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Peer Effects and Risk Sharing in Experimental Asset Markets

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Non-Technical Summary

Peer effects and social influences play an important role in financial markets. Nobel prize winner Robert Shiller wrote in 1993 “[i]nvesting 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.”

Nowadays, technology allows traders to actively seek each other’s influence. One online platform, eToro, lets members not only engage in financial trading, but also follow other members’ activity. Indeed, every trade is made public on their website and tied to a profile name. Social trading platforms are growing rapidly. Memberships rose to 3 million customers in the case of eToro, similar platforms like Zulutrade and Currensee are also experiencing substantial growth.

This study is about the importance of social influence on experimental asset markets. The experimental markets are computerized, student subjects trade with each other and are paid according to their earnings in the market.

The study is conducted in the laboratory, as using field data to achieve a clean statistical identification of social influence is difficult for individual behavior, and nigh impossible for aggregate outcomes. In particular, when observing similarity between individual and group behavior, the reason might be twofold. First, individuals may be influenced by other group members. So, the change in behavior would indeed be due to social interaction. Second, the individual is a member of a specific peer group, because he shares characteristics with other group members. For example, groups of friends often share interests and hobbies or have similar occupations. This self-selection might also lead to similar behavior. The experimental environment allows us to construct groups of people at random to rule out the second possibility.

We are interested in the impact of social influence on an essential function of markets, namely that both parties can trade assets to mutually insure each other. This allows subjects who prefer safe to risky portfolios to use the market to improve upon their initial position. The more subjects take advantage of that opportunity, the better markets work. This study shows that the degree of social influence affects the proper functioning of financial markets as a device to share risk efficiently.

The degree of social influence in our experiments varies between four different conditions. Traders in the first condition have no information about each other, in three other conditions there is scope for social influence. In the second condition, subjects observe the portfolios of others while they are trading. Either the highest or the lowest performer is publicly announced in the third and fourth condition. Apart from these manipulations, social interaction is minimal throughout the experiment. Subjects are not allowed to communicate with each other. This allows us to see whether simply observing the trades and portfolios of others affects behavior.

The results show that displaying information about others leads to less risky portfolios. By the end of the experiment, subjects in the condition with information bear on average 36 % less risk. Highlighting the worst performer, on top of information about others, leads to even less risk taking. On the contrary, announcing the best performer reverses these results. Portfolios in this condition are, on average, as risky as in the condition without information.

Our results show that information about what others are doing has a big influence on the outcome of experimental markets and may lead to more efficient outcomes. However, much depends on the way the decisions of others are presented. Putting a lot of emphasis on the best performers might lead to more risk taking and, in our setting, worse outcomes for participants. By contrast, highlighting those hurt by risk taking leads to better diversification in the market. These findings are important to keep in mind when one wants to create a prudent investment culture, either in a company or an online trading platform.

Peer Effects and Risk Sharing in Experimental Asset Markets*

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Abstract

Previous research has documented strong peer effects in risk taking, but little is known about how such social influences affect market outcomes. Since the consequences of social interactions are hard to isolate in financial data, we design an experimental asset market with multiple risky assets and study how exogenous variation in real-time information about the portfolios of peer group members affects aggregate and individual risk taking. We find that peer information reduces under-diversification through changes in risk attitudes that last beyond the market environment. The effect of information depends on its framing: highlighting the highest earning trader increases willingness to take risk and average exposure in the market. Our results show that peer information is an important determinant of earnings volatility in financial markets, and we discuss implications for institutional design.

JEL-codes: D53, D83, G11.

Keywords: peer effects, laboratory experiments, risk taking, asset markets.

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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. Others' portfolio choices may transmit investment information through social learning or their earnings 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 trader's portfolios. Such networks are enjoying a fast growing membership of 'social traders'.[1] Simon and Heimer (2012) show that trading on social platforms is characterized by substantial peer effects.

More generally, a nascent literature on social aspects of financial decision making, reviewed in more detail below, has confirmed the importance of peer influences in portfolio choice and individual decision under risk. Despite this recognition, we know little about the effects of social influences in risk taking on market outcomes. 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 produce market equilibria with both high and low levels of risk taking.

In this paper, we investigate novel experimental markets with multiple risky assets designed to allow for variation in individual and aggregate risk taking. In these markets, we study the impact of information about the portfolios of a randomly composed peer group. 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. 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 clean evidence of peer effects on individual and aggregate risk taking in the market. 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*. We show that in the presence of positional concerns, our markets may exhibit multiple equilibria that vary in the degree of risk taking. At the same time, our design controls for well-studied

[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.

peer effects related to information cascades and herding, as the fundamental value of assets and market structure are common knowledge amongst participants.

Our main result is that availability of information about the portfolio's of peers increases diversification and lowers average risk taking, measured by portfolio exposure, by 36% at the end of the experiment relative to the no-information case. Relative performance concerns matter: Exposure is lowest on average when the lowest earning trader is highlighted at the end of each round. By contrast, when the highest earning trader is highlighted, aggregate risk taking does not differ significantly relative to markets without information. We find that these effects of peer information operate through a shift in risk attitudes as measured on a separate task. This shift in risk attitudes is sufficiently strong that it outlasts the market environment.

To our knowledge, this is the first examination of peer information and aggregate risk taking in a controlled market environment. Contrary to conventional wisdom, we show that social interactions may help to improve portfolio diversification and reduce risk taking in financial markets. Thus, together with the previous literature, our results suggest that peer influences have complex effects in financial markets, highlighting the importance of the nascent field of 'social finance' (Han and Hirshleifer, 2013; Hirshleifer, 2014). Moreover, as we discuss in more detail in the conclusion, we believe our results have implications for corporate governance. For example, they suggest that highlighting the actual losers from risky investment strategies within organizations or on social trading sites can help foster a prudent investment culture.

Our results contribute to several strands of literature on the social aspects of portfolio choice in both finance and economics. First, there is a sizable literature in finance on peer effects 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 (Kelly and Gráda, 2000; Hong *et al.*, 2005; Shive, 2010; Hackethal *et al.*, 2014) and risky lifestyle choices (Card and Giuliano, 2013). While these field 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. 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. There is evidence from the lab (Lahno and Serra-Garcia, 2015), the field (Bursztyn *et al.*, 2014) and neuroeconomics (Bault *et al.*, 2011) that both learning and income comparisons are responsible for the observed peer effects.

Our paper builds on this literature and goes a step further by looking at the consequences of peer effects on market outcomes. While our study is not designed to identify the exact nature of peer effects, we do find that positional preferences play a role for aggregate risk taking. Moreover, we identify a novel channel of peer influence via shifts in risk attitudes, contributing to an emerging literature on the determinants of risk aversion (Mengel *et al.*, 2014; He and Hong, 2014; Cohn *et al.*, 2015).

We also contribute to the literature on experimental asset markets. This literature has hardly considered peer information, with the exception of Schoenberg and Haruvy (2012) and Oechssler *et al.* (2011), who study the effects of information within the design of Smith *et al.* (1988). 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. The authors observe that communication among peers reduces price bubbles, and suggest that communication with others reduces overconfidence about own abilities.

Compared to these studies, our work considers a different and new market environment that that allows us to ask different questions. First, as portfolios are reset in our experiment in each period, there is no scope for speculation across periods – one source for the formation of bubbles in experimental asset markets. Instead, we focus on diversification and risk taking. Second, we give participants portfolio information during the trading period, which allows them to condition their portfolio choices on those of others. Third, traders do not differ in terms of information on dividend realizations.

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 (e.g. Charness and Rabin, 2002; Luttmer, 2005), 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 section, we describe our research questions and the chosen methodology in more detail. We then explain the details of the design in Section 3 and present our results in Section 4. Section 6 discusses the interpretation of the results and potential implications.

2 Research Questions and Methodology

While the literature cited above demonstrates convincingly that peer effects exist, it does not tell us much about their implications. 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.

Most studies on experimental asset markets are concerned with the price formation of risky assets within the canonical design of Smith *et al.* (1988). However, this standard design is less suitable to study aggregate risk taking and sharing in markets, as risk can only be transferred, not diversified. Therefore, we design a novel market for several risky assets with negatively correlated returns, which allows traders to share risk perfectly. The asset structure is exceedingly simple, which makes the risk sharing strategy salient to the participants and relevant as a theoretical benchmark. In addition, since participants have full information about the market structure and the fundamental value of the assets, there is no scope for herding or information cascades. Finally, our markets provide a natural measure for aggregate exposure or risk taking, facilitating comparisons across experimental conditions.

Before we turn to the effects of peer information, we establish a benchmark in our market environment by investigating trading when subjects only care about private earnings. In Appendix A, we provide a general equilibrium analysis of our markets under these conditions. We show that when all traders are weakly risk averse, the market has a unique equilibrium that features perfect risk sharing. Using the equilibrium prediction as a benchmark, we can study the degree and determinants of under-diversification, which is also found in the portfolios of real-world investors (Goetzmann and Kumar, 2008). While this is an important feature in financial markets that can we be well studied by experiments, there is little research in this area.[2] Our first research question is thus as follows.

Research Question 1 *To what extent do participants use markets to reduce risk and diversify their portfolio?*

A condition without peer information is useful to address this question not because it is necessarily the most realistic (in fact, we argued that it is not), but because the lack of peer information means that subjects can focus entirely on the risk profile of their portfolio.

Our second and main research question concerns the effect of peer information.

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

To answer this question we compare an asset market with private information with a market where traders have information about the portfolios of a selected group of 'peers'. In this treatment, we do not provide salient payoff rankings or income comparisons. Therefore, there are no clear reasons to hypothesize ex-ante that peer information will have an effect on market outcomes.

[2] Bossaerts *et al.* (2007) test and reject the prediction that subjects hold a multiple of the market portfolio. Camerer and Kunreuther (1989) study an experimental insurance market and find that insurance prices approach expected value.

In the field, payoff comparisons are sometimes very salient. 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'). Fehr and Schmidt (1999) have modeled such motivations of 'envy' or relative income position. In Appendix A we provide a general equilibrium analysis based on this model, where we examine the effect of such preferences on (symmetric) competitive equilibria in our markets. We show that if people derive disutility from earning less than the group average ex-post, there exist multiple competitive equilibria that differ in the degree of aggregate risk taking.[3] The reason is that while in equilibrium people have more income risk, deviating from the group portfolio exposes the decision maker to a greater 'social risk' that she will end up earning less than the others. When people derive utility from having more than others, it is easy to show that no (symmetric) equilibria exist.

Thus, mainstream social preference models suggest that peer information may have a positive effect on risk taking in equilibrium. However, the existence of multiple equilibria invites an empirical investigation. This leads us to the following question:

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?*

To answer this question, we conduct two treatments in which we provide payoff rankings at the end of each trading period, and provide symbolic (i.e.: non-financial) rewards for either the best or the worst performer.[4] The evidence on the importance of peer comparisons leads us to believe that an emphasis on the best or worst performer will have different effects. Specifically, a recent paper by Kuziemko *et al.* (2014) provides evidence that people want to avoid occupying the last place in the earnings ranking. In our setting, subjects can do so by choosing a portfolio that has less extreme exposure than that of others. Thus, one may expect aggregate risk taking to go down compared to the case where no performance rankings were given.

There is also evidence that people change their choices under risk to come out ahead of others. Roussanov (2010) argues theoretically that a desire to get 'ahead of the Joneses' leads to less diversified portfolios. Both Fafchamps *et al.* (2014) and Dijk *et al.* (2014) show 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) shows that subjects "imitate the luckiest", which may lead to a proliferation in risk taking strategies. In our setting, taking more risk increases the chance of earning the most, so we conjecture that

[3]This 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 with a temporal dimension.

[4]Our focus on symbolic rewards, the differences in the structure of the market and our focus on risk sharing distinguish this study from the literature of tournament incentives and asset markets (James and Isaac, 2000; Robin *et al.*, 2012; Cheung and Coleman, 2014).

aggregate exposure will increase in the market when we highlight the highest earner.

Finally, to gain further insights into the sources of peer effects, we want to know the role that risk preferences play in our markets.

Research Question 4 *Does risk aversion help explain the importance of peer effects in market outcomes?*

We elicit these preferences in a separate post-markets risk taking task. In multivariate regressions we interact this variables with our exogenous treatment variations to better understand the drivers of peer effects.

3 Experimental Design

In this section, we describe the design of the experiment. Full instructions can be accessed via the online Appendix.[5]

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 dividends. Dividends depend on the "state", which is randomly determined at the end of each period. 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 chosen to be as simple as possible to avoid confusion.

	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.

Agents trade for 10 periods that last 150 seconds 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 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.

[5] Instructions can be downloaded at `http://www.austrianeconomist.com/instructionspsj.pdf`.

Random endowments. 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 0 E assets and 10 H assets. Which of those two portfolios was allocated was determined randomly where both portfolios were equally likely ex-ante. The total amount of assets in the market in each period was fixed at 50 assets of each kind.

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 shows 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).

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 in the information treatments. 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.

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 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 the subjects earns 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 an social value orientation measure based on Murphy *et al.* (2011), and asked several questions about the degree of competitiveness of participants.[6] 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 off 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.

4 Peer information and market outcomes

We first present a non-parametric analysis of the treatment effects. We then move on to a parametric multivariate analysis, discussing the effect of control variables. Additionally, we analyze the second source of exogenous information, the composition of the initial portfolios. Finally, we look at the insights that our post-market questionnaire can deliver on the sources of our treatment effects. Although stock prices in our experiments exceed the fundamental value of 50 persistently, they tend to be fairly stable across periods and treatments. A similar stability is observed for the number of transactions (liquidity) across treatments. Therefore –to keep the main body of the paper brief– we postpone our analysis of prices and transactions to Appendix B.[7] Additionally in Appendix D, we provide summary statistics for various key variables in table 6.

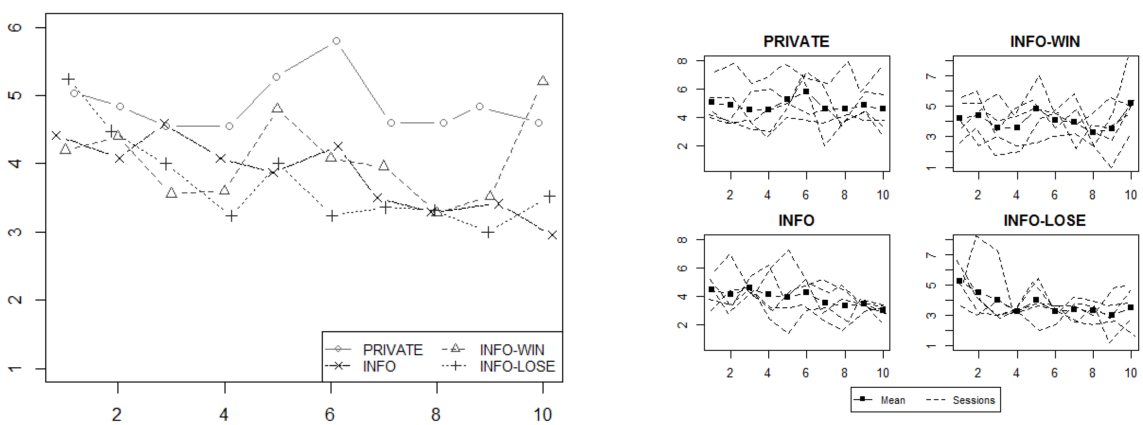
[6]However, since these data seemed noisy and did not provide much explanatory power, we have left them out of the analysis. An earlier working paper version of SAFE working paper 67, showed some analysis of the results of the SVO task.

[7]The results in this section are robust to the inclusion of prices as a control variable. Since prices and other market outcomes are determined simultaneously, they are endogenous. To a certain degree, we can circumvent this problem by exploiting the fact that prices are highly persistent. Hence, the first transaction price of a session. is a suitable proxy for the average price of a session. Including this proxy in the regressions run in this section, does not change results.

4.1 Risk sharing across information conditions

To investigate the 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. Our results 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 1a shows the dynamics of mean exposure by treatment over the 10 trading periods. 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.



(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 traders' 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.

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 column (1) of Table 3, where we interact treatment dummies with the period to capture the time trends that are apparent in Figure 1a.[8] 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.[9]

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.[10] This yields identical coefficients for the interactions between the period and treatments. The treatment dummies in column (2) capture period 10 averages of exposure. They show that in the INFO treatment, subjects collect on average 1.6 boxes (36%) less than in the PRIVATE treatment. Most of this effect is eliminated if the highest earner is highlighted. In contrast at the beginning of the experiment, in period 1, exposure shows no treatment differences. So these differences emerge over the course of the experiment, as captured in the time trends.

In column (3) we introduce the share of males in the group as a control variable, as this has

[8] 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.

[9] 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.

[10] 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 ($p = 0.584$).

	(1)	(2)	(3)	(4)
	FE	RE1	RE2	RE3
Period	-0.0189	-0.0189	-0.0189	-0.0189
	(0.0507)	(0.0486)	(0.0488)	(0.0492)
Period x INFO	-0.142**	-0.142**	-0.142**	-0.142**
	(0.0657)	(0.0629)	(0.0633)	(0.0638)
Period x INFO-WIN	0.172**	0.172***	0.172***	0.172***
	(0.0628)	(0.0602)	(0.0605)	(0.0610)
Period x INFO-LOSE	-0.0182	-0.0182	-0.0182	-0.0182
	(0.0702)	(0.0672)	(0.0676)	(0.0681)
INFO (d)		-1.618**	-0.779	10.31**
		(0.677)	(0.535)	(4.528)
INFO-WIN (d)		0.940*	0.684	-5.893
		(0.530)	(0.477)	(4.659)
INFO-LOSE (d)		-0.237	-0.409	-12.82***
		(0.395)	(0.464)	(3.647)
Share Male			1.672	0.870
			(1.215)	(1.197)
Bombchoice			0.212*	0.408**
			(0.120)	(0.180)
Bombchoice x INFO				-0.758**
				(0.316)
Bombchoice x INFO-WIN				0.474
				(0.325)
Bombchoice x INFO-LOSE				0.890***
				(0.257)
Constant	3.749***	4.787***	0.358	-2.496
	(0.111)	(0.638)	(2.030)	(2.884)
Observations	200	200	200	200
R^2	0.112	0.145	0.233	0.320

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) - (5) show results of random effect regressions. Column (2) shows a regression, where in addition to the independent variables from (1) treatment dummies are introduced. Column (3) introduces session averages of gender and choice in the BRET task (bombchoice). Column (4) in addition interacts bombchoice with treatment dummies. Period 10 is the base period. Standard errors clustered by session in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

been a focus of the previous literature (Eckel and Füllbrunn, 2015).[11] Overall, 87 of the subjects were male. We compute the share of male participants in each session and find that there is substantial variation, with the share varying between 20 and at most 60 percent. Despite this, we do not find evidence of gender effects in any of our model specifications.

We also include "Bombchoice", the average number of boxes collected by group members in the BRET task, which is our measure of risk attitudes. As expected, we see a positive coefficient, indicating that a higher exposure correlates with more risk taking in the BRET. In column (4) we interact risk attitudes with the treatment, because the nature of risk may differ by treatment. Whereas only financial risk is present in the PRIVATE treatment, in the INFO treatments "social risk" of falling behind your peers plays a role (see Appendix A for a discussion of the nature of social risk in markets). The results show that the sign of the coefficient for risk attitudes differs by treatment. In the PRIVATE and INFO-LOSE treatment, we see a strong and significant correlation between risk attitudes and exposure. The sign is positive, indicating that more risk loving attitudes correspond to higher exposure, as one would expect. However, this correlation turns insignificant for the INFO and INFO-WIN treatments ($p = 0.17$ and $p = 0.52$ respectively).[12] In addition, we see a strong effect of the inclusion of the interaction on the coefficients of the treatment dummies, which switch sign and become large for the INFO and INFO-LOSE treatment. This suggests that risk aversion is a strong determinant of treatment differences. Given that the BRET was conducted after the market we need to control for potential endogeneity of bomb choices before we give a causal interpretation. In Section 5, we discuss the relationship between exposure and market outcomes in more detail.[13]

Dispersion. One aspect of dispersion is how exposure is distributed amongst subjects. Are a few subjects taking a lot of risk, while most others are hedging? The answer is provided in Figure 2, which displays the distribution of exposure by treatment. The distribution is rather smooth with a mode around 3 in the first five rounds of all treatments. In the second half of the experiment we see clear shift across all exposure levels towards smaller exposures in the INFO and INFO-LOSE treatments. By contrast, in the PRIVATE and (to a lesser extent) in the INFO-WIN treatment we see a move from intermediate levels of exposure to more extreme

[11] 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.

[12] Note that we use nested dummies, so the effect of (e.g.) the INFO treatment is not just measured by the coefficient in front of the Bombchoice x INFO variable, but it is measured by the sum of the Bombchoice and Bombchoice x INFO variables ($= 0.408 - 0.758$). F-tests on the sums of the relevant coefficients yield the p-values mentioned in the text.

[13] The treatment averages of exposure hide the dispersion between sessions, which is shown in Figure 1b. Eyeballing the data, it seems that the session variances are higher in the PRIVATE and INFO-WIN treatments. The statistics support this observation to some degree. We compute the variance of mean exposure in the last 5 periods between the 5 sessions in each treatment and perform a Kruskal-Wallis test. The null hypothesis of identically distributed variances is rejected at marginal significance ($p = 0.054$). In paired treatment tests, we find no significant differences between the INFO-WIN and the other treatments. However, a Mann-Whitney test rejects the null of equal medians between PRIVATE and INFO and PRIVATE and INFO-LOSE at 5% significance.

levels.

Seen over all periods and treatments, 89,7% of all subjects have an end-of-period exposure of 9 or less, while 5.3% of subjects have an exposure of 11 or more. Since all subjects started with an initial exposure of 10, we can conclude that the large majority of subjects use the market to reduce exposure. On the other hand, only 14.4% of the observations are fully hedged portfolios, so only a small minority decreases financial risk maximally.[14]

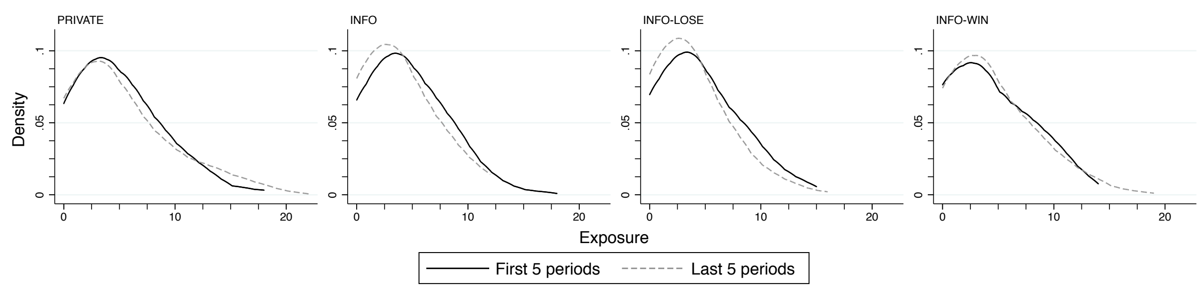


Figure 2: **Exposure distribution by treatment.** The figure above shows kernel density estimates for end of period exposure where each treatment is tabulated separately. The sample is split in two parts, with the solid line representing first five periods and the dashed line the last five periods.

Summary 1 *We find evidence that about 90% of subjects reduce risk through asset markets, although there is substantial heterogeneity in exposure. 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.*

Note that similar results hold for the variability of earnings, defined as end of period standard deviation of exposure by session. We reproduce Table 3 with the standard deviation of earnings as the dependent variable. The results show that the variability of earnings in the last period is 34% lower in the INFO, treatment than in the PRIVATE treatment. The regression results can be found in Appendix D, table 7.

4.2 Composition of the starting portfolio

The random variation in the starting portfolios constitutes a second source of exogenous variation beside the treatment variations which allow us to study peer effects in our setup. At the beginning of each period each subject randomly obtains either a portfolio with 10 E assets and

[14]This may be suggestive of an endowment effect. However, it is not clear that endowment effects occur for financial assets, as Svirsky (2014) shows that there is no endowment effect for money or for goods that are mostly used in exchange. Moreover, if anything one would expect the endowment effect to decrease with experience, which is contradicted by the upward trend in prices (see Appendix B).

0 H assets or a portfolio with 10 H assets and 0 E assets. This implies that there are always 3, 4 or 5 subjects with the same portfolio in each group.

The clearest predictions emerge from a situation where portfolios are allocated such that all 5 subjects in a group have the same portfolio (and traders in the other groups all hold opposite portfolios). Consider a group where 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.

In column (1) of Table 4 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, and the effect is large. 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 results hold in the random effects regression in column (2), where we add treatment dummies and a gender control variable.

Summary 2 *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.*

	(1) FE	(2) RE1	(3) RE2
Period x INFO	-0.166***	-0.167***	-0.166***
	(0.0465)	(0.0442)	(0.0448)
Period x INFO-WIN	0.177**	0.177***	0.177***
	(0.0635)	(0.0605)	(0.0613)
Period x INFO-LOSE	-0.0101	-0.0103	-0.0101
	(0.0749)	(0.0720)	(0.0726)
Equal spf x INFO (d)	0.406	0.423	0.418
	(0.874)	(0.827)	(0.836)
Equal spf x INFO-WIN (d)	-1.762*	-1.797**	-1.808**
	(0.897)	(0.858)	(0.866)
Equal spf x INFO-LOSE (d)	-0.630	-0.615	-0.633
	(0.897)	(0.858)	(0.862)
INFO-WIN (d)		1.025*	-0.685
		(0.579)	(1.504)
INFO-LOSE (d)		-0.206	-0.0399
		(0.475)	(1.411)
Share Male		0.231	-0.570
		(1.492)	(2.395)
Soc. Infl.			0.00727
			(2.189)
Soc. Infl. x INFO-WIN			2.815
			(2.301)
Soc. Infl. x INFO-LOSE			-0.0951
			(1.928)
Constant	3.416***	3.047***	3.328***
	(0.136)	(0.559)	(0.763)
Observations	150	150	150
R^2	0.161	0.120	0.165

Table 4: 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. Column (3) adds a variable "social influence" (Soc. Infl.) and interacts it with treatment dummies. Soc. Infl. is self reported, as in Figure 3c and takes on values between 0 and 2, where a higher value corresponds to a trader being more susceptible to social influence of others. Period 10 is the base period. Standard errors clustered by session in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3 The strategy questionnaire

To further investigate social influences in the market, we considered the 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, and especially in the INFO treatments. Indeed, 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 ($p = 0.145$).

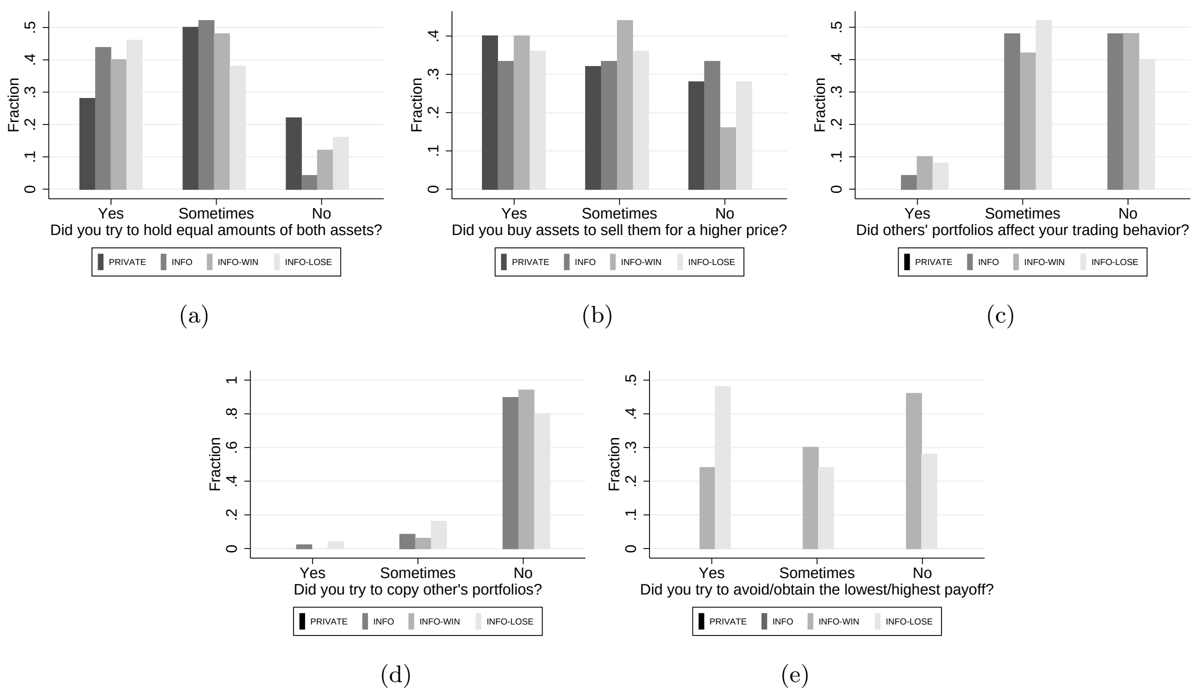


Figure 3: Distribution of questionnaire answers by treatment. Each panel shows mean answers elicited in a questionnaire after trading. Questions (a) and (b) relate to general trading strategies, hedging and arbitrage respectively. These questions were asked in each treatment. Questions (c) and (d) asked 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.

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 few subjects attempt to copy portfolios. This is consistent with the idea that the structure of the assets is too simple for social learning 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. Indeed, a Mann-Whitney test rejects the equality of the two distributions ($p = 0.0146$). This finding is in line with evidence that subjects exhibit 'last place aversion' found in Kuziemko *et al.* (2014).

The questionnaire allows us to test the importance of social influence on exposure when peer information is available. In column (3) of Table 4, we include in the model the average session score for the question "Did the portfolios of others influence your trading behavior?". This variable "Soc. Infl." ranges from 0 to 2, where a higher value indicates a higher self-reported social influence. The model also includes interactions with treatment dummies to see how social influence matters in different treatments. While none of the coefficients for the interaction terms is significant, controlling for "Soc. Infl." changes the sign and significance of the dummy for the INFO-WIN treatment. This indicates that increased exposure in the INFO-WIN treatment is due to social influence, corroborating the idea that competition for the first place leads to more risk taking.

Summary 3 *The fraction of subjects who report that they attempted to hedge increases in the INFO and INFO-LOSE treatment relative to the PRIVATE treatment. The majority of subjects indicate that at least part of the time they sought to avoid the worst payoff or obtain the best payoff. The self-reported degree of "social influence" drives up aggregate exposure in the INFO-WIN treatment relative to the other INFO treatments.*

Our results thus indicate the existence of peer effects. Such peer effects can take different forms, but one common definition is that individuals start acting more alike when they are grouped together. In Appendix C we investigate whether such conformism among peers is an important driver of our treatment effects. For that purpose we decompose the variances of end-of-period portfolios into within- and between group variances. Using this method we find no statistical evidence for conformity of asset holdings among peers.

5 Markets and risk attitudes

The fact that the bomb risk elicitation task (BRET) took place after the experimental market allows us to study the influence of market conditions on risk attitudes, and contribute to an emerging literature on the determinants of such attitudes mentioned in the introduction.

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.

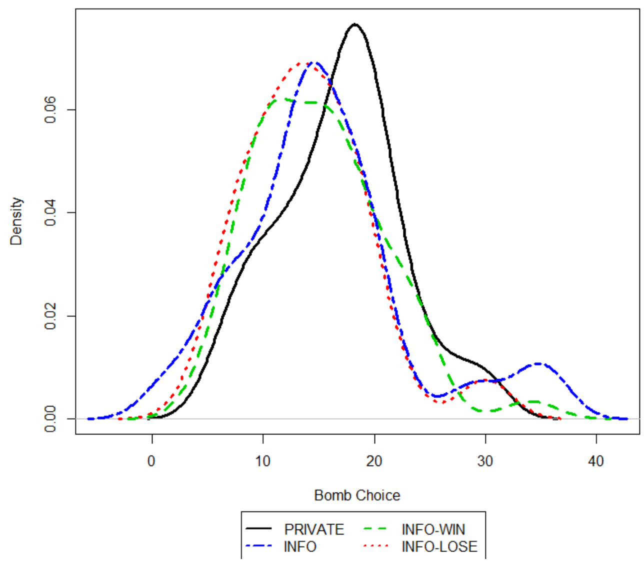


Figure 4: **Kernel density estimates for the Bomb Risk Elicitation Task (BRET)**, Crosetto and Filippin (2013). Estimates are made separately for each treatment. Higher numbers in the BRET signify a higher tolerance for risk. Risk neutrality corresponds to a choice of 18.

Table 5 reports the results of OLS regressions in which we investigate the effects of market conditions on risk attitudes in more detail.[15] 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 over the 10 trading rounds, and realized market earnings, which had been communicated to subjects just prior to the elicitation. While the coefficient for exposure has an expected positive sign, it is not significant, indicating that market exposure and risk choices are far from perfectly correlated.

[15]Note that for 7 of our 198 participants individual BRET measures are missing, since their zLeafs 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.

In column (3) we add control variables that relate to group behavior and relative earnings. We do not find an effect of the average exposure of other group members or of the relative payoff ranking, either in the PRIVATE or INFO treatments. However, we find that controlling for social variables turns the coefficient for the INFO-WIN dummy to be large and significant, indicating that competing for the highest payoffs in the market leads to substantial increase in willingness to take risk beyond the market environment.

To see whether earning recognition as the best or worst performer affects risk preferences, we also include the number of stars accumulated by a subject in the INFO-WIN and INFO-LOSE treatment, but do not find a significant effect on risk taking. In addition, we exploit the fact that there is randomness in the allocation of stars to construct a measure of frustration or disappointment with a lack of social recognition. "Missed Stars" indicates the total number of stars the player could have gotten if the state of the world had been the opposite in each round.

We find a strong and significant negative effect of missed stars on risk taking in the INFO-WIN treatment. To investigate if this effect is really due to social framing or simply to the payoff consequences of the realized dividends, we use the INFO treatment as a control, as this treatment implements the same payoff consequences without the framing. In the final column we therefore compute the fictitious number of stars and missed stars that would have occurred in the INFO treatment, if stars had been awarded as in the INFO-WIN treatment. Including this control variable has no effect, so we conclude that it is really the social framing that drives the effects of (not getting) stars on risk attitudes.

Summary 4 *Peer information and relative payoff framing in the market affect the willingness to take risk afterwards. Participating in a market with peer information causes subjects to become more cautious, but this effect is largely reversed when there were symbolic rewards for earning the highest payoffs. When bad luck prevents recognition as the highest earner, subjects become more cautious.*

It is clear that the effects of information conditions and framing on risk taking after the market is very similar to the induced shifts in aggregate exposure in the market documented in Section 4. This observation suggests the hypothesis that the shift in risk attitudes occurred during market trading activity, and not after the last period. This is consistent with the dynamics of the treatment effect displayed in Figure 1a, and suggests shifting risk attitudes are in fact an important driver of the differences in market outcomes.

Evidence for this hypothesis comes from the final column of Table 3, where we include "Bombchoice" (i.e. the group average of the bomb choice) as a right-hand side variable, interacted with treatment dummies. While the endogeneity implies that it is hard to interpret the coefficients, we find the inclusion of "Bombchoice" as a control variable has a large effect on the treatment dummies and reverses their signs. For instance, the coefficient for the INFO treatment

	(1)	(2)	(3)	(4)
INFO (d)	-2.593**	-2.427**	-4.755	-6.129
	(1.128)	(1.185)	(3.727)	(4.478)
INFO-WIN (d)	0.750	0.726	3.507**	4.416*
	(1.144)	(1.173)	(1.706)	(2.242)
INFO-LOSE (d)	-0.189	-0.228	-0.425	0.439
	(1.137)	(1.140)	(1.515)	(1.929)
Asset market profit		-0.00143	-0.000732	-0.000757
		(0.00154)	(0.00278)	(0.00282)
Male		0.257	0.0234	0.00652
		(0.819)	(0.820)	(0.828)
Avg. Exposure		0.0699	0.129	0.0750
		(0.186)	(0.199)	(0.208)
Avg. Other Group Exposure			0.0130	0.0771
			(0.480)	(0.495)
Rank Payoff Period			-0.655	-0.661
			(0.914)	(0.923)
Rank Payoff Period x INFO			0.761	0.785
			(0.796)	(0.818)
Stars x INFO-WIN			-0.164	-0.161
			(0.464)	(0.469)
Stars x INFO-LOSE			0.641	0.688
			(0.775)	(0.789)
Missed Stars x INFO-WIN			-1.376***	-1.335**
			(0.519)	(0.525)
Missed Stars x INFO-LOSE			-0.511	-0.477
			(0.956)	(0.961)
Fictitous Stars x INFO				0.273
				(0.490)
Missed Fic. Stars x INFO				0.255
				(0.568)
Constant	16.76***	17.67***	18.79***	19.10***
	(0.816)	(2.044)	(2.570)	(2.624)
Observations	191	191	191	191
R^2	0.038	0.045	0.089	0.091

Table 5: 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. Column (3) adds Stars, symbolic rewards for the best(worst) subject in the INFO-WIN (INFO-LOSE) treatment. The assignment of these symbolic rewards depends on the random state of the world. Missed Stars are the symbolic rewards a subject could have gotten, but did not get due to chance. Additionally column (3) controls for rank in the payoff relevant period, its interaction with the INFO dummy, and average exposure of others in the group. Column(4) adds both Stars and Potential Stars a subject would have gotten in the INFO treatment, if Stars would have been assigned as in the INFO-WIN treatment. Individual robust standard errors in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

now becomes positive and large, suggesting that in the absence of a shift in risk attitudes, peer information would have a positive effect.

Summary 5 *Our estimates of treatment effects reverse sign when controlling for shifts in risk attitudes, indicating that shifting risk attitudes are an important channel for the transmission of peer effects in markets.*

6 Discussion and Conclusion

Gathering evidence from the previous sections, we can now answer our research questions from Section 2. Research Question 1 concerns the degree of diversification in our novel markets. We find that although 90% of subjects use the market to diversify risk, a substantial exposure remains in the PRIVATE treatment. This is in line with findings that actual portfolios of American investors display significant under-diversification (Goetzmann and Kumar, 2008). Given that the asset structure in our experimental market is exceedingly simple, this finding suggests that lack of information amongst investors or behavioral biases are not the only drivers of under-diversification.

The answer to Research Question 2, the main focus of this paper, is that information about the portfolios of others increases risk sharing and reduces the variance of earnings in our experimental markets. With respect to Research Question 3, we find evidence that relative performance matters and that positional preferences play a role. In a post-market questionnaire, the majority of subjects indicate that at least part of the time, their trading strategies were aimed at earning the most or avoid earning the least. When the best earning trader in the peer group is highlighted, exposure levels are indistinguishable from the no-information case. Subjects are influenced by the portfolio composition of the peer group in a way that is consistent with a preference to come out ahead. By contrast, when the lowest earning trader is highlighted, exposure is slightly, although insignificantly reduced relative to the information only case. The fact that the information treatment without explicit performance rankings and with focus on the lowest earner are similar may indicate that 'last place aversion' matters even if rankings are not explicitly introduced (Kuziemko *et al.*, 2014).

With respect to our last research question, we find that peer information increases risk aversion amongst subjects as measured in an independent task. In fact, we show that the shift in risk attitudes is an important driver behind the finding that peer information mitigates risk taking in the market. The interplay between risk attitudes and peer behavior is a potentially complex two-way process: decreasing exposure levels by peers lowers individual willingness to take risk and vice versa. The nature and timing of our measurements does not allow us further speculation on this process, but we believe this is an interesting topic for future research, also in light of previous results (Cohn *et al.*, 2015).

The finding that peer influences reduce risk taking is in contrast with most of the literature, which associates social aspects of trading with increased volatility and 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 reduces price bubbles.

In combination with these earlier findings, our results suggest not only that peer effects are pervasive in financial markets, but that they are likely to affect choices in many different ways, some of which may be stabilizing and others destabilizing. 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, 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 investor 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. These ideas extend to the evaluation of 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.[16] 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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[16] 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

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

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.[17]

Equilibrium

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

[17] 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).

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* $\{x_i \in \mathbb{R}_+^2 \mid px_i \le p\omega_i\}$
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:

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

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:

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

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

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

So every equilibrium satisfies:

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

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 $\frac{1}{1+\alpha} \le x \le 1+\alpha$, 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 $\frac{1}{1+\alpha} \le x \le 1+\alpha$ implies $\frac{1}{1+\alpha} \le \frac{1}{x} \le 1+\alpha$, 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.

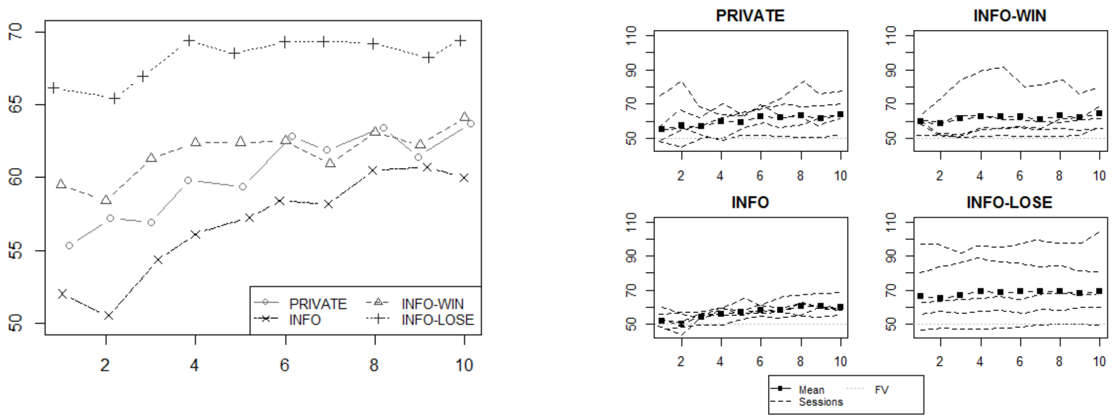
Appendix B: Prices and Transactions

Prices. In Appendix A, we use a general equilibrium model to analyze our economy both with and without social preferences. In all the equilibria of our models, the two risky assets trade at the same price. The predicted price depends on the assumptions made on risk aversion. Under the standard assumption that all traders are slightly risk averse, we would expect both assets to trade slightly below the expected value of 50.

We find that relative prices are indeed close to one in all sessions (Mann-Whitney $p = 0.92$).[18] Absolute prices are depicted in Figure 5a, revealing some interesting patterns. First, with the exception of a few sessions in the PRIVATE and INFO-WIN treatments, prices are quite stable within sessions, displaying a strong path dependency.[19] There is no evidence of bubbles, but

[18] Similarly, looking at transactions, we find no significant difference in the number of transactions between asset E on the one and asset H on the other hand. Neither is there a significant difference in volatility between the two assets.

[19] The correlation between the first period's first price in each session with the average price of the last 9 periods in each session is 0.93 and highly significant, $p < 0.001$.



(a) Mean prices across treatments.

(b) Mean prices by treatment and session.

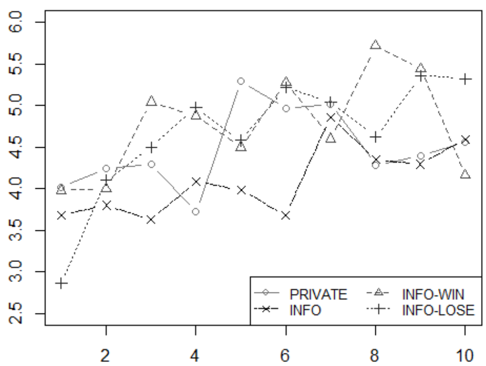
Figure 5: Time series of transactions prices. The panel on the left (a), shows mean transaction prices for each of the four treatments. Each time series corresponds to one treatment mean. Panel (b) on the right hand side plots treatment means alongside session means. Each dashed line corresponds to an individual session.

this is to be expected given that portfolios are reset each trading period.

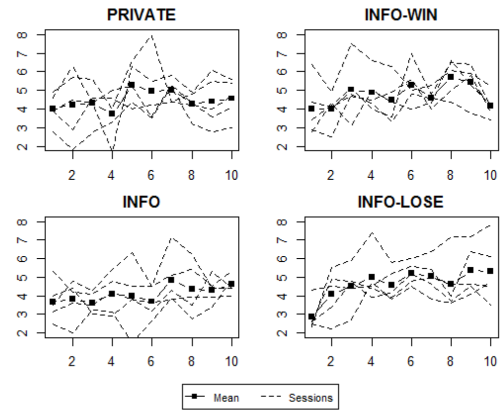
Second, in almost every session prices are substantially above the fundamental value of 50, and prices are trending upward over time in all treatments. This is somewhat puzzling, as the BRET shows that most subjects are risk averse (see Section 5). While the high prices may seem suggestive of an endowment effect, Svirsky (2014) shows that there is no endowment effect for money or exchange goods. Moreover, if anything one would expect the endowment effect to decrease with experience, which is contradicted by the upward trend in prices.

Finally, while average prices in the INFO-LOSE treatment are higher than in the other treatments, this hides a very large dispersion in prices between sessions. While prices hovered slightly below 50 in one session of the INFO-LOSE treatments, they were around 100 in another session. The latter observation is hard to reconcile with utility maximizing agents.

Transactions. Transactions average 4.5 per trader and period, Figure 6a shows a rising number of transactions over time. Additionally, the number of transactions in the INFO treatment seems to be somewhat lower, than in the other treatments. This might due to the session with only 8 traders, since markets might be less liquid with only 8 participants. Indeed, transactions per trader in the session with only 8 subjects are significantly lower, than in the other 19 sessions ($p < 0.001$). Dropping this session from the analysis and performing a series of pairwise Mann-Whitney tests , only the difference between INFO-WIN and INFO is significant ($p = 0.003$). Despite the lower number of transactions in the INFO treatment than in the INFO-WIN, average exposure is lower in the INFO treatment. So treatment specific effects on transactions are unlikely to be the source of the differential trends in exposure reduction we observe.



(a) Per trader mean transactions across treatments.



(b) Mean prices by treatment and session.

Figure 6: Time series of the number of transactions. The panel on the left (a), shows mean transactions 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.

Summary 6 *Prices are rather stable within sessions, although they trend up over time in all treatments. In the INFO-LOSE treatment prices between sessions range from around 50 to around 100, which is hard to reconcile with utility maximization. Transactions show a slight upward trend.*

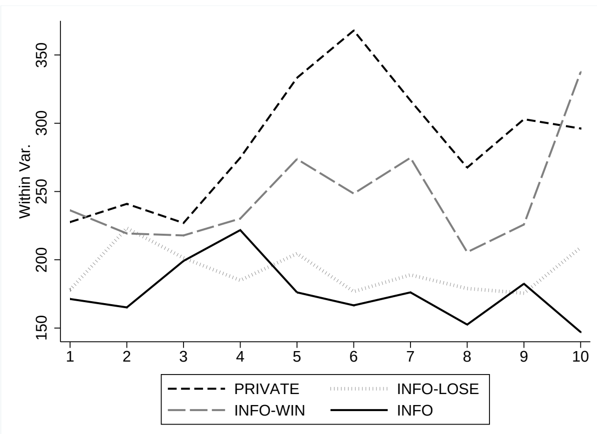
Appendix C: Ingroup conformism

Lastly, one common definition of peer effects is that individuals start acting more alike when they are grouped together. In our context, this implies that participants in the INFO treatment, within the same group, have a more similar portfolio than across groups, in particular if compared to the PRIVATE treatment. as follows:

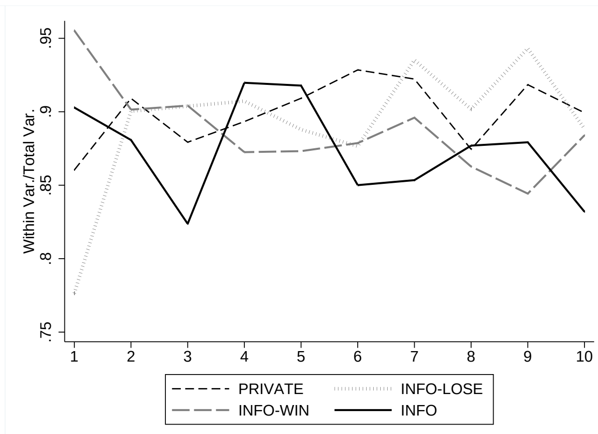
$$
\begin{aligned}
TV &:= \sum_{i=1}^{10} \left(x_i^H - 5\right)^2 + \left(x_i^E - 5\right)^2 \\
&= \sum_{i=1}^{10} \underbrace{\left(x_i^H - \bar{x}_i^H\right)^2 + \left(x_i^E - \bar{x}_i^E\right)^2}_{\text{Within group variance (WV)}} + \underbrace{\left(\bar{x}_i^H - 5\right)^2 + \left(\bar{x}_i^E - 5\right)^2}_{\text{Between group variance (BV)}} + \Delta, \qquad (2)
\end{aligned}
$$

where $\bar{x}_i^a$ are average holdings of asset a in the group of individual i, x_i^a are individual i's holdings of asset a and Δ is a co-variance term.[20]

Figure 7 shows our measure of within group variation (Panel (a)). It is clear that within variance is highest in the PRIVATE and INFO-WIN treatments, but this difference may simply reflect the higher exposure in those treatments.[21] Indeed, when we look at Panel (b), which displays the share of within group variance of total variance (WV/TV), there are no observable time trends or differences between treatments. This implies that there is no significant drive towards conformity over time in any of the treatments. These findings show that the prevalence of symmetric equilibria in which all group members hold the same portfolios, as predicted by simple social preference models (see Appendix A), does not seem to be consistent with observed behavior in our setting. This is also reflected in the fact that in all treatments about 90% of all the variation is within groups rather than between groups.



(a)



(b)

Figure 7: **Time paths of total session variance and within group variance as defined in Equation 2.** Panel a) shows the within group variance over time by treatment. Panel (b) shows the ratio of within group variance to total variance over time by treatment.

Summary 7 *We do not find evidence of group conformism, as portfolio variation within groups as a share of total portfolio variation is constant over time and treatments.*

[20]Naturally, there are other ways of looking group conformity, for example by looking at the variance or direction of exposure. Analysis of these two examples yields similar results as the current one.

[21]Note, for the PRIVATE treatment we always assign half of the participants to "groups" randomly in our analysis.

Appendix D: 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 6: 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.

	(1) FE	(2) RE1	(3) RE2	(4) RE3
Period	0.570	0.570	0.570	0.570
	(5.011)	(4.798)	(4.823)	(4.862)
Period x INFO	-9.495	-9.495*	-9.495*	-9.495*
	(5.721)	(5.477)	(5.506)	(5.550)
Period x INFO-WIN	14.68**	14.68***	14.68***	14.68***
	(5.230)	(5.007)	(5.033)	(5.074)
Period x INFO-LOSE	4.674	4.674	4.674	4.674
	(3.871)	(3.706)	(3.725)	(3.755)
INFO (d)		-106.0**	-62.20	429.7
		(45.78)	(39.02)	(291.7)
INFO-WIN (d)		98.99**	85.53**	-98.73
		(38.98)	(41.93)	(311.0)
INFO-LOSE (d)		16.30	8.379	-777.0***
		(37.90)	(41.40)	(227.1)
Share Male			79.57	71.98
			(83.63)	(72.09)
Bombchoice			11.59	21.61*
			(8.048)	(12.09)
Bombchoice x INFO				-33.07
				(20.23)
Bombchoice x INFO-WIN				13.65
				(20.18)
Bombchoice x INFO-LOSE				56.13***
				(15.80)
Constant	278.6***	329.3***	93.66	-70.41
	(8.702)	(43.27)	(137.4)	(190.2)
Observations	200	200	200	200
R^2	0.061	0.120	0.178	0.262

Table 7: The dependent variable is end of period standard deviation of earnings. 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) - (5) show results of random effect regressions. Column (2) shows a regression, where in addition to the independent variables from (1) treatment dummies are introduced. Column (3) introduces session averages of gender and choice in the BRET task (bombchoice). Column (4) in addition interacts bombchoice with treatment dummies. Period 10 is the base period. Standard errors clustered by session in parentheses. Significance levels are denoted by * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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