Motivated Beliefs, Social Preferences, and Limited Liability in Financial Decision-Making *

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Abstract

Using a new experimental design, we compare how subjects form beliefs in an investor-client setup under varying degrees of liability. Our results reflect the importance of social preferences when making investment decisions for others. We show that when investors have no liability, those with stronger social preferences are more optimistic about the probability that their investment results in a gain. In other words, we find that social preferences appear to be correlated with motivated beliefs. This finding suggests the existence of cognitive biases in financial decision-making and supports the recent literature on the formation of motivated beliefs under limited liability (Bénabou and Tirole, 2016; Barberis, 2015).

Keywords Moral Hazard · Experiment · Motivated Beliefs · Social Preferences

JEL Classification C91 · D84 · G11 · G41

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1 Introduction

Most people hold certain moral beliefs and will strive to uphold them to maintain a positive self-view (Festinger, 1962; Epley and Gilovich, 2016). Yet quite often, they are confronted with situations in which their actions are in conflict with their principles. This conflict creates a psychological discomfort that psychologists refer to as "cognitive dissonance" (Festinger, 1962). A common way to deal with such tension is to modify one's beliefs by, for example, appropriately shifting the likelihood of an outcome to justify a selfish action (Haisley and Weber, 2010; Gino et al., 2016) or by selectively overweighting certain types of information (Zimmermann, 2020; Eil and Rao, 2011). An example would be to smoke and believe that smoking is not that harmful (McMaster and Lee, 1991) or to convince oneself that those out-of-reach grapes are certainly sour (Æsop, 1914). In other words, when our actions are not aligned with our views, we might form *motivated beliefs* in a trade-off between holding accurate or desirable beliefs (Bénabou and Tirole, 2016).

In finance, the formation of such motivated beliefs can lead investors to stay in low-performing investments (Goetzmann and Peles, 1997; Cheng et al., 2014), induce the disposition effect (Chang et al., 2016), and give rise to increased risk-taking under limited liability (Barberis, 2015). Concerning the latter, Barberis (2015) argues that because of the limited liability and the moral hazard associated with it, investors might inadvertently bias downwards the risk perception of their investments to maintain a positive self-image while still profiting from their risky investments.[1]

This paper uses experimental methods to test whether limited liability and *social preferences* induce motivated beliefs in financial decision-making. Using a novel experimental design, we compare subjects' risk assessment and investments when making investment decisions for others under varying degrees of liability. In all treatments, subjects are matched in pairs of one investor and one client. The task of investors is to evaluate different assets and decide how much of their client's endowment to invest in an asset. In control rounds, gains and losses are evenly split between the investor and the client. In

[1]Note that while this phenomenon holds a strong resemblance to what Bénabou et al. (2018) call "absolving narratives," the motivated beliefs in Barberis (2015) and Bénabou (2015) are fundamentally different, as they are not formed after the realization of the investment but rather when making the investment. In other words, the type of motivated beliefs we are interested in are *decision-related*, not *outcome-related*.

treatment rounds, the gains are also split evenly, however, if the investment goes sour, investors face no liability and the client absorbs all of the losses. By evaluating the beliefs of investors under treatment and control, we can isolate the effect that the different degrees of liability have on the investors' beliefs.

When we study the belief formation of all subjects, we cannot detect a statistical bias in beliefs. Yet, if we look specifically at those subjects who share some of the endowment in a dictator game (i.e., those that are not entirely selfish), we observe that subjects invest more and expect significantly higher returns under treatment than control. These results indicate that social preferences - measured through a standard dictator game (Forsythe et al., 1994) - play an important role in the formation of motivated beliefs. That is, we show that, as suggested by Barberis (2015), Bénabou (2015), and Bénabou and Tirole (2016), subjects with social preferences form motivated beliefs to self-justify their increase in investments. Using mediation analysis (Imai et al., 2011), we quantify the effect of these motivated beliefs and estimate that they are responsible for around one third of the increase in investments when there is no liability.

Our research is part of a trend in behavioral finance that uses experiments to understand belief formation and decision-making in financial markets (e.g., Nosić and Weber, 2010; Bosch-Rosa et al., 2018; Weber et al., 2018). More precisely, we contribute to two strands of the literature: that of cognitive biases in financial environments and that of decision-making for others. In the first strand Chang et al. (2016) and Mayraz (2017) are close to our research. The first paper finds that cognitive dissonance can explain the disposition effect, while the second finds that "wishful thinking" systematically distorts asset price beliefs. Yet, none of these two papers links investors' beliefs to decision-making on behalf of clients. In the second strand, Füllbrunn and Luhan (2020) show that, when investing for others, limited liability increases risk-taking by triggering egoistic preferences. This result is replicated by Kling et al. (2022) in a related setup with the knowledge of the clients' risk preferences. However, in these papers there is no ambiguity in the investments so there is no scope to study the formation of motivated beliefs. Moreover, none of the previous papers directly *measures* the impact of social preferences. To our knowledge, we are the first to empirically study and quantify the joint effect of limited liability and social preferences on motivated beliefs. In this sense, the closest paper is Bosch-Rosa et al. (2019) which also studies the formation of motivated beliefs, but does so using a different experimental setup where investors do not share the gains with clients.[2] More importantly, while our paper studies social preferences, Bosch-Rosa et al. (2019) is silent on this topic.

To conclude, our contribution to the literature is to analyze how limited liability and social preferences affect beliefs and investment decisions. This contribution is relevant as a) it contributes to the growing literature on "motivated beliefs" (Bénabou and Tirole, 2011, 2016; Gino et al., 2016) by shedding light on the effects that incentives have on beliefs in financial decision-making, b) it clarifies the channels through which limited liability induces an increase in risk-taking, and c) provides quantifiable evidence on the importance of social preferences in shaping decision-making for others, an understudied topic in the literature (Füllbrunn et al., 2020, 2022b).

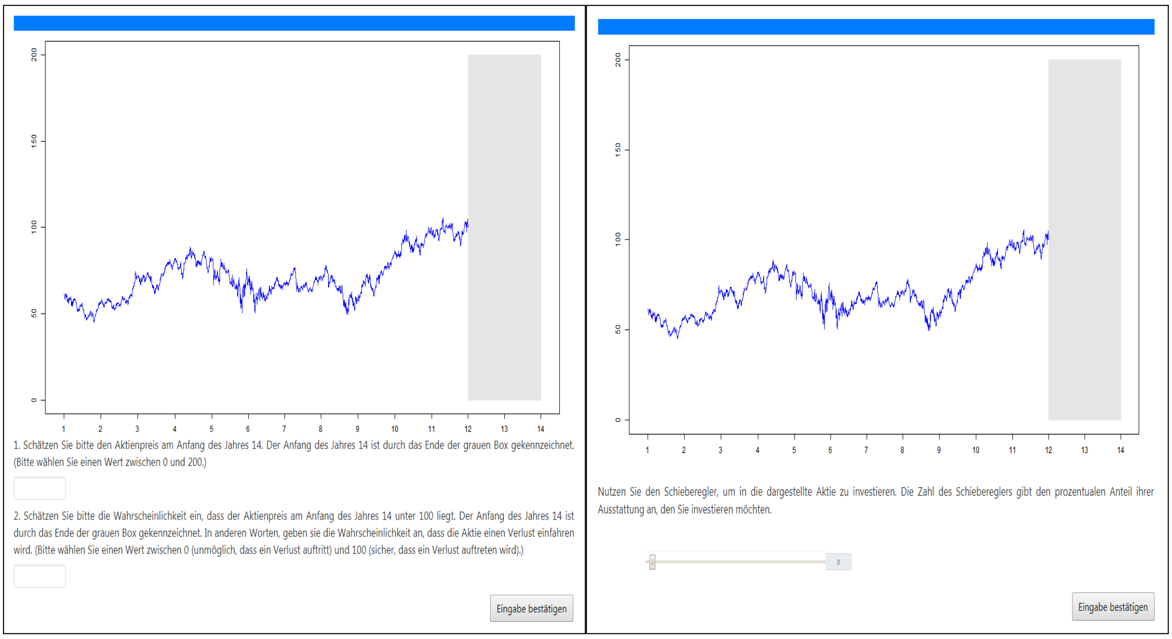
The paper is organized as follows. Section 2 presents our experimental design. Section 3 presents the experiment's results. Section 4 discusses our results. Finally, Section 5 concludes.

2 Experimental Design

Our experiment elicits beliefs and investment decisions under varying degrees of liability in a context of decision-making for others. At the beginning of the experiment, subjects are matched in pairs and assigned either the role of *investor* (denoted as Type A) or of *client* (denoted as Type B).[3] Matches and roles are maintained throughout the entire experiment. Yet, subjects do not learn about their role until the end of the experiment, i.e. there is role uncertainty. This design allows us to implement a strategy method (Selten, 1967; Engelmann and Strobel, 2004) where all subjects play *as if* they were a Type A player.

[2]In Bosch-Rosa et al. (2019) the incentive structure is such that the setup resembles more that of institutional investors and tax payers than our investor-client setup in which the client and the investor share profits. Further, the investment asset in Bosch-Rosa et al. (2019) is an abstract binary asset that pays a fixed return if successful, while in this paper we use real market data. This approach brings us closer to the decisions made in financial markets and allows us to model payoffs not only based on whether the asset went up in price but also by *how much*, resulting in more nuanced experimental data.

[3]To keep the framing neutral, in the instructions (see Appendix C) we use the terms Type A and Type B to refer to investors and clients.



(a) Assessment Screen (b) Investment Screen

Figure 1: (a) Screen for the belief elicitation phase. Subjects are asked for the probability that the price of this asset will be above 100 at the beginning of the 14th year and for an exact estimate of this price. (b) Screen for the investment phase. Subjects are asked to use a slider to indicate how much of the client's endowment they want to invest into the asset. Notice that the graph presented in these screens is one of the randomly generated graphs used during practice rounds. For more details on practice rounds, see the instructions in Appendix C.

The core of our experiment is divided into three consecutive rounds of control and three of treatment. In each round both members of the pair are endowed with € 10 and presented with the *assessment screen* (left panel of Figure 1). In this screen subjects see the daily prices of an anonymous stock from the DAX40 (Germany's prime blue-chip stock market index) for 11 consecutive years (see Figure 2).[4] Subjects know that the data come from the DAX40 but are not told the exact years of the data nor the company's name. Additionally, they are told that all time series have been normalized such that the price at the beginning of the 12th year is always 100.[5]

[4]Figure 4 in Appendix B presents the full time-series for each of the assets.

[5]The data was normalized as follows: Each element of the time series was divided by the price at the beginning of the 12th year (i.e. the last observable stock price) and then multiplied by 100. The normalization procedure was unknown to subjects and was implemented to make the decisions across rounds comparable.

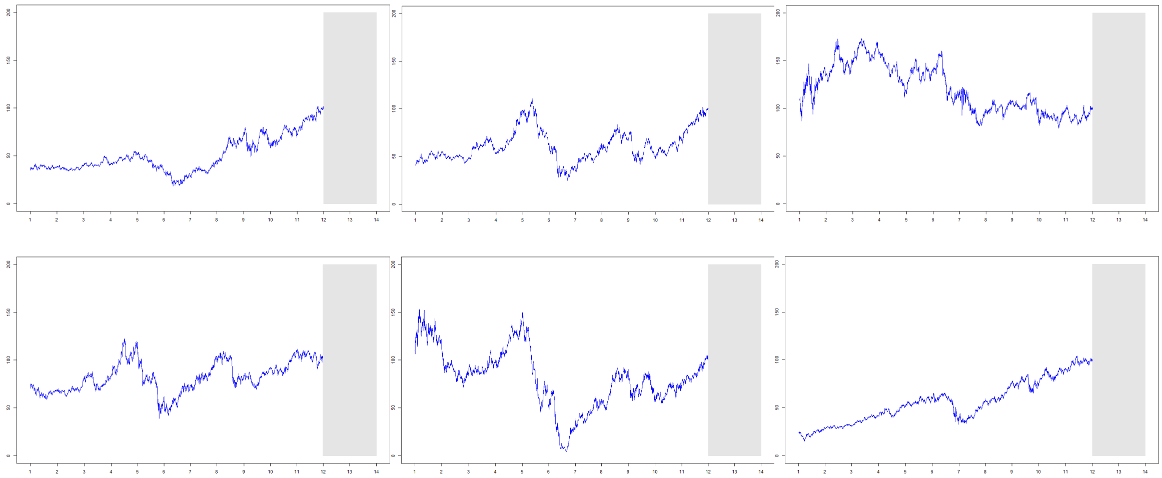


Figure 2: The six assets presented to subjects. From left to right and from top to bottom: (1) Bayerische Motoren Werke AG, 27-Jun-03–27-Jun-16; (2) Daimler AG, 20-Jun-03—20-Jun-16; (3) Deutsche Telekom AG, 10-Sep-02—10-Sep-15; (4) Siemens AG, 05-Jan-04—05-Jan-17; (5) Infineon Technologies AG, 08-Jul-03—08-Jul-16; (6) Linde AG, 18-Dec-02—18-Dec-15. All data are downloaded from Google Finance.

The task of subjects in the assessment screen is to guess the asset price at the beginning of the 14th year (henceforth, the price prediction) and to assess the probability that the asset price will be above 100 at that point (henceforth, the gain probability).[6] To incentivize each choice in the assessment screen, we use the binarized scoring rule (Hossain and Okui, 2013), where subjects' payoff is either € 0 or € 3. The binarized scoring rule is incentive compatible and is robust to any risk preferences subjects might have. Yet, following Danz et al. (2022) subjects are not given the details of the binarized scoring rule, but rather they are told that the payment rule is designed so that they can secure the largest chance of winning the prize by reporting their most accurate guess. Once subjects complete the assessment screen, they move to the *investment screen* (right panel of Figure 1).

In the investment screen, the task of subjects is to invest as much as they want of their matched subject's € 10 into the asset they just assessed.[7] The net return (R_A) to

[6]Eliciting beliefs before the investment decision allows to measure the formation of motivated beliefs cleanly, free of other behavioral biases such as wishful thinking. This approach assumes that cognitive dissonance is an explicit contributor to the decision-making process (e.g., Rabin, 1994; Konow, 2000; Oxoby, 2004). Alternatively, cognitive dissonance may arise in retrospect to self-justify (the outcomes of) past decisions (e.g., Akerlof and Dickens, 1982; Goetzmann and Peles, 1997; Chang et al., 2016).

[7]Recall that because we are using the strategy method, all subjects will play *as if* they were Type A.

the investment (I_A) for Type A subjects is determined by the amount invested and the difference between the price at the beginning of the 12th year ($price_{t=12} = 100$) and the price at the beginning of the 14th year ($price_{t=14}$). Formally,

$$R_A = I_A \times \left(\frac{price_{t=14}}{100} - 1 \right) \tag{1}$$

Any amount that Type A subjects do not invest in the asset (10 - I_A) is assumed to go into a risk-free asset with no returns.

To incentivize Type A's investment decision, in control rounds any gains from profitable investments (i.e., $price_{t=14} \geq 100$) are split evenly across Type A and Type B subjects. Similarly, any losses of unprofitable investments (i.e., $price_{t=14} < 100$) are also shared evenly between Type A and Type B players. As a result, in control rounds the incentives for Type A and Type B subjects are perfectly aligned and can be written as:

$$\Pi_A^C = \Pi_B^C = \Pi^C = R_A \times 0.5 + 10. \tag{2}$$

By contrast, Type A subjects are not liable for any losses in treatment rounds. In such cases, Type B subjects cover the entirety of the losses if the investment goes sour. Hence, in treatment rounds, the incentives of Type A and Type B players are not aligned and can be written as:

$$\Pi_A^T = \begin{cases} R_A \times 0.5 + 10, & \text{if } p_{t=14} \geq 100 \\ 10, & \text{if } p_{t=14} < 100, \end{cases} \tag{3}$$

for Type A players and

$$\Pi_B^T = \begin{cases} R_A \times 0.5 + 10, & \text{if } p_{t=14} \geq 100 \\ R_A + 10, & \text{if } p_{t=14} < 100, \end{cases} \tag{4}$$

for Type B players.

After making their investment decisions, subjects immediately move to the next round, where they are presented with a new assessment screen containing a different asset. This sequence of assessing and investing in assets is repeated three times, after which the instructions for the second part of three rounds are read aloud. Importantly, subjects do not get any feedback between rounds and only at the end of the experiment they are told about their final payoffs and player type. Furthermore, to control for order effects, half of the sessions started with control rounds and half with treatment rounds.

In total, across both parts, we elicit six times the gain probability, the price prediction, and the investment decision for each subject. To avoid hedging, subjects are paid for only one of their six choices for the gain probability, the price prediction, and the investment (be it in control or treatment).[8] The computer randomly and independently chooses the payoff-relevant decisions; so a subject might get paid for the accuracy of her gain probability in round six, her price prediction in round three, and her investment in round four.

2.1 Personality Traits

After the six rounds of belief and investment assessment, subjects participate in several tasks in which we elicit their personality traits. These tasks include risk, ambiguity, and loss aversion measures through a modified version of the multiple price lists used in Rubin et al. (2017). Additionally, we measure subjects' cognitive ability through the CRT (Frederick, 2005), CRT2 (Thomson and Oppenheimer, 2016), and eCRT (Toplak et al., 2014) questions as well as their personality through the short version of the Big Five personality traits by Rammstedt and John (2007). To measure the social preferences of our subjects, we include a dictator game (Forsythe et al., 1994) in which each subject uses a slider to split € 3 (in increments of one eurocent) with her assigned partner. As in the investment rounds, in the dictator setup we also employ the strategy method such that all subjects play *as if* they were the dictator. Finally, subjects are asked to state their gender, field of study, and age.

3 Results

Following our pre-registration, 235 subjects were recruited through the Online Recruitment System for Economic Experiments (Greiner, 2015).[9] Sessions lasted approximately 90 minutes and were run at the Experimental Economics Laboratory of the Technische Universität Berlin. Subjects made on average € 19.94 and the experiment was pro-

[8] See Blanco et al. (2010) for a discussion on how to avoid hedging in belief elicitation contexts.

[9] The number of subjects is odd because five minutes into one session one of the subjects had to leave given to an indisposition. Similarly, another subject left at the end of the control rounds due to an indisposition, so we use only her control round decisions.

grammed and conducted using O-Tree (Chen et al., 2016).[10] There was no show-up fee on top of the direct experimental payoffs and subjects gave informed consent at the beginning of the sessions.

3.1 Investment Decisions and Motivated Beliefs

In Figure 3 we present the box plots for the investment decision, the gain probability, and the price prediction across all rounds of treatment and control. The median value is marked with a red circle and the exact numerical value is stated above this circle.[11] It is clear that subjects invest more in treatment than in control. We also observe an increase in the gain probability but a striking similarity in the price prediction across treatments.

To statistically analyze the differences in behavior and beliefs across treatment and control, we follow our pre-registration and use a Mann-Whitney U test and a Fisher-Pitman permutation test for each graph. The one-tailed p-values for both tests can be found in Table 7 of Appendix A.[12] The results show that investments are statistically different across treatment and control in all but one case. On the other hand, we cannot reject the equality across treatments for the gain probability or the price prediction.

In Table 1 we run a series of OLS regressions with the investment (columns (1) - (4)), the gain probability (columns (5) - (7)), or the price prediction (columns (8) - (10)) as the dependent variable. Our main explanatory variable is the dummy $Treatment$, which takes value unity if the observation corresponds to a treatment round and zero otherwise. Our controls are the amount given in the dictator game ($Dictator$), a dummy indicating whether or not the subject is female ($Female$), the number of correctly answered CRT questions (CRT), and the measures of risk, ambiguity, and loss aversion ($Risk$, $Loss$, and $Ambiguity$ respectively). For the investment, we also control for the gain probability ($Prob$) or the price prediction ($Price$). Finally, we indicate in the table whether the regression controls for the order of the treatments or the graph fixed effects. All standard errors are clustered at the subject level.

[10] Of the average final payoffs, approximately 75% (i.e., € 15) come from the investment and belief elicitation tasks, while the rest comes from the different personality measures.

[11] In Figure 5 of Appendix B we reproduce Figure 3 breaking down the data for each graph.

[12] The test compares the investment, the gain probability, or the price prediction for each graph when the graph was used in control rounds against when it was used in treatment rounds.

	Investment				*Prob*			*Price*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment	9.095***	8.505***	7.771***	8.719***	1.387	0.991	1.211	0.0820	-0.317	-0.973
	(1.749)	(1.644)	(1.528)	(1.500)	(1.162)	(1.080)	(0.901)	(1.017)	(0.918)	(0.789)
Dictator		-0.0324	-0.0368*	-0.0320		0.00604	0.00646		-0.000607	-0.00460
		(0.0213)	(0.0191)	(0.0209)		(0.0108)	(0.00872)		(0.0112)	(0.00895)
Female		-6.167**	-7.641***	-7.290***		1.990	0.837		1.663	0.346
		(2.778)	(2.356)	(2.514)		(1.739)	(1.449)		(1.819)	(1.504)
CRT		0.189	0.369	-0.216		-0.242	-0.659**		0.600	0.761**
		(0.527)	(0.500)	(0.544)		(0.335)	(0.267)		(0.383)	(0.298)
Ambiguity		-0.922**	-0.906**	-0.701		-0.0223	0.205		-0.328	-0.313
		(0.440)	(0.412)	(0.438)		(0.217)	(0.240)		(0.280)	(0.272)
Risk		-0.303	0.181	-0.0531		-0.653**	-0.397		-0.370	0.0621
		(0.455)	(0.425)	(0.461)		(0.264)	(0.252)		(0.320)	(0.284)
Loss		-1.263***	-1.033**	-1.165**		-0.310	-0.210		-0.145	0.0604
		(0.477)	(0.437)	(0.455)		(0.260)	(0.197)		(0.271)	(0.205)
Prob			0.740***							0.661***
			(0.0383)							(0.0310)
Price				0.675***			0.693***			
				(0.0417)			(0.0313)			
Constant	43.79***	77.67***	22.48*	3.804	55.11***	74.54***	-1.346	104.8***	109.4***	60.13***
	(1.419)	(12.41)	(12.32)	(14.12)	(0.936)	(7.435)	(6.461)	(0.888)	(8.107)	(6.460)
N	1407	1407	1407	1407	1407	1407	1407	1407	1407	1407
adj. R^2	0.018	0.142	0.419	0.361	0.000	0.136	0.532	-0.001	0.107	0.516
Big Five	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Order Dummy	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Graph Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1: OLS regression. In Columns (1)-(4) the dependent variable is the investment decision (*Investment*). In Columns (5)-(7) and (8)-(10) the dependent variables are the gain probability (*Prob*) and the price prediction (*Price*), respectively. All standard errors are clustered at the subject level.

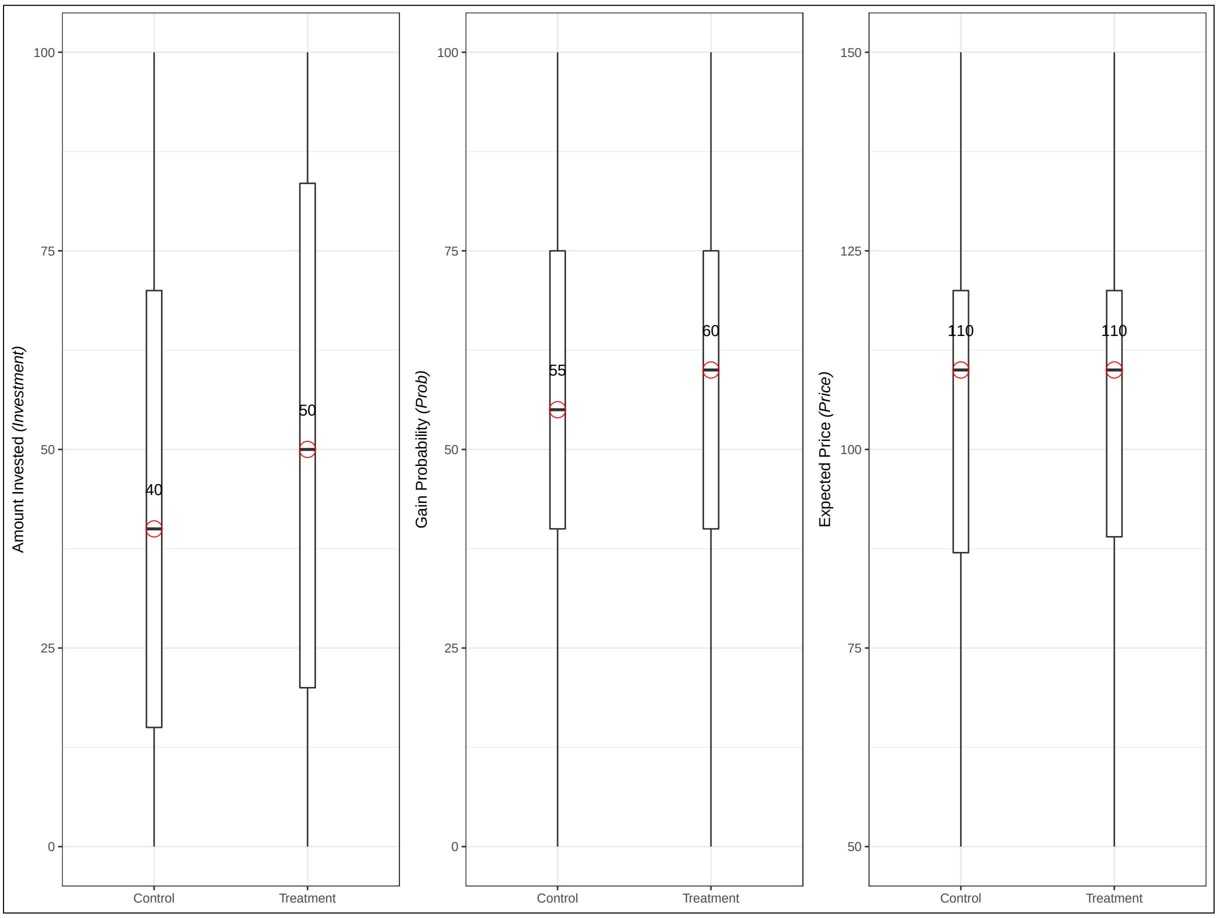


Figure 3: Overview of the data. In the vertical axis, we plot the amount invested (*Investment*), the gain probability (*Prob*), and the price prediction (*Price*), respectively. In the horizontal axis, we separate by treatment. The lower and upper bar of the box represent the first and third quartiles of the data. The red circle marks the median value, and above the numerical value is written in numbers. Note that the scale of the first two figures goes from 0 to 100 while we limit the third figure to ranges from 50 to 150 for legibility reasons.

The results of Table 1 show that the behavior of subjects seems to be internally consistent as subjects invest significantly more when they expect a higher gain probability or a higher price (see columns (3) and (4), respectively). Furthermore, they confirm that our treatment has an impact on subjects as we observe that subjects invest, on average, about 8% more of the client's endowment when there is no liability. However, we cannot detect the presence of motivated beliefs as the coefficient of *Treatment* is positive in columns (5) to (7), but it is not statistically different from zero. Similarly, *Treatment* is not significantly different from zero for the price prediction and, against our predictions, it even has a negative sign. Overall, we cannot detect the formation of motivated beliefs under limited liability using our full sample of subjects.

Result 1: *We do not detect the formation of motivated beliefs using the full sample of subjects.*

3.2 Social Preferences and Motivated Beliefs

Barberis (2015) and Bénabou (2015) suggest that social preferences play an important role in the formation of motivated beliefs. After all, if there is no "morally questionable" behavior or any perception of it, there is no need to form motivated beliefs to self-justify any action that might harm a third party. Yet, our initial analysis does not clarify the role of social preferences in our experimental design. To study how social preferences affect our treatment, in Table 2 we replicate part of Table 1 and include an interaction between the amount given in the dictator game and the treatment dummy. The results show that social preferences have a differential impact in treatment rounds, pushing subjects towards lowering their investment while increasing the gain probability. As suggested by the theory, those subjects who feel guiltier about making large investments need to form motivated beliefs to self-justify their actions.

Result 2: *Social preferences are an important determinant in the formation of motivated beliefs in treatment rounds.*

Given the importance of social preferences in our setup, we follow List (2006) and create a dichotomous differentiation between the *entirely selfish* (in our case, those subjects that gave zero in the dictator game) and everyone else. Of the 235 subjects in our experiment 53 (approximately 22%) are *entirely selfish* and keep the whole dictator endowment for themselves (see bar graph of donated money in the dictator game in Figure 6 of Appendix B). Because such subjects only add noise to our analysis, in Table 3 we reproduce Table 1 excluding the *entirely selfish* subjects.[13] As expected, the treatment effect on subjects' investment is large and statistically significant but smaller than that in

[13]It is important to note that dropping these subjects was not pre-registered. All of the analysis from this point is exploratory analysis.

	Investment		*Prob*	*Price*
	(1)	(2)	(3)	(4)
Treatment	16.91***	15.70***	-1.670	0.973
	(2.952)	(3.081)	(1.390)	(1.456)
Dictator	0.00746	0.00218	-0.00735	0.00472
	(0.0174)	(0.0191)	(0.0107)	(0.0104)
Treatment × *Dictator*	-0.0888***	-0.0679***	0.0280**	-0.0189
	(0.0225)	(0.0250)	(0.0123)	(0.0118)
Female	-7.449***	-7.041***	0.829	0.349
	(2.388)	(2.508)	(1.450)	(1.506)
CRT	0.391	-0.197	-0.664**	0.765**
	(0.500)	(0.545)	(0.267)	(0.298)
Ambiguity	-0.917**	-0.711	0.208	-0.315
	(0.412)	(0.438)	(0.240)	(0.272)
Risk	0.170	-0.0643	-0.392	0.0601
	(0.425)	(0.461)	(0.253)	(0.284)
Loss	-1.051**	-1.188***	-0.208	0.0598
	(0.437)	(0.455)	(0.198)	(0.205)
Prob	0.746***			0.663***
	(0.0374)			(0.0308)
Price		0.674***	0.694***	
		(0.0412)	(0.0313)	
Constant	17.12	0.0377	0.203	58.99***
	(12.19)	(13.97)	(6.614)	(6.503)
N	1407	1407	1407	1407
adj. R^2	0.427	0.366	0.533	0.517
Big Five	Yes	Yes	Yes	Yes
Order Dummy	Yes	Yes	Yes	Yes
Graph Fixed Effects	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: OLS regressions with interaction. In Columns (1) and (2) the dependent variable is the investment decision (*Investment*). in Columns (3) and (4) the dependent variables are the gain probability (*Prob*) and the price prediction (*Price*) , respectively. All standard errors are clustered at the subject level.

	Investment				*Prob*			*Price*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treatment	7.671***	6.971***	5.180***	6.640***	2.846**	2.339*	2.022*	0.959	0.459	-1.081
	(1.989)	(1.849)	(1.627)	(1.603)	(1.347)	(1.240)	(1.066)	(1.116)	(0.989)	(0.877)
Dictator		0.0140	-0.00338	0.0278		0.0227*	0.0359***		-0.0192	-0.0341***
		(0.0249)	(0.0238)	(0.0251)		(0.0126)	(0.0119)		(0.0143)	(0.0127)
Female		-5.788**	-6.804***	-6.575***		1.328	0.574		1.091	0.217
		(2.860)	(2.432)	(2.514)		(1.950)	(1.689)		(2.077)	(1.771)
CRT		0.566	0.848*	0.411		-0.369	-0.517*		0.214	0.457
		(0.506)	(0.454)	(0.482)		(0.337)	(0.302)		(0.352)	(0.308)
Ambiguity		-0.703	-0.617	-0.452		-0.112	0.128		-0.347	-0.274
		(0.455)	(0.436)	(0.415)		(0.254)	(0.294)		(0.332)	(0.333)
Risk		-0.0423	0.333	0.108		-0.491*	-0.347		-0.208	0.115
		(0.435)	(0.403)	(0.366)		(0.289)	(0.295)		(0.355)	(0.331)
Loss		-0.918*	-0.762*	-0.963**		-0.204	-0.247		0.0627	0.197
		(0.476)	(0.421)	(0.445)		(0.296)	(0.225)		(0.316)	(0.240)
Prob			0.765***							0.658***
			(0.0397)							(0.0364)
Price				0.721***			0.690***			
				(0.0387)			(0.0349)			
Constant	42.52***	49.38***	-5.136	-36.55***	54.38***	71.22***	-11.03	104.6***	119.2***	72.28***
	(1.511)	(11.88)	(10.98)	(11.60)	(1.048)	(7.489)	(7.275)	(0.971)	(7.567)	(6.878)
N	1089	1089	1089	1089	1089	1089	1089	1089	1089	1089
adj. R^2	0.014	0.142	0.456	0.408	0.002	0.147	0.534	-0.001	0.114	0.516
Big Five	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Order Dummy	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Graph Fixed Effects	No	Yes	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: OLS regressions of subjects with social preferences. In Columns (1)-(4) the dependent variable is the investment decision (*Investment*). In Columns (5)-(7) and (8)-(10) the dependent variables are the gain probability (*Prob*) and the price prediction (*Price*), respectively. All standard errors are clustered at the subject level.

Table 1. More interestingly, once we drop the "non-social" subjects, decreasing liability results in a positive increase in stated beliefs. This shift is statistically significant for the baseline specification in column (5) at the conventional 5% (p-val=0.036), but not for the full specification in column (7) (p-val=0.059). As in the full set, our treatment does not affect the price predictions of subjects.[14] Overall, it is clear in Table 3 that subjects (even if they hold social preferences) invest more in treatment than in control rounds. Moreover, in line with the theory, subjects form optimistic beliefs about the investments to self-justify these higher investments.

Result 3: *Subjects who hold social preferences form motivated beliefs.*

3.3 The Impact of Motivated Beliefs on Investment

While our results point to the formation of motivated beliefs, a question still lingers: how much of the observed increase in investment is due to motivated beliefs and how much is due to the change in the incentive structure? In other words, how much do motivated beliefs matter towards the final investment? To answer this question we use causal mediation analysis and follow Imai et al. (2011) and Imai et al. (2013), who show that an instrumental variable (IV) approach can be used to disentangle the effects of a mediator of interest (i.e., motivated beliefs) from all other potential effects of the treatment (e.g., the change in the incentive structure). In our case, the IV regression is:

$$Prob_{i,r} = \alpha_0 + \alpha_1 \times Treatment_{i,r} + \alpha_2 \times Graph_{i,r} + \epsilon_{i,r}, \tag{5}$$

$$Investment_{i,r} = \beta_0 + \beta_1 \times \widehat{Prob_{i,r}} + \beta_2 \times Treatment_{i,r} + u_{i,r}. \tag{6}$$

In the first stage (Equation (5)), we regress subject i's reported gain probability in round r ($Prob_{i,r}$), on the treatment dummy ($Treatment_{i,r}$) and the dummies for the six different graphs in each session ($Graph_{i,r}$). In the second stage (Equation (6)), we regress the percentage of the endowment invested by subject i in round r ($Investment_{i,r}$) and the predicted probabilities ($\widehat{Prob_{i,r}}$) from Equation (5). This model allows us to disentangle the indirect effect of the treatment that is mediated through beliefs by exploiting the

[14] In Figure 7 of Appendix B, we reproduce Figure 3 separately for the non-social (entirely selfish) and social subjects.

variation of $Graph_{i,r}$ *across* the treatment rounds. Because $Graph_{i,r}$ varies within each treatment, we can include $Treatment_{i,r}$ in the second stage and isolate the direct effect that our treatment has on beliefs independent of any other effects. For this approach to work, our main identifying assumption is that $Graph_{i,r}$ only affects the investment decision through a shift in beliefs about the gain probability of the investment.

Table 4 shows the results from the first stage.[15] The results indicate that the variation in graphs has a large impact on beliefs and that the treatment has a positive coefficient which is significant at the 10% (α_1=2.022 with p-val = 0.059 in the complete specification). Table 5 presents the second-stage results using the estimates from Table 4. On average, an increase in the perceived success probabilities by 1 percentage point increases the investment by approximately 1 percentage point (β_1) in all three specifications. This effect is statistically significant at the 1% level. The direct treatment effect (β_2) is approximately 4.7 percentage points and also statistically significant at the 1% level in the complete specification.

As shown in Imai et al. (2011), we can now compute the average effect of the treatment on the investment *that is mediated through beliefs* as the product of α_1 and β_1. Imai et al. (2011) call this the complier average mediation effect (CACME).[16] By contrast, the complier average direct treatment effect (CADE) captures all causal mechanisms of limiting liability on investment *that do not work through changes in beliefs* and is given by β_2 in Equation (6). Therefore, using the first- and second-stage results from Tables 4 and 5, we obtain the indirect treatment effect, which is $2.022 \times 0.990 \approx 1.980$ in specification (3). Table 6 uses bootstrapped standard errors to test whether the effect of motivated beliefs on the investment, $\alpha_1 \times \beta_1$, is statistically significant. We find that the effect of motivated beliefs is statistically significant at the 5% for the complete specification (3), but not for the incomplete ones.

[15]Notice that columns (2) and (3) are identical to the specifications of columns (6) and (7) in Table 3, however, in Table 4 we show the dummies for the different graphs instead of the personality controls.

[16]More precisely, the CACME is the average effect of the change in investment that is mediated through beliefs, *among those subjects whose beliefs are affected by the treatment* (see Imai et al. (2011) for a longer discussion).

	Prob		
	(1)	(2)	(3)
Treatment	2.345*	2.339*	2.022*
	(1.234)	(1.240)	(1.066)
$Graph_2$	-23.58***	-23.58***	-8.261***
	(2.471)	(2.485)	(1.696)
$Graph_3$	-9.824***	-9.824***	-5.186***
	(2.588)	(2.603)	(1.678)
$Graph_4$	-9.469***	-9.476***	-3.756**
	(2.290)	(2.306)	(1.830)
$Graph_5$	-7.950***	-7.956***	-5.996***
	(2.435)	(2.447)	(1.652)
$Graph_6$	7.713***	7.707***	5.251***
	(2.036)	(2.048)	(1.644)
Constant	61.82***	71.22***	-11.03
	(1.660)	(7.489)	(7.275)
N	1089	1089	1089
adj. R^2	0.145	0.147	0.534
Controls	No	Yes	Yes
Price Exp	No	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: First stage of mediation analysis. All standard errors are clustered at the subject level.

	Investment		
	(1)	(2)	(3)
$\widehat{Prob}$	1.017***	1.015***	0.990***
	(0.0864)	(0.0869)	(0.151)
Treatment	4.777**	4.691**	4.727***
	(1.840)	(1.849)	(1.653)
Constant	-12.79**	-23.31*	-25.71**
	(5.013)	(12.91)	(11.43)
N	1089	1089	1089
adj. R^2	0.108	0.144	0.407
Controls	No	Yes	Yes
Price Exp	No	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Second stage of mediation analysis. All standard errors are clustered at the subject level.

	Investment		
	(1)	(2)	(3)
Indirect Treatment Effect (CACME)	2.385*	2.359*	1.980**
	(1.234)	(1.225)	(0.945)
Direct Treatment Effects (CADE)	4.776***	4.690***	4.727***
	(1.623)	(1.582)	(1.529)
Observations	1089	1089	1089
Controls	No	Yes	Yes
Price Exp	No	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Indirect (CACME) and direct treatment effects (CADE). Standard errors obtained from bootstrapping by resampling observations (with replacements) for 1,000 times.

Result 4: *Of the approximately 6.5% average investment increase in treatment rounds, around 2% is due to motivated beliefs.*

4 Discussion

In this paper we investigate whether investors form motivated beliefs under different degrees of limited liability. As shown in Füllbrunn et al. (2020) and Füllbrunn and Luhan (2020), such convex incentive structures involve a tension between egoistic and social preferences for the decision maker. This tension creates a mental discomfort which investors can confront by forming motivated beliefs to self-justify any selfish behavior (e.g. Rabin, 1994; Barberis, 2015; Bénabou, 2015). Of course, such motivated beliefs will only occur if investors hold social preferences. If investors are *entirely selfish* and do not hold any social preferences, then they will not perceive their increase in risk-taking as "morally questionable," and will not need to bias their beliefs.

In our paper we cannot detect any effect of motivated beliefs when studying the entire sample. However, when we study the sample of subjects with social preferences, then we detect the formation of motivated beliefs. We believe there are two reasons for our initial lack of results. The first one is the introduction of the strategy method. This design choice has an obvious trade-off; on the one hand, we double the number of observations per session, drastically reducing the experiment's economic and time-consumption costs. On the other hand, some treatments might have less of a "bite" under such experimental design as the strategy method provides a lower bound for testing for treatment effects (Brandts and Charness, 2011). Because motivated beliefs are a subtle mechanism, the strategy method might have dampened the effect of knowing with certainty that any action could potentially affect the passive investor in a negative way.

The second reason that might have weakened our results is the presence of subjects with no social preferences. Giving zero in the dictator game was the preferred option of more than one-fifth of our subjects who, therefore, fall into the *entirely selfish* category (as defined in List (2007)). Because such subjects do not need to form motivated beliefs, their presence only adds noise to our data and significantly dampens our treatment effect. This is clear from Table 2, where we see a strong interaction effect between social preferences and our treatment. Given this interaction, we restrict our data set to subjects with social preferences.[17] Using this subset of subjects, we detect the formation of motivated beliefs when subjects have no liability (see Table 3). This result goes in line with the theory, as it confirms experimentally that motivated beliefs depend on the social preferences of subjects and that such motivated beliefs do have an impact in their behavior and choices. In fact, through mediation analysis, we quantify the effect of motivated beliefs on the subjects' investment and show that of the total increase of investment in treatment rounds (approx. 6.5%), around a 2% can be attributed to the formation of motivated beliefs.

Given the negative reputation of the finance industry among the general public (e.g. Sapienza and Zingales, 2012; Cohn et al., 2014; Zingales, 2015), it is natural to wonder, whether financial professionals have social preferences similar to our experimental subjects and, consequently, whether our results would replicate among this population. Fortunately, there is an extensive literature showing that the behavior and social preferences of financial professionals are not substantially different from that of the general

[17]Note that the exclusion of the purely selfish subjects is a conservative cutoff, as it is well-known that the implied uncertainty of the strategy method dissipates selfish behavior in dictator games (e.g. Sefton, 1992; Iriberri and Rey-Biel, 2011; Mesa-Vázquez et al., 2021). This means that our cutoff includes less subjects than it would if we had implemented a direct-response method.

population (e.g. Füllbrunn et al., 2022a; Huber and König-Kersting, 2022).[18] In fact, van Hoorn (2015) finds that financial professionals show a *higher* standard of morality than the general population in financial environments, while Kirchler et al. (2018) and Lindner et al. (2021) find that financial professionals are more strongly motivated by *self-image* concerns than university students. In addition, there is evidence that (in general) treatment effects are qualitatively equal between students and financial professionals (Fréchette, 2015; Weitzel et al., 2019). In a nutshell, this literature helps to dispel any concerns that our results would not replicate with financial professionals and, in fact, it may even suggest the plausibility of stronger effects.

5 Conclusion

Cognitive dissonance is the psychological discomfort that arises when one cannot rationalize two conflicting views or actions. A common way to deal with this tension is to form motivated beliefs (Festinger, 1962). For instance, financial investors might be excessively optimistic about their investments under limited liability (Barberis, 2015; Bénabou, 2015; Bénabou et al., 2018). Such motivated beliefs occur when investors hold social preferences and want to keep a positive self-image, while at the same time being aware that if they are not paying for the losses, then someone must be. By convincing themselves that the investment is sounder than it is, investors suppress the tension between more monetary gains and their scruples, allowing them to make larger investments with less moral questioning.

To study the formation of such motivated beliefs, we run a novel experiment in which subjects make investment decisions under different degrees of liability. In control rounds, subjects split evenly any gains and losses generated by their decisions with their assigned partner. However, in treatment rounds the assigned partner is responsible for all eventual losses derived from the investment. Because we elicit the risk assessment of investors for

[18]To be more precise, the literature has found that financial professionals are no more selfish (van Hoorn, 2015; Duchêne et al., 2021; Holmén et al., 2021), are equally altruistic (Holmén et al., 2021) and share similar social values with the general population (van Hoorn, 2015). Moreover, some recent research has found that financial professionals are equally honest than the general population (e.g. Rahwan et al., 2019; Huber and Huber, 2020; Holmén et al., 2021), contrary to the early findings in this area (Cohn et al., 2014).

the same investment under varying degrees of liability, our design allows us to detect any motivated beliefs resulting from the change in limited liability.

However, when analyzing the beliefs of our full set of subjects we cannot detect the formation of motivated beliefs in treatment rounds. Yet, once we limit our set to those subjects that are not *entirely selfish* (i.e., subjects with social preferences), then we detect motivated beliefs in the treatment rounds. Moreover, we also show that the stronger the social preferences, the more optimistic the beliefs are when there is no liability. Finally, we use mediation analysis to quantify the impact of such motivated beliefs on the investments that subjects make when there is no liability. Of the approximately 6.5% average increase in investment that we observe in treatment rounds, we conclude that around 2% is due to the formation of motivated beliefs. In summary, we show that : 1) limited liability can result in motivated beliefs, 2) social preferences are a crucial driver of such motivated beliefs in financial investing, and 3) motivated beliefs have a real impact in the investment decisions.

One of the implications of our results is that limited liability induces investors to form motivated beliefs about their investments and to make larger investments than they would otherwise do. Such bias can be extremely costly for individual investors and firms (Bénabou, 2015), but it is especially dangerous if it is collectively shared by the financial sector, as these biased beliefs might reinforce bubble formation or trigger a crisis (Bénabou and Tirole, 2016).

There is some skepticism about extrapolating results from undergraduate students into financial professionals (see, e.g. Huber and König-Kersting (2022) for a thorough discussion). However, the recent literature shows that experimental treatment effects have qualitatively similar results with financial professionals than with undergraduate laboratory subjects (e.g., Weitzel et al., 2019; Fréchette, 2015). Therefore, we believe that our results should raise some concern about the impact of motivated beliefs in the financial industry and highlight the need to incorporate behavioral insights into financial regulation.

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A Additional Tables

	$H0$: Treatment = Control	Graph 1	Graph 2	Graph 3	Graph 4	Graph 5	Graph 6
M-W	Investment	0.030	0.018	0.065	0.003	0.034	0.013
	Gain Probability	0.446	0.278	0.480	0.160	0.247	0.060
	Price Prediction	0.145	0.084	0.274	0.496	0.220	0.076
F-P	Investment	0.034	0.020	0.052	0.002	0.033	0.014
	Gain Probability	0.457	0.408	0.446	0.211	0.784	0.052
	Price Prediction	0.812	0.239	0.515	0.543	0.827	0.126

Table 7: Non-parametric tests. One-tailed p-values resulting from Mann Whitney U test (M-W) and Fisher-Pitman test (F-P) comparing the decisions of subjects across treatment and control for each graph. In all cases the null hypothesis (H0) is equality between treatments.

Trait	Gender	CRT	Ambiguity Av	Risk Av	Loss Av	Agreeable	Conscientious	Neurotic	Open	Extroverted
M-W p-val	0.100	0.902	0.658	0.929	0.066	0.712	0.766	0.138	0.289	0.733
F-P p-val	0.130	0.991	0.500	0.791	0.209	0.847	0.471	0.183	0.344	0.835

Table 8: Randomization. Two-tailed p-values resulting from Mann Whitney U (M-W) and a Fisher-Pitman (F-T) test comparing the personality traits of subjects across treatment order. In all cases the null hypothesis (H0) is equality between treatment orders.

	Investment		
	(1)	(2)	(3)
Indirect Treatment Effect (CACME)	1.008	0.993	1.215
	(1.017)	(0.999)	(0.838)
Direct Treatment Effects (CADE)	7.702***	7.609***	7.608***
	(1.593)	(1.562)	(1.551)
Observations	1407	1407	1407
Controls	No	Yes	Yes
Price Exp	No	No	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Indirect (CACME) and direct treatment effects (CADE) for the full set of subjects. Standard errors obtained from bootstrapping by resampling observations (with replacements) for 1,000 times.

B Additional Figures

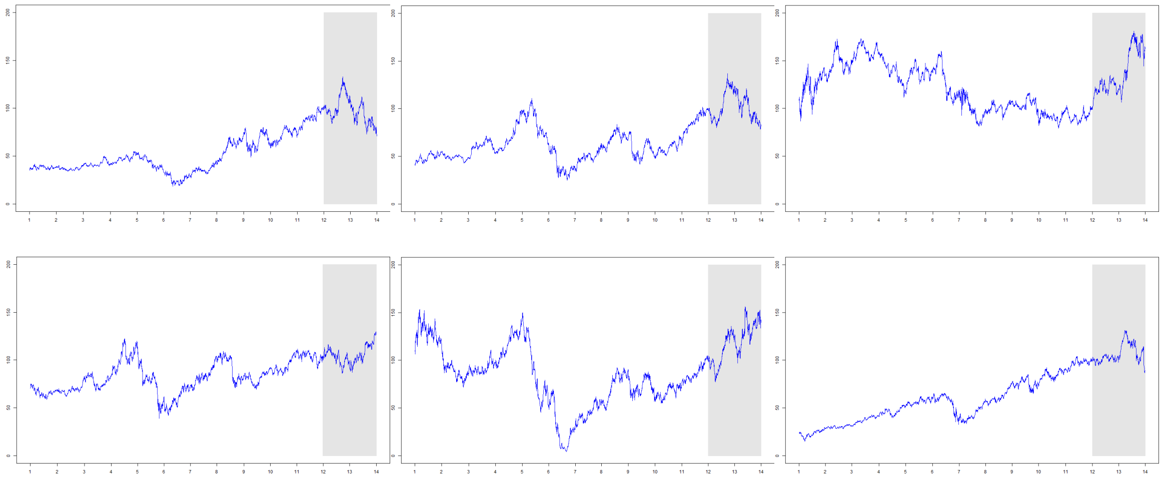

Figure 4: The full time series of the six assets used for the final summary page and for calculation of the payoffs. From left to right and from top to bottom: (1) Bayerische Motoren Werke AG, 27-Jun-03–27-Jun-16; (2) Daimler AG, 20-Jun-03—20-Jun-16; (3) Deutsche Telekom AG, 10-Sep-02—10-Sep-15; (4) Siemens AG, 05-Jan-04—05-Jan-17; (5) Infineon Technologies AG, 08-Jul-03—08-Jul-16; (6) Linde AG, 18-Dec-02—18-Dec-15. All data are downloaded from Google Finance.

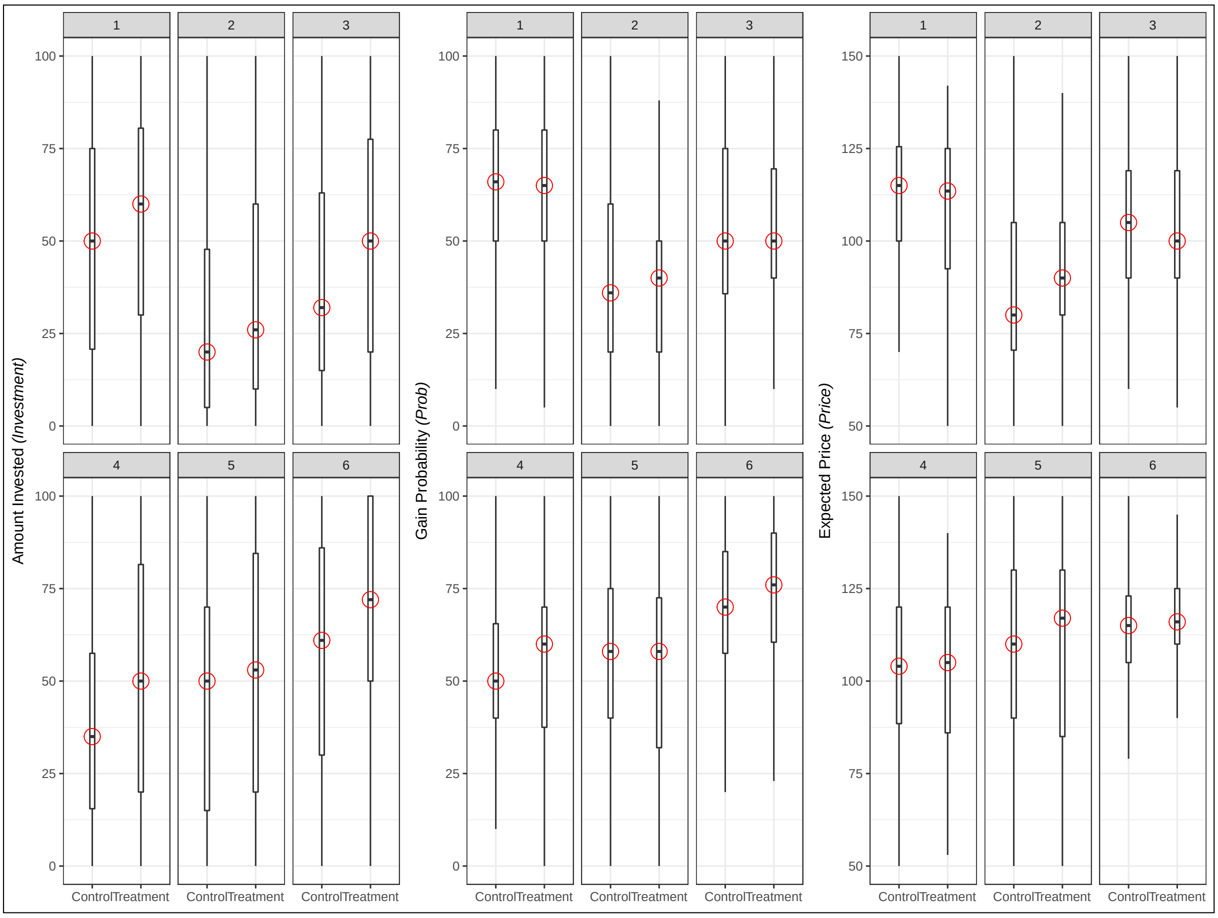

Figure 5: Overview of the data by shown graph. In the vertical axis, we plot the amount invested ($Investment$), the gain probability ($Prob$), and the price prediction ($Price$), respectively. In the horizontal axis, we separate by treatment. The lower and upper bar of the box represent the first and third quartiles of the data. The red circle marks the median value. Note that the scale of the first two figures goes from 0 to 100 while we limit the third figure to ranges from 50 to 150 for legibility reasons.

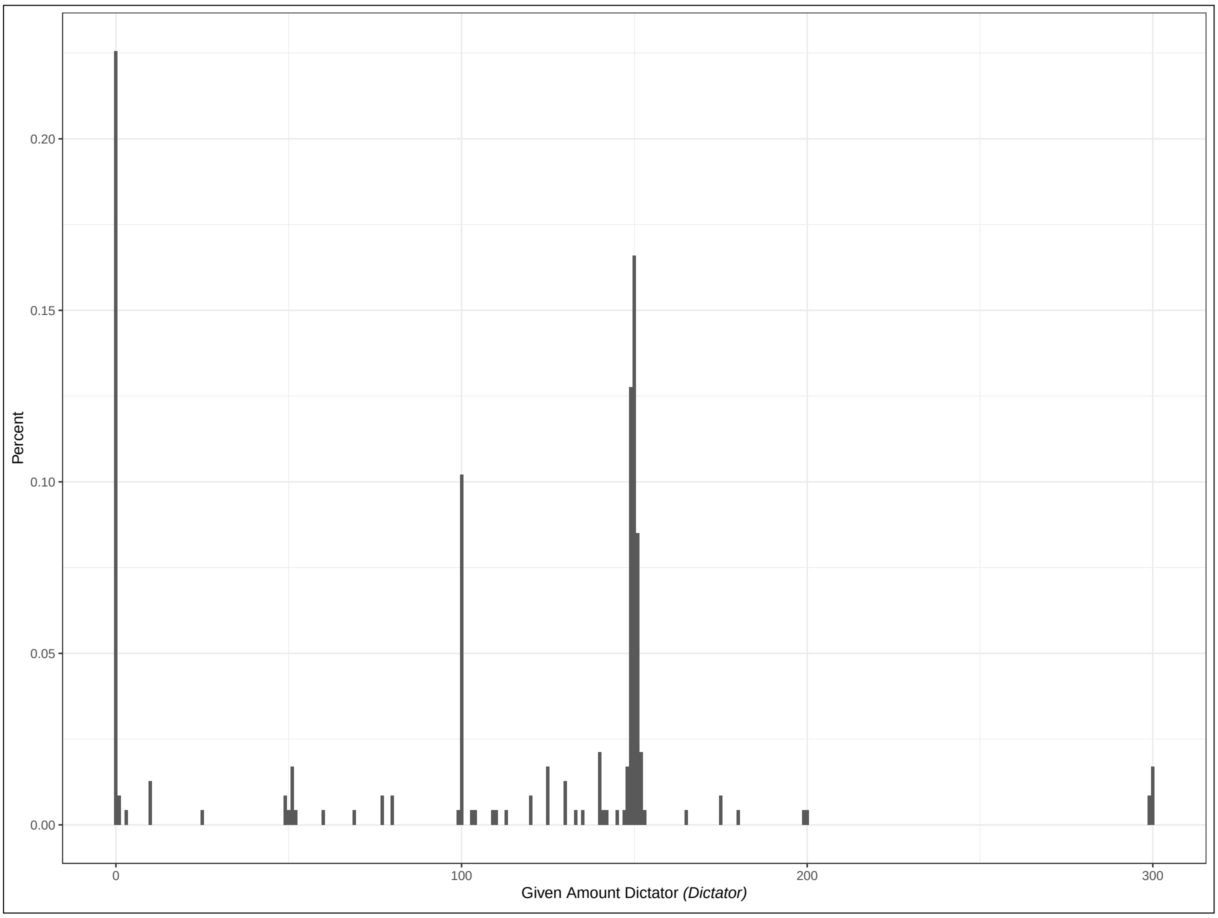

Figure 6: Amount in eurocent given in the dictator game. The vertical axis plots the percentage of subjects that chose the amount to give to their matched pair, which are plotted in the horizontal axis.

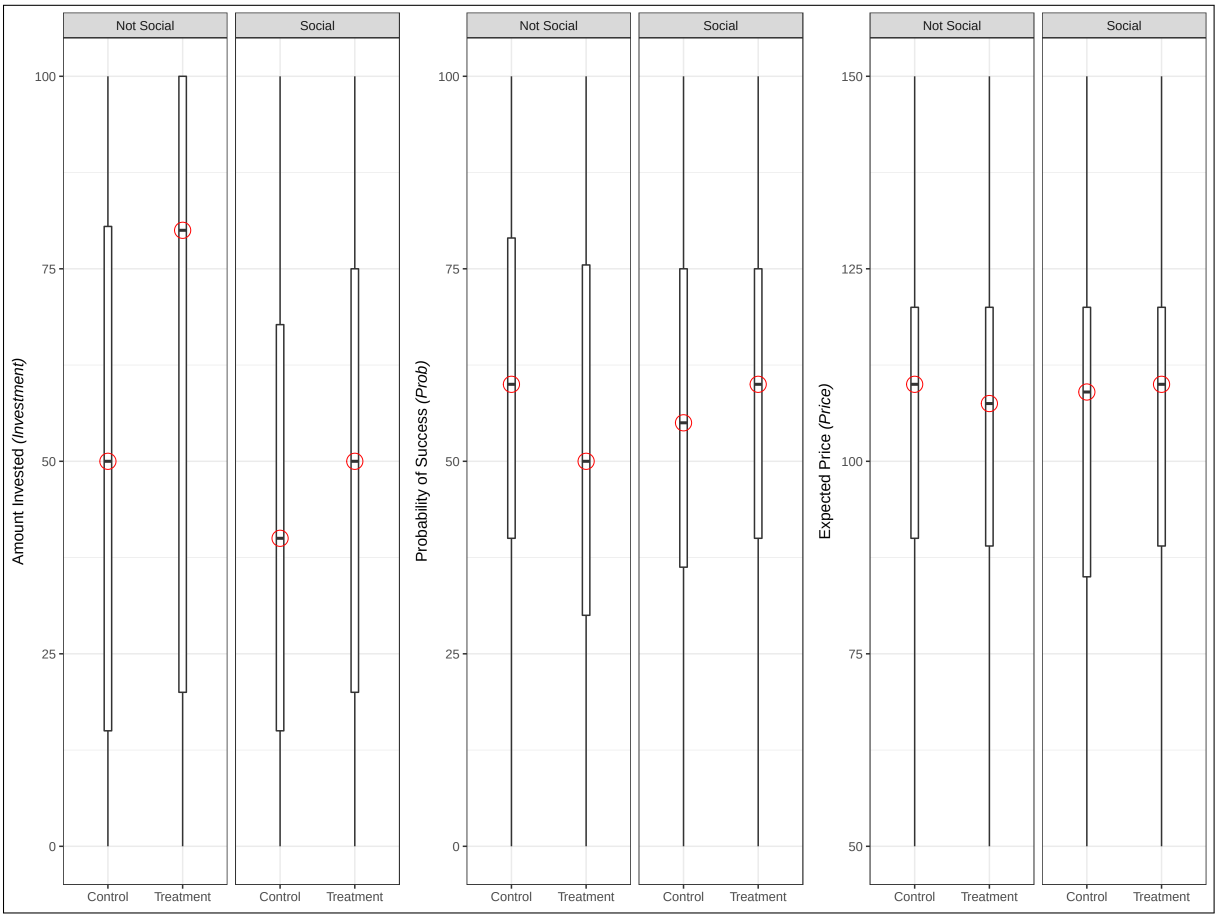

Figure 7: Overview of the data by social preferences. In the vertical axis, we plot the amount invested, the gain probability, and the price prediction respectively. In the horizontal axis, we separate by treatment. The graphs are separated by those who donated zero in the dictator game (non-social) and those that donated strictly more than zero (social). In all cases, the lower and upper bar of the box represent the first and third quartile of the data. The red circle marks the median value. Note that the scale of the first two figures goes from 0 to 100 while we limit the third figure to ranges from 50 to 150 for legibility reasons.