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Peer effects and risk sharing in experimental asset markets[☆]

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ABSTRACT

We investigate the effect of introducing information about peer portfolios in an experimental Arrow–Debreu economy. Confirming the prediction of a general equilibrium model with inequality averse preferences, we find that peer information leads to reduced variation in payoffs within peer groups. Information also improves risk sharing, as the data suggests that experiencing earnings deviations from peers induces a shift to more balanced portfolios. In a treatment where we highlight the highest earner, we observe a reduction in risk sharing, while highlighting the lowest earner has no effects compared to providing neutral information. Our results indicate that the presence of social information and its framing is an important determinant of equilibrium in financial markets.

1. Introduction

Traders in financial markets do not interact merely through prices. The investment choices of others are a source of information and a potential aspiration point for one's own earnings. Shiller (1993, p.167) argues that "Investing in speculative assets is a social activity. Investors spend a substantial part of their leisure time discussing investments, reading about investment, or gossiping about others' successes or failures in investing." Modern technology facilitates peer influences: social trading networks like eToro or Zulutrade provide rankings of investor performance and allow investors to immediately observe and copy other traders' portfolios. Such networks are enjoying a fast growing membership of 'social traders'.[1]

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[1] Between 2010 and 2016 the number of eToro-investors doubled from 1.5 to 4 million users. In roughly the same period eToro raised additional 31.5 million US Dollars to expand their businesses: financial instruments traded on eToro today range from indices, commodities, currencies and stocks to Bitcoin. Simon and Heimer (2012) show that trading on social platforms is characterized by substantial peer effects.

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Social comparisons in trader interactions may affect equilibrium in asset markets. In particular, people who are afraid to fall behind others may display conformity in portfolio choices, leading to multiple market equilibria (Heidhues and Riedel, 2007; Schmidt, 2011). To date, there has been little empirical investigation of the impact of social concerns on general equilibrium outcomes. One reason is that equilibrium outcomes are hard to identify with observational data, and so are the mechanisms behind peer influences on investors. In actual markets, people match assortatively, making it hard to distinguish social influence from selection. Controlled laboratory studies that can disentangle such effects have focussed on individual decisions instead of market interactions.

We study the effect of peer information on risk sharing in experimental asset markets. Participants trade two risky assets with perfectly negatively correlated returns across two income states. In a set of treatments we introduce information about the portfolios of a "peer group" composed of other, randomly selected participants. Exogenous variation in information availability and content allows us to test its effect on market outcomes, specifically whether peer information induces conformity in equilibrium portfolio choice. Indeed, we find that peer information reduces within-group variation in peer earnings in each income state. The introduction of peer information also increases diversification, causing risk taking to drop 27% by the end of the experiment. This last finding appears to be driven by a form of social learning: subjects react to being "earning outliers" within their group by reducing their exposure.

Some of our treatments have rankings that symbolically highlight either the highest or lowest performer, a feature of many types of investor information.[2] In line with the notion that positional concerns matter for market outcomes, we find that the social framing of peer information matters. Symbolic recognition for the highest earner partially negates the decrease in portfolio diversification that we see in the treatments with information but without rankings or in treatments with a spotlight on the lowest earner.

To our knowledge, this is the first evidence that peer information affects equilibrium outcomes in asset markets, and provides a social benchmark that reduces risk taking. These findings highlight social influences on market outcomes through different channels than herding or bubble formation, which are the focus of the current literature. A better understanding of these channels is crucial at a time when online technology makes it ever easier to compare our investments and outcomes to those of others.

2. Literature

Our paper contributes to several strands of literature in both finance and economics on the social aspects of market behavior. The design is inspired by theories about the relation between social preferences and equilibrium outcomes in markets for risky assets (Heidhues and Riedel, 2007; Schmidt, 2011). These theories predict that social preferences can lead to multiple equilibria, as we also demonstrate in our model in Appendix A. We indeed find evidence for conformity that is associated with multiple equilibria. To our knowledge, there has been little empirical investigation of the role of social preferences in markets for uncertain assets, even though there is a large literature on social preferences in markets with certain outcomes (e.g. Dufwenberg et al., 2011; Fehr and Schmidt, 1999).

There are a few papers that look at the effect of peer information in experimental asset markets, but these are guided by different questions. Schoenberg and Haruvy (2012) show that seeing the earnings of the highest earning individual reduces satisfaction and increases the prevalence of price bubbles. Oechssler et al. (2011) enable subjects to chat with one another during the trading phase, where a subset of traders has superior information regarding fundamentals. Communication reduces the likelihood of price bubbles. Mengel and Peeters (2015) find that social comparisons within markets reduce participants' willingness to take risks relative to a non-market setting. Compared to these papers, we investigate a different set of hypotheses. Most importantly, we do not look at bubbles: since portfolios are reset in each period, there is little scope for speculation. We are also not concerned with herding, i.e., people discarding their private information, as there is no asymmetric information in our markets. Instead, we focus on the importance of preferences over relative income, and our main outcome variable is not the price of the asset, but the amount of conformity and diversification.

There is a sizable literature that aims to identify peer effects in individual financial decisions. Part of this literature uses field data in stock market participation combined with information on social ties or spatial distribution of traders. Several papers show that peers choices matter in stock market participation (Hong et al., 2004; Kaustia and Knüpfer, 2012), trading decisions (Hackethal et al., 2014; Hong et al., 2005; Kelly et al., 2000; Shive, 2010) and risky lifestyle choices (Card and Giuliano, 2013). These papers sometimes use network data, or approximate peers by spatial proximity, but typically cannot disentangle the mechanisms of peer influence. An exception is Bursztyn et al. (2014), who conduct a field experiment in which they can distinguish between the channels of learning and social preferences, showing that both channels matter.

In addition, a rapidly growing number of laboratory experiments corroborates the existence of peer effects in risk taking (see Trautmann and Vieider, 2012, for an overview). Gantner and Kerschbamer (2018) show theoretically that "convex" social preferences lead to conformity and confirm this experimentally. Linde and Sonnemans (2012) and Schwerter (2013) demonstrate that portfolio choices depend on a "social reference point", the income of another participant in the experiment. Dijk et al. (2014) and Fafchamps et al. (2015) find that under-performers start taking more risk in later decision rounds to catch

[2] Social trading websites often highlight the highest earners in a given period or asset class, and so do investor magazines like *Investment Week*, which issues a fund manager of the year award.

Table 1
The dividend structure of the assets, expressed in experimental currency.

	Hot weather	Cold weather	Exp. Dividend
Ice-cream (I)	100	0	50
Gloves (G)	0	100	50

up with the others. Lahno and Serra-garcia (2015) demonstrate that both learning and income comparisons play an important role in decision making under uncertainty, Bault et al. (2011) and Frydman (2015) show similar findings with additional neurological evidence. Kirchler et al. (2018) show that rankings induce financial professionals to take more risk. By contrast, Corazzini and Greiner (2007) do not find an effect of peer information in sequential risky decisions. Our paper goes beyond this literature, by showing that peer influences affect not just individual portfolio choices, but also the outcomes of markets consisting of many traders who interact in real time.

Finally, we contribute to the experimental literature testing general equilibrium predictions in asset markets. The literature finds mixed results regarding the predictive power of general equilibrium theory. Whether a market reaches equilibrium depends on the precise details of the market's design. Our results without peer information are comparable to studies with similar market designs. Bossaerts et al. (2007) look at portfolio choice in a large-scale market with a more complex asset structure, and, like our paper, find persistent deviations from predicted equilibrium holdings. The experimental markets in Weber et al. (2000) are almost identical to our markets without peer information, and we replicate their findings of imperfect risk sharing and substantial overpricing of assets.

3. Market design

In this section, we describe the design of the experiment. Full instructions can be accessed via the online Appendix.[3]

3.1. Payoffs and market structure

We conduct an experimental open book, multi-unit double auction. Each session consists of one market with 10 traders. All payoffs are denoted in experimental currency (ECU) where 100 ECU = 1.50 euros. There are two equiprobable states of nature and two tradable assets that generate dividends. Traders are also endowed with cash, which pays no interest. Dividends depend on the "state", which is randomly determined at the end of each period. This asset structure is similar to that in Weber et al. (2000). To make the asset structure less abstract and reduce confusion among subjects (see Kirchler et al., 2012), assets are framed as stocks in an "Ice-cream" (I) and a "Glove" (G) manufacturer, and the state of the world is described as either "hot" or "cold" weather. The dividend structure given in Table 1 was also chosen to be as simple as possible to avoid confusion.

Agents trade for 10 periods that last 150 s each. Short selling and borrowing are not allowed. At the beginning of each period, the endowment portfolio for each trader is randomly chosen (see below), at the end of each period the state is randomly determined and payoffs are realized. The monetary payoff of each agent is determined at the end of the experiment by randomly selecting a single period for payment. In order to preserve social comparisons, this randomization was done at the session level, so that each subjects' payoffs are based on earnings in the same period.

3.2. Random endowments and zero aggregate risk

Asset holdings were reset after each trading period. At the beginning of each period, each trader received a cash endowment of 500 ECU. To encourage trading, each subject started out with a relatively skewed portfolio, which consisted of either 10 I assets and 0 G assets, or of 0 I assets and 10 G assets. In total, five of each of those two kinds of portfolios were randomly allocated to the traders. This ensured a random composition of endowments in each peer group in each round, while keeping the total amount of assets in the market fixed at 50 assets of each kind. Thus aggregate risk was zero in each market and each round.

3.3. Peer information and treatments

In each session, we divided subjects into two "peer groups" of 5 traders, indicated in the instructions as the "red" and "blue" group. Traders could trade with participants from either group. To ensure that income comparisons could take place only within the peer group, the realization of the state was independent for both groups, so it was possible that the weather was "hot" in one group and "cold" in the other. Subjects learned only the income realization for their own group and not that for the other group.

[3] Link to online Appendix. The instructions also feature screen-shots of the user interface.

Table 2
Example of peer portfolio information. This example reflects the beginning of the trading period. In the INFO-WIN treatment, all columns are visible. The last column's caption reads "Highest Earnings" and signifies the number of times a trader had the highest earnings in his reference group in previous rounds. Correspondingly in the INFO-LOSE treatment, the column's caption reads "Lowest Earnings" and shows how often a trader had the lowest earnings within the group. In the INFO treatment the last column is missing. In the PRIVATE treatment, additionally only the row marked YOU is visible. The table is updated in real time during the trading round.

ID	I Assets	G Assets	ECU	Earnings HOT	Earnings COLD	Lowest/highest earnings
2	10	0	500	1500	500	***
5	10	0	500	1500	500	
YOU	0	10	500	500	1500	*
3	0	10	500	500	1500	**
1	10	0	500	1500	500	

In some of the treatments, subjects received information about the portfolios of their peer group, which was presented at the top of the trading screen as in Table 2. The first column shows the subject ID, the second and third show the number of each asset in the portfolio, the fourth column shows the amount of ECU held, the fifth and sixth column show the (hypothetical) payoffs of the current portfolio in case of hot and cold weather. The final column shows the highest or lowest earner in previous rounds (see below).

We conduct the following treatments:

PRIVATE. Subjects had no information about the other traders, except what they knew from the general instructions, and from the posted bids and asks. Table 2 was therefore empty, except for the row of the subject (YOU). Information provision about the own portfolio was thus constant across treatments. In addition, the last column was missing from the table. Traders were still assigned to one of two (placebo) groups for determining payoffs (see above), but they were ignorant of being part of that group.

INFO. During the trading period, subjects were informed about the portfolios of their reference group (i.e. either the blue or the red group) as indicated in Table 2. This information was updated in real time so that any new trade would immediately be reflected in the table. The last column was missing from this table.

INFO-WIN. Subjects received the same information as in the INFO treatment. At the end of each trading period, after the state of the world had been determined we provided earnings rankings within each peer group. Additionally the "highest earning trader" received a purely symbolic 'star'. Accumulated stars were displayed in the last column of Table 2, and could be observed by all subjects in the peer group in all subsequent rounds.

INFO-LOSE. This treatment was identical to the INFO-WIN treatment, except that the "lowest earning trader" was announced and got a star instead of the highest earning trader.

Differences in outcomes between the PRIVATE and INFO treatment allow us to identify the impact of peer information on market outcomes. The INFO-WIN and INFO-LOSE treatment identify the additional effects of performance rankings, where the former provides a symbolic reward for high earnings and the latter a symbolic penalty for low earnings. Note that instructions were the same for all participants within a given treatment, and all participants have full information about the market structure and fundamental value of the assets to rule out herding or information cascades.

3.4. Elicitation of risk preferences and background information

After market trading had concluded, we elicited some further information about the preferences and background of the participants.

Risk preferences. We measured risk preferences using the bomb risk elicitation task (BRET) developed by Crosetto and Filippin (2013). Subjects had to choose how many boxes to collect from a pile of 36 boxes. With each collected box, subjects earned a monetary payment of 10 ECU (=15 eurocents). One randomly chosen box contained a bomb. The participant did not know in which box the bomb was located, and if she collected it she earned nothing. Thus, the risk of earning nothing increases exponentially with each collected box while payoffs increase linearly, so that the decision when to stop collecting is a good proxy for subjects' risk preferences (Crosetto and Filippin, 2013). Another reason to choose this task is that it is easy to explain to subjects.

Strategy questionnaire. We asked subjects directly about their trading strategies, including whether they engaged in speculation or tried to equalize the number of both assets in their portfolio, and, in the INFO treatments, whether they were influenced by other traders' portfolios. Answer were made on a three-point scale ('Yes', 'Sometimes', 'No').

Finally, we asked some standard control questions such as gender, field of studies, and previous participation in asset market experiments.[4]

[4] In the first wave of sessions we elicited a measure of social value orientation based on Murphy et al. (2011) at the end of the experiment. We did not have a clear hypothesis on these variables. We found that these data were noisy and did not have any explanatory power. Since the elicitation was rather time consuming we did not elicit them in the second wave (see Footnote [5]).

3.5. Procedures

All sessions were conducted at the Frankfurt Laboratory for Experimental Economic Research at the Goethe University Frankfurt, the first 20 in the spring of 2014, additional eight sessions in the winter of 2017. Treatments were balanced over time.[5] Subjects were recruited using ORSEE (Greiner, 2003). In each treatment, we conducted 7 sessions/markets with 10 traders each. One session in the INFO treatment was run with 8 instead of 10 subjects, so a total of 278 subjects participated in the experiment. The experiment lasted approximately 90 min. Average earnings were 22.86 euros, with a minimum of 10.34 euros and a maximum of 33.82 euros.

After the experimenter had read the instructions out loud at the beginning of the experiment, subjects answered a number of control questions to test understanding and played a practice round to familiarize themselves with the trading environment. Instructions for the elicitation of risk preferences and questionnaires were provided on screen. Programming was done in z-Tree (Fischbacher, 2007). At the end of the experiment, subjects were called forward one by one and paid privately.

4. Hypotheses

The PRIVATE treatment functions as a baseline against which we evaluate the effects of peer information. Under the assumption that all traders are self-interested and risk averse, a common assumption in asset pricing models (e.g. Bossaerts et al., 2007), Arrow-Debreu general equilibrium theory predicts that the unique competitive equilibrium in the PRIVATE treatment features full risk sharing. We verify this in our theoretical model in Appendix A. We expect the risk sharing strategy to be salient since the asset structure is simple. Since all investors have the same information there is no scope for herding (in the sense of Bikhchandani et al., 1992). Furthermore, as endowments are reset in each period, there is very little scope for speculation. Because there is no aggregate market risk, both asset prices should be equal to expected value to avoid the existence of arbitrage opportunities.

Despite these considerations, earlier research on similar markets has found imperfect risk sharing. Weber et al. (2000) study a similar market design and find that the existence of an endowment effect results in overpricing and under-diversification of portfolios. Bossaerts et al. (2007) look at portfolio choice in a large-scale market with a more complex asset structure, and also find persistent deviations from predicted equilibrium holdings. Ackert et al. (2016) look at portfolio choice outside a market context, and show that behavioral biases lead people away from portfolio diversification.

4.1. The effect of peer information

One well-established result in the social preference literature is that people dislike earning less than their peers (e.g. Bolton and Ockenfels, 2000; Fehr and Schmidt, 1999; Zizzo and Oswald, 2001). In Appendix A, we model such preferences in the context of a general equilibrium setting in a financial market like ours, and show that such preferences translate into a desire for conformity. Specifically, holding a portfolio that diverges from that of the other group members creates a *social risk* of earning less than the others. If subjects are sufficiently concerned about this risk, multiple equilibria exist in which all traders in a peer group hold the same portfolio. Some equilibria feature imperfect risk sharing, even if traders are risk averse over their own monetary outcomes. When traders are approximately risk neutral over their own monetary payoffs, as may be the case in our markets with relatively small stakes, equilibria may feature arbitrary large amounts of risk taking.

To investigate these issues, the INFO treatment introduces peer information, and thus the possibility to compare one-self to others. The trading screen in the INFO treatment not only gave a real-time overview of all portfolios in the group, but it also showed the payoffs of each group member in each state of the world for the current portfolios. This allowed an easy comparison of payoffs in both states with those of other subjects.

Hypothesis 1. The within-group variance of earnings in each state of the world will be lower in the INFO treatment than in the PRIVATE treatment.

4.2. The effect of symbolic rewards

Performance rankings for financial professionals are commonplace in the finance industry (Kirchler et al., 2018). For instance, the social trading websites mentioned in the introduction often highlight the highest earners in a given period or asset class. To simulate these conditions, we conduct two treatments in which we provide payoff rankings at the end of each trading period, and provide symbolic, non-financial recognition for either the best or the worst performer.[6] We

[5] We ran these extra sessions in order to investigate a curious, non-hypothesized pattern: the first 20 sessions showed that risk aversion was significantly higher after the INFO treatments compare to the PRIVATE treatment. To investigate more deeply whether this change was due to the different market experiences in these treatments, the sessions in 2017 featured an additional risk aversion task *before* the markets started. The risk aversion effect appeared not to be robust in our new sessions. Specifically, we did not run these sessions to improve *p*-values, as all the same differences between our four treatments were present and statistically significant in the original sessions (see Baghestanian et al., 2014).

[6] Our focus on *symbolic* recognition distinguishes our setup from the literature on tournament incentives and asset market bubbles (Cheung and Coleman, 2014; James and Isaac, 2000; Robin et al., 2012). Other differences are in the structure of the asset market and our focus on risk sharing.

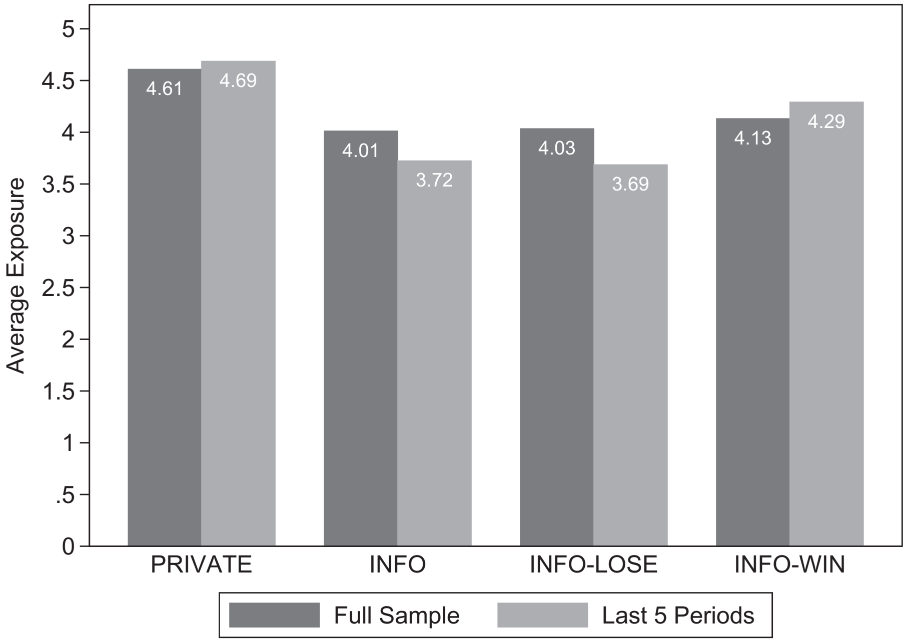


Fig. 1. *Mean exposure for all periods and for the last five periods* in each of the four different treatments. Exposure is defined as the absolute difference between holdings of the two assets. It is a measure of the riskiness of a trader's portfolio.

hypothesize that introducing symbolic rewards for the *highest* earner will increase aggregate exposure, because taking more risk increases the chance of earning the most.[7]

When it comes to the effects of highlighting the *lowest* earner, there is evidence that people dislike occupying the last place in earnings ranking (Kuziemko et al., 2014), and generally dislike earning less than others (Fehr and Schmidt, 1999). Participants in our markets can avoid being the lowest earner by choosing a less extreme risk exposure than others. Over time, competition for income ranks will therefore lead to increasing diversification, compared to the case where no performance rankings were given.

Hypothesis 2. Compared to the INFO treatment, the introduction of rankings and symbolic recognition leads to

(a) higher average portfolio risk in the INFO-WIN treatment, where we highlight the highest earner.
(b) lower average portfolio risk in the INFO-LOSE treatment, where we highlight the lowest earner.

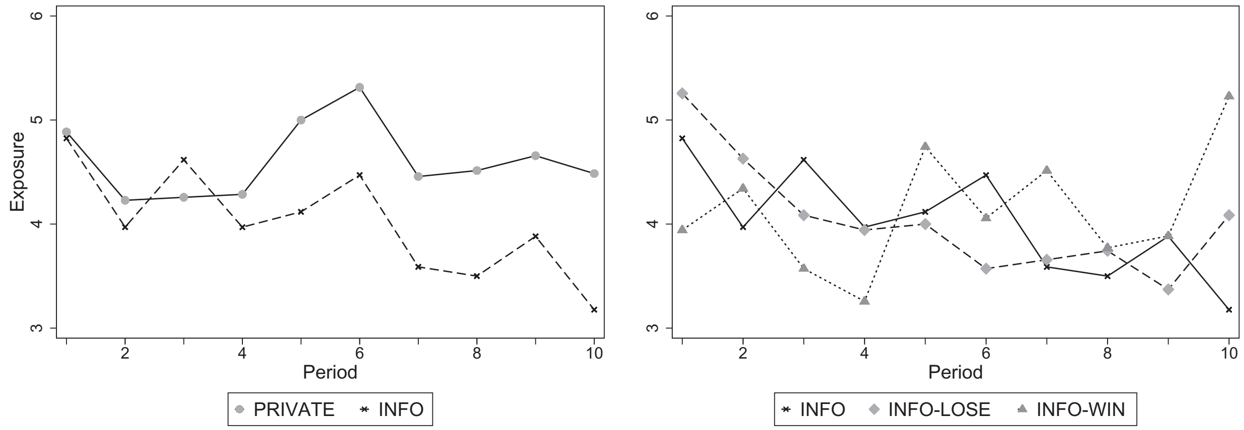
5. Market outcomes

Before we test our hypotheses, we provide a graphical overview of the primary market outcome – risk taking – across treatments. Our measure is the absolute difference between the number of I and the number of G assets in the end-of-period portfolio. We refer to this measure of riskiness of individual portfolios as "exposure". An exposure of for example 4 implies a payoff difference of 400 ECU (6 Euros) between both states of the world. We look at end of period data only, as these reflect the result of trading in the session aggregated over a given period.

Exposure across all sessions was on average 4.2. Fig. 1 shows averages by treatment over all periods and for the last five periods, where behavior may have converged more closely to equilibrium. In addition, Fig. 2 shows the dynamics of mean exposure by treatment over the 10 trading periods. Appendix B provides the descriptive statistics in Table B.1 and Table B.2, as well as graphs of the time series individual sessions in Fig. B.1.

In the first period, mean exposure levels are comparable across treatments. After that, exposure in the PRIVATE treatment stays roughly constant, while there is a drop in exposure in the INFO treatment, see Fig. 2(a). Similarly, Fig. 2(b) shows that exposure in the INFO-LOSE treatment drops initially and stabilizes in the last five periods. The INFO-WIN treatment displays quite some volatility in exposure levels, with a pronounced upward jump in the last period.

[7] Roussanov (2010) shows theoretically that a desire to get 'ahead of the Joneses' may lead to less diversified portfolios. Fafchamps et al. (2015), Dijk et al. (2014) and Kirchler et al. (2018) show experimentally that low earners in the early part of their respective experiments adopt more risky strategies to catch up with those who are performing better. Bault et al. (2008) show that gains loom larger than losses when in competition with others, and people take more risk if they can get ahead of a prudent opponent. A strategy of "imitate the luckiest" may also lead to a proliferation of risk taking (Offerman and Schotter, 2009). Symbolic awards for the highest earner also have important effects on effort outside financial markets (Kosfeld and Neckermann, 2011).



(a) Mean exposure PRIVATE vs INFO. (b) Mean exposure INFO treatments.

Fig. 2. *Time series of exposure.* The panel on the left, (a), shows mean end of period exposure for the PRIVATE and the INFO treatment. Each time series corresponds to one treatment mean. Panel (b) on the right hand side plots the treatment average for all INFO treatments. INFO-treatments give traders information on the portfolios of their exogenous reference group. INFO-WIN and INFO-LOSE, in addition, give a symbolic reward to either the best or the worst performer in each period respectively. In the PRIVATE treatment, traders do not have information about other traders.

Given that each trader started with an initial exposure of 10, it is clear that markets are used to reduce portfolio risk. However, perfect risk sharing is not achieved in any single period. This failure to fully diversify is in line with previous evidence of Weber et al. (2000) and Bossaerts et al. (2007). The presence of risk seeking traders who drive exposure upwards may be a reason why our markets fail to achieve perfect diversification.[8] Another reason may be that traders display an endowment effect, as demonstrated in Weber et al. (2000). This last explanation is consistent with market prices in our experiment, which are substantially above the fundamental value of 50. Appendix C provides a more in-depth analysis of prices.

We now turn to a more detailed discussion of our hypotheses with the associated statistical tests. Section 6 discusses in detail the non-hypothesized drop in exposure in the INFO treatment.

5.1. Conformity in asset markets

Hypothesis 1 predicts that due to preferences over relative payoffs, peer information induces conformity and reduces the variation in group payoffs in each state. To investigate this hypothesis, we use within-group variance of earnings in each payoff state as a measure of conformity.[9] For every peer group of five traders, we calculate the within-group variance of earnings (GVar) in period t as follows:

$$GVar_t := \sum_{i \in K} \left(x^H_{i,t} - \bar{x}^H_{i,t}\right)^2 + \left(x^C_{i,t} - \bar{x}^C_{i,t}\right)^2. \tag{GVar}$$

Here, K is the set of group members, $\bar{x}^a_{i,t}$ is the average payoff of this group if the state of the world is $a \in \{H, C\}$, and $x^a_{i,t}$ is the corresponding payoff of an individual i.

We find that GVar is higher in the PRIVATE compared to the INFO treatment, but this could simply be due to the higher level of exposure in these sessions. To control for this, we normalize the group variance by dividing with the group's share of total variance within a session (TVar). To calculate the latter, we use the fact that the average payoff in each period is the starting value of each portfolio, namely 1000 units of experimental currency:

$$TVar_t := \sum_{i \in K} \left(x^H_{i,t} - 1000\right)^2 + \left(x^C_{i,t} - 1000\right)^2. \tag{TVar}$$

Thus, our measure of conformity GVar/TVar does not depend on the overall variance in exposure within the session. We average over all periods for a session, leaving us with one observation per peer group (2 observations per session, and

[8] Indeed in the BRET, 30% of traders make risk seeking choices. Consistent with this line of reasoning, we find a modest, although statistically insignificant rank-correlation between average session exposure and average session risk tolerance ($\rho = 0.30$ and $p = 0.12$).

[9] We use earnings rather than portfolios or exposure, because the social preferences models we use to derive our hypotheses (see Appendix A) are defined over payoffs. Measures based on portfolio holdings may not neatly map into payoffs due to differences in cash holdings and/or intra-period gains and losses. The design facilitated payoff comparisons, as the trading screen in the INFO treatments showed the (virtual) earnings of each group member in each state of the world, which were updated in real time.

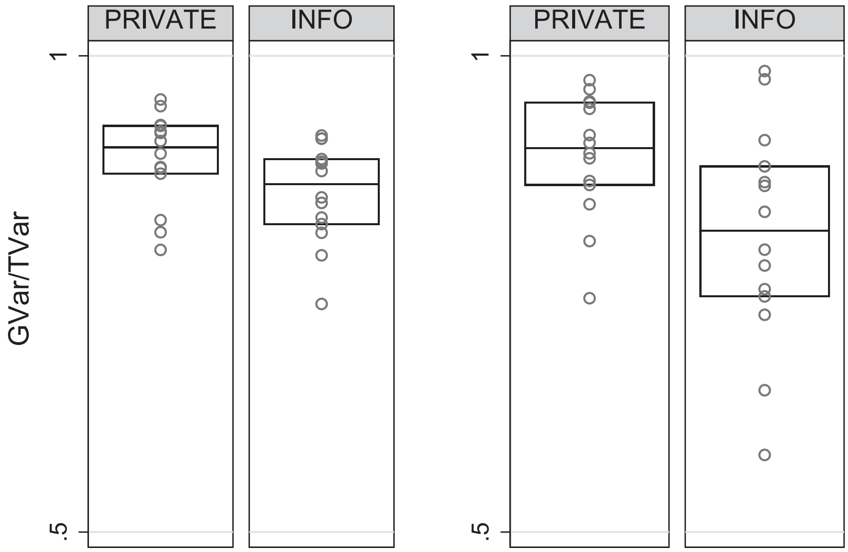


Fig. 3. *Conformity measure (GVar/TVar) by treatment* averaged over all periods (two leftmost panels) and over the last five periods (two rightmost panels). Each panel shows means with 95% confidence intervals and distribution of individual observations.

14 observations per treatment). The observations in both the PRIVATE and INFO treatment are represented graphically in Fig. 3.

We test for treatment differences statistically using non-parametric Wilcoxon rank-sum test (also called Mann–Whitney-*U*-test or MWU), and find that the distribution of GVar/TVar is significantly different in the INFO compared to the PRIVATE treatment ($p = 0.033$, one-sided MWU test; averages are 0.89 and 0.85 for PRIVATE and INFO, respectively). Because we are testing equilibrium predictions, we should allow for an initial convergence period. Indeed, Fig. 2(a) shows that there are trends in exposure in the INFO treatment. Therefore, we perform the same analysis for the second half of the experiment only (i.e., the last 5 periods), and find that the significance of the result increases ($p = 0.022$, one-sided MWU test; averages of 0.90 and 0.81 for PRIVATE and INFO, respectively). The finding that conformity becomes more pronounced over time is consistent with the idea that this is an equilibrium phenomenon.[10]

How does conformity come about? As derived in Appendix A, in the INFO-treatment equilibria might obtain where all group members hold more of one asset than the other. Thus, in these equilibria participants should skew their acquisitions towards one of the two assets. In the PRIVATE treatment, there is no reason for group members to hold the same portfolio, and hence we should not expect skewed patterns of acquisition. To test whether such asymmetric trade flows do indeed characterize our INFO treatment, we define “risk transfer” between groups as the amount by which either group increased its payoff in the HOT or COLD state:

$$\Delta x_t := \left| \sum_{i \in K} (x_{i,t} - y_{i,t}) \right| \qquad \text{(Risk Transfer)}$$

where x denotes stock-holding at the end of a period and y at beginning of a period, t the period, and i is a subject in group K. Δx_t is a measure of the net increase in a given asset in a group during the trading period under consideration. We take the absolute value in order to get a measure that is the same for both groups, so there is only one observation per period and session.

In the PRIVATE treatment, we expect both groups to hold the same portfolio on average. Since the average group endowment consists of both assets in equal proportion, risk transfer should be zero. In the INFO treatment however, members of one group might accumulate more of one asset, resulting in a positive risk transfer. We test this hypothesis with a MWU test using 14 observations, for both the complete sample (averaging all periods) and the last five periods. Despite the relatively low power of the test, we find suggestive evidence of increased risk transfer in the INFO treatment, with (one-sided) p-values close to or just below conventional significance levels ($p = 0.056$ for the complete sample and $p = 0.042$ for the last five periods).

Summary 1. In line with Hypothesis 1, we find evidence for conformity: Compared to the PRIVATE treatment, the within group variation of income in each payoff state is lower in the INFO treatment. We find suggestive evidence that increased conformity is achieved by an increased risk transfer (skewed trading pattern) between groups.

[10] These results are robust to running an OLS regression instead of a non-parametric test that allows us to additionally control for risk aversion, the share of males in the session and the composition of starting portfolios.

Table 3
INFO treatments only. The dependent variable is average end of period exposure in a given period. Column (1) shows the results of a fixed effect regression. The independent variables are a period variable and an interaction of the treatment dummy and the period variables. Columns (2) and (3) show results of random effect regressions. Column (2) introduces a treatment dummy, column (3) the share of male participants and average choice in the BRET. Period 10 is the base period. Standard errors, clustered on session level, in parentheses. Significance levels on two-sided tests are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) FE	(2) RE1	(3) RE2
Period X INFO	−0.137***	−0.137***	−0.137***
	(0.0336)	(0.0321)	(0.0322)
Period X INFO-WIN	0.213***	0.213***	0.213***
	(0.0635)	(0.0606)	(0.0609)
Period X INFO-LOSE	0.00186	0.00186	0.00186
	(0.0663)	(0.0633)	(0.0636)
INFO-WIN		1.047**	0.999**
		(0.470)	(0.417)
INFO-LOSE		0.000519	−0.0310
		(0.525)	(0.492)
Share Male			0.629
			(1.082)
Bombchoice			0.0700
			(0.0720)
Constant	3.774***	3.424***	2.079**
	(0.128)	(0.225)	(1.018)
Observations	210	210	210
R^2	0.102	0.069	0.098

In Section 6, we investigate the relation between conformity and exposure levels.

5.2. The effect of explicit rankings

We now turn to a test of Hypothesis 2, about the effect of introducing explicit rankings. To this end, we compare the INFO treatment with the INFO-WIN and INFO-LOSE treatment in which the highest and lowest earner in each period were highlighted with a star.

Figs. 1 and 2(b) show that the differences in average exposure between the INFO treatments are modest at most. However, there are some trends, with exposure in the INFO-WIN treatment staying flat or even going up, while it goes down in the other INFO treatments. The most conservative statistical test is to compare the distribution of exposure between these treatments non-parametrically, collapsing all 100 individual observations per session (10 periods times 10 traders) into a single mean, yielding 7 observations per treatment. Using MWU tests, we find no significant differences between the INFO treatments, either for the full sample or for the last five periods.

Obviously, taking session averages neglects a lot of information and reduces the power of the test, leading to the possibility of type II errors. To increase statistical power and to be able to control for the trends apparent in the graphical analysis, we conduct panel regressions using period averages, yielding 10 observations per session. A fixed-effect specification is presented in column (1) of Table 3, which allows us to control for session-specific unobservables such as endogenous differences in session prices or unobserved differences in group composition. We interact treatment dummies with the period variable to capture the time trends apparent in Fig. 2(b). We find evidence for a highly significant negative trend in the INFO and INFO-LOSE treatments, while there is no clear trend in the INFO-WIN treatment.[11]

Columns (2) and (3) show the results of random effects estimations in order to more directly test the effect of the treatment manipulations. To best capture the convergence throughout the experiment, we choose period 10 as a base period, so the treatment dummies capture last period averages of exposure. They show that in the INFO-WIN treatment, subjects have on average 1 unit higher exposure than in the INFO treatment. These differences emerge over the course of the experiment, as evidenced by the significantly different time trends between treatments. The results are robust to including controls in column (3).[12]

The statistical difference between the INFO-WIN treatment and the other INFO treatments is largely driven by the last period. When this period is excluded, the results become statistically insignificant. Perhaps subjects aim to “win” the final period, which may have more significance for them than the other periods (we thank an anonymous referee for pointing this out). However, in the absence of more information about subjects’ thought processes, we have no way of convincingly

[11] This result is echoed by a two-sided non-parametric Jonckheere–Terpstra test applied to the session means in each period. This test shows a significant downward trends for both INFO and INFO-LOSE ($p = 0.025$ and $p = 0.004$ respectively), but not for INFO-WIN (or PRIVATE).

[12] These result are robust to excluding any individual session and re-estimating the regressions with the restricted sample.

testing this theory. In Appendix D, we do further test the presence of positional concerns exploiting the variation in starting portfolios. We find evidence for a desire to come out on top of others in the INFO-WIN treatment.

Summary 2. Contrary to Hypothesis 2(b), there are no significant differences in exposure between the INFO and INFO-LOSE treatments on any of our tests. Both treatments display a significant negative trend in exposure. There is no such trend in the INFO-WIN treatment, and we find evidence that in line with Hypothesis 2(a), exposure in the INFO-WIN treatment is higher than in the INFO treatment by the end of the experiment.

6. Peer information and diversification

The previous section showed that introducing peer information increases diversification over time, at least as long as the highest earner is not highlighted. Fig. 2(a) shows no such trend in the PRIVATE treatment, leading to a substantial difference in exposure by the end of the experiment. We did not hypothesize this result, but it is of interest nevertheless. It presents a contrast to much of the experimental finance literature, in which peer influences are often associated with more volatile payoffs due to speculation or herding behavior. However, these motives cannot play a role here: the lack of private information in our setting minimizes scope for herding or information cascades, and because portfolios are reset in each period, speculation is not attractive. In this section we take a closer look at these dynamics. The reader should keep in mind that all the analyses in this section are *post-hoc*, i.e. conceived after the data were gathered.

As a starting point, Fig. 1 shows the mean exposure in the PRIVATE and INFO treatment, demonstrating that the difference increases over time. Following the statistical approach outlined in Section 5.2, we first take the most conservative test to compare the INFO and PRIVATE treatment, by collapsing each session into a single observation, yielding 7 observations per treatment. We find no significant difference on a two-sided MWU test for all periods ($p = 0.48$) or the last 5 periods ($p = 0.20$).

As in the previous section, we are concerned with the low power of these tests and the lack of controls for time trends and personal characteristics. In Table 4, we therefore report panel regressions using period averages with 10 observations per session. A fixed-effect specification is presented in column (1) of Table 4. We interact treatment dummies with the period variable to capture the time trends apparent in Fig. 2(a). It shows a highly significant negative trend in the INFO treatments, which is absent in the PRIVATE treatment.

In columns (2) and (3) we present the results of random effects estimations. Since period 10 is chosen as a base period, the treatment dummies capture last period averages of exposure. They show that in the INFO treatment, subjects have on average 1 unit lower exposure than in the INFO treatment, a drop of 27% that is significant at the 5% level. These differences emerge over the course of the experiment, as evidenced by the significantly different time trends between treatments.

The results are robust to including controls in column (3), where in line with the literature, the share of male traders increases risk taking (Eckel and Füllbrunn, 2015). It is curious that the share of males does not have a similarly strong effect in the INFO treatments, see Table 3. To explore this further, we extend the regression model in Table 4, column (3), with an interaction the INFO treatment dummy and Share Male. We find that the drop in the INFO treatment is almost entirely due to the behavior of male subjects. While we have no clear explanation for this finding, it is an interesting observation that could be addressed in future research.

Table 4
PRIVATE and INFO treatment only. The dependent variable is average end of period exposure in a given period. Column (1) shows the results of a fixed effect regression. The independent variables are a period variable and an interaction of the treatment dummy and the period variables. Columns (2) and (3) show results of random effect regressions. Column (2) introduces a treatment dummy, column (3) the share of male participants and average choice in the BRET. Period 10 is the base period. Standard errors, clustered on session level, in parentheses. Significance levels on two-sided tests are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) FE	(2) RE1	(3) RE2
Period	0.00918	0.00918	0.00918
	(0.0410)	(0.0392)	(0.0395)
Period X INFO	−0.146**	−0.146***	−0.146***
	(0.0533)	(0.0509)	(0.0513)
INFO		−1.225**	−1.062**
		(0.534)	(0.447)
Share Male			3.484**
			(1.628)
Bombchoice			−0.00153
			(0.0355)
Constant	4.037***	4.650***	2.980***
	(0.120)	(0.483)	(0.785)
Observations	140	140	140
R^2	0.083	0.084	0.189

Table 5
Panel regressions of exposure on lagged deviations from group payoffs. columns (1) and (2) include fixed effects, columns (3) and (4) report Arellano–Bond estimators for exposure in $t-1$. To explore learning, columns (2) and (4) use data from the first half of the experiment only. Standard errors, clustered for columns (1) and (2), robust for (3) and (4), in parentheses. Significance levels on two-sided tests are denoted * $p<0.10$, ** $p<0.05$, *** $p<0.01$

	(1) FE	(2) FE5	(3) AB	(4) AB5
IndVar_{t-1}	0.000806	−0.000742	0.0000587	0.0000357
	(0.000611)	(0.00182)	(0.00178)	(0.00199)
IndVar_{t-1} X INFO	−0.00161*	−0.00398**	−0.00400	−0.00397**
	(0.000928)	(0.00194)	(0.00255)	(0.00201)
Exposure_{t-1}			1.042***	0.793*
			(0.263)	(0.468)
$\text{Exposure}^2{}_{t-1}$			−0.0860***	−0.0798**
			(0.0213)	(0.0337)
Constant	4.231***	4.713***	2.872***	3.688***
	(0.0755)	(0.157)	(0.613)	(1.114)
Observations	1242	552	1104	414
R^2	0.003	0.039		

6.1. Conformity and social reinforcement

We now explore whether the drop in exposure in the INFO treatment is linked to the conformity documented in Section 5.1. One reason to think that this may be the case is a form of social reinforcement learning: subjects in the INFO treatments whose payoffs deviate strongly from their peer group may learn from this experience, and try to avoid extreme payoffs in the next period. To do so, they would have to reduce exposure, thus explaining the gradual drop in exposure in the INFO treatments.

To investigate whether such "social reinforcement" explains the results, we propose a measure of individual earning deviations that is similar to the within-group deviation measure (GVar) defined above. Again, we use deviations in earnings rather than exposure, because social preference models are defined over payoffs (see Footnote 9). Our measure of individual variation (*IndVar*) is given by

$$IndVar_{i,t} = \left(x^H_{i,t} - \bar{x}^H_{i,t}\right)^2 + \left(x^C_{i,t} - \bar{x}^C_{i,t}\right)^2. \tag{IndVar}$$

IndVar is the squared deviation of (virtual) earnings $x_{i,t}$ from the average of person's i's group $\bar{x}_{i,t}$ summed over both states in period t. This variable also captures our theoretical model with $v(\cdot)$ as a square function.[13]

Following the reasoning above, we hypothesize that exposure is influenced negatively by the disutility of being a social outlier (as measured by *IndVar*) in the previous period $t-1$. We therefore regress exposure on lagged levels of *IndVar*, including fixed effects for each subject. The random variation in starting portfolios combined with random resolution of uncertainty provides variation in *IndVar* that allows our identification. Since the learning effect should be more pronounced in early periods, we present results both for all periods and for the first half of the experiment only.

Column (1) in Table 5 shows that individuals in the INFO treatment reduce their exposure after having a high *IndVar*, i.e., after having dissimilar (potential) payoffs compared to their peers, where the dummy is significant at marginal levels. Column (2) presents results for the first half of the experiment only. In line with a learning interpretation, the coefficient becomes larger and now reaches significance at the 5% level. Since individual exposure potentially follows an autoregressive process, fixed effect panel regression might be biased. We therefore also use dynamic panel methods (Arellano and Bond, 1991) to control for lagged exposure as well as its squared value in columns (3) and (4). The results demonstrate that lagged exposure indeed has significant explanatory value. The coefficient for the presence of peer information for the first five periods is of similar size, but reaches significance at the 5% level.

While more research is needed to confirm these non-hypothesized findings, we find evidence that peer information helps subjects in learning to diversify. Such a "social reinforcement" channel can explain both increased conformity and decreasing exposure in the INFO but not in the PRIVATE treatment. It also explains why exposure should stabilize after some periods, as within-group deviations shrink over time and the impetus for learning diminishes. A back-of-the-envelope calculation suggests that quantitatively, the social outlier effect is large enough to (more than) explain the drop in exposure in the INFO treatment.[14]

[13] Note that our theory in Appendix A focuses on a reference group of higher earners. However, as we point out, this is merely a simplification, and the theoretical results are robust to including a disutility of earning more than others. In the following, average group exposure is used. The results are also robust to instead using the average exposure of *other* group members.

[14] For instance, the average level of *IndVar* equals about 170 in the first round. If we take the Arellano–Bond estimate from Table 5, we find that this should imply a drop in exposure of $170 * 0.004 = 0.68$ in the second round of the INFO treatment. This is somewhat smaller than the actual drop in the second round, but quite a bit larger than the average drop over all periods, estimated in Table 4. These calculations should be taken with a large grain of salt, as they contain strong simplifying assumptions regarding the linearity of the effect and the use of average exposure among other things.

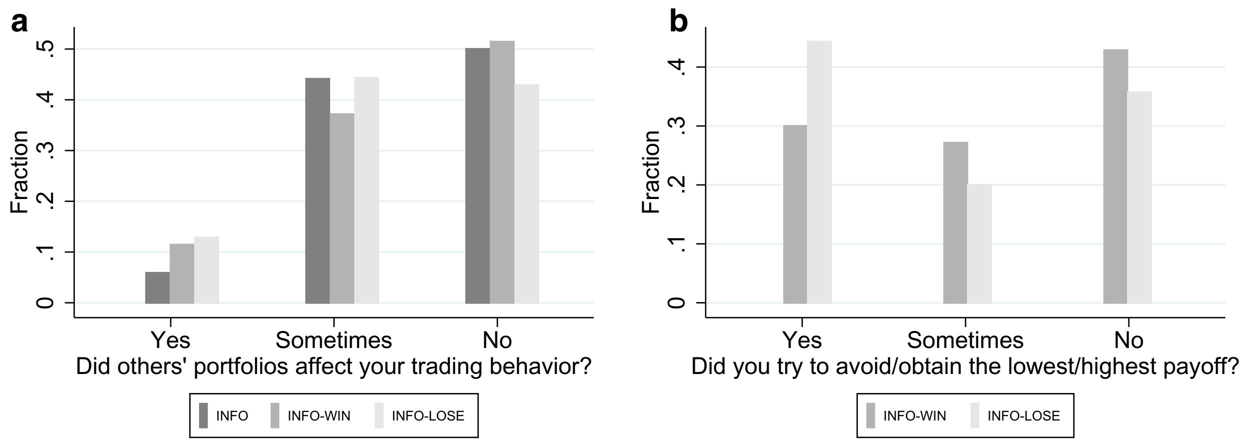


Fig. 4. Distribution of post-trading questionnaire answers by treatment.

Summary 3. As a result of a downward trend in the INFO treatment, exposure at the end of the experiment is significantly lower than that in the PRIVATE treatment. We find evidence that subjects in the INFO treatments reduce exposure after having payoffs that deviate from their peers.

6.2. Self-reported social influence

To better understand subjects' decisions, we look at the self-reported assessments of social influence gathered in the questionnaire. Since these reports were made at the end of the experiment and do not refer to particular situations or periods, the results can at most be indicative of the trading strategy. Also, the reports would not capture subconscious peer influences.

Fig. 4(a) shows the answer to the question whether the portfolios of others influenced their trading behavior. Answers were provided on a three-point scale. More than half of the subjects say they were influenced at least sometimes, which indicates that people did pay attention to the portfolios of others. There is little difference between the three conditions with peer information.

The INFO-WIN and INFO-LOSE treatments potentially induce positional concerns. Therefore, we asked whether traders in these treatments aspired to have the highest payoff in the INFO-WIN treatment and to avoid the lowest payoff in the INFO-LOSE treatment. Panel (b) of Fig. 4 shows that more than half of the subjects tried to obtain the highest payoff at least some of the time, whereas almost three-quarters say they tried to avoid earning the lowest payoff at least some of the time. Thus, our symbolic awards appear to have motivated at least some of the participants in their trading behavior. Indeed, subjects who self-report an inclination to pursue the highest payoff within their group at least sometimes, have higher average exposure relative to their group members (two-sided MWU, $p = 0.037$). This is in line with Kirchler et al. (2018), who show that symbolic ranking affect risk taking behavior among financial professionals, as well as with the literature on positional preferences cited in the literature section. We find no such correlation for subjects who said they wanted to avoid having the lowest payoff.

7. Conclusion

Our findings show that social influences are important determinants of equilibrium in asset markets. In line with the predictions of a general equilibrium model with social preferences, we find evidence that information about peers' portfolios reduces the variance of income in peer groups. We also observe that information about the portfolios of others increases risk sharing and reduces the variance of earnings in our experimental markets, except when the highest earner is highlighted. Our results are consistent with the idea that positional concerns are an important driver of risk sharing in financial markets, and provide an impetus for models that incorporate such concerns.

The effect of earning comparisons highlights a different kind of social influence than is present in the existing (experimental) finance literature. In fact, the lack of private information in our setting minimizes scope for traditionally studied peer effects such as "information cascades" or herding. Also, because portfolios are reset in each period, speculation is not attractive. The experiment demonstrates that peer effects matter even in the absence of these motives, and suggests peer portfolios provide a social benchmark against which subjects learn to conform and diversify. Future research should verify these effects both in the lab and in the field. Replication efforts by other researchers are particularly important, since some of our comparisons yield statistical significance in parametric analysis but not on the most conservative tests.

Generally, there is a need to investigate the impact of availability of peer information in its increasingly diverse forms. For instance, we know very little about the effect of different economic "narratives" on market equilibrium and stability.

Furthermore, trading platforms often emphasize success stories and spectacular profits, which will likely result in higher aggregate exposure.[15] A more detailed understanding of the social side of markets may help the design of more stable, better functioning markets.

Appendix A. General equilibrium with social preferences

Here we model an economy that resembles our experimental setup. Consider an endowment economy with two equally probable states of the world $s \in \{1, 2\}$, and two state-contingent commodities x_s, where x_1 pays 1 in state one and 0 in state two, and vice versa for x_2.

There is a continuum of agents distributed on [0,2]. Each agent i belongs to either one of two peer groups 'red' and 'blue', defined as $r = \{i : i \in [0, 1)\}$ and $b = \{i : i \in [1, 2]\}$, where we denote the peer group of agent i by $g_i \in \{r, b\}$. Every agent randomly receives an initial endowment of either $\omega = (1, 0)$ or $\omega = (0, 1)$, where each is equally likely. We denote by $x_i = (x_{1i}, x_{2i})$ the state contingent commodity vector of agent i.

The utility of agent i who belongs to group g_i is given by

$$V_i = E[u(x_{si})] - \alpha E_s\left[v\left(\int_{g_i} (x_{sj} - x_{si})\mathbf{1}_{x_{sj}>x_{si}}\mathrm{d}j\right)\right], \tag{A.1}$$

where $u(\cdot)$ is the utility derived from the own monetary payoffs, and $v(\cdot)$ represents social preferences: agents are envious when their ex-post income is less than the income of their peers x_j within their group, i.e., other red or blue agents, while they do not care about their consumption relative to the group they do not belong to. In other words, agents want to "keep up with the Joneses", where the Joneses consist of a subset of society, i.e. immediate neighbors, colleagues or a different reference group of interest. We will assume that $u(\cdot)$ is increasing and concave. Moreover, we assume $v(\cdot)$ to be increasing, strictly concave and differentiable, with positive derivative at the origin given by $\left.\frac{dv}{dx_{si}}\right|_{v=v(0)} := v_0 > 0$.

This utility function implies that an agent faces two kinds of risk. First, she faces 'consumption risk', which stems from variance in the payoff x_i and the assumption that the u is concave. Agents can minimize consumption risk to zero by choosing a balanced portfolio and consuming the same in each state of the world. Second, she faces 'social risk', which occurs when she deviates from the portfolio held by other group members, which implies a positive variance of the second term of the utility function. The agent's optimal portfolio choice may require her to trade off these two kinds of risk.

Note that we make several simplifying assumptions. First, we assume that all agents have the same social preferences. Second, we abstract from disutility from experiencing advantageous inequality, i.e. our utility function is equivalent to the inequality aversion model by Fehr and Schmidt (1999), where the guilt parameter β is set to zero. Note that all theoretical results would continue to hold if people (also) experienced such disutility, as it would be an additional source for conformism.[16]

Equilibrium

Suppose now that agents can trade assets for prices $p = (p_1, p_2)$. Each agent i in the economy solves the following problem:

$$\max_{x_{1i}, x_{2i}} \frac{1}{2}u(x_{1i}) - \frac{\alpha}{2}v\left(\int_{g_i} (x_{1j} - x_{1i})\mathbf{1}_{x_{1j}>x_{1i}}\mathrm{d}j\right) + \frac{1}{2}u(x_{2i}) - \frac{\alpha}{2}v\left(\int_{g_i} (x_{2j} - x_{2i})\mathbf{1}_{x_{2j}>x_{2i}}\mathrm{d}j\right)$$
$$\text{s.t} \quad px_i \le p\omega_i.$$

We consider competitive equilibria (CE) of the economy:

Definition 1. A CE consists of an allocation $\{x_i^*\}_{i\in[0,2]}$ and a system of prices $p = (p_1, p_2)$, such that:

1. For every i, x_i^* maximizes utility in the budget set $\{x_i \in \mathbb{R}_+^2 \mid px_i \le p\omega_i\}$
2. Markets clear: $\int_0^2 x_i^* \mathrm{d}i = \int_0^2 \omega_i \mathrm{d}i$.

[15] eToro provides salient rankings of the most successful traders. Simon and Heimer (2012) show that best short-term performers in their (undisclosed) trading site actively and successively promote their portfolios among members of the social trading site under study via the built-in chat interface. Hence, even if the corresponding platform does not highlight the best short-term performer directly but simply enables peers to communicate with one another, the effects of social trading on risk sharing can be undermined. Interestingly, Han and Hirshleifer (2016) argue that the social transmission of investment ideas is biased. People rather communicate their investment successes than losses. This bias in communication can explain the social transmissions of more risky investment strategies (Kaustia and Knüpfer, 2012).

[16] There are also other ways to model social preferences in the presence of uncertainty. Specifically, consistent with a concern for procedural fairness, utility can be defined over expected levels of inequality, rather than the expected utility of inequality in each state of the world. Our results do not hold if agents care about inequality purely procedurally, but will hold qualitatively if their utility is a mixture of procedural and inequality concerns, as proposed by Saito (2013).

Furthermore, we define a “symmetric equilibrium” as a CE in which all agents in the same peer group have the same portfolio allocation $x_{si} = \bar{x}_{sr}$ for all $i \in [0, 1)$ and $x_{si} = \bar{x}_{sb}$ for all $i \in [1, 2]$. Feasibility implies that in such an equilibrium, agents from the other group hold the mirrored portfolio $\bar{x}_{sb} = 1 - \bar{x}_{sr}$.

We obtain the following result

Proposition 1. *For any $z \in [-\alpha v_0, \alpha v_0]$, the economy has a symmetric CE characterized by $p_2 = p_1 = 1$ such that $u'(x^*_{2r}) - u'(x^*_{1r}) = u'(1 - x^*_{1b}) - u'(1 - x^*_{2b}) \le |z|$.*

Proof of Proposition 1. Consider the candidate symmetric equilibrium in which all red agents consume $x_s = \bar{x}_{rs}$ and blue agents consume $x_{sb} = 1 - \bar{x}_{sr}$ in state s, and $p_2 = p_1$.

For any red agent it is optimal not to switch consumption from state 1 to state 2 if:

$$\frac{1}{2}u'(\bar{x}_{2r}) - \frac{1}{2}u'(\bar{x}_{1r}) - \frac{\alpha}{2}v_0 \le 0$$

Conversely it is not optimal to switch consumption from state 2 to state 1 if:

$$\frac{1}{2}u'(\bar{x}_{1r}) - \frac{1}{2}u'(\bar{x}_{2r}) - \frac{\alpha}{2}v_0 \le 0$$

So every equilibrium satisfies:

$$-\alpha v_0 \le u'(\bar{x}_{1r}) - u'(\bar{x}_{2r}) \le \alpha v_0 \tag{A.2}$$

Analogous reasoning holds for blue agents. Feasibility implies that $x_{1b} = 1 - x_{1r}$. If we define $z := u'(\bar{x}_{1r}) - u'(\bar{x}_{2r})$, we find that $u'(\bar{x}_{1b}) - u'(\bar{x}_{2b}) = u'(1 - \bar{x}_{1r}) - u'(1 - \bar{x}_{2r}) = u'(\bar{x}_{2r}) - u'(\bar{x}_{1r}) = -z$. Since $z \in [-\alpha v_0, \alpha v_0]$ implies $-z \in [-\alpha v_0, \alpha v_0]$, any allocation that satisfies (A.2), satisfies the analogue condition for blue agents.

Finally, since $\int x^*_i di = \int \omega_i di$, excess demand is zero for each market and prices $p_1 = p_2$ clear both markets. □

Proposition 1 says that there is a range of symmetric equilibria, where each agent holds the same portfolio as all other agents in her peer group. This multiplicity is caused by the existence of social preference, which cause a kink in the agent's utility functions at the level of the peer group's consumption, so the optimal portfolio depends on the portfolio of the others.

In particular, since z may be different from 0, there exist equilibria where the red agents consume more in state 1 and the blue agents in state 2 or vice versa, so that risk sharing is imperfect even though $u(\cdot)$ is concave. These equilibria occur because an agent who deviates towards a more balanced portfolio will reduce his income risk, but will increase her social risk since she now faces the possibilities of falling behind his peers in at least one of the income states. The larger the social concerns α, the larger is the deviation from the balanced portfolio that can be sustained as an equilibrium. Note that equilibria that feature imperfect insurance are inefficient: all (risk-averse) agents are better off ex-ante (have a higher expected utility) in the perfect risk sharing equilibrium. Note also that without social preferences ($\alpha = 0$), multiplicity disappears and only a CE with perfect risk sharing remains.

If agents are (approximately) risk neutral over their monetary payoffs, we can provide some further results:

Proposition 2. *If agents are risk neutral over monetary payoffs,*

(a) *all competitive equilibria are symmetric.*
(b) *any symmetric allocation that satisfies feasibility and the individual budget constraints is a CE.*

Proof. *Proof of (a).* Assume an asymmetric equilibrium exists. For now assume that in equilibrium, within the red peer group only two different consumption vectors $\bar{x}^1_g$ and $\bar{x}^2_g$ are consumed by a non-empty subset of traders, such that $\cup^2_{j=1}\{i : x_i = \bar{x}^j_g\} = [0, 1)$. There is no aggregate risk in the market, hence $p_1 = p_2$. So for any trader in the red peer group consuming a linear combination $\gamma x^1_i + (1-\gamma)x^2_i$ $\gamma \in (0, 1)$ is feasible. Because $v(\cdot)$ is strictly concave, such a linear combination yields higher social utility than the vectors it is composed of. Moreover $E[u(x)]$ is constant for any portfolio that satisfies the budget constraint. So there exist feasible consumption vectors which yield a higher utility than the initially proposed asymmetric equilibrium. Since this argument generalizes to the blue group and to instances of three or more subsets of agents within one peer group having different consumption vectors, we arrived at a contradiction.

Proof of (b). Risk neutrality implies that $u'(x)$ is constant, so $u'(x^*_{2r}) - u'(x^*_{1r}) = u'(1 - x^*_{1b}) - u'(1 - x^*_{2b}) = 0$. Thus, Proposition 1 is satisfied for any z. □

Proposition 2(a) shows that when agents are (approximately) risk neutral over their own payoffs, social preferences always lead groups to coordinate upon only one allocation. Because agents are indifferent between all allocations that give them the same expected payoffs, considerations of social risk means that having different portfolios from others can never be optimal. Proposition 2(b) is a simple corollary of Proposition 1, and shows that risk neutrality implies that social preferences can lead to portfolio's that are arbitrarily skewed.

Appendix B. Descriptive results

Table B.1
This table reports various summary statistics for all sessions as a total and each treatment individually. Variables reported are number of sessions, number of participants, number of male participants, average end of period exposure, standard deviation of end of period profits as well as average Bomb Choice.

	All	PRIVATE	INFO	INFO-WIN	INFO-LOSE
Sessions	28	7	7	7	7
Participants	278	70	68	70	70
Male	133	34	30	32	37
Avg. Exposure	4.20	4.67	3.74	4.30	3.69
Sd. Profits	291.16	331.77	259.79	302.90	263.35
Avg. Bomb Choice	15.30	16.84	15.33	14.92	14.00

Table B.2
Average end-of-period exposure by period and treatment.

Period	PRIVATE	INFO	INFO-WIN	INFO-LOSE
1	4.89	4.82	3.94	5.27
2	4.23	3.97	4.34	4.63
3	4.25	4.62	3.57	4.09
4	4.29	3.97	3.26	3.94
5	5.00	4.12	4.74	4.00
6	5.31	4.47	4.06	3.57
7	4.46	3.59	4.51	3.66
8	4.51	3.50	3.77	3.74
9	4.66	3.88	3.89	3.37
10	4.49	3.18	5.22	4.09

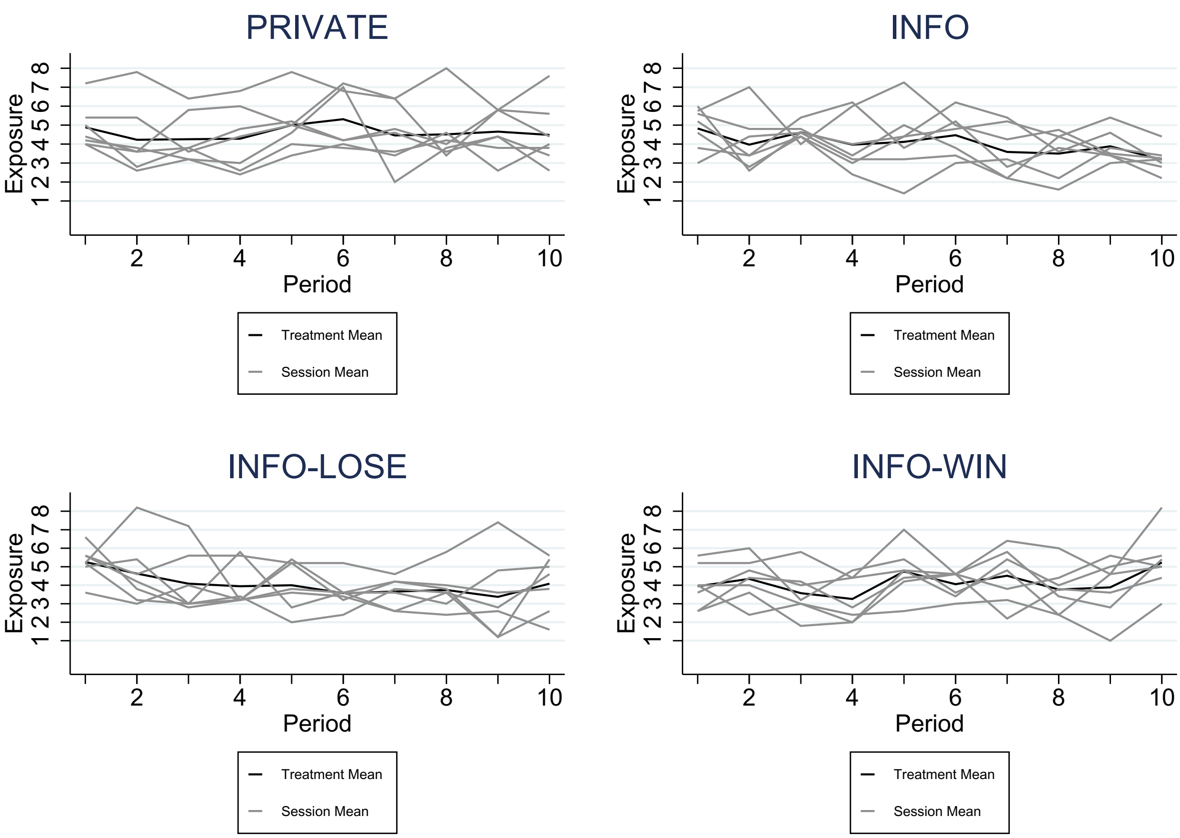


Fig. B.1. *Time series of exposure.* Exposure is defined as the absolute difference between holdings of the two assets. The figure plots treatment means alongside session means. Each line corresponds to an individual session. INFO-treatments give traders information on the portfolios of their exogenous reference group. INFO-WIN and INFO-LOSE, in addition, give a symbolic reward to either the best and the worst performer in each period respectively. In the PRIVATE treatment, traders do not have information about other traders.

Appendix C. Prices

In equilibrium, we expect both assets to be equally priced. We do indeed find strong support for this prediction, as prices of asset G and I are statistically indistinguishable (two-sided Wilcoxon signed rank test on both median and mean prices $p = 0.86$ and 0.57, respectively), so in the remainder, we pool prices for both assets.

In addition, because there is no aggregate risk in the market, prices of the assets should be equal to the fundamental value. Fig. C.1 shows average transaction prices over all 10 trading periods, and Appendix B contains disaggregated graphs

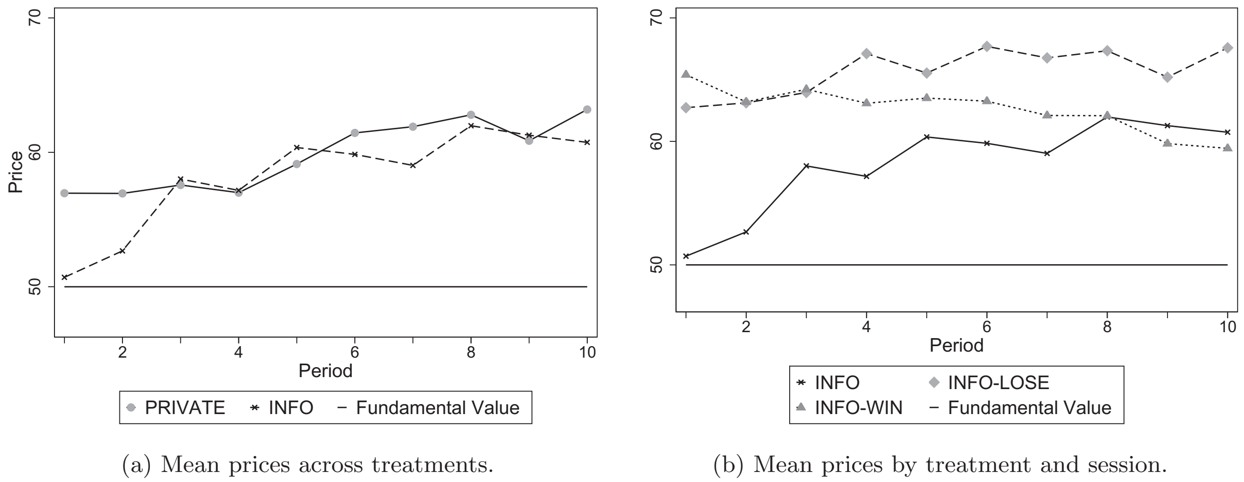


Fig. C.1. *Time series of transactions prices.* Data are pooled between asset I and G. The panel on the left (a), shows mean transaction prices for the PRIVATE and INFO treatment. Panel (b) on the right hand plots prices from the INFO treatments. The pointed line corresponds to the fundamental value (FV).

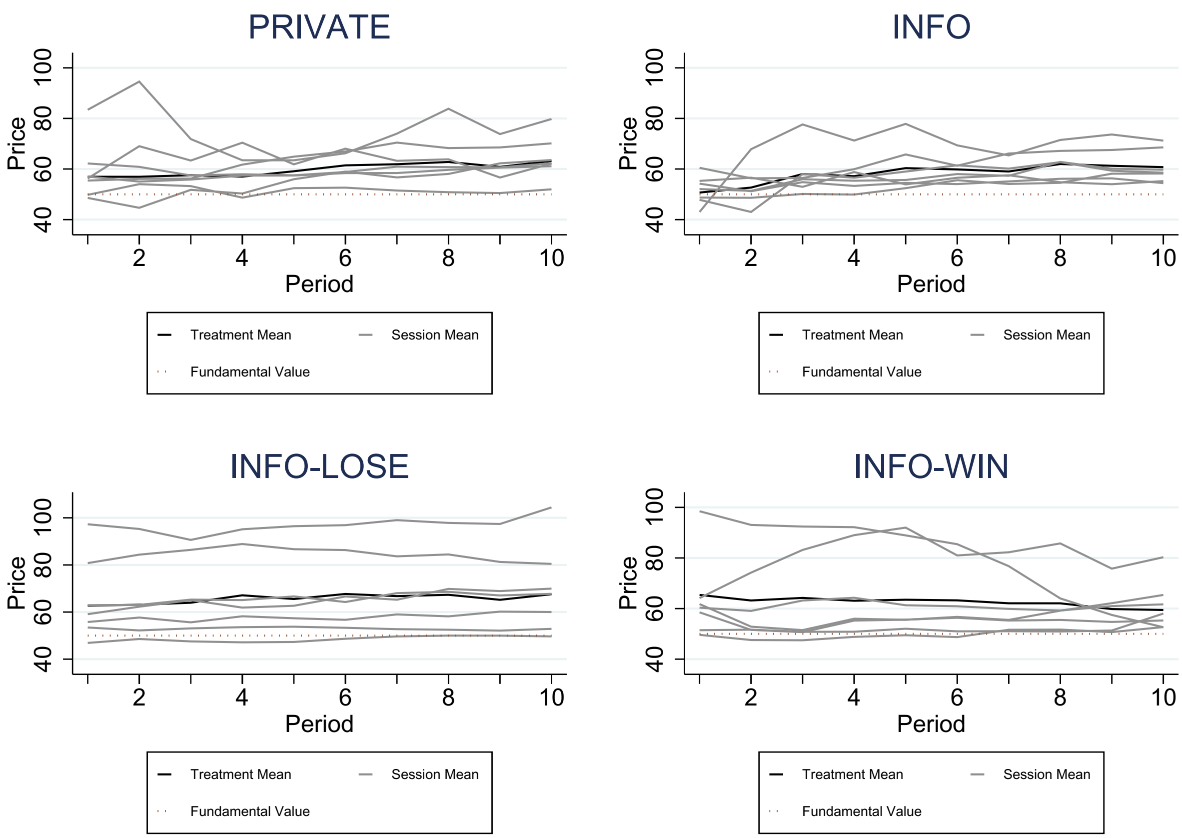


Fig. C.2. *Time series of transactions prices.* Data are pooled between asset I and G. The plot shows treatment means alongside session means. Each dashed line corresponds to an individual session, the pointed line to the fundamental value (FV), and the connected black squares to the treatment mean.

per sessions. The left panel shows average treatment prices for the PRIVATE and INFO treatment, the right panel average treatment prices for the treatments with information.

Most sessions exhibit average prices that are above the fundamental value of 50. In some outlier sessions these deviations are large (see Fig. C.2). Median prices are 59 for asset G and 60 for asset I, and mean prices are 61.3 and 61.7, respectively. Two-sided Wilcoxon signed rank tests on median ($p = 0.86$) and mean ($p = 0.57$) session prices are far from statistically insignificant, so we cannot reject the equilibrium prediction. Appendix C has more details on the (dynamics of) prices across the different treatments. On average, the magnitude of overvaluations is consistent with the findings of Weber et al. (2000).

We find no evidence of a treatment effect on either average session prices or the number of transactions. However, Fig. C.1 shows that prices in the PRIVATE treatment exhibit most volatility within sessions as prices rise and fall considerably between periods. In contrast, prices change relatively little between periods in all treatments with information. To investigate this statistically, we define volatility as the standard deviation of prices within a session and find that we can reject the hypothesis of equally distributed volatility in PRIVATE compared to the treatments with peer information at marginal significance (Two-sided Mann–Whitney-U, $p = 0.098$).

Appendix D. Starting portfolios and exposure

Hypothesis 2 is predicated on the idea that people compete for income ranks. Here we look for additional evidence whether the differences in exposure seen in the INFO-WIN and INFO-LOSE treatments are indeed due to such competition. For identification, we use the exogenous variation in the starting portfolios.

At the beginning of each period, each subject randomly obtains either a portfolio with 10 I assets and 0 G assets or a portfolio with 10 G assets and 0 I assets. Since subjects in the INFO-treatment have information about their peer's portfolios, social concerns may lead them to react to the composition in starting portfolios. One particularly interesting case is when all 5 subjects in a group have the same portfolio (and traders in the other groups all hold opposite portfolios). In this case, positional concerns would trigger different reactions in the INFO-WIN and INFO-LOSE treatments.

To see why, suppose all subjects initially hold 10 I shares. In this case, a subject in the INFO-WIN treatment who manages to have lower exposure than her peers at a reasonable price might not only have lower monetary risk than her peers, but also a 50% chance of being the highest earner in her group (namely when the state is "cold" and the G shares pay out). Thus, if traders are motivated to be the highest earner, we would expect subjects to decrease their exposure more in the INFO-WIN treatment, in a period where everyone has the same starting portfolio. In the INFO-LOSE treatment, a subject

Table D.1
The dependent variable is average end of period exposure in a given period. Only sessions from INFO-treatments are included in the regressions. Column (1) shows a fixed effect regression. Columns (2) and (3) show results of random effect regressions. The independent variables in (1) are a period variable and interactions of treatment dummies and the period variable. "All equal spf" is a dummy variable, that is equal to 1 if everybody within an exogenous references group has the same starting portfolio and 0 otherwise. This variable is interacted with treatment dummies with base period 10. Results in column (2) are controlled for treatment dummies, in column (3) additionally for the share of male participants and average choice in the BRET task. Standard errors clustered by session in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) FE	(2) RE	(3) RE2
Period x INFO	-0.139^{***}	-0.140^{***}	-0.140^{***}
	(0.0340)	(0.0341)	(0.0341)
Period x INFO-WIN	0.215^{***}	0.215^{***}	0.216^{***}
	(0.0602)	(0.0604)	(0.0606)
Period x INFO-LOSE	0.00782	0.00853	0.00854
	(0.0643)	(0.0651)	(0.0653)
All equal spf x INFO (d)	0.219	0.278	0.311
	(0.564)	(0.556)	(0.557)
All equal spf x INFO-WIN (d)	-1.575^{**}	-1.671^{***}	-1.695^{***}
	(0.567)	(0.568)	(0.573)
All equal spf x INFO-LOSE (d)	−0.592	−0.665	−0.668
	(0.589)	(0.602)	(0.599)
INFO-WIN (d)		1.110^{**}	1.065^{**}
		(0.485)	(0.438)
INFO-LOSE (d)		0.0535	0.0293
		(0.545)	(0.514)
Share Male			0.563
			(1.058)
Bombchoice			0.0721
			(0.0725)
Constant	3.790^{***}	3.401^{***}	2.050^{*}
	(0.125)	(0.244)	(1.049)
Observations	210	210	210
R^2	0.117	0.085	0.113

who reduces exposure more than her peers reduces income risk, but increases the risk that she will be the lowest earner when the I shares pay out. As a consequence one would expect subjects to be more reluctant to reduce exposure than with other distributions of the starting portfolio.

In column (1) of Table D.1 we run a fixed effect regression on the INFO treatments, including a dummy variable "All equal spf" that is 1 in periods where all subjects have the same starting portfolio (spf) and 0 otherwise. Our hypothesis regarding the INFO-WIN treatment is confirmed: Consistent with a desire to be the highest earner, subjects reduce exposure more when they share the same starting portfolio. With an additional reduction of more than 1.5 units of exposure, this effect is substantial. However, our hypothesis in the INFO-LOSE treatment is not confirmed, which is somewhat surprising, since in the questionnaire about half of the subjects indicate that they want to avoid having the lowest payoffs (see below). These same results hold in the random effects regression in columns (2) where we add treatment dummies, and in column (3) where we add controls for risk aversion and gender composition.

Summary 4. When all subjects in the peer group have the same starting portfolio, average exposure is reduced by 1.6 units in the INFO-WIN treatment, consistent with a desire to come out ahead of the others. This is consistent with hypothesis 2(a).

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.euroecorev.2019.04.001.

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