreted jointly. In particular, the implied difference between the high- and low-risk profiles in the Good state is given by the sum of the *High Risk* and interaction coefficients. In column (4), this difference is approximately -3.71. Thus, the asymmetric treatment does not exhibit the strong risk-state differential observed in the symmetric treatment. Rather, transfer behavior in the two risk profiles is broadly similar once the income state and their interaction are taken into account. The similarity of the estimates across columns (3) and (4) further indicates that the main results are robust to the inclusion of individual-level controls.

Among the control variables, *Investment* enters with a negative and statistically significant coefficient in both the symmetric and asymmetric specifications, indicating that subjects who invest more make smaller transfers. Since a larger investment reflects lower risk aversion, this finding suggests that more risk-averse subjects are more willing to engage in informal risk sharing, consistent with the idea that individuals who place greater value on reducing income risk have stronger incentives to participate in reciprocal transfer arrangements. The coefficient on *Female* is positive and statistically significant, implying that female subjects transfer more than male subjects. This finding contrasts with Charness and Genicot (2009), who report significantly higher transfers among male subjects, and with Jindapon, Sujarittanonta and Viriyavipart (2026), who also find a positive, although statistically insignificant, coefficient for males.

Finally, the coefficients on *Segment* and *Period* are negative, indicating that transfers gradually decline as the experiment progresses. The negative and statistically significant coefficient on *Period* in both treatments indicates that transfer amounts tend to decline over successive periods within a segment, while the negative *Segment* coefficient is statistically significant in the symmetric treatment but small and statistically insignificant in the asymmetric treatment. This gradual decline in transfer behavior is consistent with the findings of both Charness and Genicot (2009) and Jindapon, Sujarittanonta and Viriyavipart (2026), who also document declining transfers over time. The consistency of this pattern across studies suggests that transfer behavior may weaken as repeated interactions progress, although the period effects alone do not identify the mechanism underlying this decline.

As a robustness check, Appendix Table A.2 reports the same Tobit specifications using only the first period of each segment. The main patterns are broadly consistent with the full-sample results: the Good State effect remains positive and significant in both treatments, while the Good State × High Risk interaction remains positive and significant in the symmetric treatment. Appendix Table A.3 further reports pooled specifications using both symmetric and asymmetric treatments, estimated over all periods and using only Period 1 observations. The results are broadly consistent with the main specifications, with the Good State effect and its interaction with High Risk remaining positive and significant, while the reduced Period-1 sample again results in lower statistical precision. Overall, these robustness checks suggest that the main state-dependent patterns are not driven solely by behavior that emerges later in the experiment or by estimating the two treatments separately.

Finally, Appendix Table A.4 examines the extensive margin by estimating the probability of making a positive transfer using random-effects panel logit models. The results confirm the strong state dependence in transfer behavior: subjects are substantially more likely to make a positive transfer in the Good State in both the symmetric and asymmetric treatments. Thus, the differences in transfer behavior documented above reflect not only variation in transfer amounts but also differences in the likelihood of engaging in risk sharing.

Overall, Table 4 establishes two important features of the data. First, transfers are strongly state contingent: subjects transfer substantially more when they are in the Good state. Second, the strength of this state dependence differs across risk configurations. In the symmetric treatment, high risk amplifies the difference between transfers made in the Good and Bad states, whereas transfer behavior is considerably more similar across the two risk profiles in the asymmetric treatment. These patterns motivate a direct comparison of transfer behavior across the four risk configurations, which we turn to next.

4.3 Transfer Behavior across Risk Configurations

Table 5 compares transfer behavior across the four risk configurations. Models (5)–(8) use indicators for *Asymmetric* risk, *High Risk*, and their interaction. The four configurations are therefore represented as follows: LL is the omitted category; HH has *High Risk*=1; LH has *Asymmetric*=1; and HL has *Asymmetric*=1, *High Risk*=1, and *Asymmetric*×*High Risk*=1. The coefficients and their appropriate combinations therefore allow us to recover the relative transfer levels associated with each risk configuration.

The benchmark repeated-game model predicts that equilibrium transfers are highest when both players face high risk, while the three remaining configurations should generate similar transfer levels. The collective prediction is $T_{HH} > T_{HL} = T_{LH} = T_{LL}$.

The Good-state estimates in columns (5) and (6) provide the most direct comparison with this prediction. In column (6), for example, the estimated transfer levels relative to the LL baseline are 30.792 for HH, 31.168 for LH, and 30.849 (from 31.168+30.792-31.111) for HL. Thus, the estimated transfer levels in the three configurations involving either high risk or asymmetric risk are very similar, while transfers in LL are substantially lower. The corresponding ordering is therefore approximately $T_{HH} \approx T_{HL} \approx T_{LH} > T_{LL}$. The same pattern is obtained in column (5), indicating that the configuration-specific comparisons are not sensitive to the inclusion of the individual-level controls.

The results therefore provide an interesting departure from the benchmark prediction. The model assigns a special role to the HH configuration, predicting that transfers should be highest when both players face high risk. In the data, however, the transfer level in HH is not statistically distinguishable from those in either heterogeneous-risk configuration, and HL and LH are likewise statistically indistinguishable. Taken together, the pairwise

Table 5: Random-effects Tobit Estimates in Good and Bad States

	(5) Good State	(6) Good State	(7) Bad State	(8) Bad State
Asymmetric (A)	23.382^{***}	31.168^{***}	-4.263^{**}	-7.567^{***}
	(3.780)	(3.357)	(2.113)	(1.290)
High Risk (H)	29.441^{***}	30.792^{***}	-6.294^{***}	-6.992^{***}
	(2.448)	(2.399)	(1.154)	(1.106)
A x H	-31.570^{***}	-31.111^{***}	4.386^{**}	5.543^{***}
	(3.403)	(3.451)	(1.759)	(1.598)
Investment		-0.468^{***}		-0.520^{***}
		(0.108)		(0.049)
Female		18.849^{***}		3.586^{***}
		(3.396)		(1.058)
Segment	0.836	0.791	-2.107^{***}	-2.123^{***}
	(0.544)	(0.542)	(0.259)	(0.257)
Period	-0.697^{***}	-0.662^{***}	-0.175^{***}	-0.171^{***}
	(0.122)	(0.123)	(0.062)	(0.061)
Constant	14.138^{***}	3.247	-4.663^{***}	4.905^{***}
	(3.535)	(4.537)	(1.766)	(1.779)
Observations	3168	3168	3168	3168

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors are reported in parentheses.

Notes: The dependent variable is the transfer amount. All models are estimated using random-effects Tobit specifications with left-censoring at zero. Models (5) and (6) report estimates for the Good state, while Models (7) and (8) report estimates for the Bad state. Models (6) and (8) additionally control for investment and gender. All specifications include segment and period controls. A denotes the asymmetric treatment, and H denotes the high-risk situation.

tests indicate that we cannot reject equality of transfer levels across HH, HL, and LH. At the same time, each of these three configurations generates significantly higher transfers than LL. Thus, rather than responding to the precise combination of the two players' risk profiles, subjects appear to respond to whether the relationship involves substantial exposure to income risk. When both players face low risk, the gains from transferring income across states are relatively limited, whereas the presence of high risk for at least one player is associated with substantially greater transfer behavior. Importantly, this pattern holds whether the counterpart faces the same level of risk or a different level of risk. The finding therefore suggests that heterogeneous risk does not weaken informal risk sharing; instead, transfer behavior under heterogeneous risk is comparable to that observed under symmetric high risk and substantially greater than under symmetric low risk.

The Bad-state estimates in columns (7) and (8) provide complementary evidence. Transfer amounts are considerably smaller in the Bad state, where subjects have fewer resources available for transferring to their counterparts. Transfers are also lower in the HH, HL, and LH configurations than in LL. This pattern is consistent with the larger income differential between the two players in these configurations, which leaves the player in the Bad state with relatively less income and therefore reduces the scope for transfers in that state. The configuration differences are less pronounced in the Bad state than in the Good state. Since the theoretical risk-sharing arrangement primarily involves transfers from the player receiving the Good-state income to the player receiving the Bad-state income, the Good-state estimates provide the most direct comparison for the four hypotheses.

The control variables in Table 5 exhibit patterns broadly similar to those reported in Table 4. Investment is negatively associated with transfers, female subjects make larger transfers, and transfers tend to decline over segments and periods. The inclusion of these controls does not materially change the configuration-specific pattern in the Good state.

As a robustness check, Table A.5 reports random-effects Tobit estimates using only transfers made in Period 1 of each segment. The Good-state results are broadly consistent with the main estimates, while the configuration differences are not statistically significant in the Bad state. Overall, the Period-1 estimates suggest that the main configuration pattern is already present at the beginning of each segment and is not driven solely by behavior accumulated over repeated interactions.

The configuration analysis above focuses on the intensive margin, namely the amount transferred. Because the descriptive results also indicate differences in the incidence of positive transfers across configurations, Appendix Table A.6 examines whether these differences are also evident at the extensive margin. The results are broadly consistent with the main findings. In the Good State, high-risk and asymmetric risk exposure are associated with a greater likelihood of making a positive transfer, whereas in the Bad State the corresponding effects are generally negative. Thus, the configuration differences documented in the main Tobit estimates are reflected not only in transfer amounts but also in the decision to engage in risk sharing.

Overall, the results reveal a clear and systematic distinction between the LL configuration and the other three configurations. Thus, the benchmark model captures the importance of risk exposure for transfer behavior but does not account for the observed similarity across the three configurations involving high or asymmetric risk. Most importantly, heterogeneous risk does not undermine informal risk sharing: both heterogeneous-risk configurations generate transfer levels comparable to those observed under symmetric high risk and substantially above those under symmetric low risk.

4.4 Reciprocity and Dynamic Risk Sharing

Table 6 extends the specifications reported in Table 4. Models (9)–(12) mirror Models (1)–(4), respectively, but add transfers received from the counterpart in the previous period. This allows us to examine whether current transfer decisions respond to previous interactions. As in Table 4, the specifications distinguish between the symmetric and asymmetric treatments, with and without the individual-level controls for *Investment* and *Female*.

The results show a strong and consistent reciprocal response across treatments and specifications. In particular, the coefficient on the lagged transfer received in the previous period is positive and highly significant. The response is especially strong when the counterpart was in the *Good State* in the previous period, with coefficients close to one in

Table 6: Random-effects Tobit Estimates with Lagged Received Transfers

	(9) Symmetric	(10) Symmetric	(11) Asymmetric	(12) Asymmetric
Good State (G)	42.271^{***}	41.769^{***}	77.774^{***}	77.737^{***}
	(2.563)	(2.567)	(3.223)	(3.169)
High Risk (H)	-12.092^{***}	-10.740^{***}	7.140^{**}	6.583^{**}
	(3.156)	(3.095)	(3.294)	(3.206)
G × H	38.790^{***}	38.693^{***}	-9.453^{**}	-9.653^{**}
	(3.777)	(3.757)	(3.790)	(3.755)
Lag received when G	0.999^{***}	1.031^{***}	1.053^{***}	1.059^{***}
	(0.197)	(0.195)	(0.237)	(0.234)
G × Lag received when G	-0.386	-0.387	-0.002	-0.036
	(0.273)	(0.271)	(0.357)	(0.352)
Lag received when B	-0.065	-0.066^{*}	-0.044	-0.048
	(0.040)	(0.039)	(0.038)	(0.038)
G × Lag received when B	0.448^{***}	0.442^{***}	0.438^{***}	0.438^{***}
	(0.047)	(0.047)	(0.047)	(0.047)
Investment		-0.565^{***}		-0.733^{***}
		(0.110)		(0.108)
Female		13.975^{***}		6.814
		(3.350)		(5.088)
Segment	-1.534^{**}	-1.400^{**}	0.320	0.225
	(0.614)	(0.609)	(0.627)	(0.619)
Period	-0.375^{***}	-0.389^{***}	-0.670^{***}	-0.631^{***}
	(0.141)	(0.140)	(0.148)	(0.146)
Constant	-33.188^{***}	-23.668^{***}	-46.069^{***}	-28.020^{***}
	(3.497)	(4.702)	(5.454)	(6.250)
Observations	2848	2848	2848	2848

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors are reported in parentheses.

Notes: The dependent variable is the transfer amount. The models are estimated using random-effects Tobit specifications with left-censoring at zero. Models (9) and (10) use observations from the symmetric treatments, while Models (11) and (12) use observations from the asymmetric treatments. Investment and female controls are included only in Models (10) and (12). All specifications include segment and period controls. G denotes the Good state (high-income realization), and H denotes the high-risk situation. Lagged received transfer denotes the transfer received from the counterpart in the previous period. The omitted category is the Bad state under the low-risk situation.

both treatments. This indicates an approximately one-for-one reciprocal response: larger transfers received from a counterpart who was in the *Good State* are associated with approximately equally larger subsequent transfers to that counterpart.

In contrast, a transfer received when the counterpart was in the *Bad State* has little direct effect on the subject's subsequent transfer. However, its interaction with the subject's current *Good State* is positive and statistically significant. Thus, when the counterpart was in the *Bad State* in the previous period and increased the transfer received by the subject, the subject responds by increasing their current transfer primarily when they are themselves in the *Good State*. This pattern is consistent with the subject responding reciprocally when they have sufficient resources available to make a transfer.

Importantly, the estimated reciprocal effects are similar across specifications with and without additional controls. Overall, the results provide evidence consistent with reciprocity in transfer behavior: subjects' current transfers are positively associated with transfers received from their counterparts in previous periods, with the association depending on the counterpart's previous income state and the subject's current income state. This pattern is consistent with reciprocity playing a role in sustaining informal risk sharing over time.

5 Discussion and Concluding Remarks

This paper examines how heterogeneity in income risk affects informal risk sharing in repeated interactions. We develop a theoretical model of voluntary risk sharing between two risk-averse individuals facing different income-risk profiles and test its predictions using a controlled laboratory experiment. By holding expected income, the correlation of income shocks, the continuation probability, and the institutional environment constant across treatments, the experimental design allows us to identify the effect of heterogeneous risk exposure on informal risk-sharing behavior.

The experimental evidence yields three main findings. First, consistent with the theoretical predictions, transfers are higher under the symmetric high-risk profile than under the symmetric low-risk profile. Moreover, transfers under the high-risk profile constitute a larger proportion of the transfer required to equalize post-transfer incomes, indicating that greater risk exposure is associated with greater transfer behavior rather than merely increasing the efficient transfer level. Second, average transfer amounts are comparable between the symmetric high-risk and asymmetric risk profiles, but the underlying behavioral patterns differ. Subjects facing heterogeneous risk are significantly more likely to make positive transfers, whereas subjects in the symmetric high-risk profile transfer larger amounts conditional on transferring. This difference reflects, in part, the larger transfer required to reduce the wider income gap under the symmetric high-risk profile. Thus, heterogeneous risk is associated with more frequent participation in risk sharing, whereas subjects facing symmetric high risk tend to make larger transfers conditional on transferring. Third, the greater frequency of transfers under heterogeneous risk is associated with post-transfer allocations that are systematically closer to the efficient risk-sharing benchmark.

These findings contribute to the literature on informal risk sharing in several ways. First, they complement the work of Jindapon, Sujarittanonta and Viriyavipart (2026), who examine how the correlation of income shocks influences repeated informal risk sharing. Whereas they vary the correlation of income realizations while holding the risk environment fixed, the present study holds the correlation of income shocks constant and instead examines how heterogeneity in risk exposure affects cooperative behavior. Taken together, these studies broaden our understanding of how different dimensions of the risk environment shape informal risk sharing. Second, our findings suggest that similarity in risk exposure is not necessary for successful cooperation. While previous studies have argued that similarity between interacting individuals can promote cooperation through mechanisms such as shared identity or social affiliation, we find that subjects facing heterogeneous risk are more likely to engage in voluntary risk sharing than subjects facing homogeneous low-risk environments and achieve average transfer levels comparable to those under homogeneous high-risk environments.

These findings also have relevance for informal risk-sharing arrangements in households and social networks, where individuals often face different sources or degrees of income risk. For example, within households or extended families, one member may have relatively stable wage income while another depends on agricultural, self-employment, or other more volatile sources of income. Similarly, members of informal networks may differ in their exposure to employment, business, or other idiosyncratic shocks. Our results suggest that such differences in risk exposure need not undermine reciprocal transfers. Instead, heterogeneous risk can coexist with a relatively high propensity to engage in informal risk sharing, although the size of transfers may depend on the resources available to the transferring individual. More broadly, the findings suggest that the functioning of informal risk-sharing relationships depends not only on whether individuals face similar risks, but also on how differences in risk exposure shape their opportunities and incentives to provide reciprocal support.

Finally, while the benchmark repeated-game model correctly predicts greater cooperation under high-risk than under low-risk environments, it substantially underpredicts cooperation when risk exposure is heterogeneous. This discrepancy suggests that factors not captured by the benchmark self-interest framework—such as reciprocity, social preferences, or beliefs about future interactions—may contribute to transfer behavior. The finding that current transfers are positively associated with transfers received from counterparts in previous periods is consistent with reciprocity playing a role in sustaining informal risk sharing over time.

Several directions remain for future research. An important next step is to examine how heterogeneous risk exposure and the correlation of income shocks jointly influence informal risk sharing within a unified experimental design. Such a design would allow researchers to investigate whether these two dimensions reinforce or offset one another in sustaining cooperation. Future research could also explore the behavioral mechanisms underlying the higher propensity to cooperate under heterogeneous risk, including signaling, reciprocity, and social preferences, as well as extend the analysis to larger groups, alternative network structures, or environments with endogenous risk choices.

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Appendix

A Additional Tables and Figures

Table A.1: Transfer Behavior in Period 1 across Risk Profiles and Income States

	Symmetric		Asymmetric	
Risk Profile	HH	LL	LH	HL
Good-State Transfers				
Average Transfer	56.37	31.53	54.08	52.64
	(6.48)	(3.54)	(5.20)	(4.91)
Average Transfer | Transfer > 0	65.77	41.74	63.23	61.42
	(6.84)	(3.95)	(5.30)	(5.04)
Positive Transfer (%)	85.71	75.56	85.53	85.71
	(4.21)	(4.56)	(4.06)	(3.84)
% of Initial Income	20.50	14.01	24.04	19.14
	(2.36)	(1.57)	(2.31)	(1.79)
No. of Observations	70	90	76	84
Bad-State Transfers				
Average Transfer	2.16	3.52	4.54	2.95
	(0.55)	(1.04)	(1.24)	(0.71)
Transfer (% of Initial Income)	8.63	4.70	6.05	11.79
	(0.20)	(0.46)	(0.55)	(0.26)
Average Transfer | Transfer > 0	7.19	12.19	14.65	8.62
	(1.29)	(3.00)	(3.24)	(1.58)
Positive Transfer (%)	30.00	28.89	30.95	34.21
	(5.52)	(4.80)	(5.07)	(5.48)
No. of Observations	70	90	84	76
Net Transfers (Good-State – Bad-State Transfers)				
Average Net Transfer	54.21	28.01	51.13	48.11
	(6.55)	(3.71)	(5.37)	(5.03)
Average Net Transfer | Net Transfer > 0	63.58	42.69	64.85	59.78
	(6.94)	(4.10)	(5.36)	(5.04)
Positive Net Transfer (%)	85.71	68.89	80.26	82.14
	(4.21)	(4.91)	(4.60)	(4.20)
% of First-Best Net Transfer	0.434	0.373	0.511	0.481
	(0.052)	(0.050)	(0.054)	(0.050)
No. of Observations	70	90	76	84

Note: Standard errors are reported in parentheses.

Table A.2: Random-effects Tobit Estimates given Symmetric and Asymmetric Risks (Period 1 Only)

	(1) Symmetric	(2) Symmetric	(3) Asymmetric	(4) Asymmetric
Good State (G)	56.970***	57.236***	83.023***	83.023***
	(6.682)	(6.698)	(7.940)	(7.937)
High Risk (H)	−0.350	−0.190	1.893	2.053
	(7.632)	(7.647)	(8.363)	(8.365)
G × H	20.352**	20.057**	−5.415	−5.475
	(9.836)	(9.856)	(10.775)	(10.778)
Investment		−0.416		0.054
		(0.352)		(0.283)
Female		9.484		0.214
		(10.210)		(8.256)
Segment	0.336	0.341	0.105	0.106
	(1.529)	(1.532)	(1.730)	(1.726)
Constant	−31.700***	−25.699*	−30.793***	−32.452**
	(8.108)	(15.436)	(8.574)	(14.079)
Observations	320	320	320	320

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors are reported in parentheses.

Notes: The dependent variable is the transfer amount in Period 1 of each segment. All models are estimated using random-effects Tobit specifications with left-censoring at zero. Models (1)–(2) report estimates for the symmetric treatment, and Models (3)–(4) for the asymmetric treatment. Models (2) and (4) additionally control for individual investment and gender. *Good State* indicates that the subject receives the high income in the current state, and *High Risk* indicates that the subject faces the high-risk income profile. The omitted category is the Bad state under the low-risk profile.

Table A.3: Random-Effects Tobit Estimates of Transfer Amounts: Pooled Specifications

	(5) All periods	(6) All periods	(7) Period 1	(8) Period 1
Good State (G)	50.376***	49.333***	57.761***	58.060***
	(2.373)	(2.360)	(7.123)	(7.150)
High Risk (H)	−14.855***	−12.813***	−0.621	−0.444
	(3.050)	(3.007)	(8.229)	(8.257)
G x H	46.623***	46.492***	21.675**	21.394**
	(3.715)	(3.693)	(10.589)	(10.625)
Asymmetric Treatment	−11.403**	−7.607**	2.180	2.191
	(4.848)	(3.269)	(9.237)	(9.276)
H x Asymmetric	22.273***	19.521***	3.016	2.784
	(4.742)	(4.273)	(11.370)	(11.418)
G x Asymmetric	38.549***	40.873***	24.942**	24.511**
	(3.591)	(3.576)	(10.159)	(10.199)
G x H x Asymmetric	−56.052***	−57.259***	−28.040*	−27.552*
	(5.238)	(5.221)	(14.611)	(14.672)
Investment		−0.616***		−0.164
		(0.079)		(0.226)
Female		10.705***		5.719
		(2.015)		(6.570)
Segment	−0.841*	−1.061**	0.178	0.193
	(0.447)	(0.430)	(1.156)	(1.159)
Period	−0.629***	−0.567***		
	(0.102)	(0.098)		
Constant	−36.631***	−21.737***	−32.468***	−31.592***
	(2.914)	(3.910)	(7.434)	(11.104)
No. of Observations	6336	6336	640	640

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Standard errors are reported in parentheses.
Notes: The dependent variable is the transfer amount. All models are estimated using random-effects Tobit specifications with left-censoring at zero. Models (5)–(6) use observations from all periods, while Models (7)–(8) use only Period 1 observations from each segment. All specifications pool the symmetric and asymmetric treatments. G denotes the Good state (high-income realization), H denotes the high-risk situation, and A denotes the asymmetric-risk treatment. The omitted category is the Bad state under low risk in the symmetric treatment. Models (6) and (8) additionally control for investment and gender. All models include segment controls; Models (5)–(6) also include period controls.

Table A.4: Average Marginal Effects from Random-Effects Panel Logit Models of Transfer Incidence

	(9) Symmetric	(10) Symmetric	(11) Asymmetric	(12) Asymmetric
Good State (G)	0.562^{***}	0.478^{***}	0.737^{***}	0.717^{***}
	(0.026)	(0.046)	(0.020)	(0.027)
High Risk (H)	-0.069^{***}	-0.073^{***}	0.023	0.023
	(0.026)	(0.025)	(0.021)	(0.021)
G x H	0.122^{***}	0.121^{***}	-0.076^{***}	-0.077^{***}
	(0.033)	(0.032)	(0.028)	(0.028)
Segment	-0.025^{***}	-0.025^{***}	-0.018^{***}	-0.018^{***}
	(0.006)	(0.005)	(0.005)	(0.005)
Period	-0.008^{***}	-0.007^{***}	-0.005^{***}	-0.005^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Investment		-0.006^{*}		-0.003
		(0.003)		(0.002)
Female		0.206^{**}		0.065
		(0.098)		(0.067)
Observations	3168	3168	3168	3168

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors are reported in parentheses.

Notes: The dependent variable is an indicator equal to one if the subject makes a positive transfer and zero otherwise. All models are estimated using random-effects panel logit specifications and report average marginal effects. Models (9)–(10) report estimates for the symmetric treatment, while Models (11)–(12) report estimates for the asymmetric treatment. Models (10) and (12) additionally control for investment and gender. All specifications include segment and period controls. G denotes the Good state (high-income realization), H denotes the high-risk situation, and A denotes the asymmetric-risk treatment.

Table A.5: Random-effects Tobit Estimates in Good and Bad States (Period 1 Only)

	(13) Good State	(14) Good State	(15) Bad State	(16) Bad State
Asymmetric (A)	23.761^{**}	23.451^{**}	1.002	0.844
	(9.386)	(9.375)	(4.330)	(4.364)
High Risk (H)	18.786^{***}	18.655^{***}	-3.361	-3.367
	(6.442)	(6.446)	(3.580)	(3.601)
A x H	-20.848^{**}	-20.761^{**}	0.208	0.338
	(9.075)	(9.084)	(4.962)	(5.020)
Investment		-0.099		-0.141
		(0.312)		(0.140)
Female		4.561		4.781
		(8.975)		(4.087)
Segment	3.638^{**}	3.639^{**}	-1.978^{**}	-2.060^{**}
	(1.470)	(1.472)	(0.825)	(0.830)
Constant	15.863^{**}	16.096	-4.557	-3.381
	(7.863)	(14.142)	(3.913)	(6.295)
Observations	320	320	320	320

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$ Standard errors are reported in parentheses.

Notes: The dependent variable is the transfer amount in Period 1 of each segment. All models are estimated using random-effects Tobit specifications with left-censoring at zero. Models (13)–(14) report estimates for the Good state, while Models (15)–(16) report estimates for the Bad state. Models (14) and (16) additionally control for investment and gender. A denotes the asymmetric treatment, and H denotes the high-risk situation.

Table A.6: Average Marginal Effects from Random-Effects Panel Logit Models of Transfer Incidence by Income State

	(17) Good State	(18) Good State	(19) Bad State	(20) Bad State
Asymmetric (A)	0.148^{**}	0.136^{**}	-0.064	-0.070
	(0.073)	(0.066)	(0.066)	(0.068)
High Risk (H)	0.068^{**}	0.063^{**}	-0.080^{***}	-0.087^{***}
	(0.031)	(0.027)	(0.031)	(0.030)
A x H	-0.090^{**}	-0.088^{**}	0.068^{*}	0.073^{**}
	(0.037)	(0.035)	(0.035)	(0.034)
Segment	-0.009^{*}	-0.009^{*}	-0.030^{***}	-0.033^{***}
	(0.005)	(0.005)	(0.008)	(0.008)
Period	-0.010^{***}	-0.010^{***}	-0.003^{**}	-0.003^{***}
	(0.002)	(0.001)	(0.001)	(0.001)
Investment		-0.006^{***}		-0.004
		(0.002)		(0.002)
Female		0.128^{*}		0.075
		(0.075)		(0.055)
Observations	3168	3168	3168	3168

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors are reported in parentheses.

Notes: The dependent variable is an indicator equal to one if the subject makes a positive transfer and zero otherwise. All models are estimated using random-effects panel logit specifications and report average marginal effects. Models (17)–(18) report estimates for the Good State, while Models (19)–(20) report estimates for the Bad State. Models (18) and (20) additionally control for investment and gender. All specifications include segment and period controls. A denotes the asymmetric treatment, and H denotes the high-risk situation.

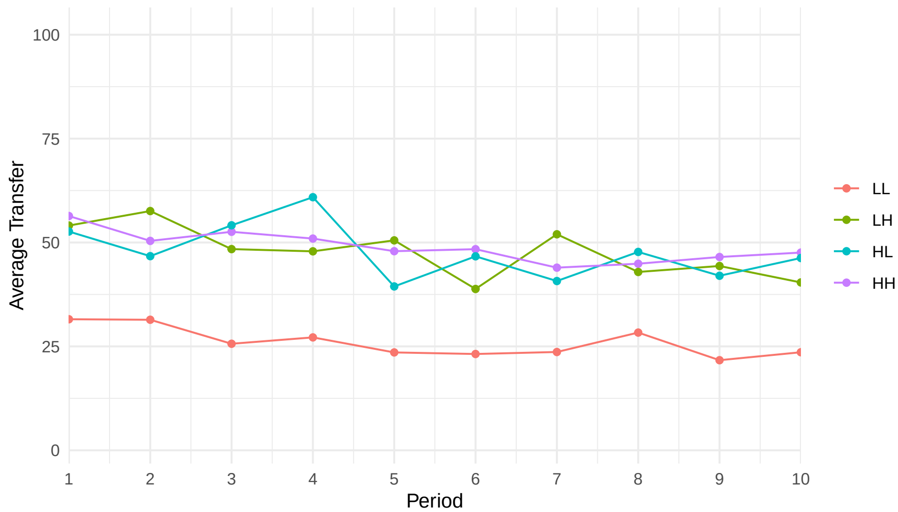

Figure A.1: Average Transfers in the High-Income State by Period and Risk Profile

B Instructions

Welcome to our study. At this time, please make sure you have turned off and put away all personal electronic devices. This study contains 2 parts and will take no more than 60 minutes. You will be paid your earnings from each part of the study in addition to the $7.50 participation payment in cash. Your earnings will depend on the decisions you and others make in this study, so it is important that you fully understand these instructions. These earnings will be denominated in experimental currency units (or ECUs for short). At the end of the study, ECUs will be converted into dollars at the exchange rate of 10 ECUs for 1 dollar and will be paid to you privately in cash. If you have a question at any point, please raise your hand.

Symmetric Treatment

Part 1 of the study consists of 5 segments.

- In each of these segments, all participants will be randomly matched with one other person, randomly assigned a color, either red or blue, and randomly assigned a situation, either 1 or 2.
- The person you are matched with is called your counterpart. The identity of your counterpart will not be revealed to you. You only know that your counterpart will be the same person throughout a segment.
- The color assigned to you will be different from the color assigned to your counterpart. The color assigned to you will remain the same throughout a segment.
- The situation assigned to you will be the same as the situation assigned to your counterpart. The situation assigned to you will remain the same throughout a segment.

Each segment consists of an uncertain number of periods. The number of periods in a segment is determined as follows:

- For each period, the computer has randomly selected a number from 1,2,...,10, each with a 10% chance, for the entire session to determine whether another period will follow.
- If the selected number is from 1,2,...,9, the next period will follow. If the selected number is 10, the segment will end.
- We will reveal the selected number to you at the end of each period. So, at the beginning of each period, you only know that there is a 90% chance that another period of the same segment will follow and there is a 10% chance that the segment will end after this period.
- When a segment ends, each participant will be randomly matched with a different counterpart. You will be matched with 5 different counterparts in 5 segments. The

color and the situation assigned to you in the next segment may or may not be different from those assigned to you in the current segment.

Each period consists of 2 stages.

Stage 1

- If the situation assigned to you is situation 1, you will receive an initial income of 225 ECUs and a 50% chance of losing 150 ECUs of your initial income.
- If the situation assigned to you is situation 2, you will receive an initial income of 275 ECUs and a 50% chance of losing 250 ECUs of your initial income.
- There are two balls in a box; one is red and one is blue. The computer will randomly select a ball and the color of the selected ball will be revealed to both participants.
- If the selected ball is red, the red participant will lose 150 ECUs in situation 1 or 250 ECUs in situation 2.
- If the selected ball is blue, the blue participant will lose 150 ECUs in situation 1 or 250 ECUs in situation 2.
- So, only one participant, either you or your counterpart, will lose ECUs in Stage 1 and there are two possible values for each participant's net income in stage 1:
  - 225 ECUs or 75 ECUs, each with a 50% chance, if the situation assigned to you is situation 1.
  - 275 ECUs or 25 ECUs, each with a 50% chance, if the situation assigned to you is situation 2.

Stage 2

- You and your counterpart will be notified of each other's net income from stage 1. Then, you and your counterpart simultaneously choose an ECU amount to transfer to the other person. You will know the amount that your counterpart transfers to you after you have chosen your amount of transfer to him or her. The history of each participant's net income and transfer in each period will be available on the bottom of your screen.

- The amount that you can transfer to your counterpart is any value from zero to the net income from stage 1. Type in the transfer amount and click the "Submit" button. If you transfer X ECUs to your counterpart while he or she transfers Y ECUs to you, then your earnings for this period are your net income – X + Y ECUs.

How do we calculate your cash earnings from Part 1?

- Even though you will participate in many periods from 5 segments and the computer will calculate your earnings in ECUs for all of these periods, the computer will randomly select **only 1 period** to convert your earnings into dollars for your cash payment.

- If situation 1 was assigned to you in stage 1 of the selected period, your earnings from this part of the study will be 225 – X + Y ECUs or 75 – X + Y ECUs, each with a 50% chance.

- If situation 2 was assigned to you in stage 1 of the selected period, your earnings from this part of the study will be 275 – X + Y ECUs or 25 – X + Y ECUs, each with a 50% chance.

- At the end of the study, you will learn which period is selected and your earnings from that period which will be converted into dollars at the rate of 10 ECUs for one dollar. Your possible earnings from this part are between $0 and $30.00.

- Before you proceed to segment 1, please answer the following quiz questions to make sure you fully understand the instructions. Your quiz answers will not affect your earnings from this part. If an answer is wrong and you do not understand why it is wrong, please raise your hand.

Asymmetric Treatment

Part 1 of the study consists of 5 segments.

- In each of these segments, all participants will be randomly matched with one other person, randomly assigned a color, either red or blue, and randomly assigned a situation, either 1 or 2.
- The person you are matched with is called your counterpart. The identity of your counterpart will not be revealed to you. You only know that your counterpart will be the same person throughout a segment.
- The color assigned to you will be different from the color assigned to your counterpart. The color assigned to you will remain the same throughout a segment.
- The situation assigned to you will be different from the situation assigned to your counterpart. The situation assigned to you will remain the same throughout a segment.

Each segment consists of an uncertain number of periods. The number of periods in a segment is determined as follows:

- For each period, the computer has randomly selected a number from 1,2,...,10, each with a 10% chance, for the entire session to determine whether another period will follow.
- If the selected number is from 1,2,...,9, the next period will follow. If the selected number is 10, the segment will end.
- We will reveal the selected number to you at the end of each period. So, at the beginning of each period, you only know that there is a 90% chance that another period of the same segment will follow and there is a 10% chance that the segment will end after this period.
- When a segment ends, each participant will be randomly matched with a different counterpart. You will be matched with 5 different counterparts in 5 segments. The

color and the situation assigned to you in the next segment may or may not be different from those assigned to you in the current segment.

Each period consists of 2 stages.

Stage 1

- If the situation assigned to you is situation 1, you will receive an initial income of 225 ECUs and a 50% chance of losing 150 ECUs of your initial income.
- If the situation assigned to you is situation 2, you will receive an initial income of 275 ECUs and a 50% chance of losing 250 ECUs of your initial income.
- There are two balls in a box; one is red and one is blue. The computer will randomly select a ball and the color of the selected ball will be revealed to both participants.
- If the selected ball is red, the red participant will lose 150 ECUs in situation 1 or 250 ECUs in situation 2.
- If the selected ball is blue, the blue participant will lose 150 ECUs in situation 1 or 250 ECUs in situation 2.
- So, only one participant, either you or your counterpart, will lose ECUs in Stage 1 and there are two possible values for each participant's net income in stage 1:
  - 225 ECUs or 75 ECUs, each with a 50% chance, if the situation assigned to you is situation 1.
  - 275 ECUs or 25 ECUs, each with a 50% chance, if the situation assigned to you is situation 2.

Stage 2

- You and your counterpart will be notified of each other's net income from stage 1. Then, you and your counterpart simultaneously choose an ECU amount to transfer to the other person. You will know the amount that your counterpart transfers to you after you have chosen your amount of transfer to him or her. The history of each participant's net income and transfer in each period will be available on the bottom of your screen.

- The amount that you can transfer to your counterpart is any value from zero to the net income from stage 1. Type in the transfer amount and click the "Submit" button. If you transfer X ECUs to your counterpart while he or she transfers Y ECUs to you, then your earnings for this period are your net income – X + Y ECUs.

How do we calculate your cash earnings from Part 1?

- Even though you will participate in many periods from 5 segments and the computer will calculate your earnings in ECUs for all of these periods, the computer will randomly select **only 1 period** to convert your earnings into dollars for your cash payment.

- If situation 1 was assigned to you in stage 1 of the selected period, your earnings from this part of the study will be 225 – X + Y ECUs or 75 – X + Y ECUs, each with a 50% chance.

- If situation 2 was assigned to you in stage 1 of the selected period, your earnings from this part of the study will be 275 – X + Y ECUs or 25 – X + Y ECUs, each with a 50% chance.

- At the end of the study, you will learn which period is selected and your earnings from that period which will be converted into dollars at the rate of 10 ECUs for one dollar. Your possible earnings from this part are between $0 and $35.00.

- Before you proceed to segment 1, please answer the following quiz questions to make sure you fully understand the instructions. Your quiz answers will not affect your earnings from this part. If an answer is wrong and you do not understand why it is wrong, please raise your hand.

C Experiment Screenshots

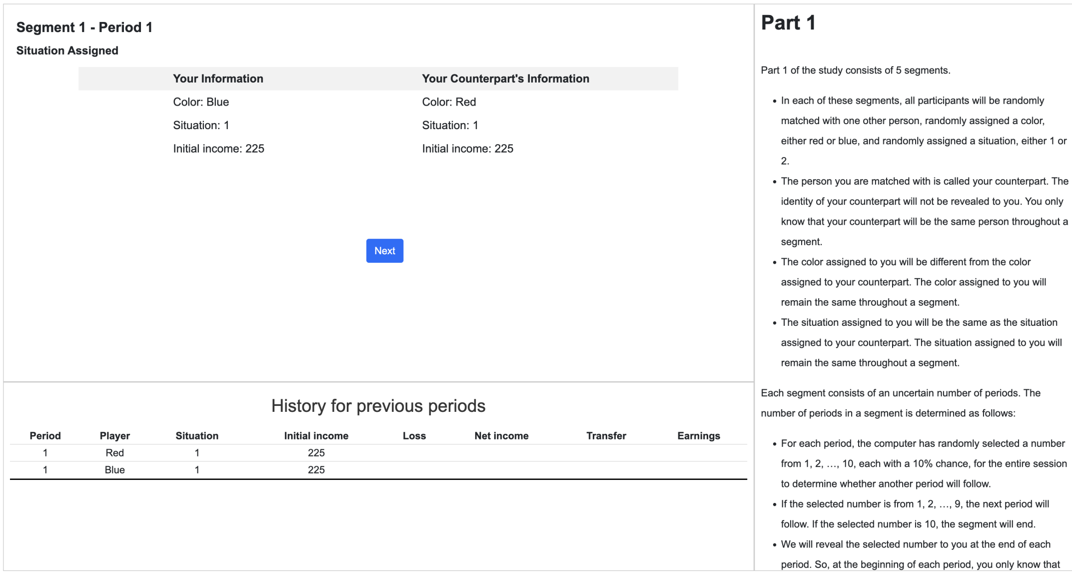

Figure C.1: Symmetric Treatment

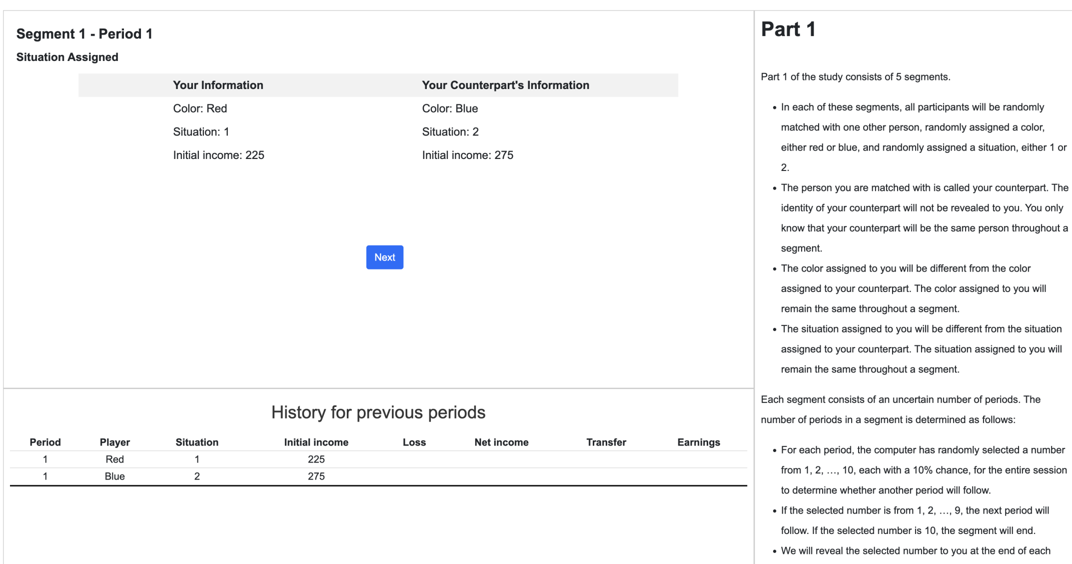

Figure C.2: Asymmetric Treatment

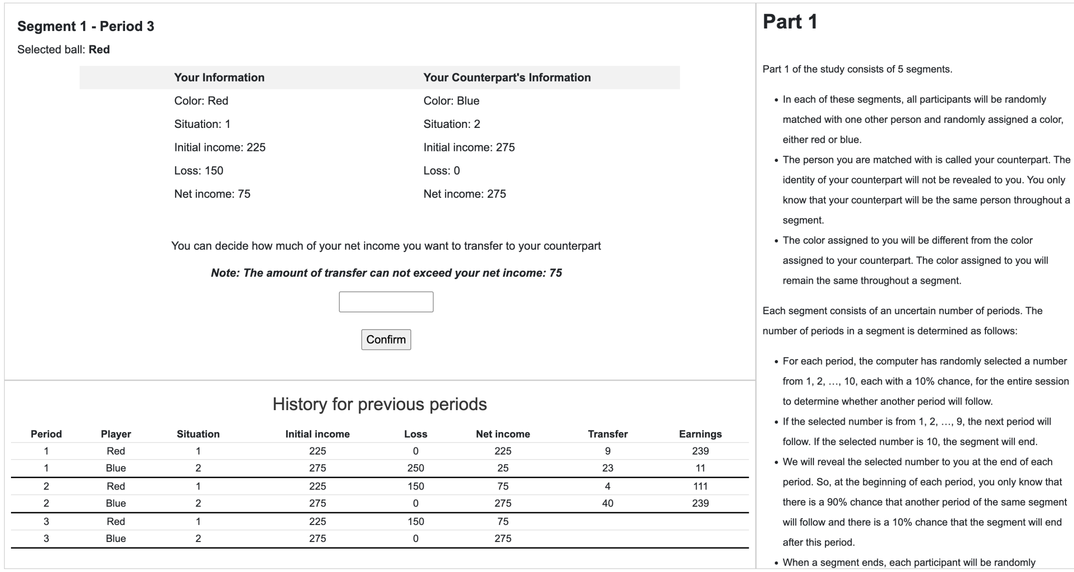

Figure C.3: Decision Screen