Peer Effects and Risk Sharing in Experimental Asset Markets*

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June 24, 2016

Abstract

Social influences are pervasive in financial markets. We investigate a simple experimental Arrow-Debreu economy to perform controlled tests of a broad set of hypotheses about the effect of information about peer behavior on market outcomes and risk sharing. In the absence of peer information, we find large deviations from a salient risk sharing benchmark in both prices and portfolios. Risk sharing improves with peer information, although this effect virtually disappears when the highest earners are made salient. We find evidence that observational learning, preferences for relative position and spillovers in risk preferences all affect market outcomes.
JEL-codes: D53, D83, G11.
Keywords: peer effects, laboratory experiments, risk taking, asset markets.

*The authors would like to thank the program for Sustainable Architecture for Finance in Europe (SAFE) at the Goethe University Frankfurt for financial support. We are highly indebted to Sascha Baghestanian who provided extensive feedback and commentary and was influential in shaping the analysis. In addition, we thank Michael Haliassos, David Schindler, Oege Dijk, Jona Linde, Leonie Gerhards, Heiner Schumacher, Devesh Rustagi, Matthias Blonski, and seminar participants in at the Goethe University Frankfurt, the University of California at Santa Barbara, Copenhagen University, Aarhus University and at the Labsi Workshop on Behavioral and Experimental Finance 2014 for useful comments.

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1 Introduction

Trading financial assets is an activity with a strong social component in which traders interact in other ways than merely through market prices. Investment choices of others may transmit information or may provide an aspiration point for 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 through social trading networks like eToro or Zulutrade that 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]

A nascent literature on social aspects of financial decision making, reviewed in more detail below, has confirmed the importance of peer influences in individual decision making under risk. Despite this recognition, we know little about the effects of social influences on aggregate market outcomes like the degree of risk sharing and the price level. One reason is that such knowledge is hard to obtain with observational data, because one needs to identify individual investor information and isolate possible peer effects from political and macro-economic shocks. Furthermore, peer groups form endogenously in the field, making it hard to distinguish influence from selection. Theory does not settle the question either because, as we show below, peer effects can affect markets through multiple channels and generate multiple equilibria.

To overcome these issues, we study peer effects in risk sharing in experimental markets that provide a transparent test of the predictions of Arrow-Debreu general equilibrium theory. Besides cash, our markets feature two risky assets with perfectly negatively correlated returns across two income states. This asset structure is a simplified version of asset pricing experiments that often feature dynamic asset values, three or more tradable assets and multiple income states. The simplicity of the design and the fact that portfolios are reset in each trading round also minimizes the potential for price bubbles. Under the common assumption that agents are risk averse, our markets have a unique and salient equilibrium characterized by perfect risk sharing and prices that are at the fundamental value.

In this setting, we contrast market outcomes when participants have only private information and when they have information about the portfolios of a peer group, consisting of other, randomly selected participants. The availability of such information is characteristic for actual investors and our design resembles the environment of online trading platforms that revolve around such information. However, whereas group formation and information is always endogenous in the field, the laboratory environment allows us to exogenously vary different aspects of peer information. First, we implement exogenous variation in *information availability* about peers' portfolios to generate

[1] Between 2010 and 2013 the number of eToro-investors doubled from 1.5 to 3 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.

clean evidence of peer effects on portfolio choice and exposure. Second, we study the effect of exogenous differences in *information content* by randomly generating new portfolios for each peer group member in each new trading period. Third, we study the effect of positional concerns by *highlighting either the lowest earner or the highest earner.*

Our three sources of random variation allow us to test novel hypotheses about social influences on risk sharing in markets. To do so we compare the risk taking, as measured by portfolio exposure, and price levels in markets with and without peer information. In line with some of the earlier literature, we find that risk sharing is far from perfect. While most subjects reduce their risk through the market, they only diversify about half their risk on average. In addition, prices are substantially above the fundamental value in most markets, consistent with an endowment effect in portfolio valuations that limits the ability of market participants to coordinate on mutual insurance.

The introduction of peer information causes risk taking to drop by 36% towards the end of the experiment. This is not due to a reduction in overpricing, as average prices do not change significantly compared to the baseline. Rather, self-reports and regression analysis indicate that information availability changes trading strategies. While we do not find clear evidence for learning-based mechanisms, our post-market measurement of risk attitudes indicates that peer information induces a decrease in risk tolerance consistent with the increase in portfolio diversification.

Introducing symbolic recognition for the lowest or highest earning trader also affects market outcomes. Exposure is lowest on average when the lowest earner is highlighted at the end of each round. By contrast, when the highest earner is highlighted, aggregate risk taking increases and does not differ significantly relative to markets without information. These results are driven by positional preferences, as many subjects report a motivation to avoid being the lowest earner or to become the highest earner. When the best performer is highlighted, participants "imitate the luckiest" and trade strategically to increase the chance to come out ahead.

To our knowledge, this is the first demonstration that information about peer portfolios and social rankings affects market outcomes. Contrary to conventional wisdom, we show that social interactions may help to improve portfolio diversification and reduce risk taking in financial markets. Our results also demonstrate that peer influences operate through several different channels, highlighting the complexity of peer effects in markets, and the importance of the nascent field of 'social finance' (Han and Yang, 2013; Hirshleifer, 2014). In the conclusion we discuss the implications of our results for the governance and design of trading environments.

2 Literature

Our results contribute to several strands of literature on the social aspects of market behavior in both finance and economics. First, we contribute to experimental literature on testing general equilibrium predictions. Most studies in this literature focus on prices, finding support for the predictions of standard asset pricing and general equilibrium models (e.g. Asparouhova *et al.*, 2003; Bossaerts and Plott, 2004). 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 ours. We replicate their findings that risk sharing is imperfect. When it comes to prices, Weber *et al.* (2000) finds modest overpricing for positively framed asset payoffs and strong overpricing for negatively framed assets, which they attribute to an endowment effect. We find substantive overpricing for positively framed assets, suggesting that an endowment effect may be present in the positive domain as well.

The literature on experimental asset markets has also mostly ignored the effects of peer information, with the exception of Schoenberg and Haruvy (2012), Oechssler *et al.* (2011), and Mengel and Peeters (2015). 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. Chatting 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. We investigate a different set of hypotheses. First, we don't look at bubbles, as there is no asymmetric information in our markets, and as portfolios are reset in each period there is little scope for speculation. Instead, we focus on diversification and risk taking. Second, we give participants portfolio information during the trading period, which allows us to investigate the effect of such information on trading and market outcomes.

With respect to peer effects in financial decisions, there is a sizable literature using field data in stock market participation and trading. This literature exploits information on social ties or spatial distribution of traders to show that peer decisions matter in stock market participation (Hong *et al.*, 2004; Kaustia and Knüpfer, 2012), trading decisions (Bursztyn *et al.*, 2014; Kelly *et al.*, 2000; Hong *et al.*, 2005; Shive, 2010; Hackethal *et al.*, 2014) and risky lifestyle choices (Card and Giuliano, 2013). While these studies use various ingenious strategies to disentangle peer effects from other influences, they cannot provide the clean exogenous variation that the laboratory affords.

Indeed, a rapidly growing number of laboratory experiments corroborates the existence of peer effects in risk taking and illuminates its sources (Trautmann and Vieider, 2012). Viscusi *et al.* (2011) show that individuals reconsider risky investments when they observe peer decisions. 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.* (2014) find that under-performers start taking more risk in later decision rounds to catch up with the others. Lahno and Serra-garcia (2014) and Bault *et al.* (2011) demonstrate that both learning and income comparisons play an important role in decision making under uncertainty. Our paper builds on this literature and goes a step further by looking at the consequences of peer effects on market outcomes. We find that both imitation and positional preferences play a role for aggregate risk taking. Moreover, we find suggestive evidence of a novel channel of peer influence via shifts in risk attitudes, contributing to an emerging literature that shows how risk attitudes are shaped by previous income realizations (Mengel *et al.*, 2012; He and Hong, 2014; Cohn *et al.*, 2015).

Finally, our results contribute to the literature on social preferences in market environments. Although it is well-established in the behavioral economics literature that people have preferences over how their payoffs compare to others, there is discussion about the importance of such preferences for market outcomes. A literature starting with Roth *et al.* (1991) and Fehr and Schmidt (1999) shows that social preferences have little influence on the outcomes of competitive bargaining situations. However, Heidhues and Riedel (2007) show that social preferences matter for competitive equilibrium outcomes when trade is conducted in risky assets (see also Gebhardt, 2004; Schmidt, 2011). In this paper, we provide evidence that social concerns do indeed matter for outcomes in markets for risky assets.

This paper proceeds as follows. In the next two sections, we describe our research questions and the market design in more detail. We present the main results in Section 5 and discuss the potential channels behind the observed peer effects in Section 6. Section 7 discusses the interpretation of the results and potential implications.

3 Methodology, Research Questions and Hypotheses

While the literature cited above demonstrates that peer effects exist in individual investment choices, it does not tell us how important they are in a trading environment, nor does it tell us how peer information affects aggregate market outcomes. The effect of peer influences on market outcomes is difficult to investigate in the field, as one needs to identify peer interactions and isolate their effects from those of political and macroeconomic shocks. Therefore we turn to experimental simulations in the laboratory.

We investigate markets for two risky assets and two states of the world. There is an equal supply of both assets, which have perfectly negative correlation in returns across states, allowing traders to share risk perfectly. Thus, the asset structure is exceedingly simple and suggests a salient hedging strategy. Weber *et al.* (2000) employ a similar market design to analyze the existence of an endowment effect in portfolio choice. We provide a detailed description of the market design in the next section.

Here, we develop our research questions and the hypotheses underlying our statistical tests. First, Arrow-Debreu general equilibrium theory delivers clear predictions for the baseline scenario without peer information. As we show in Appendix A, the unique competitive equilibrium in our markets implies full risk sharing under the condition that all traders are risk averse, which is a common assumption in asset pricing models (e.g. Bossaerts *et al.*, 2007). Furthermore, because there is no aggregate market risk, both asset prices should be equal to expected value to avoid the existence of arbitrage opportunities. Our first research question is therefore as follows.

Research Question 1 *Do markets with private information conform to the predictions of the risk sharing equilibrium (RSE), i.e. perfect risk sharing and asset prices that are equal to the expected* *value?*

Our asset markets are uniquely suited to test the implications of the RSE. There is no scope for herding or information cascades as endowments are reset in each period. Moreover, the simplicity of the asset structure makes the risk sharing strategy salient. We will compare our results to those of the earlier literature (cited above), that shows imperfect risk sharing and overpricing in markets with more complex asset structures.

Our second research question regards the effects of peer information. As we argued in the introduction, information about peer portfolios is an increasingly important aspect of financial markets, as witnessed by the rise of social trading websites. To investigate the effect of such information, we compare an asset market with private information with a market where traders have real-time information about the portfolio composition of a randomly selected group of other participants. Apart from this information, we do not provide any rankings or social benchmarks.

Research Question 2 *How does information about others' portfolios affect diversification and aggregate risk taking?*

We hypothesize that peer information will allow people to learn from each others' choices which in turn may affect market outcomes. In principle there are many ways in which people can learn, depending on their goals and the behavior of others. However, in light of the salient risk sharing benchmark, we hypothesize that observing the diversified portfolios of others may help participants to understand the benefits of diversification and lead to a decrease in aggregate risk taking.

Our third research question relates to the effects of providing social reference points that are often salient in the field. For example, professional money managers may derive status and additional clients from beating their rivals and individual investors may care about the status they derive from their income relative to that of the neighbors ('keeping up with the Joneses'). 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.[2]

Research Question 3 *What is the effect of explicit payoff comparisons with an emphasis on either a) the lowest earner, or b) the highest earner, on diversification and aggregate risk taking?*

When it comes to the effects of highlighting the *lowest* earner, we test two different hypotheses. Both these hypotheses are based on 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). Our first hypothesis is that we will see *conformism* in portfolio composition within peer groups. In Appendix A we show formally how disutility from falling behind can lead to multiple competitive equilibria where group members have identical portfolios, where exposure levels differ

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

between equilibria. Deviating from the group portfolio exposes the decision maker to a 'social risk' that she will end up earning less than the others.[3]

Note that the conformism hypothesis requires coordination on a particular portfolio by the entire group, which may be difficult to achieve. An alternative hypothesis, which does not depend on such coordination, is that aggregate exposure will go down when the lowest earner is highlighted. For a given set of peer portfolios, participants in our markets can avoid being the lowest earner by choosing a less extreme risk exposure than others. Such *competition for income ranks* will lead to a dynamic where participants increase their diversification over time, compared to the case where no performance rankings were given. Note that this hypothesis is based on non-equilibrium reasoning, as it does not suppose that all traders play best responses to each other simultaneously.

When it comes to introducing symbolic rewards for the *highest* earner, we hypothesize that this will increase aggregate exposure, because taking more risk increases the chance of earning the most. Roussanov (2010) shows theoretically that a desire to get 'ahead of the Joneses' may lead to less diversified portfolios. Both Fafchamps *et al.* (2014) and Dijk *et al.* (2014) show experimentally that low earners in earlier rounds adopt risky strategies to catch up with winners. 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. Finally, Offerman and Schotter (2009) show that subjects "imitate the luckiest", which may lead to a proliferation of risk taking.

4 Market Design

In this section, we describe the design of the experiment. Full instructions can be accessed via the online Appendix.[4]

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 dividend. 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" (E for the German "Eis-Creme") and a "Glove" (H for the German "Handschuhe") 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 seconds each. Short selling and borrowing are not

[3]Conformism is a common finding in models where peer effects play a role, see e.g. Card and Giuliano (2013). Our model is similar to Gebhardt (2004), who studies multiple equilibria in general equilibrium in markets that are segregated in time.

[4]Instructions can be downloaded here.

	Hot weather	Cold weather	Exp. Dividend
Ice-cream (E)	100	0	50
Gloves (H)	0	100	50

Table 1: The table shows the dividend structure in the experiment.

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 payoffs of each agent are 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.

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 E assets and 0 H assets, or of 0 E assets and 10 H 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.

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 subjects 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.

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 money amounts 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.

INFO. During the trading period, subjects were informed about the portfolios of their reference

ID	E Assets	H 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	

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. 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.

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 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.

Elicitation of preferences and background information. We conduct several elicitation tasks after market trading has been concluded to obtain information about the preferences and background of the participants.

Risk preferences. We measure 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 earn a monetary payment of 10 ECU (=15 cents). One randomly chosen box contains a bomb. The participant doesn't know in which box the bomb is located, and if she collects it, she earns 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.

In addition, we elicited a measure of social value orientation based on Murphy *et al.* (2011), and asked several questions about the degree of competitiveness of participants.[5] Finally, we ask some standard control questions such as gender, field of studies, and previous participation in asset market experiments.

Procedures. All sessions were conducted at the Frankfurt Laboratory of Experimental Economics at the Goethe University Frankfurt in the spring of 2014. Subjects were recruited using ORSEE (Greiner, 2003). In each treatment, we conducted 5 sessions/markets with 10 traders each. One session in the INFO treatment was run with 8 subjects, so a total of 198 subjects participated in the experiment. The experiment lasted approximately 90 minutes. Average earnings were 23.35 euros, with a minimum of 10.34 euros and a maximum of 33.82 euros.

After the experimenter 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.

5 Market outcomes

We first present a graphical overview of all our results. We then move on to a more detailed discussion of our treatment effects with the associated statistical tests. In the next section, we discuss the channels behind the treatment effects.

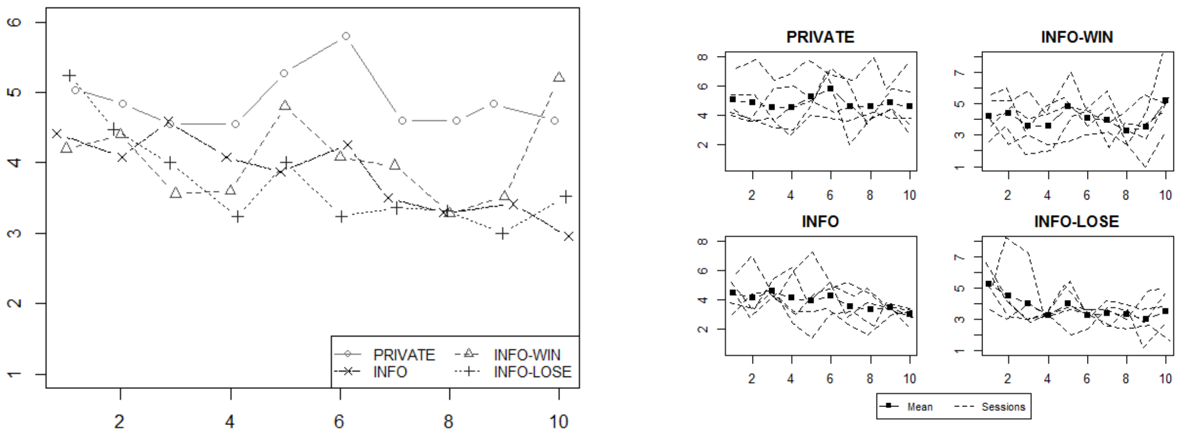
5.1 Graphical evidence

Here we provide a graphical overview of the results, relating to exposure and prices.

[5]However, since these data seemed noisy and did not provide much explanatory power, we have left them out of the analysis. An earlier working paper version of SAFE working paper 67, showed some analysis of the results of the SVO task.

Exposure. To investigate levels of risk taking in the market, we look at absolute exposure. Exposure for each individual is defined as the absolute difference between the number of E and the number of H assets in the end-of-period portfolio. An absolute exposure of, say, 4 implies a difference of 400 ECU (6 euros) in payoffs between both states of the world. The effects of the treatments on exposure are robust to other specifications of risk taking, such as exposure divided by the expected values of individual portfolios. We look at end-of-period data only, as these reflect the result of trading in the session aggregated over a given period.

Figure 1 shows the dynamics of mean exposure by treatment over the 10 trading periods. In the PRIVATE-treatment, exposure remains relatively stable over all 10 periods. In the INFO and INFO-LOSE treatment the figure shows a downward trend in exposure. In the initial periods a similar trend is apparent in the INFO-WIN treatment, however spikes occur in period 5 and 10.



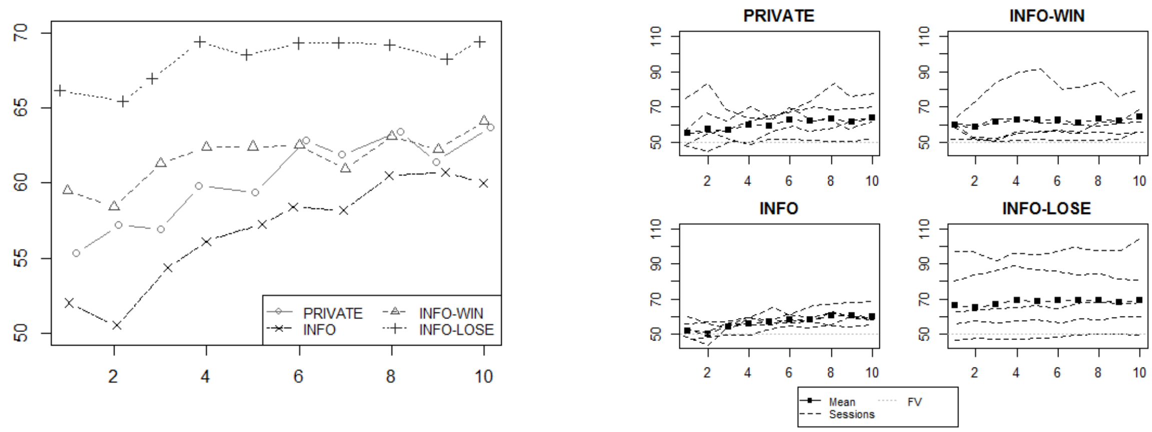
(a) Mean exposure across treatments.

(b) Mean exposure by treatment and session.

Figure 1: **Time series of exposure.** 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. The panel on the left (a), shows mean end of period exposure for each of the four treatments. Each time series corresponds to one treatment mean. Panel (b) on the right hand side plots treatment means alongside session means. Each dashed 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 did not have information about other traders.

Prices. Figure 2 shows average transaction prices over all 10 trading periods. The left panel shows average treatment prices, the right panel average session prices, separately for each of our four treatments. Prices are pooled between asset E and H since, as we show in the next section, price levels for both assets are statistically indistinguishable. The left panel shows that prices in all treatments trend slightly upwards. Prices in the PRIVATE treatment, as can be seen in the right panel, show most volatility within sessions. There, prices rise and fall considerably between periods. In contrast, prices change relatively little between periods in all treatments with information.

Most sessions exhibit average prices that are above the fundamental value. Even if the assets are undervalued in some sessions, these undervaluations are usually small. Overvaluations however can be substantial, reaching up to twice the fundamental value. Prices are closest to fundamental value in the INFO treatment, and apart from one session, also in the INFO-WIN treatment. In the INFO-LOSE treatment, prices vary most between sessions. In one session prices are persistently close to twice the fundamental value, in another they hug the fundamental value.



(a) Mean prices across treatments. (b) Mean prices by treatment and session.

Figure 2: **Time series of transactions prices.** Data are pooled between asset E and H. The panel on the left (a), shows mean transaction prices for each of the four treatments. Each time series corresponds to one treatment mean. Panel (b) on the right hand side plots 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.

5.2 Arrow-Debreu equilibrium

In this section, we test and discuss the results of the data in relation to the RSE outlined in Appendix A. The equilibrium posits three main results for rational, risk averse traders: the relative price of both assets should be one, and agents should hold riskless portfolios after trading. In addition, because there is no aggregate market risk, prices should equal the fundamental value.

First, the RSE dictates that all participants should hold a riskless portfolio after trading when there are no peer effects, i.e. in the PRIVATE treatment. While traders use the asset market to reduce their portfolio risk, average exposure in the PRIVATE treatment is 4.87. This deviation from theoretical prediction might be due to the presence of risk-seeking agents in which case the equilibrium predictions need no longer hold. Given that the risk-seeking trader will want to hold a risky portfolio, at least some risk-averse agents will also have to hold a risky portfolio, leading on average to non-zero exposure. According to their choices in the BRET there is a substantial number of risk-seeking traders in the PRIVATE treatment with 18 out of 50 traders being classified as risk seeking, and in each session there is at least one risk seeking trader. However, while the correlation between risk aversion and average exposure in the PRIVATE treatment is positive, it is insignificant (Spearman rank-correlation $\rho = 0.6$, p = 0.28). While this might be due to the test's low power with only 5 observations, using individual level data ($N = 200$) does not yield a significant correlation either.

Second, we evaluate relative prices, where the average transaction price per session constitutes a data point. To increase power, we use data from each period and session, i.e. all treatments, which is theoretically valid as equilibrium price predictions don't depend on social information. This leads to $N = 200$ observations. The hypothesis that the difference between mean transaction prices of asset H and E is zero cannot be rejected (Wilcoxon signed-rank test, $p = 0.62$). Also summary statistics show the similarities between both assert: average transaction prices are 62.7 and 63, median transaction prices 59, and 60 for asset H and E respectively.

Third, the price in terms of cash should be equal to the fundamental value. While both assets are priced correctly relative to each other, there is significant mis-pricing in terms of cash. Using the average transaction price of both assets jointly, the hypothesis that prices equal the fundamental value can be rejected (MWU, $p < 0.001$). In many sessions, prices are far above the fundamental value, in one session even double the fundamental value.

These deviations from the fundamental value are puzzling as they introduce opportunities for risk-reducing arbitrage. In case of prices above the fundamental value, agents can sell off any stock in their portfolio, and decrease their exposure. For risk averse agents, this is beneficial in two ways. It reduces the riskiness of their portfolio, and also increases its expected payoff. So rational agents should increase their supply of assets, which in turn would drive prices down - at least after some time.

The endowment effect can provide another explanation for the high price level. If agents suffered from the endowment effect, ask prices would be inflated relative to bid prices. Note however that high ask-bid ratios are not a sufficient statistic for the endowment effect, because this effect partially might be due to the curvature of the utility function. However we can construct a hypothetical benchmark that determines how much risk aversion might influence ask-bid ratios. For each level of exposure, we can calculate how much an agent would be willing to pay for a unit reduction of exposure and how much she would be willing to pay for a unit increase in exposure. The computations rest on the assumption that subjects have power utility, where the coefficient of risk aversion is implied by the BRET. The empirical ask-bid ratios are much larger than the ones implied by hypothetical computations (2.52 vs 1.09), a paired t-test shows this difference to be highly significant (p < 0.001). We interpret this as supporting evidence for the endowment effect.

Another possible explanation is that equilibria in continuous double auctions are typically not obtained instantaneously. As Asparouhova *et al.* (2011) show, there might many transactions that are optimal only locally, before the market reaches the RSE. These transactions do not necessarily take place at equilibrium prices. Sluggish equilibration thus provides one possible explanation for deviation of prices from equilibrium predictions initially, but does not explain their persistence across rounds.

Prices are not only high, but also very persistent. Figure 2 shows that even for sessions with high prices, there is no apparent downward trend. Statistically, the first transaction price in each session correlates highly with average prices, even if we exclude the first period from session averages ($\rho = 0.93$ and $p < 0.001$). The high correlations in prices are consistent with traders anchoring on the first transaction price. Baghestanian and Walker (2015) show that such anchoring plays an important role in (experimental) markets.[6]

Summary 1 *We observe substantial deviations from the risk sharing equilibrium. Portfolios in the PRIVATE treatment have an average exposure of 4.9. Although the relative price of assets is one, as predicted by equilibrium theory, prices often exceed the fundamental value substantially. Prices within sessions are highly correlated across periods, consistent with anchoring, and ask-bid ratios are very high, consistent with the endowment effect.*

5.3 The effect of peer information

We now turn to the effect of peer information, comparing the INFO treatments to the PRIVATE treatment with respect to both prices and exposure.

Exposure. As Figure 1a shows, in the first period mean exposure levels are comparable across treatments. After that, while exposure in the PRIVATE treatment stays roughly constant, we see a drop in exposure in the INFO treatment. In period 10, subjects in the INFO treatment have an average exposure of only 64% of those in the PRIVATE treatment (2.96 vs. 4.60). Similarly, 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 notable upward jump in the last period.

Statistically, there is a need to address the fact that observations in our sample are not independent between periods and within sessions. The most radical way to address this issue is to take means over all observations in a session, yielding 5 observations per treatment. To control for initial dynamics in the peer information treatments, we take averages over the last 5 periods only. A Kruskal-Wallis test with the null hypothesis that all treatment averages are drawn from the same distribution does not yield significant results ($p = 0.136$). However, a series of Mann-Whitney tests on differences between pairs of individual treatments, shows a significant difference between the PRIVATE and the INFO-LOSE treatment ($p = 0.024$).

A less radical way to deal with dependence is to run regressions where we take session means in every period to obtain an independent observation. Session specific effects can capture anything that is particular to a session over the course of the experiment. This analysis is presented in

[6] Both overpricing and persistence are consistent with Weber *et al.* (2000), who investigate very similar markets. They find higher overpricing when asset returns are framed as losses, but also find overpricing in the gain frame. This is consistent with the idea that an endowment effect is weakened, but not eliminated when returns are framed as gains, as in the present study.

column (1) of Table 3, where we interact treatment dummies with the period to capture the time trends that are apparent in Figure 1a.[7]

The INFO dummy takes the value of 1 in all the INFO treatments, so that the INFO-WIN and INFO-LOSE dummies only measure the additional effect of providing payoff comparisons. The results confirm the visual impressions and show that peer information significantly reduces exposure over time. In addition, highlighting the best performer in the INFO-WIN treatment increases exposure significantly. In fact, the time trend of exposure in this treatment is indistinguishable from the PRIVATE treatment. We test these differences using a standard F-test on the sum of the Period x INFO and Period x INFO-WIN variable ($p = 0.65$). Put differently, highlighting the best performer tends to undermine the exposure-reduction effects of peer information.[8]

The inclusion of session fixed effects means that we cannot include any session-specific control variables. In columns (2)-(4) we therefore conduct several random effects estimations which include control variables based on additional elicitation tasks.[9] This yields identical coefficients for the interactions between the period and treatments. Since period 10 is chosen as a base period, the treatment dummies in column (2) capture last period averages of exposure. They show that in the INFO treatment, subjects have on average 1.6 (36%) lower exposure than in the PRIVATE treatment, and most of this effect is eliminated if the highest earner is highlighted. These differences emerge over the course of the experiment, as captured by the time trends.

In column (3) we introduce the share of males in the group as a control variable, as this has been a focus of the previous literature (Eckel and Füllbrunn, 2015).[10] Although there is substantial variation, with the share of males varying between 20 and at most 60 percent, we do not find evidence of gender effects in any of our model specifications.

In column (3) we also introduce risk tolerance as measured with BRET. The variable "Relative bombchoice" takes session averages of BRET choice and subtracts the treatment mean. Given that the BRET was administered after trading concluded, not subtracting the treatment mean could pose an endogeneity problem, as we discuss in Section 6.3. Regardless whether measured relative to the treatment mean, or in absolute terms, risk tolerance has the expected effect of increasing exposure. However, the coefficient is only weakly significant.

[7]We also tested for dynamic panel structures using the GMM methods presented in Arellano and Bond (1991); Arellano and Bover (1995) and Blundell and Bond (1998). A univariate analysis of our main left-hand side variable (average exposure) shows no significant autocorrelation structure. We still included the lagged dependent variable into our regressions, using the appropriate GMM estimation methods. The lagged variable is never significant at a 10% level and has little to no impact on the significance of other variables. Hence, we focused on fixed- and random effects estimators. Regression-tables related to dynamic panel methods are not presented for the sake of brevity but can be made available upon request.

[8]If we exclude the last period where a large spike in exposure occurs, the coefficient for INFO-WIN is no longer significant ($p = 0.37$), so it is statistically indistinguishable from the INFO-treatment. However, the spike in the last period is not generated by the individual behavior of a few subjects and is preceded by yet another increase in average exposure levels between periods 8 and 9. Hence it is not clear whether the spike in the last period is simply an outlier, which we might want to control for, or reflects a treatment specific effect.

[9]A Hausmann test on the specification in Column 1 cannot reject that the null hypotheses that there are no systematic differences between the fixed and random effects coefficients ($p = 0.584$).

[10]However, in contrast to Eckel and Füllbrunn (2015) there is no room for inter-period speculation in our design, which could be the main source of gender specific effects in standard experimental asset markets.

	(1)	(2)	(3)
	FE	RE1	RE2
Period	-0.0189	-0.0189	-0.0189
	(0.0507)	(0.0486)	(0.0488)
Period x INFO	-0.142**	-0.142**	-0.142**
	(0.0657)	(0.0629)	(0.0633)
Period x INFO-WIN	0.172**	0.172***	0.172***
	(0.0628)	(0.0602)	(0.0605)
Period x INFO-LOSE	-0.0182	-0.0182	-0.0182
	(0.0702)	(0.0672)	(0.0676)
INFO (d)		-1.618**	-1.330**
		(0.677)	(0.533)
INFO-WIN (d)		0.940*	0.853*
		(0.530)	(0.476)
INFO-LOSE (d)		-0.237	-0.458
		(0.395)	(0.464)
Share Male			1.672
			(1.215)
Relative Bombchoice			0.212*
			(0.120)
Constant	3.749***	4.787***	3.917***
	(0.111)	(0.638)	(0.692)
Observations	200	200	200
R^2	0.112	0.145	0.233

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: 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, interactions of treatment dummies and the period variables. Columns (2) and (3) show results of random effect regressions. Column (2) introduces treatment dummies, column (3) session averages of gender and choice in the BRET task relative to the treatment mean. Period 10 is the base period. Standard errors clustered by session in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Prices. Testing for treatment differences in price levels, we use a series of MWUs, where we analyze all pairwise combinations of treatments and use mean session prices as data points. This yields no statistical evidence that prices vary systematically between treatments. However, these tests lack power, because we have only five observations for each treatment. Using period averages instead of session averages would yield additional observations, but would also lead to serious dependency issues as prices are highly persistent. In addition, there is no evidence that price levels have significant influence on either the number of transactions within a session or average session exposure (Spearman rank correlation $\rho = -0.22$, $p = 0.35$ and $\rho = 0.24$, $p = 0.30$ respectively).

Summary 2 *Average exposure drops significantly in the INFO and INFO-LOSE treatments relative to the PRIVATE treatment. By period 10 exposure is 36% lower in the INFO treatment than in the PRIVATE treatment. In the INFO-WIN treatment average exposure is more volatile over rounds and statistically indistinguishable from the PRIVATE treatment.*

6 Channels of peer influence

In this section, we analyze the data in the INFO treatments in more detail, in order to study the potential channels behind the peer effects as hypothesized in Section 3. In turn we will discuss observational learning, social preferences for relative income position, and spill-overs in risk preferences.

6.1 Observational learning

In this section, we investigate whether the drop in exposure in the INFO treatment is due to a specific kind of peer effect, namely observational learning. We use "observational learning" as a broad term to indicate the general influence of the observed portfolio choices of other subjects on participants' strategies. As such, imitation would fall in this category as well.

Strategy questionnaire. A first way to look at this kind of peer influence are the self-reports elicited in the strategy questionnaire, where we asked subjects about their trading strategies. Answers were provided on a three-point scale. Figure 3 shows the questions together with the distribution of answers in each treatment. Panel (a) shows that a majority of subjects tried to hedge at least part of the time, especially in the INFO treatments where about 95% of subjects say they try hedge at least sometimes. A Mann-Whitney test rejects equality of the answer distributions between the treatments INFO and PRIVATE ($p = 0.018$) and, marginally between INFO-LOSE and PRIVATE ($p = 0.088$) but not between INFO-WIN and PRIVATE ($p = 0.119$). Panel (b) shows that more subjects say they used speculative strategies (within period) in the INFO-WIN treatment than in the INFO treatment, but this difference is not statistically significant ($p = 0.145$). Panel (c) shows little difference between the INFO treatments in self-reported social influences; more than half of the subjects say they were influenced at least sometimes. Panel (d) shows that

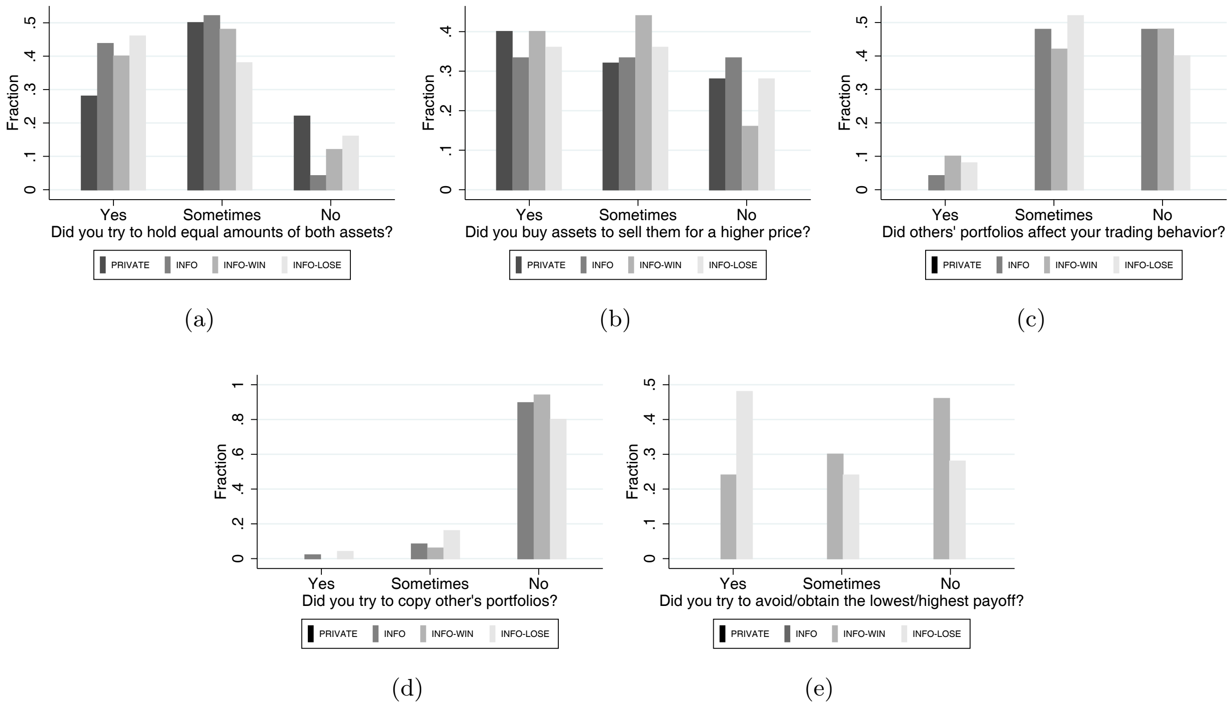


Figure 3: **Distribution of questionnaire answers by treatment.** Each panel shows mean answers elicited in a questionnaire after trading. Questions (a) and (b) relate to general trading strategies, hedging and arbitrage respectively. These questions were asked in each treatment. Questions (c) and (d) asked traders whether showing the portfolios of others influenced their behavior in general, and whether they actively tried to copy others' portfolios. These were only elicited in INFO treatments. Question (e) asked whether traders aspired to have the highest payoff in the INFO-WIN treatment, and whether traders avoided having the lowest payoff in the INFO-LOSE treatment.

few subjects attempt to copy portfolios. This is consistent with the idea that the structure of the assets is too simple for learning about fundamentals to play a large role. Panel (e) shows the answers to two different questions in the INFO-LOSE and INFO-WIN treatment. It reveals a striking difference, as the percentage of subjects who say that they sought to avoid the lowest payoff in the INFO-LOSE treatment is roughly double that of those who wanted to obtain the highest payoff in the INFO-WIN treatment.

Regression analysis. We use regression analysis to investigate the impact of previously observed portfolio choices by group members. As remarked in Section 3, we are specifically interested in seeing whether observing diversification strategies by others will lead participants to choose more diversification themselves.

In contrast to previous sections, the question of social influence cannot be addressed with aggregated session data so we turn to individual data. Analysis at the individual level cannot rely on exposure as a dependent variable, because due to the limited number of assets, observations of exposure are not independent. To overcome this dependency we construct a binary measure of low exposure, according to the following formula:

$$\text{Low Exposure}_{i,t} = \begin{cases} 1 \text{ if exposure}_{i,t} \leq 1 \\ 0 \text{ otherwise.} \end{cases} \tag{1}$$

Here, exposure refers to end of period exposure, i denotes the subject, t the current period, and a value of 1 signifies that exposure was low. Any subject has *Low Exposure* in a given period if her exposure was at most 1. This threshold is chosen, because it is the lowest threshold that still solves the problem of mechanical dependency.[11] All our results are qualitatively robust to choosing a threshold of 2 or 3.

As our independent variable, we construct an index that captures how often a trader could observe peers having *Low Exposure*. Each instance of *Low Exposure* in the peer group is treated symmetrically, regardless of peer identity or period:

$$\text{Low Exposure Group}_{i,t} = \frac{1}{t-1}\frac{1}{N-1}\sum_{j \neq i}^{n}\sum_{\tau=1}^{t-1}\text{Low Exposure}_{j,\tau} \tag{2}$$

where again i denotes the subject, and t is the current period, moreover N is the group size and group members are indexed $1, .., n$. When it comes to periods, our results are robust to using autoregressive or a moving-average-process specifications, in which more recent periods have greater weight.

With respect to the asymmetry of peer observations, in the INFO-WIN and INFO-LOSE treat-

[11] Consider the following example. Nine subjects within a period are classified as having *Low Exposure*. If the threshold for *Low Exposure* is an exposure of 0, these nine subjects would all have an exposure of zero implying zero exposure for the tenth subject as well. If the threshold is 1, the tenth subject can either have *Low Exposure*, or not, regardless of the other nine having *Low Exposure*.

	(1) ALL	(2) INFO	(3) INFO-WIN	(4) INFO-WIN	(5) INFO-LOSE	(6) INFO-LOSE
Low Group Exp	-0.162*	-0.309**	-0.00626		-0.150	
	(0.0766)	(0.0700)	(0.170)		(0.121)	
Low Exp Stars				0.584*		-0.0883*
				(0.250)		(0.0391)
Period	0.0166***	0.0179*	-0.00432	-0.0156	0.0161	0.0141
	(0.00532)	(0.00674)	(0.00776)	(0.0112)	(0.00969)	(0.00977)
Period x INFO-WIN	-0.0206**					
	(0.00887)					
Period x INFO-LOSE	-0.000330					
	(0.00999)					
Constant	0.412***	0.468***	0.323***	0.207**	0.431***	0.395***
	(0.0302)	(0.0402)	(0.0605)	(0.0700)	(0.0543)	(0.0398)
Observations	1332	432	450	450	450	450
R^2	0.007	0.015	0.001	0.011	0.007	0.007

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 4: Fixed effect regression with clustered standard errors in parenthesis. Low exposure is the dependent variable. Low exposure is 1 if exposure is smaller or equal than 1. Column (1) shows results for all treatments. Column (2) for the INFO treatment, columns (3) and (4) for the INFO-WIN treatment and columns (5) and (6) for the INFO-LOSE treatment. Low Group Exp is the average of past observed low exposure within group. Low Stars Exp is the average of low observed exposure by subjects with most stars. Period 10 is the base period. Standard errors clustered by session in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ment, where symbolic stars next to their portfolio make some subjects more salient for their peers. We therefore construct another variable for these treatments analogous to *Low Exposure Group*. The variable *Low Exposure Stars* aggregates the number of instances that subjects with most stars had *Low Exposure*. We again take averages over periods, and in case multiple subjects had most stars, we also average by the number of subjects with most stars. Furthermore, we assume that subjects with most stars are not influenced by others.

Table 4 shows results from regressions of low exposure on variables of social influence. In column (1) results for all treatments are presented. On average, observing low exposure among peers, makes subjects less likely to have low exposure themselves. This contrarian peer influence is driven by observations from the INFO treatment, as shown in column (2) which features data from the INFO treatment only. By contrast, if we focus on the INFO-WIN column (3) or INFO-LOSE column (5) treatments in isolation, the effect is smaller and insignificant. Although the effect in the INFO treatment implies that peer portfolios matter, it does not provide an intuitive explanation for the drop in exposure in this treatment.

Nevertheless, we observe marginally significant social influence in both the INFO-WIN and INFO-LOSE treatment. Columns (4) and (6) show that participants in these treatments react to the portfolio choices of peers with most stars, instead of the average peer. In the INFO-LOSE treatment, subjects behave dissimilar to those who had the lowest payoff repeatedly. If those who received most stars in the INFO-LOSE treatment had low exposure, their peers are ceteris paribus less likely to have low exposure themselves. Since the lowest earners in each treatment typically had high exposure, this effect implies a reduction in risk taking. Conversely, in the INFO-WIN treatment, subjects tend to behave similar to those who gathered many stars. If those subjects with most stars had low exposure, their peers are more likely to have low exposure themselves. This latter result is in line with an "imitation of the luckiest", as in Offerman and Schotter (2009), and implies an increase in risk taking.

Summary 3 *Participants are influenced by their peers' history of exposure. A majority in the INFO-treatments self-reports to be influenced by others' portfolios. In the INFO-treatment, participants are less likely to have low exposure if their peers had low exposure. In the INFO-WIN treatment participants are more likely to have low exposure if their peers with most stars held portfolios with low exposure. In the INFO-LOSE treatment, this influence is reversed.*

6.2 Preferences for relative income

We now analyze the effects of preferences for relative income in the INFO-WIN and INFO-LOSE treatments. Here subjects were confronted with explicit rankings and symbolic recognition was given to the best and worst performers in each round. In the introduction, we identified two different theories of positional preferences with different behavioral implications, which we test in turn.

Conformism. The first theory, expanded in Appendix A is based on a general equilibrium model where agents experience disutility from earning less than their peers. This theory predicts conformism within peer groups, because it is impossible to fall behind the others only when you have the same portfolio as your group members. Applied to our setting, we would expect that subjects have a more similar portfolio within groups than across groups. This effect should be especially strong in the INFO-LOSE treatment, where earning less than the others is made salient.

To investigate this hypothesis, we provide a measure of similarity by decomposing the total empirical variance of exposure in each session in within group and between group variance: For the PRIVATE treatment, where no groups were formed, we randomly assign participants to "groups" ex-post in order to conduct our comparisons.

Within group variance is highest in the PRIVATE and INFO-WIN treatments, but this difference may simply reflect the higher exposure in those treatments. This suspicion is confirmed when we analyze within group variance as a share of total variance. There are no differences between treatments in this measure, and no significant drive towards conformism over time in any of the treatments. Moreover, in all treatments about 90% of all the variation is within groups rather than between groups.

Summary 4 *We do not find evidence for conformism, as variance of exposure within groups as a share of total variance of exposure shows no difference between treatments.*

Competition for income rank. The second theory of positional concerns is that subjects compete for income rank, either by trying to avoid being the lowest earner in the INFO-LOSE treatment, or by trying to be the highest earner in the INFO-WIN treatment. As we mentioned in Section 3, this is consistent with higher risk taking in the INFO-WIN and lower risk taking in the INFO-LOSE treatment, which we observe in our data.

A first piece of evidence that there was competition for income ranks comes from the strategy questionnaire. Panel e) shows that more than half of the subjects tries 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 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 (MWU, $p = 0.025$).

Furthermore, we can use the exogenous variation in the starting portfolios to look at competition for ranks. At the beginning of each period each subject randomly obtains either a portfolio with 10 E assets and 0 H assets or a portfolio with 10 H assets and 0 E assets. We can exploit the fact that occasionally, all 5 subjects in a group have the same portfolio (and traders in the other groups all hold opposite portfolios). To see how this works, suppose all subjects initially hold 10 E shares. In this case, a subject in the INFO-WIN treatment who manages to diversify more than his peers will have both lower risk *and* increases his chances of being the highest earner (namely when the state is "cold" and the H shares pay out). Thus, we would expect subjects to decrease their exposure more in the INFO-WIN treatment. By contrast, in the INFO-LOSE treatment, a subject who reduces exposure more than his peers reduces income risk, but increases the risk that she will be the lowest earner when the E 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.

	(1) FE	(2) RE1
Period x INFO	-0.166***	-0.167***
	(0.0465)	(0.0442)
Period x INFO-WIN	0.177**	0.177***
	(0.0635)	(0.0605)
Period x INFO-LOSE	-0.0101	-0.0103
	(0.0749)	(0.0720)
All equal spf x INFO (d)	0.406	0.423
	(0.874)	(0.827)
All equal spf x INFO-WIN (d)	-1.762*	-1.797**
	(0.897)	(0.858)
All equal spf x INFO-LOSE (d)	-0.630	-0.615
	(0.897)	(0.858)
INFO-WIN (d)		1.025*
		(0.579)
INFO-LOSE (d)		-0.206
		(0.475)
Share Male		0.231
		(1.492)
Constant	3.416***	3.047***
	(0.136)	(0.559)
Observations	150	150
R^2	0.161	

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 5: 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. In column (2), additionally, we introduce a dummy variable "All equal spf" that is equal to 1 if everybody within an exogenous references group had the same starting portfolio and 0 otherwise and interact it with treatment dummies. Period 10 is the base period. Standard errors clustered by session in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In column (1) of Table 5 we run a fixed effect regression on the INFO treatments, including a dummy variable "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 almost two 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. These same results hold in the random effects regression in column (2), where we add treatment dummies and a gender control variable.

Summary 5 *When all subjects in the peer group have the same starting portfolio, average exposure is reduced by 1.8 units in the INFO-WIN treatment, consistent with a desire to come out ahead of the others.*

6.3 Peer influences in risk attitudes

The fact that the bomb risk elicitation task (BRET) took place after the experimental market, means that we can study the influence of market conditions and outcomes on risk attitudes. We don't have specific hypotheses on these influences, as there is little theory available about the determinants of risk attitudes. However, as we mentioned in the literature section, an emerging literature that shows previous market experiences can have a lasting influence on risk perceptions.

Figure 4 shows the results of the BRET across treatments, where the horizontal axis displays the number of boxes collected. Crosetto and Filippin (2013) show that a risk neutral person who maximizes expected utility should collect exactly half of the boxes, 18 in our case, and that collecting more boxes corresponds to a risk loving attitude. The graph shows that the majority of subjects is risk averse in all treatments, but less so in the PRIVATE treatment. A Mann-Whitney test rejects the null hypothesis that the distribution of bomb choice in the PRIVATE treatment is identical to the distribution in the INFO ($p = 0.086$), the INFO-WIN ($p = 0.064$) and the INFO-LOSE ($p = 0.0076$) treatments.

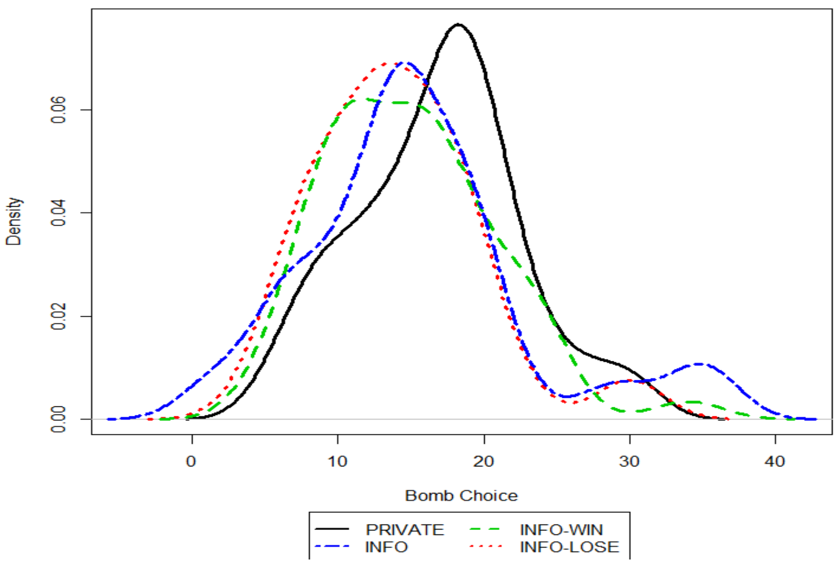


Figure 4: **Kernel density estimates for the Bomb Risk Elicitation Task (BRET)**, Crosetto and Filippin (2013). Estimates are made separately for each treatment. Higher numbers in the BRET signify a higher tolerance for risk. Risk neutrality corresponds to a choice of 18.

Table 6 reports the results of multivariate OLS regressions of risk attitudes on market conditions.[12] In column (1), we run a regression of the number of individual boxes gathered on treatment dummies and confirm that subjects in the INFO treatments collect on average about 2.6 boxes less, which represents a drop of 15% relative to the mean of the PRIVATE treatment (16.8 boxes). In column (2), we add controls for gender and individual market behavior, including average exposure

[12]Note that for 7 of our 198 participants individual BRET measures are missing, since the experimental software malfunctioned. These malfunctions seem to have occurred randomly and are not clustered in specific sessions. We have no reason to think that these seven randomly distributed missing observations bias our results.

	(1)	(2)
INFO (d)	-2.593**	-2.427**
	(1.128)	(1.185)
INFO-WIN (d)	0.750	0.726
	(1.144)	(1.173)
INFO-LOSE (d)	-0.189	-0.228
	(1.137)	(1.140)
Asset market profit		-0.00143
		(0.00154)
Avg. Exposure		0.0699
		(0.186)
Male		0.257
		(0.819)
Constant	16.76***	17.67***
	(0.816)	(2.044)
Observations	191	191
R^2	0.038	0.045

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 6: The dependent variable is choice in the BRET. All columns show the results of OLS regressions. All sessions are included. The independent variables in (1) are treatment dummies. In column (2), we additionally control for gender, earnings in the asset market and average subject exposure. Individual robust standard errors in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

over the 10 trading rounds, and realized market earnings, which had been communicated to subjects just prior to the elicitation. Column (2) shows that it is the availability of peer information, not market outcomes that influences risk attitudes.

Note that both the qualitative and quantitative estimates of the effect of information on risk attitudes mirror those of the exposure levels in the market, suggesting that shifts in risk preferences may play a role in the treatment effects in exposure. However, the individual correlation between risk preferences and exposure is low, so it is unlikely that changes in risk attitudes are the only driver of reduced exposure in the INFO treatments.

Summary 6 *Peer information in the market affects the willingness to take risk afterwards. Participating in a market with peer information causes subjects to become more cautious.*

7 Discussion and Conclusion

Gathering evidence from the previous sections, we can now answer our research questions from Section 3. Research Question 1 concerns the degree of diversification in our novel markets. We find that although 90% of subjects in the PRIVATE treatment use the market to diversify risk, about half of the initial exposure remains undiversified. This finding is in line with field evidence that actual portfolios of American investors display significant under-diversification (Goetzmann and Kumar, 2008). Given the simple asset structure in our experimental market, our results suggests that lack of information amongst investors is not the (only) driver of such under-diversification.

In the PRIVATE treatment we find imperfect risk sharing and overpricing of both assets, which is in line with earlier studies. The strong autocorrelations of prices within sessions is not necessarily inconsistent with equilibrium theory, but suggests that subjects are unsure of their valuations and anchor on early, partly arbitrary transaction prices. This interpretation is in line with the evidence in Baghestanian and Walker (2015), and implies that market outcomes will typically exhibit strong path dependencies. Moreover, the fact that asset prices start and remain substantially above fundamental value suggests an endowment effect that hampers risk sharing, in line with Weber *et al.* (2000).

Turning to Research Question 2, which concerns the effects of peer information on market outcomes, we observe that information about the portfolios of others increases risk sharing and reduces the variance of earnings in our experimental markets. Our analysis does not point at a "smoking-gun", or a single explanation for this peer effect. Instead, our results indicate that a number of mechanisms may be at work. First, we find that observed portfolios of others affect trading strategies. Although we did not uncover a direct connection of diversification strategies by different group members, our results show that many subjects regard the choices of others as relevant.

Second, we find that risk attitudes are affected by information conditions. Subjects who were exposed to peer information behave more cautiously even after the market has ended. Both the qualitative and quantitative estimates of the treatment effects in risk attitudes mirror those of the exposure levels in the market. This suggests that the interplay between risk attitudes and peer behavior is potentially a two-way process: decreasing exposure levels by peers may lower individual willingness to take risk and vice versa. The nature and timing of our measurements limits further interpretations, but we believe this is an important topic for future research, also in light of previous results showing the importance of market experience in risk attitudes (Cohn *et al.*, 2015).

Concerning Research Question 3, we find that the framing of social information matters for market outcomes. When the best earning trader in the peer group is highlighted, exposure levels are indistinguishable from the no-information case. This is driven by preferences to come out ahead of other players, as is apparent in self-reported descriptions of trading strategies, regressions of portfolio choices based on observed choices of others, and a tendency to "imitate the luckiest".

By contrast, in the condition where the lowest earning trader is highlighted, we find a tendency to move away from the risk levels chosen by the worst earning subjects in previous rounds. Since the latter subjects typically took on substantial risk, such a strategy implies an increase in diversification. Given the large amount of subjects reporting their desire to avoid the last place in the INFO-LOSE treatment, it is possible that such dynamics are at work in the INFO treatment too, despite the absence of explicit rankings. Subjects in the INFO treatment may have figured out over time that a simple strategy of diversifying more than the others minimizes the chance of coming out last.

Our finding that peer information reduces risk taking is in contrast with most of the (experimental) finance literature, which associates social aspects of trading with increased volatility and price bubbles. For example, the experimental literature about financial markets has linked bubble formation to social learning (Bikhchandani *et al.*, 1992; Anderson and Holt, 1997) and the presence of tournament incentives (James and Isaac, 2000; Cheung and Coleman, 2014). We provide a counterweight to these approaches, and our findings mesh well with those of Oechssler *et al.* (2011) who find that communication actually reduces price bubbles.

Our results suggest not only that peer effects are pervasive in financial markets, but that they affect portfolio choices through several different channels, some of which may lead to more, and others to less risk taking. This complexity is mirrored in discussions of peer effects in real world markets. For example, Shiller (2005) argues that peer effects were largely responsible for the rise in stock market participation in the 1990s and the resulting increase in risk taking. On the other hand, Heaton and Lucas (2000) show that the bubble coincided with a rise in mutual fund investment and an associated increase in diversification. Guiso and Jappelli (2005) and Georgarakos and Pasini (2011) show that mutual fund investment is itself predicted by the degree of an investors' social interactions. Thus, these two simultaneous trends demonstrates that peer influences have complex and possibly contradictory effects on risk taking.

When it comes to harnessing peer effects for financial stability and risk sharing, our results offer a ground for both hope and caution. Although we show that information about others' trades can reduce exposure, the results depend crucially on how this information is presented. The results of the INFO-WIN treatment suggest that an investment climate that emphasizes success stories and spectacular profits will likely result in higher aggregate exposure than a focus on the fortunes that are lost in stock investment. This insight applies to newly emerging social trading platforms that allow individual investors to observe portfolios of peers and enable them to mimic compelling exposure levels. Our results indicate that these networks may, in principle, reduce under-diversification and act as stabilizing factors for financial markets. However, our findings also suggest that this beneficial aspect can be undermined if social trading platforms emphasize the best short-term performing portfolio, as they in fact tend to do.[13] Our study indicates that an additional spotlight on the worst short-term performing traders or portfolios may contribute to better risk sharing among social traders.

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[13]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.

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Appendix A: General Equilibrium with Social Preferences

Here we model an economy that resembles our experimental setup. Consider an endowment economy with a continuum of agents on $[0, 2]$. There are 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. We denote by $x_i = (x_{1i}, x_{2i})$ the state contingent commodity vector of agent i.

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 'red agent' has an endowment of $\omega_r = (1, 0)$ and every 'blue agent' has an endowment $\omega_b = (0, 1)$. The utility of agent i who belongs to group g_i is given by

$$V_i = E\left[u\left(x_{si} - \alpha \int_{g_i} (x_{sj} - x_{si})\mathbf{1}_{x_{sj} > x_{si}} \mathrm{d}j\right)\right], \tag{3}$$

where $u()$ is concave and differentiable and x_j is the consumption of the other agents in i's peer group. Thus, the second term in the utility function represents social preferences: agents are envious when they consume less than their peers 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. This utility function is equivalent to the social preference model of Fehr and Schmidt (1999) (where the guilt parameter β is set to zero for simplicity). Note that we assume for simplicity that all agents have the same social preferences.

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 utility function 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.[14]

Equilibrium

Suppose now that agents can trade assets for prices p_1 and p_2. We consider (symmetric) competitive equilibria (CE) of the economy:

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

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

Thus, each agent i solves the following problem:

$$\begin{aligned} &\max_{x_{1i},x_{2i}} \frac{1}{2}u(x_{1i} - \alpha \int_{g_i} (x_{1j} - x_{1i})\mathbf{1}_{x_{1j}>x_{1i}} \mathrm{d}j) + \frac{1}{2}u(x_{2i} - \alpha \int_{g_i} (x_{2j} - x_{2i})\mathbf{1}_{x_{2j}>x_{2i}} \mathrm{d}j) \\ &\text{s.t} \quad px_i \leq p\omega_i. \end{aligned}$$

We obtain the following result

Proposition 1 *The economy has a range of CE's characterized by $p_2 = p_1 = 1$ and $\frac{u'(c_{2r}^*)}{u'(c_{1r}^*)} = \frac{u'(c_{1b}^*)}{u'(c_{2b}^*)} = x$, for $x \in \left[\frac{1}{1+\alpha}, 1+\alpha\right]$.*

Proof of Proposition 1. We focus on symmetric equilibria in which all red agents consume $c = \bar{c}_r$. We use the budget constraint of the red agent, which using Walras law yields: $x_{2r} = \frac{p_1}{p_2}(1 - x_{1r})$. Now it is optimal not to switch consumption to state two if:

$$\begin{aligned} & -\frac{1}{2}u'(\bar{c}_{1r})(1+\alpha) + \frac{p_1}{p_2}\frac{1}{2}u'(\bar{c}_{2r}) \leq 0 \\ \Leftrightarrow \quad & \frac{p_1}{p_2}\frac{u'(x_{2r})}{u'(x_{1r})} \leq 1+\alpha \end{aligned}$$

Conversely it is not optimal to switch consumption to state one if:

$$\begin{aligned} & -\frac{1}{2}u'(\bar{c}_{2r})(1+\alpha) + \frac{p_2}{p_1}\frac{1}{2}u'(\bar{c}_{1r}) \leq 0 \\ \Leftrightarrow \quad & \frac{p_2}{p_1}\frac{u'(x_{1r})}{u'(x_{2r})} \geq \frac{1}{1+\alpha} \end{aligned}$$

[14]There are 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 pure procedurally, but will hold qualitatively if their utility is a mixture of procedural and inequality concerns, as proposed by Saito (2013).

So every equilibrium satisfies:

$$\frac{1}{1+\alpha} \leq \frac{p_1}{p_2} \frac{u'(x_{2r})}{u'(x_{1r})} \leq 1+\alpha$$

Analogous reasoning holds for blue agents.

Let $p_1 = p_2$ and consider an allocation for which $\frac{u'(x_{2r})}{u'(x_{1r})} = x$ for some $\frac{1}{1+\alpha} \leq x \leq 1+\alpha$, so this an optimum for the red agent. It follows from the budget constraint, that $x_{1r} = 1 - x_{2r}$. Moreover, the feasibility condition implies that $x_{1b} = 1 - x_{1r}$. Together, this implies that $\frac{u'(x_{2b})}{u'(x_{1b})} = \frac{1}{x}$. Since $\frac{1}{1+\alpha} \leq x \leq 1+\alpha$ implies $\frac{1}{1+\alpha} \leq \frac{1}{x} \leq 1+\alpha$, the allocation is optimal for the red agents. Since demand for both goods is the same, $p_1 = p_2$ clears both markets and which establishes the existence of a range of CE. ■

Proposition 1 says that there is a range of symmetric equilibria. This multiplicity is caused by the existence of the consumption externality. The externality causes a kink in the agent's utility functions at the level of the peer group's consumption, so the optimal choice depends on the choices of the others.

In particular, since x may be different from 1, 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. These equilibria occur because an agent who deviates towards a more balanced portfolio may reduce his income risk, but will increase his social risk since he 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 agents are better off ex-ante (have a higher expected utility) in the perfect risk sharing equilibrium.

Corollary 1 *For $\alpha = 0$, the economy has a unique equilibrium characterized by $p_2 = p_1 = 1$ and $x_{1r} = x_{2r} = x_{1b} = x_{2b}$, i.e. perfect insurance.*

This result depends on the strong assumption that utility is concave in own consumption for all agents, so that they are averse to consumption risk. In the absence of social risk, any allocation that featured asymmetric portfolios would therefore imply the existence of a mutually beneficial trade. More realistic assumptions that allow for heterogeneity in risk preferences would lead to more complicated equilibria.

Appendix B: Additional Tables

	All	PRIVATE	INFO	INFO-WIN	INFO-LOSE
Sessions	20	5	5	5	5
Participants	198	50	48	50	50
Male	87	26	17	20	24
Avg. Exposure	4.13	4.87	3.85	4.06	3.74
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 7: 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.