ESSAYS ON BEHAVIORAL MARKET DESIGN

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To Susi.

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Contents

1 Introduction

Market design aims at improving specific markets in which actual people with all their facets interact. Therefore, in order to design the rules in a given market, the designer can not only rely on standard economic models based on the assumptions of a homo economicus, but needs to account for behavioral preferences and how they interact with the given market.

In four chapters, this dissertation investigates how non-standard preferences such as motivated beliefs, reference dependence or norm conformity influences outcomes on certain markets. To do so, I apply behavioral theory showing that seemingly small design changes, i.e. changes that would have no impact under standard preferences, can lead to improvements, and test experimentally whether these improvements actually materialize. In chapters 2 to 4 I focus on procurement auctions, where relatively small savings can lead to large increases in profit margin. [1] In these chapters I demonstrate how the market designer can exploit behavioral biases of bidders by implementing seemingly minor changes in design. In chapter 5 I move away from procurement to a more general framework, and show how behavioral biases of individuals can have an impact on collective outcomes in large markets.

In Chapter 2 titled *Procurement Design with Loss Averse Bidders*, which is joint work with Philippe Gillen and Nicolas Fugger, we show that when agents have expectations based loss averse preferences, it is always better for the auctioneer to conduct a multi-stage mechanism as compared to a single-stage mechanism. First, we derive a revenue equivalence principle, implying that for a fixed multi-stage structure revenues do not depend on the payment

[1] As confirmed by the consulting company Oliver Wyman, suppliers are e.g. responsible for roughly 60% of the value added of a car. Combined with relatively low margins in the automotive industry, this means that small savings lead to large increases in margins.

rule. We then introduce a simple mechanism that outperforms any sealed bid auction, the 'tournament': In this mechanism, bidders are first split into two subgroups of equal size, and then have to submit a bid. In each subgroup only the highest supplier moves forward to the final round, where both finalists are asked to submit another bid, by which the winner is determined. By conducting such a mechanism, the auctioneer takes advantage of the bidder´s (expectations based) loss aversion: After moving forward to the final, bidders become more attached to winning the auction, and are as a consequence willing to bid more aggressively as compared to a single-stage mechanism. Finally we derive the optimal two-stage mechnism that optimally balances competition and attachement in the final round.

In Chapter 3 titled *Motivated Beliefs in Auctions*, I show that when bidders can form motivated beliefs about their winning probability in auctions, the auctioneer is better off if he decreases the time between bidding and revelation of results. When agents form beliefs about an uncertain event they face a tradeoff: Optimism increases ex ante savoring, while pessimism leads to less disappointment ex post. Hence optimal expectations depend on the time left until the uncertainty is resolved, i.e. the time one can savor ex ante by being (too) optimistic. I apply a decision theory model of Gollier and Muermann on First Price Auctions, and show that by decreasing the time between bids and revelation of results, the auctioneer can induce bidders to forego optimism, leading to more aggressive bids and thereby higher revenues for the auctioneer. Finally I test these predictions experimentally.

Chapter 4 with the title *Auction Experiments with a Real Effort Task*, which is joint work with Philippe Gillen and Nicolas Fugger, aims to develop a novel experimental tool set to increase the external validity of auction experiments. We propose an alternative experimental design that, in contrast to standard induced values frameworks, allows us to capture two-dimensional prospect theory and common value effects, two phenomena that are highly relevant in procurement practice. In experiments with our proposed design subjects bid a number of slider tasks in order to win a monetary price. Testing our design in the laboratory, we find evidence for both loss-aversion and common values.

In Chapter 5 titled *Social Norms, Sanctions, and Conditional Entry in Markets with Externalities: Evidence from an Artefactual Field Experiment*, which is joint work with Philippe Gillen, Nicolas Fugger, Vitali Gretschko and Peter Werner, we show the importance of Norm Conformity on markets where trade leads to negative externalities. We conduct a large-scale market experiment with a representative sample of the German population in which sellers and buyers can engage in profitable trade which, however, destroys a donation for a good cause. Moreover,we test whether buyers and sellers focus on social norms when they decide to trade and to what extent external observers are willing to sanction immoral trading activities. We find that the majority of sellers and buyers act in a moral way by notentering the market at all. The desire for norm conformity seems to be an important driver of market behavior: A substantial share of buyers and sellers make their market entry conditional on what other traders do. Furthermore, the large majority of observers is willing to incur personal costs in order to punish participants who decide to tradeand thus to sanction immoral behavior. Additional analyses reveal that some demographic characteristics of the participants are significantly correlated with moral behavior in the present setting.

2 Procurement Design with Loss Averse Bidders

Abstract

We show that it is beneficial for a buyer to conduct a multi-stage mechanism if bidders are loss averse. In a first step, we derive a revenue equivalence principle. Fixing the multi-stage structure, the revenue is independent of the chosen payment rule. Secondly, we introduce a simple two-stage mechanism which always leads to a decrease in procurement costs compared to any single-stage auction. Finally we derive the optimal efficient two-stage mechanism.

2.1 Introduction

Procurement plays an important role both in the public and private sector. In Europe public procurement represented around 17% of the GDP in 2007.[2] In many sectors of the industry the role of procurement is even more pronounced. The consulting company Oliver Wyman reports that suppliers are responsible for roughly 60% of the value added of a car.[3] Hence, small savings in average procurement costs translate to a substantial increase in overall profit margins.

In the past few decades reverse auctions have been established as one of the main tools to select suppliers and to determine prices in many industries. Depending on factors like size or complexity of a project, the procurement designer usually commits to a certain auction format. In the academic literature on auctions, it is typically assumed that the auction designer chooses

[2] Internal Market Scoreboard, n^o 19, July 2009

[3] `https://www.oliverwyman.com/our-expertise/industries/automotive/procurement.html`

between a first-price or second-price payment rule and decides if she wants to conduct a static or dynamic auction. In the static formats, each bidder submits a sealed bid and the lowest bidder gets the contract. The dynamic formats typically considered are the Dutch auction and the English auction. In the English auction the price is decreased over time and bidders can drop out. It ends when the second-last bidder drops out. The winner is the last active bidder and he is paid the last displayed price. In the English auction the price increases over time and the first bidder who accepts the current price receives the contract and is paid the accepted price. In addition to the four auction formats described, the auction designer could also determine the number of stages.

In single-stage auctions, suppliers hand in an offer once and the contract is allocated based on these offers. In multi-stage auctions, the first rounds are usually conducted to reduce the set of suppliers that can participate in the final round.[4] Talks with practitioners suggest that especially in strategically important projects, multi-stage auctions are the preferred choice.

Interestingly, economic theory suggests that the use of multi-stage mechanisms cannot increase revenues above those that are achievable by one-stage mechanisms[5] when agents have standard preferences. However, if bidders are loss averse, the auction designer can increase her revenue by conducting multi-stage mechanisms. Proceeding to the next stage affects a bidder's winning probability and he therefore adjusts his reference point. The auction designer can exploit her influence on the bidders' reference points. Following Kőszegi and Rabin (2006), we assume reference points are based on rational

[4]Note that in these mechanisms, suppliers are typically restricted to hand in (weakly) more attractive offers in subsequent rounds.

[5]We consider settings in which the time between the different stages is rather short and suppliers cannot adjust their product during the auction.

expectations.[6]

A supplier who proceeds to the final stage of the multi-stage mechanism updates his winning probability. He knows that winning is now more likely than before. Loss aversion implies that such a bidder gets more attached to winning and is willing to make a more attractive offer, since losing in the final round would cause a high disutility. These additional gains and losses are anticipated by the agent before the auction and factored into his first-round bid. A straightforward way of implementing such a mechanism is by conducting a two-stage tournament. Suppliers compete in two semifinals and only the best supplier of each semifinal proceeds to the final stage.[7]

In line with von Wangenheim (2019), we assume that bidders evaluate outcomes in two dimensions, a money dimension and a good dimension.[8] Consider a key account manager working for a supplier of a car manufacturer. When competing for a strategically important contract, he thinks in two independent dimensions: In the money domain, all monetary details such as his own costs, negotiated piece prices, investments etc. are captured. Independent of these details, the manager evaluates his chances of winning the contract and therefore getting a high level of recognition within his company. If this is the case, the buyer of the car manufacturer could exploit this behavior when designing her procurement mechanism.

In this paper, we first derive a revenue equivalence principle for bidders that are loss averse in the good domain. For a fixed multi-stage structure,

[6]There is an ongoing debate on how the reference point is formed. Some studies suggest that it is mainly driven by expectations, whereas others hold that it is mostly given by the status quo. For a discussion, see Heffetz and List (2014) and references therein.

[7]If the number of suppliers is odd, one can conduct semifinals that are symmetric in expectation.

[8]Lange and Ratan (2010) compare how the consideration of a one-dimensional reference point differs from the consideration of a two-dimensional reference point. They show that it can strongly affect predictions and argue that in most real world settings the consideration of a two-dimensional reference point is more reasonable.

meaning which and how many bidders advance in the individual stages, the auctioneer's revenue is not dependent on the payment rule she chooses. This result considerably simplifies the analyses and allows us to concentrate on the structure of multi-stage mechanisms. Furthermore, as a side result, this entails that all single-stage static auctions lead to the same expected costs.

The main result of this paper is that the symmetric two-stage tournament always leads to a decrease in procurement costs compared to any (standard) single-stage auction. This result is robust, as it does not require knowledge about bidders' loss aversion. Hence, by conducting such a mechanism, the procurement designer's revenue strictly improves compared to all standard auctions if agents are loss averse, and makes no difference if not.

Finally, we derive the optimal efficient two-stage mechanism. When conducting two-stage mechanisms the procurement designer is confronted with a trade-off: On the one hand, she wants to maximize the attachment to winning the contract, and hence induce large winning probabilities to low-cost types. On the other hand, she cannot neglect high-cost types, either. If high-cost types have an already very low chance of winning the project, they might insure themselves from a deviation from their expectation by bidding even lower. Taking into account the bidders' degree of loss aversion, the optimal mechanism thus creates the level of uncertainty that optimally solves this trade-off.

2.2 Related Literature

Our paper contributes to the literature on expectations-based loss aversion. The concept of loss aversion has been studied since the seminal paper of Kahneman, Knetsch, and Thaler (1990). In their paper, they introduce the endowment effect and experimentally show that a subjects' valuation for a certain good increases when they are physically endowed with the good. According to this strand of literature subjects have a reference point and a deviation from this reference point in direction of losses has a larger impact on utility than a deviation in direction of gains.

A discussion around the formation of these reference points has risen in the literature. Kőszegi and Rabin (2006) suggest that the reference point is based on rational expectations. In an auction, this means that bidders have a certain probability of winning in mind and feel losses and gains compared to these expectations. As a consequence, a bidder expecting to win a good with a high probability suffers more from not winning than if he gauged his chances of winning as slim.

Our paper is most closely related to von Wangenheim (2019), who compares a sealed-bid second-price auction to an English auction assuming that bidders are loss averse and that their reference point is given by rational expectations. While both formats are strategically equivalent in independent private value settings if bidders have standard preferences, he shows that the second-price sealed-bid auction dominates the English auction if bidders are loss averse. The intuition is as follows: At the beginning of the English auction a bidder has the same chance of winning as in the second-price sealed-bid auction. However, during the course of the English auction the winning probability decreases and the bidder becomes less attached to the good. As a consequence, his willingness to pay decreases and he will drop out before the price is reached that he would have bid in the second-price sealed-bid auction.

Similar to von Wangenheim (2019), Ehrhart and Ott (2014) compare two standard auction formats for bidders with reference-dependent preferences. Comparing the Dutch auction to the English auction they show that the

Dutch auction outperforms the English auction. The intuition is closely related to von Wangenheim (2019) and to our paper. For a given valuation a bidder has the same winning probability at the beginning of the Dutch auction and the English auction. However, while the winning probability decreases during the course of the English auction, it increases during the course of the Dutch auction. Hence, the attachment to the good is larger in the Dutch auction and bidders are thus willing to bid more aggressively. Similarly, a bidder who advances a stage in our setting also updates his winning probability and therefore his attachment to the good increases. This, in return, increases the bid he is willing to submit.

Banerji and Gupta (2014) and Rosato and Tymula (2019) provide evidence for the effect of expectations-based loss aversion in auction environments. In a setting in which participants compete in a second-price auction for a real good, they observe that bidders bid less when their winning probability was smaller. This observation stands in contrast to the predictions of standard theory which implies that subjects have a dominant strategy of bidding their true valuation independent of their winning probability. In contrast to that, loss aversion implies that a bidder with a higher chance of winning is more attached to the good and, hence, willing to bid more.

In contrast to the existing paper on auctions with loss averse bidders, we do not concentrate on comparing standard auction formats but investigate the following question: How can an auctions designer exploit bidders' loss aversion to increase her revenue?

Given this research question our work is also related to Maskin and Riley (1984) who also investigate how the auction designer can increase her revenue if bidders have a behavioral bias, in their case risk aversion. Similar to us, they present an optimal mechanism that needs to be finetuned to bidders' risk preferences and seems too complex to be implemented in practice. While our management implication is that simple two-stage mechanisms outperform one-stage auctions if bidders are loss averse, they show that first-price auctions outperform second-price auctions if bidders are risk averse.

Another related paper is Engelbrecht-Wiggans and Katok (2007). They analyze how the auction designer can exploit regret aversion of bidders. They show that the right information design, namely revealing the best bid but concealing all other bids, allows the auction designer to increase her revenue.

2.3 Model

In this section, we introduce the formal model. We consider $n \geq 2$ ex-ante symmetric bidders competing for one indivisible good. The value v_i of bidder $i \in \{1, \dots, n\}$ for the good is privately drawn from a distribution F, $v_i \overset{\text{iid.}}{\sim} F[0,1]$. F is assumed to have a differentiable density f which is strictly positive on its support $[0,1]$. Moreover, F is common knowledge. Bids are placed after learning the value for the good.

For loss aversion we follow Kőszegi and Rabin (2006). We assume that bidders are loss averse in the good domain g representing the item the winner of the auction receives.[9] Furthermore, we assume bidders to be narrow-bracketers, following the definition of von Wangenheim (2019). Let x^m be the price a bidder pays if he wins and x^g a binary variable that is equal to one if the bidder wins the good and zero else. For an outcome $x = (x^c, x^g)$, valuation v for the good, and the reference consumption $r^g \in \{0, 1\}$, agent's

[9] We assume that bidders are not loss averse in the money domain. This assumption is in line with Horowitz and McConnell (2003), who argue that the endowment effect is "highest for non-market goods, next highest for ordinary private goods, and lowest for experiments involving forms of money."

utility is given by

$$u(x|r^g) = x^c + vx^g + \mu^g(vx^g - vr^g). \tag{1}$$

Following Kőszegi and Rabin (2006), we assume μ^g to be a piecewise linear function with a kink at zero,

$$\mu^g(y) = \begin{cases} \eta^g y & \text{if } y \geq 0 \\ \lambda^g \eta^g y & \text{if } y < 0. \end{cases} \tag{2}$$

Here μ^g denotes the gain-loss utilities in the good dimension, where $\eta^g > 0$ and $\lambda^g > 1$. We assume non-dominance-of-gain-loss-utility, which means for a multi-stage mechanism with k stages $\eta^g(\lambda^g - 1) \leq 1/k$.[10] The importance of the non-dominance-of-gain-loss-utility bounds on η^i and λ^i are laid out in Herweg, Müller, and Weinschenk (2010). To summarize, if $\eta^g(\lambda^g - 1) > 1/k$, a decision maker might choose stochastically dominated choices because he ex-ante expects to experience a net loss. For example, such a decision maker might choose a payment of zero over a lottery with slim chances of winning a strictly positive amount of money to avoid the disappointment, should he lose.

The interpretation of this gain-loss utility is that bidders perceive, in addition to their classical utility, a feeling of gain or loss, depending on the deviation from their reference consumption.

The reference point in our paper is assumed to be determined by rational expectations following Kőszegi and Rabin (2006).

[10] This bound for non-dominance-of-gain-loss-utility is derived in Section 2.4.1.

2.3.1 Equilibrium Concept

Following von Wangenheim (2019), we adapt Kőszegi and Rabin (2006)'s equilibrium concept under uncertainty, according to which bidders form their strategy after learning their valuation. We apply the concept of unacclimated personal equilibria, which is, as argued by Kőszegi and Rabin (2006), the appropriate concept in auction settings. Fixing the opponents' strategies, let $H(b, v_i)$ denote i's payoff distribution given his draw v_i from a continuous distribution $F(v)$ and his bid b. A bid b^* constitutes an unacclimated personal equilibrium (UPE), if for all b

$$U[H(b^*, v_i) \big| H(b^*, v_i)] \geq U[H(b, v_i) \big| H(b^*, v_i)]. \tag{3}$$

That means, given your reference point is determined by the payoff distribution resulting from an (exogenous) bid b^*, it is a best response to bid b^*.

2.3.2 Multi-Stage Mechanisms

In a multi-stage mechanism, bidders participate in k stages and submit a bid in each one of them. The rules of the mechanism include how many stages there are and which bidders advance to the next stage. Bids are binding and cannot be lowered in subsequent stages.

As an example, consider four bidders and a mechanism with two stages. In the first stage, the semi-final, all four bidders submit an offer. The two bidders with the highest offers then advance to the final, where they submit another offer. The highest offer in the final is then the winner of the auction.[11]

[11] We call this mechanism the "play-offs", it is analysed in section section 2.4.1.

In this section, we introduce the formal notation for multi-stage mechanisms. To completely characterize a multi-stage structure, we need to define the number of stages k and for each of the k stages, which of the bidders advance to the next stage. For N bidders, let $\mathfrak{B} = \left\{ {}^jB_1, {}^jB_2, \dots, {}^jB_N \right\}$ be the set of bids for each bidder in a stage $j \leq k$. We restrict ourselves to multi-stage mechanisms that are symmetric in expectation. This means that in some stage j of the mechanism, each bidder has the same expectation of number of opponents he is facing even if there are asymmetric groups.[12] Borrowing from order statistics notation, a multi-stage mechanism is then defined by $\left(\boldsymbol{\mu}, \mathfrak{M}\right)$, with $\boldsymbol{\mu}$ the payment rule and

$$\mathfrak{M} = \left\{ \underbrace{\left\{ o_1, \overbrace{\bigcup_{i=1}^{a_1} \left\{ {}^1B_i^{(o_1)} \right\}}^{\substack{\text{set of bidders}\\ \text{advancing to}\\ \text{stage 2}}} \right\}}_{\text{Stage 1}}, \underbrace{\left\{ o_2, \bigcup_{i=1}^{a_2} \left\{ {}^2B_i^{(o_2)} \right\} \right\}}_{\text{Stage 2}}, \dots, \underbrace{\left\{ o_k, \overbrace{\left\{ {}^kB_1^{(o_k)} \right\}}^{\substack{\text{highest bidder}\\ \text{wins the good}\\ \text{in final stage}}} \right\}}_{\text{Stage k}} \right\}. \tag{4}$$

Here the o_j are the number of bidders per subgroup in stage j and a_j the number of bidders advancing from stage j to $j+1$.[13] It must hold that $a_i \leq o_i$ and $o_j \leq N$ where N is the total number of bidders.

[12] If there are asymmetric groups, the probability of being matched to a specific group has to be stated.

[13] This implies that only the highest o_{j+1} bidders of each subgroup advance from stage j to $j+1$.

2.4 Analysis

The theory section is structured as follows. In subsubsection 2.4.1 we derive general properties of the equilibrium bidding behavior in one- and multi-stage mechanisms. In subsubsection 2.4.2 we show that fixing the multi-stage structure implies a revenue equivalence principle: the chosen payment rule does not affect the expected revenue of a mechanism. We then present a robust, easily implementable improvement over one-stage mechanisms in subsubsection 2.4.3 and finally derive the optimal efficient two-stage mechanism in subsubsection 2.4.4.

2.4.1 Bidding Behavior

One-Stage Mechanisms Assume that the bidders have standard preferences and let bidders participate in a standard auction A.[14] Further assume that the other bidders bid according to an increasing and absolutely continuous bidding function β^A. The payment rule of the auction is denoted by $\boldsymbol{\mu}^A(b_i, b_{-i})$ and the expected payment by $m^A(b_i)$. Define $G(b) := F_1^{(N-1)} \circ \beta^{A^{-1}}(b)$ the winning probability with a bid b in the auction. Then the expected utility of bidder i having value v_i and bidding b is given by

$$u_i^A(v_i, b) = G(b)v - m^A(b). \tag{5}$$

[14] Krishna (2009) defines a standard auction as an auction where the person who bids the highest amount is awarded the object.

We now introduce loss aversion with bidders being loss averse only in the good domain. Given a reference bid b^*, the expected utility is then given by

$$
\begin{aligned}
u_i^A(v_i, b|b^*) &= G(b)v - m^A(b) \\
\boxed{\text{feeling of gain, good domain}} \quad & \quad + G(b)(1 - G(b^*))\mu^g(v - 0) \qquad (6) \\
\boxed{\text{feeling of loss, good domain}} \quad & \quad + (1 - G(b))G(b^*)\mu^g(0 - v) \\
&= G(b)v - m^A(b) \\
& \quad + G(b)(1 - G(b^*))\eta^g v \qquad (7) \\
& \quad + (1 - G(b))G(b^*)\eta^g \lambda^g(-v)
\end{aligned}
$$

Bidders optimize u_i^A with respect to b.

Multi-Stage Mechanisms As a first step, we show that in equilibrium, bidders submit the same bid in every stage of the mechanism if non-dominance-of-gain-loss-utility holds.

Proposition 1. *In a multi-stage mechanism, bidders submit the same bid in every stage.*

Proof. Consider bidder i. Assume the other bidders bid according to an increasing, absolutely continuous bidding function β_j^{MS}, where j denotes the stage. The structure of the multi-stage mechanism, i.e. how many bidders advance in the individual stages and how many opponents they face in each stage, is then encoded in the probabilities to reach the individual stages of the mechanism. Let ϕ_j be defined such that $\phi_j \circ F \circ \beta_j^{MS^{-1}}$ is the probability of reaching stage $j+1$ given the bidder reached stage j. [15] Let $\vec{b} = (b_1, b_2, \ldots, b_k)$ be the vector of bids of bidder 1. This means that the

[15] The $\phi_j \circ F$ are expressions of probability and thus inherit the properties of the original distribution functions.

ex-ante probability to win the auction is given by

$$\text{Prob}^{\text{ex-ante}}(\text{win with } b) = \prod_{j=1}^{k} \phi_j(b_j) =: H\left(\vec{b}\right). \tag{8}$$

Note that to simplify the notation, we define that advancing to stage $k+1$ means winning the auction.

It is useful to define the probability to reach stage l, given that the bidder reached stage i. Let $i < l$. Then Φ_i^l is given by

$$\begin{aligned}
&\text{Prob}\left(\text{get to } l \text{ with } \vec{b} \mid \text{get to } i \text{ with } \vec{b}\right) && (9)\\
=\ &\frac{\text{Prob}\left(\text{get to } l \text{ with } \vec{b} \;\&\; \text{get to } i \text{ with } \vec{b}\right)}{\text{Prob}\left(\text{get to } i \text{ with } \vec{b}\right)} && (10)\\
=\ &\frac{\text{Prob}\left(\text{get to } l \text{ with } \vec{b}\right)}{\text{Prob}\left(\text{get to } i \text{ with } \vec{b}\right)} = \prod_{j=i}^{l-1} \phi_j(b_j) := \Phi_i^l\left(\vec{b}\right) && (11)
\end{aligned}$$

The probability to win the auction given the bidder reached stage i is given by

$$\text{Prob}(\text{win with } \vec{b} \mid \text{reached } i) = \Phi_i^{k+1}\left(\vec{b}\right). \tag{12}$$

For each stage l, given a reference bid b_l^*, the bidder experiences a gain-loss utility in expectation. On one hand, the bidder might win with his bid b_l but has expected to lose with the reference bid b_l^*. He then experiences a gain in the good domain with respect to the reference outcome. On the other hand, the bidder might lose in one of the stages with his bid b_l but has expected to win with the reference bid b_l^*. He then experiences a loss in the good domain. This holds true for every stage.

Consider a standard auction based payment rule, $\boldsymbol{\mu}^{MS}$. The expected payment of the multi-stage mechanism composed by the expected amount a bidder has to pay and the probability of him having to pay it,

$$m^{MS}\left(\vec{b}\right) = \text{Prob}\left(\text{having to pay with } \vec{b}\right)\mathbb{E}\left[\boldsymbol{\mu}^{MS}\;\middle|\;\vec{b},\vec{b}_{-i}\right] \tag{13}$$

$$=: P^{\text{pay}}\left(\vec{b}\right)\mathbb{E}\left[\boldsymbol{\mu}^{MS}\;\middle|\;\vec{b},\vec{b}_{-i}\right]. \tag{14}$$

For the first-, second-, ...-price auction, we have $P^{\text{pay}}\left(\vec{b}\right) = H\left(\vec{b}\right)$, while for the all-pay auction we have that $P^{\text{pay}}\left(\vec{b}\right) = 1$. Generally, $P^{\text{pay}}\left(\vec{b}\right)$ either depends linearly on the ϕ_i for $i \in \{1,\ldots,k\}$ or is constant.[16] This means that it holds for all $j < k$,

$$\frac{\partial\, m^{MS}\left(\vec{b}\right)}{\partial\left(\phi_j\left(\vec{b}\right)\right)} \leq \frac{m^{MS}\left(\vec{b}\right)}{\phi_j\left(\vec{b}\right)}. \tag{15}$$

Combining the results from above, we arrive at the following utility function

[16]The fringe case where $\mathbb{E}\left[\boldsymbol{\mu}^{MS}\;\middle|\;\vec{b},\vec{b}_{-i}\right]$ consists of a lottery that explicitly depends on a ϕ_i with $i \in \{1,\ldots,k-1\}$ is excluded here. The lottery may depend on $\vec{b}$.

for loss averse bidders in multi-stage mechanisms,

$$\begin{aligned}
u^{MS}(v_i, \vec{b} \mid \vec{b}^*) &= H\left(\vec{b}\right) v_i - m^{MS}\left(\vec{b}\right) \\
&\quad + \underbrace{\sum_{i=1}^{k} \Phi_1^{k+1}\left(\vec{b}\right)\left(1 - \Phi_i^{i+1}\left(\vec{b}^*\right)\right)\mu^g(v-0)}_{\text{expecting to win with } \vec{b}\text{, to lose with } \vec{b}^*} \qquad (16) \\
&\quad + \underbrace{\sum_{i=1}^{k} \Phi_0^{i}\left(\vec{b}\right)\left(1 - \Phi_i^{i+1}\left(\vec{b}\right)\right)\Phi_i^{k+1}\left(\vec{b}^*\right)\mu^g(0-v)}_{\text{expecting to lose with } \vec{b}\text{, to win with } \vec{b}^*} \\
&= H\left(\vec{b}\right) v_i - m^{MS}\left(\vec{b}\right) \\
&\quad + \sum_{i=1}^{k} \Phi_1^{k+1}\left(\vec{b}\right)\left(1 - \Phi_i^{i+1}\left(\vec{b}^*\right)\right)\eta^g v \qquad (17) \\
&\quad + \sum_{i=1}^{k} \left(\Phi_0^{i}\left(\vec{b}\right) - \Phi_0^{i+1}\left(\vec{b}\right)\right)\Phi_i^{k+1}\left(\vec{b}^*\right)\eta^g\lambda^g(-v).
\end{aligned}$$

Note that we can bound m^{MS} from above depending on v_i and $\vec{b}^*$ since a bidder will not submit bids that result in a negative expected utility,

$$\begin{aligned}
&u^{MS}(v_i, \vec{b} \mid \vec{b}^*) \overset{!}{>} 0 \\
\Rightarrow \quad & m^{MS}\left(\vec{b}\right) \overset{!}{<} H\left(\vec{b}\right) v_i \\
&\quad + \sum_{i=1}^{k} \Phi_1^{k+1}\left(\vec{b}\right)\left(1 - \Phi_i^{i+1}\left(\vec{b}^*\right)\right)\eta^g v \qquad (18) \\
&\quad + \sum_{i=1}^{k} \Phi_0^{i}\left(\vec{b}\right)\left(1 - \Phi_i^{i+1}\left(\vec{b}\right)\right)\Phi_i^{k+1}\left(\vec{b}^*\right)\eta^g\lambda^g(-v).
\end{aligned}$$

Also note that the right-hand side does not contain b_j outside of ϕ_j for all $j \in \{1, \ldots, k-1\}$. This means that for the first $k-1$ stages, a bidder can directly optimize over the probability of advancing to the next stage instead of optimizing over the bids that induce probabilities. Our equilibrium concept is UPE, this implies that the first-order condition for $i \in \{1, \ldots, k-1\}$, is given by

$$\left.\frac{\partial u^{MS}(v_i, \vec{b} \mid \vec{b}^*)}{\partial\left(\phi_i(b_i)\right)}\right|_{\vec{b}^*=\vec{b}} = \frac{\prod_{j=1}^{k} \phi_j(b_j)}{\phi_i(b_i)} v_i - \frac{\partial m^{MS}\left(\vec{b}\right)}{\partial\left(\phi_i(b_i)\right)} \tag{19}$$

$$+ \left.\frac{\partial}{\partial\left(\phi_i(b_i)\right)} \sum_{l=1}^{k} \prod_{j=1}^{k} \phi_j(b_j)\big(1 - \Phi_l^{l+1}\left(\vec{b}^*\right)\big)\eta^g v_i\right|_{\vec{b}^*=\vec{b}} \tag{20}$$

$$+ \left.\frac{\partial}{\partial\left(\phi_i(b_i)\right)} \sum_{l=1}^{k} \prod_{j=0}^{l-1} \phi_j(b_j)\Phi_l^{k+1}\left(\vec{b}^*\right)\eta^g\lambda^g(-v_i)\right|_{\vec{b}^*=\vec{b}} \tag{21}$$

$$- \left.\frac{\partial}{\partial\left(\phi_i(b_i)\right)} \sum_{l=1}^{k} \prod_{j=0}^{l} \phi_j(b_j)\Phi_l^{k+1}\left(\vec{b}^*\right)\eta^g\lambda^g(-v_i)\right|_{\vec{b}^*=\vec{b}}. \tag{22}$$

We now rearrange the terms. (20) simplifies to

$$\sum_{l=1}^{k} \frac{\prod_{j=1}^{k} \phi_j(b_j)}{\phi_i(b_i)}\Big(1 - \phi_l(b_l)\Big)\eta^g v_i. \tag{23}$$

For (21), we get

$$\sum_{l=i+1}^{k} \frac{\prod_{j=1}^{l-1} \phi_j(b_j)}{\phi_i(b_i)} \prod_{j=l}^{k} \phi_j(b_j)\eta^g\lambda^g(-v_i) = \sum_{l=i+1}^{k} \frac{\prod_{j=1}^{k} \phi_j(b_j)}{\phi_i(b_i)}\eta^g\lambda^g(-v_i) \tag{24}$$

$$= \frac{\prod_{j=1}^{k} \phi_j(b_j)}{\phi_i(b_i)}\eta^g\lambda^g(-v_i)(k-i). \tag{25}$$

For (22), we get

$$-\sum_{l=i}^{k} \frac{\prod_{j=1}^{l} \phi_j(b_j)}{\phi_i(b_i)} \prod_{j=l}^{k} \phi_j(b_j)\eta^g\lambda^g(-v_i) = -\sum_{l=i}^{k} \frac{\prod_{j=1}^{k} \phi_j(b_j)}{\phi_i(b_i)}\phi_l(b_l)\eta^g\lambda^g(-v_i). \tag{26}$$

Define

$$\alpha := \frac{\prod_{j=1}^{k} \phi_j(b_j)}{\phi_i(b_i)}. \tag{27}$$

We arrive at

$$
\begin{aligned}
\left.\frac{\partial u^{MS}(v_i, \vec{b} \mid \vec{b}^*)}{\partial\left(\phi_i(b_i)\right)}\right|_{\vec{b}^*=\vec{b}} = & -\frac{\partial m^{MS}\left(\vec{b}\right)}{\partial\left(\phi_i(b_i)\right)} \\
& + \alpha v_i + \eta^g v_i \alpha \sum_{l=1}^{k}(1-\phi_l(b_l)) && (28) \\
& - \eta^g \lambda^g v_i \alpha (k-i) + \eta^g \lambda^g v_i \sum_{l=i}^{k} \phi_l(b_l) \\
\geq & -\frac{m^{MS}\left(\vec{b}\right)}{\phi_i(b_i)} + \alpha v_i + \eta^g v_i \alpha \sum_{l=1}^{k}(1-\phi_l(b_l)) && (29) \\
& - \eta^g \lambda^g v_i \alpha (k-i) + \eta^g \lambda^g v_i \sum_{l=i}^{k} \phi_l(b_l) \\
\geq & -\Bigg[H\left(\vec{b}\right) v_i + \sum_{i=1}^{k} \Phi_1^{k+1}\left(\vec{b}\right)\left(1-\Phi_i^{i+1}\left(\vec{b}^*\right)\right)\eta^g v_i \\
& + \sum_{i=1}^{k} \Phi_0^{i}\left(\vec{b}\right)\left(1-\Phi_i^{i+1}\left(\vec{b}\right)\right)\Phi_i^{k+1}\left(\vec{b}^*\right)\eta^g \lambda^g(-v_i) \Bigg]_{\vec{b}^*=\vec{b}} && (30) \\
& + \alpha v_i + \eta^g v_i \alpha \sum_{l-1}^{k}(1-\phi_l(b_l)) \\
& - \eta^g \lambda^g v_i \alpha (k-i) + \eta^g \lambda^g v_i \sum_{l=i}^{k} \phi_l(b_l) \\
= & -\alpha v_i + \eta^g(\lambda^g - 1) v_i \alpha \sum_{l=1}^{k}(1-\phi_l(b_l)) \\
& + \alpha v_i + \eta^g v_i \alpha \sum_{l-1}^{k}(1-\phi_l(b_l)) && (31) \\
& - \eta^g \lambda^g v_i \alpha (k-i) + \eta^g \lambda^g v_i \sum_{l=i}^{k} \phi_l(b_l) \\
= & \ \eta^g \lambda^g v_i \alpha (i - \sum_{l=1}^{i-1} \phi_l) > 0. && (32)
\end{aligned}
$$

Note that we need to make sure that the expression in the brackets in step (30) is positive for all ϕ_j. This means it needs to hold that

$$\alpha v_i - \eta^g(\lambda^g - 1)v_i\alpha \sum_{l=1}^{k}(1 - \phi_l(b_l)) \overset{!}{\geq} 0 \tag{33}$$

$$\Leftrightarrow \quad -\eta^g(\lambda^g - 1) \overset{!}{\geq} \frac{-1}{\sum_{l=1}^{k}(1 - \phi_l(b_l))} \tag{34}$$

$$\Leftrightarrow \quad \eta^g(\lambda^g - 1) \overset{!}{\leq} \frac{1}{\sum_{l=1}^{k}(1 - \phi_l(b_l))} \tag{35}$$

$$\Leftrightarrow \quad \eta^g(\lambda^g - 1) \overset{!}{\leq} \min_{\phi} \frac{1}{\sum_{l=1}^{k}(1 - \phi_l(b_l))} \tag{36}$$

$$\Rightarrow \quad \eta^g(\lambda^g - 1) \overset{!}{\leq} \frac{1}{k}. \tag{37}$$

For every stage, a bidder experiences gain-loss utility. All-in-all, this means that the non-dominance of gain-loss utility has to hold for every stage, in total $\eta^g(\lambda^g - 1) \overset{!}{\leq} \frac{1}{k}$.

Interpreting ϕ_j as the distribution of bids that a bidder needs to beat in expectation to order to advance to stage $j + 1$, (32) implies that a bidder will always want to induce the highest possible probability to advance to the final stage with his bid $\vec{b}$. This implies that a bidder will cap his bids in stages 1 to $k - 1$ by the bid he submits in the final, pay-off relevant stage. A bidder therefore optimizes

$$\begin{aligned} u^{MS}(v_i, b|b^*) = {} & G(b)v_i - m^{MS}(b) \\ & + \sum_{i=1}^{k} \Phi_1^{k+1}(b)\big(1 - \Phi_i^{i+1}(b^*)\big)\eta^g v \\ & + \sum_{i=1}^{k} \big(\Phi_0^i(b) - \Phi_0^{i+1}(b)\big)\Phi_i^{k+1}(b^*)\eta^g\lambda^g(-v) \end{aligned} \tag{38}$$

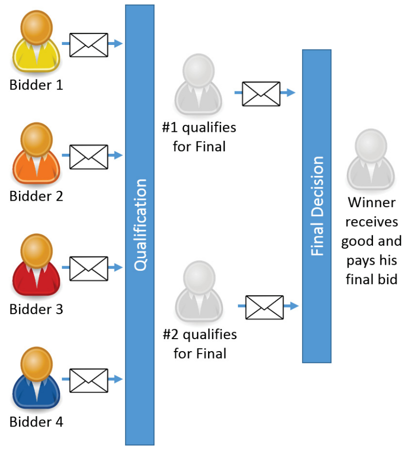


Figure 1: The first-price sealed-bid play-offs.

over b.

$\square$

Example: First-Price Sealed-Bid Play-Offs To get an idea what such a multi-stage mechanism can look like and of how to apply what we have derived so far, let us take a look at the following multi-stage mechanism with four bidders. As can be seen in *Figure 1*, the *FPSB play-offs* consists of 2 stages.

1. Out of the four bidders, the two highest bidders are advancing to the second stage.

2. Out of the two remaining bidders, the highest bid wins.

We can write $\mathfrak{M}^{PO}$ as

$$\mathfrak{M}^{PO} = \left\{ \underbrace{\left\{ 4, \left\{ B_1^{(4)}, B_2^{(4)} \right\} \right\}}_{\text{Stage 1}}, \underbrace{\left\{ 2, \left\{ B_1^{(2)} \right\} \right\}}_{\text{Stage 2}} \right\}. \tag{39}$$

The payment rule $\boldsymbol{\mu}$ is given by the first-price auction payment rule. With proposition 1, we can assume bidders to bid the same in every stage. Assume the other bidders bid according to an increasing, absolutely continuous bidding function β^P. In the first stage, bidder i advances if he beats at least the second highest opponent. This yields

$$\phi_1 \circ F = F_2^{(3)} = 3F^2 - 2F^3. \tag{40}$$

Given that the bidder reached stage two, the bidder wins if he beats his strongest opponent,

$$\begin{aligned}\phi_2 \circ F \circ \beta^{P^{-1}}(b) &= \text{Prob}\left(b > \beta^P\left(v_1^{(3)}\right) \,\middle|\, b > \beta^P\left(v_2^{(3)}\right)\right) &(41)\\ &= \frac{F\left(\beta^{P^{-1}}(b)\right)^3}{3F\left(\beta^{P^{-1}}(b)\right)^2 - 2F\left(\beta^{P^{-1}}(b)\right)^3}. &(42)\end{aligned}$$

The underlying auction format is the first-price auction, the expected payment is given by $m^T(b) = G(b)b$. The utility is then given by

$$\begin{aligned}
u^P(v_i, b|b^*) = \; & G(b\,(v_i - b) \\
& \underbrace{+F_1^{(3)}\left(\beta^{P^{-1}}(b)\right)\left(1 - F_2^{(3)}\left(\beta^{P^{-1}}(b^*)\right)\right)\eta^g v}_{\text{win but would have lost in stage 1 with } b^*} \\
& \underbrace{+F_1^{(3)}\left(\beta^{P^{-1}}(b)\right)\left(1 - \frac{F_1^{(3)}\left(\beta^{P^{-1}}(b^*)\right)}{F_2^{(3)}\left(\beta^{P^{-1}}(b^*)\right)}\right)\eta^g v}_{\text{win but would have lost in stage 2 with } b^*} \\
& \underbrace{+\left(1 - F_2^{(3)}\left(\beta^{P^{-1}}(b)\right)\right)F_1^{(3)}\left(\beta^{P^{-1}}(b^*)\right)\eta^g\lambda(-v)}_{\text{don't advance to 2nd stage but would have won with } b^*} \\
& \underbrace{+F_2^{(3)}\left(\beta^{P^{-1}}(b)\right)\left(1 - \frac{F_1^{(3)}\left(\beta^{P^{-1}}(b)\right)}{F_2^{(3)}\left(\beta^{P^{-1}}(b)\right)}\right)\frac{F_1^{(3)}\left(\beta^{P^{-1}}(b^*)\right)}{F_2^{(3)}\left(\beta^{P^{-1}}(b^*)\right)}\eta^g\lambda(-v)}_{\text{get to 2nd stage \& lose but would have won with } b^*}.
\end{aligned} \tag{43}$$

We are interested in finding the equilibrium bidding function for this multi-stage auction. Our equilibrium concept is UPE, this implies that the first-order condition is given by

$$\left(\frac{\partial u^P(v_i, b|b^*)}{\partial b}\right)\Bigg|_{b^*=\beta^P(v_i)} \stackrel{!}{=} 0. \tag{44}$$

In equilibrium it holds that $b = \beta^P(v_i)$. To simplify notation, let $F_m^{(3)} =: F_m$. The resulting ordinary differential equation admits a closed form solution,

$$\begin{aligned}
\beta^P(v_i) = \; & \frac{1}{F_1(v_i)}\int_0^{v_i} s\left(f_1(s) + \eta^g\lambda^g\left(f_2(s)F_1(s) - \left(f_2(s) - f_1(s)\right)\frac{F_1(s)}{F_2(s)}\right)\right. \\
& \left. + \eta^g f_1(s)\left(2 - \frac{F_1(s)}{F_2(s)} - F_2(s)\right)\right)ds.
\end{aligned} \tag{45}$$

2.4.2 Revenue Equivalence Principle

In this section, we show that once we fix the multi-stage structure of the procurement mechanism, a revenue equivalence principle holds. This means that an auctioneer does not need to worry about the payment rule of her mechanism.[17]

Proposition 2 (Revenue equivalence principle for loss averse bidders)**.** *Suppose that values are independently and identically distributed and that bidders are loss averse in the good domain. Fix the multi-stage structure $\mathfrak{M}$. For every standard auction payment rule $\boldsymbol{\mu}$, any symmetric and increasing equilibrium such that the expected payment of a bidder with value zero is zero, yields the same expected revenue to the seller.*

Proof. Consider multi-stage mechanism $MS = \Big(\boldsymbol{\mu}, \mathfrak{M}\Big)$, with $\boldsymbol{\mu}$ some standard auction payment rule, and fix a symmetric, strictly increasing equilibrium bidding function β^{MS}. Let $m^{MS}(v_i)$ be the equilibrium expected payment in the mechanism by bidder i with value v_i. Suppose that β^{MS} is such that $m^{MS}(0) = 0$. Define the ex-ante expected gain-loss utility in the good domain Θ^g such that

$$\begin{aligned}\Theta^g(b|\, b^*) := &\sum_{i=1}^{k} \Phi_1^{k+1}(b)\big(1 - \Phi_i^{i+1}(b^*)\big)\eta^g v \\ &+ \sum_{i=1}^{k} \big(\Phi_0^i(b) - \Phi_0^{i+1}(b)\big)\Phi_i^{k+1}(b^*)\eta^g\lambda^g(-v),\end{aligned} \tag{46}$$

yielding

$$u^{MS}(v_i, b|b^*) = \; G(b)v_i - m^{MS}(b) + \Theta^g(b|\, b^*). \tag{47}$$

Consider bidder i and suppose other bidders are following the equilibrium

[17] We consider payment rules based on standard auctions as defined by Krishna (2009). A standard auction is an auction where the highest bidder wins.

strategy β^{MS}. Consider the expected payoff of bidder i with value v_i deviating from the equilibrium bidding strategy. β^{MS} is bijective, meaning that every sensible bid b can be expressed such that $b = \beta^{MS}(z)$. The bidding function β^{MS} constitutes a UPE if and only if the utility function $u_i^{MS}(v_i, b|\beta^{MS}(v_i))$ attains its maximum at $b = \beta^{MS}(v_i)$ for all v_i. Bidder i's expected payoff is given by

$$\begin{aligned} u^{MS}\left(v_i, \beta^{MS}(z)|\beta^{MS}(v_i)\right) = G(\beta^{MS}(z))v_i - m^{MS}(z) \\ + \Theta\left(\beta^{MS}(z)|\, \beta^{MS}(v_i)\right). \end{aligned} \tag{48}$$

The first-order condition is given by

$$\begin{aligned} \frac{\partial u^{MS}\left(v_i, \beta^{MS}(z)|\beta^{MS}(v_i)\right)}{\partial z} = f_1^{(N-1)}(z)v_i - \frac{\partial}{\partial z}m^{MS}(z) \\ + \frac{\partial}{\partial z}\Theta\left(\beta^{MS}(z)|\, \beta^{MS}(v_i)\right) \stackrel{!}{=} 0. \end{aligned} \tag{49}$$

In equilibrium it is optimal to report $z = v_i$ and it holds that $b^* = \beta^{MS}(v_i)$, so we obtain that for all y,

$$\frac{\partial}{\partial y}m^{MS}(z) = f_1^{(N-1)}(y)y + \left(\frac{\partial}{\partial y}\Theta\left(\beta^{MS}(y)|\, \beta^{MS}(z)\right)\right)\Bigg|_{z=y}. \tag{50}$$

This means that

$$\begin{aligned} m^{MS}(v_i) = \cancel{m^{MS}(0)} + \int_0^{v_i} f_1^{(N-1)}(y)y dy \\ + \int_0^{v_i} \left(\frac{\partial}{\partial y}\Theta\left(\beta^{MS}(y)|\, \beta^{MS}(z)\right)\right)\Bigg|_{z=y} dy. \end{aligned} \tag{51}$$

While the right-hand side depends on the multi-stage structure $\mathfrak{M}$, it does not depend on the payment rule $\boldsymbol{\mu}$. $\square$

The result holds for $k \geq 1$ stages, so one-stage mechanisms are included.

A first application of the RET for loss averse bidders is to rank the English auction with loss averse bidders.

Proposition 3. *All static standard auction formats yield higher expected revenues with loss averse bidders than the English auction.*

Proof. From von Wangenheim (2019) we know that the English auction performs worse than the second-price auction revenue-wise. We can apply *Proposition 2* to complete the proof. □

2.4.3 A Robust Improvement Over One-Stage Mechanisms

A mechanism that is to be implemented in real-life and that exploits bidders' loss aversion should not depend on the parameters for loss aversion. An auctioneer cannot hope to be able to accurately estimate these parameters in a way that would help her design a mechanism. We will show that for a parameter space that includes the empirically found loss aversion parameters, it is beneficial for the seller to implement a simple two-stage mechanism for every value realization of every distribution function if there are more than two bidders.[18]

For an even number of bidders, $2N$, consider randomly pairing two groups of N bidders and then advance the highest bidder of each pairing to the final. For an odd number of bidders, $2N + 1$, consider randomly pairing of one group of N bidders and one group of $N + 1$ bidders. Bidders do not know in which group they are selected, they only know the a priori probability of being in the group with N bidders is 0.5. Again, the highest bidder of each pairing advances to the final. We call this multi-stage structure a

[18]See Gächter, Johnson, and Herrmann (2007) for an empirical study on individual-level loss aversion. They present evidence that λ^g lies around 2.

tournament, it can be seen in figure 2. We can write $\mathfrak{M}^T$ as

$$\mathfrak{M}^{T,\text{even}} = \left\{ \underbrace{\left\{ N, \left\{ B_1^{(N)} \right\} \right\}}_{\text{Stage 1}}, \underbrace{\left\{ 2, \left\{ B_1^{(2)} \right\} \right\}}_{\text{Stage 2}} \right\}. \tag{52}$$

$$\mathfrak{M}^{T,\text{odd}} = \left\{ \underbrace{\left\{ \{N_{P=\frac{1}{2}}, N+1_{P=\frac{1}{2}}\}, \left\{ B_1^{(N_{P=\frac{1}{2}}, N+1_{P=\frac{1}{2}})} \right\} \right\}}_{\text{Stage 1}}, \underbrace{\left\{ 2, \left\{ B_1^{(2)} \right\} \right\}}_{\text{Stage 2}} \right\}. \tag{53}$$

As shown in Proposition 2, the payment rule we choose is not relevant for the revenue. For the proof, we choose the first-price auction payment rule.

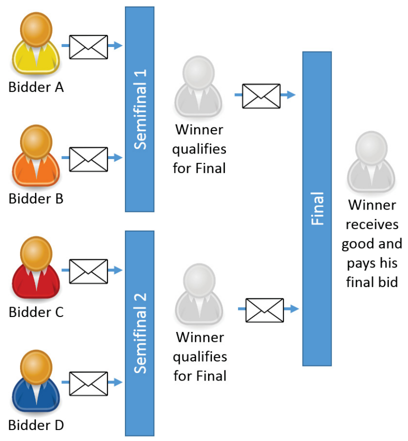


Figure 2: The tournament multi-stage structure $\mathfrak{M}^T$ for four bidders.

Proposition 4. *Assume an even number of bidders $2N \geq 4$ that are loss averse in the good domain. Assume that $\lambda \leq \frac{2N-1}{N-1}$. Then for all $\eta \geq 0$ the revenue is higher in the tournament than in any one-stage mechanism.*

Corollary 1. *Assume an even number of bidders $2N \geq 4$ that are loss averse in the good domain. Assume that $\lambda \leq \frac{2N-1}{N-1}$. In the case of the first-price, second-price or all-pay auction as underlying auction format, bids are* *higher in the tournament than in the corresponding one-stage mechanism for all types.*

Proposition 5. *Assume an odd number of bidders $2N+1 \geq 3$ that are loss averse in the good domain. Assume that $\lambda \leq \frac{4N}{2N-1}$. Then for all $\eta \geq 0$ the revenue is higher in the tournament than in any one-stage mechanism.*

Corollary 2. *Assume an even number of bidders $2N+1 \geq 3$ that are loss averse in the good domain. Assume that $\lambda \leq \frac{4N}{2N-1}$. In the case of the first-price, second-price or all-pay auction as underlying auction format, bids are higher in the tournament than in the corresponding one-stage mechanism for all types.*

Proposition 6. *For $\lambda^g \leq 2$, the tournament yields higher bids than the respective one-stage auction for all types.*

Proof of Proposition 4. Consider the first-price auction payment rule. We start with the one-stage mechanism. Assume the other bidders bid according to an increasing, absolutely continuous bidding function β^{FP} and let $G(b) = F_1^{(N-1)}\left(\beta^{FP^{-1}}(b)\right)$. The expected payment is given by

$$m^{FP}(b) = G(b)b. \tag{54}$$

The utility function is given by

$$\begin{aligned} u_i^{FP}(v_i, b|b^*) = G(b)(v-b) \\ + G(b)(1-G(b^*))\eta^g v \\ + (1-G(b))G(b^*)\eta^g\lambda^g(-v). \end{aligned} \tag{55}$$

The bidding function β^{FP} constitutes a UPE if and only if the utility function $u_i^{FP}(v_i, b|\beta^{FP}(v_i))$ attains its maximum at $b = \beta^{FP}(v_i)$ for all v_i. Differentiating u^{FP} with respect to b and plugging in the equilibrium condition $b = \beta^{FP}(v_i)$ yields the ODE,

$$\beta^{FP\prime}(v_i)F_1(v_i) + \beta^{FP}(v_i)f_1(v_i) \stackrel{!}{=} v_i f_1(v_i)\Big(1 + (1 - F_1(v_i))\,\eta^g + F_1\eta^g\lambda^g\Big) \tag{56}$$

This ODE admits a closed form solution,

$$\beta^{FP}(v_i) = \frac{1}{F_1(v_i)}\int_0^{v_i} s f_1(s)\Big(1 + \eta^g + F_1(s)\eta^g(\lambda^g - 1)\Big)ds \tag{57}$$

$$= \frac{1}{F_1(v_i)}\int_0^{v_i} s f_1(s)\Big(1 + \eta^g\big(1 - F_1(s)\big) + \eta^g\lambda^g F_1(s)\Big)ds. \tag{58}$$

The equilibrium bidding function for the tournament can be derived explicitly, too. With Proposition 1, we can assume bidders bid the same in every stage. Assume that the other bidders bid according to an increasing, absolutely continuous bidding function β^T. In the first stage, bidder i advances if he beats his $N-1$ opponents. This yields

$$\phi_1 \circ F = F_1^{(N-1)}. \tag{59}$$

This implies that advancing to the second stage is not informative in any way about the value of the remaining opponent. The intuition behind this can be understood by considering the mechanism with four bidders. Given the bidder won the first round, he may have beaten his toughest opponent already. But he also might have beaten the second or third highest bidding one,

$$
\begin{aligned}
&\text{Prob(get to 2nd round with } b) && (60)\\
&= \frac{1}{3}F_1(\beta^{T^{-1}}(b)) + \frac{2}{3}\Big(\frac{1}{2}F_2(\beta^{T^{-1}}(b)) + \frac{1}{2}F_3(\beta^{T^{-1}}(b))\Big) && (61)\\
&= F(\beta^{T^{-1}}(b)). && (62)
\end{aligned}
$$

Given that the bidder reached stage two, the bidder wins if he beats the winner of the second group given he got there,

$$
\begin{aligned}
\phi_2 \circ F \circ \beta^{T^{-1}}(b) &= \text{Prob}\left(b > \beta^T\left(v_1^{(N)}\right) \,\Big|\, b > \beta^T\left(v_1^{(N-1)}\right)\right) && (63)\\
&= \frac{F_1^{(N-1)}\left(\beta^{T^{-1}}(b)\right) F_1^{(N)}\left(\beta^{T^{-1}}(b)\right)}{F_1^{(N-1)}\left(\beta^{T^{-1}}(b)\right)} && (64)\\
&= F_1^{(N)}\left(\beta^{T^{-1}}(b)\right). && (65)
\end{aligned}
$$

As mentioned before, we have $m^T(b) = F_1^{(2N)}\left(\beta^{T^{-1}}(b)\right) b$. Then the utility is given by

$$
\begin{aligned}
u^T(v_i, b|b^*) = \; & F_1^{(2N-1)}\left(\beta^{T^{-1}}(b)\right)\left(v - b\right)\\
&+ F_1^{(2N-1)}\left(\beta^{T^{-1}}(b)\right)\left(1 - F_1^{(N-1)}\left(\beta^{T^{-1}}(b^*)\right)\right)\eta^g v_i\\
&+ F_1^{(2N-1)}\left(\beta^{T^{-1}}(b)\right)\left(1 - F_1^{(N)}\left(\beta^{T^{-1}}(b^*)\right)\right)\eta^g v_i\\
&+ \left(1 - F_1^{(N-1)}\left(\beta^{T^{-1}}(b)\right)\right) F_1^{(2N-1)}\left(\beta^{T^{-1}}(b^*)\right)(-\eta^g\lambda^g v_i)\\
&+ \left(F_1^{(N-1)}\left(\beta^{T^{-1}}(b)\right) - F_1^{(2N-1)}\left(\beta^{T^{-1}}(b)\right)\right) F_1^{(N)}\left(\beta^{T^{-1}}(b^*)\right)(-\eta^g\lambda^g v_i). \qquad (66)
\end{aligned}
$$

We are interested in finding the equilibrium bidding function for this multi-stage auction. Our equilibrium concept is UPE, this implies that the first-order condition is given by

$$\left.\left(\frac{\partial u^T(v_i, b|b^*)}{\partial b}\right)\right|_{b^*=\beta^T(v_i)} \stackrel{!}{=} 0. \tag{67}$$

We have

$$\begin{aligned}
\left.\frac{\partial}{\partial b} u^T(v_i, b|b^*)\right|_{b^*=\beta^T(v_i)} &= f_1^{(2N-1)}\left(\beta^{T^{-1}}(b)\right)\left(v-b\right)\frac{1}{\beta^{T\prime}(\beta^{T^{-1}}(b))} \\
&- F_1^{(2N-1)}\left(\beta^{T^{-1}}(b)\right) \\
&+ f_1^{(2N-1)}\left(\beta^{T^{-1}}(b)\right)\left(1-F_1^{(N-1)}(v_i)\right)\eta^g v_i \frac{1}{\beta^{T\prime}(\beta^{T^{-1}}(b))} \\
&+ f_1^{(2N-1)}\left(\beta^{T^{-1}}(b)\right)\left(1-F_1^{(N)}(v_i)\right)\eta^g v_i \frac{1}{\beta^{T\prime}(\beta^{T^{-1}}(b))} \\
&+ f_1^{(N-1)}\left(\beta^{T^{-1}}(b)\right) F_1^{(2N-1)}(v_i)\,\eta^g\lambda^g v_i \frac{1}{\beta^{T\prime}(\beta^{T^{-1}}(b))} \\
&- f_1^{(N-1)}\left(\beta^{T^{-1}}(b)\right) F_1^{(N)}(v_i)\,\eta^g\lambda^g v_i \frac{1}{\beta^{T\prime}(\beta^{T^{-1}}(b))} \\
&+ f_1^{(2N-1)}\left(\beta^{T^{-1}}(b)\right) F_1^{(N)}(v_i)\,\eta^g\lambda^g v_i \frac{1}{\beta^{T\prime}(\beta^{T^{-1}}(b))}.
\end{aligned} \tag{68}$$

In equilibrium it holds that $b = \beta^T(v_i)$. The resulting ordinary differential equation for β^T admits a closed-form solution,

$$\begin{aligned}
\beta^T(v_i) = \frac{1}{F_1^{(2N-1)}(v_i)} \int_0^{v_i} s \Bigg[& f_1^{(2N-1)}(s) \\
& + \eta^g f_1^{(2N-1)}(s)\left(2 - F_1^{(N-1)}(s) - F_1^{(N)}(s)\right) \\
& + \eta^g\lambda^g \Bigg(f_1^{(N-1)}(s) F_1^{(2N-1)}(s) \\
& \quad - f_1^{(N-1)}(s) F_1^{(N)}(s) \\
& \quad + f_1^{(2N-1)}(s) F_1^{(N)}(s) \Bigg)\Bigg] ds.
\end{aligned} \tag{69}$$

For $\beta^T(v_i) \geq \beta^{FP}(v_i)$ to hold for all v_i, a sufficient condition is that we can rank the arguments of the integrals. As a reminder, $\beta^{FP}(v_i)$ is given by

$$\beta^{FP}(v_i) = \frac{1}{F_1(v_i)} \int_0^{v_i} s f_1(s)\Big(1 + \eta^g\big(1 - F_1(s)\big) + \eta^g \lambda^g F_1(s)\Big) ds, \tag{70}$$

with $F_1 = F_1^{(2N-1)}$ and $f_1 = f_1^{(2N-1)}$. Note that the first term stemming from the standard preferences equilibrium bidding function is identical in both bidding functions. What is left are the gain-loss utility terms. This means it has to hold that

$$\begin{aligned} &\eta^g f_1^{(2N-1)}(s) \left(2 - F_1^{(N-1)}(s) - F_1^{(N)}(s)\right) \\ &\qquad -\eta^g f_1^{(2N-1)}(s)\big(1 - F_1(s)\big) \\ &+\eta^g \lambda^g \Bigg(f_1^{(N-1)}(s) F_1^{(2N-1)}(s) - f_1^{(N-1)}(s) F_1^{(N)}(s) \\ &\qquad + f_1^{(2N-1)}(s) F_1^{(N)}(s) \Bigg) \\ &\qquad -\eta^g \lambda^g \eta^g f_1^{(2N-1)}(s) F_1(s) \overset{!}{\geq} 0. \end{aligned} \tag{71}$$

Note that all terms, except the third one, include $f_1^{(2N-1)}(s) = (2N - 1)F^{2N-2}(s)f(s)$. Using the definition of the first-order statistic density for distribution functions, we have

$$f_1^{(N-1)}(s)F_1^{(2N-1)}(s) = (N-1)F^{N-2}(s)f(s)F^{2N-1}(s) \tag{72}$$

$$= \frac{N-1}{2N-1}(2N-1)F^{2N-2}(s)f(s)F^{N-1} \tag{73}$$

$$= \frac{N-1}{2N-1} f_1^{(2N-1)}(s)F_1^{(N-1)}. \tag{74}$$

Similarly, we can write the third term as

$$
\begin{aligned}
& f_1^{(N-1)}(s)F_1^{(2N-1)}(s) - f_1^{(N-1)}(s)F_1^{(N)}(s) + f_1^{(2N-1)}(s)F_1^{(N)}(s) && (75)\\
= {} & f_1^{(2N-1)}(s)\left(\frac{N-1}{2N-1}F_1^{(N-1)}(s) - \frac{N-1}{2N-1} + F_1^{(N)}(s)\right). && (76)
\end{aligned}
$$

With this, (71) simplifies to

$$
\begin{aligned}
& (\lambda^g - 1)F_1^{(N)}(s)\cancel{\left(1 - F_1^{(N-1)}(s)\right)} - \left(\frac{N-1}{2N-1}\lambda^g - 1\right)\cancel{\left(1 - F_1^{(N-1)}(s)\right)} \overset{!}{\geq} 0 && (77)\\
\Leftrightarrow \quad & (\lambda^g - 1)F_1^{(N)}(s) - \frac{N-1}{2N-1}\lambda^g + 1 \overset{!}{\geq} 0 && (78)\\
\Rightarrow \quad & \frac{N-1}{2N-1}\lambda^g - 1 \overset{!}{\leq} 0 && (79)\\
\Leftrightarrow \quad & \lambda^g \overset{!}{\leq} \frac{2N-1}{N-1}. && (80)
\end{aligned}
$$

To prove the corollary, we define

$$\gamma^{OS}(s) = s\Big(1 + \eta^g\big(1 - F_1(s)\big) + \eta^g\lambda^g F_1(s)\Big). \tag{81}$$

Note that γ^{OS} is given by the argument of the integral of β^{FP}. Similarly, define γ^T as the argument of the integral of β^T. Note that we have shown under which conditions it holds that $\gamma^{OS}(s) \leq \gamma^T(s)$. It is straightforward to compute that in the case of the second-price auction payment rule, bidding functions are given by

$$\beta^{SP}(v) = \gamma^{OS}(v) \tag{82}$$

$$\beta^{T}(v) = \gamma^{T}(v). \tag{83}$$

In the case of the all-pay auction, the bidding functions are given by

$$\beta^{SP}(v) = \int_0^v \gamma^{OS}(s) f_1(s) ds \tag{84}$$

$$\beta^{T}(v) = \int_0^v \gamma^{T}(s) f_1(s) ds. \tag{85}$$

Combining the results from this section concludes the proof to the corollary.

□

Proof of Proposition 5. Again, we consider the first-price auction payment rule. We derive the equilibrium bidding function for the tournament with an odd number of bidders in a similar way as for an even number of bidders.

With proposition 1, we can assume bidders bid the same in every stage. Assume the other bidders bid according to an increasing, absolutely continuous bidding function β^T. In the group with N bidders, a bidder advances if he beats his $N-1$ paired opponents. This yields

$$\phi_1 \circ F = F^{N-1}. \tag{86}$$

Given that the bidder reached stage two, the bidder wins if he beats the winner of the second group with $N+1$ bidders, given he got there,

$$\phi_2 \circ F \circ \beta^{T^{-1}}(b) = F_1^{(N+1)}\left(\beta^{T^{-1}}(b)\right). \tag{87}$$

In the group with $N+1$ bidders, a bidder advances if he beats his N paired opponents. This yields

$$\phi_1 \circ F = F^N. \tag{88}$$

Given that the bidder reached stage two, the bidder wins if he beats the winner of the second group with N bidders, given he got there,

$$\phi_2 \circ F \circ \beta^{T^{-1}}(b) = F_1^{(N)}\left(\beta^{T^{-1}}(b)\right). \tag{89}$$

Again we have $m^T(b) = F_1^{(2N)}\left(\beta^{T^{-1}}(b)\right) b$. Then the utility is given by

$$\begin{aligned}
u^T(v_i, b|b^*) = \; & F_1^{(2N)}\left(\beta^{T^{-1}}(b)\right)\left(v - b\right) \\
+\frac{1}{2}\Bigg[& F_1^{(2N)}\left(\beta^{T^{-1}}(b)\right)\left(1 - F_1^{(N-1)}\left(\beta^{T^{-1}}(b^*)\right)\right)\eta^g v_i \\
& + F_1^{(2N)}\left(\beta^{T^{-1}}(b)\right)\left(1 - F_1^{(N+1)}\left(\beta^{T^{-1}}(b^*)\right)\right)\eta^g v_i \\
& + \left(1 - F_1^{(N-1)}\left(\beta^{T^{-1}}(b)\right)\right) F_1^{(2N)}\left(\beta^{T^{-1}}(b^*)\right)(-\eta^g\lambda^g v_i) \\
& + F_1^{(N-1)}\left(\beta^{T^{-1}}(b)\right) F_1^{(N+1)}\left(\beta^{T^{-1}}(b^*)\right)(-\eta^g\lambda^g v_i) \\
& - F_1^{(2N)}\left(\beta^{T^{-1}}(b)\right) F_1^{(N+1)}\left(\beta^{T^{-1}}(b^*)\right)(-\eta^g\lambda^g v_i)\Bigg] \\
+\frac{1}{2}\Bigg[& F_1^{(2N)}\left(\beta^{T^{-1}}(b)\right)\left(1 - F_1^{(N)}\left(\beta^{T^{-1}}(b^*)\right)\right)\eta^g v_i \\
& + F_1^{(2N)}\left(\beta^{T^{-1}}(b)\right)\left(1 - F_1^{(N)}\left(\beta^{T^{-1}}(b^*)\right)\right)\eta^g v_i \\
& + \left(1 - F_1^{(N)}\left(\beta^{T^{-1}}(b)\right)\right) F_1^{(2N)}\left(\beta^{T^{-1}}(b^*)\right)(-\eta^g\lambda^g v_i) \\
& + F_1^{(N)}\left(\beta^{T^{-1}}(b)\right) F_1^{(N)}\left(\beta^{T^{-1}}(b^*)\right)(-\eta^g\lambda^g v_i) \\
& - F_1^{(2N)}\left(\beta^{T^{-1}}(b)\right) F_1^{(N)}\left(\beta^{T^{-1}}(b^*)\right)(-\eta^g\lambda^g v_i)\Bigg].
\end{aligned} \tag{90}$$

The bracketed expression starting in the second line accounts for the case the bidder is sorted into the N-bidder group, the bracketed expression starting in the seventh line accounts for the case the bidder is sorted into the $N+1$-

bidder group. We are interested in finding the equilibrium bidding function for this multi-stage auction. Our equilibrium concept is UPE, this implies that the first-order condition is given by

$$\left(\frac{\partial u^T(v_i, b|b^*)}{\partial b}\right)\bigg|_{b^*=\beta^T(v_i)} \stackrel{!}{=} 0. \tag{91}$$

Leaving out the arguments of the functions for the sake of readability, we have

$$\begin{aligned}
\beta^{T'}(\beta^{T^{-1}}) \cdot \frac{\partial}{\partial b} u^T(v_i, b|b^*)\bigg|_{b^*=\beta^T(v_i)} = {} & f_1^{(2N)}\Big(v - b\Big) - F_1^{(2N-1)}\beta^{T'}(\beta^{T^{-1}}) \\
& + \frac{1}{2}\Bigg[f_1^{(2N)}\left(1 - F_1^{(N-1)}\right)\eta^g v_i + f_1^{(2N)}\left(1 - F_1^{(N+1)}\right)\eta^g v_i \\
& \quad + f_1^{(N-1)} F_1^{(2N)} \eta^g \lambda^g v_i - \left(f_1^{(N-1)} - f_1^{(2N)}\right) F_1^{(N+1)} \eta^g \lambda^g v_i\Bigg] \\
& + \frac{1}{2}\Bigg[f_1^{(2N)}\left(1 - F_1^{(N)}\right)\eta^g v_i + f_1^{(2N)}\left(1 - F_1^{(N)}\right)\eta^g v_i \\
& \quad + f_1^{(N)} F_1^{(2N)} \eta^g \lambda^g v_i - \left(f_1^{(N)} - f_1^{(2N)}\right) F_1^{(N)} \eta^g \lambda^g v_i\Bigg].
\end{aligned} \tag{92}$$

In equilibrium it holds that $b = \beta^T(v_i)$. The resulting ordinary differential equation for β^T admits a closed form solution,

$$\begin{aligned}
\beta^T(v_i) = {} & \frac{1}{F_1^{(2N)}(v_i)} \int_0^{v_i} s \Bigg[f_1^{(2N)}(s) \\
& + \frac{\eta^g}{2} f_1^{(2N)}(s)\left(4 - F_1^{(N-1)}(s) - F_1^{(N+1)}(s) - 2F_1^{(N)}(s)\right) \\
& + \frac{\eta^g \lambda^g}{2}\Bigg(f_1^{(N-1)}(s) F_1^{(2N)}(s) + f_1^{(N)}(s) F_1^{(2N)}(s) \\
& \quad - \left(f_1^{(N-1)}(s) - f_1^{(2N)}(s)\right) F_1^{(N+1)}(s) \\
& \quad - \left(f_1^{(N)}(s) - f_1^{(2N)}(s)\right) F_1^{(N)}(s) \Bigg)\Bigg] ds.
\end{aligned} \tag{93}$$

Again, as a sufficient condition we want to show that we can rank the arguments of the integrals. The equilibrium bidding function of the first-price auction is now given by

$$\beta^{FP}(v_i) = \frac{1}{F_1^{(2N)}(v_i)} \int_0^{v_i} s f_1^{(2N)}(s)\Big(1+\eta^g\big(1-F_1^{(2N)}(s)\big)+\eta^g\lambda^g F_1^{(2N)}(s)\Big)ds. \tag{94}$$

As before, the first term stemming from the standard preferences equilibrium bidding function is identical in both bidding functions. What is left are the gain-loss utility terms. This means it has to hold that,

$$\begin{aligned}
\frac{\eta^g}{2} f_1^{(2N)}(s)\left(4 - F_1^{(N-1)}(s) - F_1^{(N+1)}(s) - 2F_1^{(N)}(s)\right)& \\
-\eta^g f_1^{(2N)}(s)\big(1 - F_1^{(2N)}(s)\big)& \\
+\frac{\eta^g\lambda^g}{2}\Bigg[f_1^{(N-1)}(s)F_1^{(2N)}(s) + f_1^{(N)}(s)F_1^{(2N)}(s)& \\
-\left(f_1^{(N-1)}(s) - f_1^{(2N)}(s)\right) F_1^{(N+1)}(s)& \\
-\left(f_1^{(N)}(s) - f_1^{(2N)}(s)\right) F_1^{(N)}(s)\Bigg]& \\
-\eta^g\lambda^g\eta^g f_1^{(2N)}(s)F_1^{(2N)}(s) &\overset{!}{\geq} 0.
\end{aligned} \tag{95}$$

Note that all terms, except the third one, include $f_1^{(2N)}(s) = 2NF^{2N}(s)f(s)$. Using the definition of the first-order statistic density for distribution functions and leaving the arguments of the functions out, we can write the third term as

$$\begin{aligned}
& f_1^{(N-1)}F_1^{(2N)} + f_1^{(N)}F_1^{(2N)} - \left(f_1^{(N-1)} - f_1^{(2N)}\right) F_1^{(N+1)} \\
&\qquad - \left(f_1^{(N)} - f_1^{(2N)}\right) F_1^{(N)} \\
= \; & f_1^{(2N)}\left(\frac{N-1}{2N}F_1^{(N-1)}+\frac{1}{2}F_1^{(N)} - \frac{N-1}{2N} + F_1^{(N+1)} - \frac{1}{2} + F_1^{(N)}\right).
\end{aligned} \tag{96}$$

N	1	2	3	4	5	6
Total bidders	3	5	7	9	11	13
λ^{crit}	2.0	2.6484	2.3995	2.2856	2.2222	2.1818
$\frac{4N}{2N-1}$	4.0	2.6667	2.4000	2.2857	2.2222	2.1818

Table 1: Critical λ^g values for different number of bidders.

This inequality can be solved analytically for three bidders and has to be solved numerically for more than three bidders. For three bidders the inequality simplifies to

$$\frac{1}{2} - F + \frac{1}{2}F^2 + \lambda^g\Big(- \frac{1}{4} + \frac{3}{4}F - \frac{1}{2}F^2\Big) \overset{!}{>} 0. \tag{97}$$

Since only F appears, but not its argument, we can solve the inequality without inverting F. The extremum of the left-hand side is attained at $F = \frac{3\lambda-4}{4(\lambda-1)}$, but since the coefficient of the F^2-terms is given by $\frac{1}{2}(1-\lambda)$, this is a maximum. This means that the minimum for valid valued of F is at $F = 0$ or $F = 1$. For $F = 1$, the left-hand side is always equal to zero. For $F = 0$, we have

$$\frac{2-\lambda}{4} \overset{!}{>} 0. \tag{98}$$

This is fulfilled for all $\lambda \leq 2$. For $N > 1$, meaning $5, 7, 9\ldots$ bidders, an analytic solution is not tractable. The inequality can however be solved numerically. The results can be found in Table 1, the code to compute the critical lambdas can be found in Appendix 2.6.

From the proof of the case with an even number of bidders, one might expect that the critical λ^g-values are given by the expression for an even number of bidders plus half a bidder per group in expectation,

$$\frac{2(N+\frac{1}{2})-1}{N+\frac{1}{2}-1} = \frac{4N}{2N-1}. \tag{99}$$

While this expression closely approximates the critical λ^gs for more than four bidders, the actual λ^g-values are somewhat smaller than this, as can be seen in Table 1. This is due to the fact that the order statistics for the $N+1$- and N-bidder groups depend non-linearly on the number of bidders.

The corollary is proven the exact same way as in the case for an even number of bidders. □

Proof of Proposition 6. The minimal critical λ^g is given by $\lambda^g = 2$. Together with Proposition 4 and Proposition 5, this means that for $N \geq 3$ bidders, an auctioneer is always better off if she conducts a tournament instead of the corresponding one-stage mechanism. □

Note that we derived the critical λ^g-values such that every type bids higher in the tournament than in the corresponding one-stage mechanism. If the auctioneer is solely interested in expected revenue, then the critical λ^g-values are significantly higher but depend on the distribution function and generally need to be determined numerically.

An exception is the case for $N = 4$ bidders and the uniform distribution. Here, the difference between the expected payment in tournament vs the corresponding one-stage mechanism is given by

$$\mathbb{E}\Big[m^T - m^{FP}\Big] = \frac{1}{840}\eta^g(\lambda^g + 27). \tag{100}$$

This expression is strictly positive for all admissible λ^g and η^g, meaning that the tournament always yields higher revenues than the corresponding one-stage mechanism in this setting. The same result can be derived for a total of three bidders in the case of uniformly distributed values. For $N > 4$, the critical λ^g-values have to be determined numerically, even for the uniform distribution.

2.4.4 Optimal Efficient Two-Stage Mechanism

We have already shown that the tournament poses a strict improvement over one-stage mechanisms if the auctioneer is facing loss averse bidders. Restricting ourselves to two stages, one might ask what the optimal efficient mechanism looks like. In this section we derive and discuss the optimal efficient two-stage mechanism.

Proposition 7. *Assume bidders are loss averse in the good domain and assume a general two-stage mechanism* $\left(\boldsymbol{\mu}, \mathfrak{M}\right)$ *that induces* $\varphi_1(s) = \phi_1 \circ F(s)$ *and* $\varphi_2(s) = \phi_2 \circ F(s)$*. Then the expected payment of a bidder with value* v *is given by*

$$\begin{aligned} m^{TS}(v) = \int_0^v s\Big(& f_1(s) + \eta^g f_1(s)\left[2 - \varphi_1(s) - \varphi_2(s)\right] \\ & + \eta^g \lambda^g \left[F_1(s)\varphi_1'(s) + f_1(s)\varphi_2(s) - \varphi_1'(s)\varphi_2(s)\right]\Big) ds. \end{aligned} \tag{101}$$

Proof. We start the proof by choosing the first-price payment rule. We will then use Proposition 2 to show that we can choose any standard payment rule after we have derived the two-stage structure $\mathfrak{M}$. With proposition 1, we can assume bidders bid the same in every stage. Assume the other bidders bid according to an increasing, absolutely continuous bidding function β^{TS}. Note that

$$\varphi_1\left(\beta^{TS^{-1}}(b)\right)\varphi_2\left(\beta^{TS^{-1}}(b)\right) = F_1\left(\beta^{TS^{-1}}(b)\right) \tag{102}$$

Then the utility is given by

$$
\begin{aligned}
u^{TS}(v_i, b|b^*) = \ & F_1\left(\beta^{TS^{-1}}(b)\right)(v_i - b) \\
& + F_1\left(\beta^{TS^{-1}}(b)\right)\left(1 - \varphi_1\left(\beta^{TS^{-1}}(b^*)\right)\right)\eta^g v \\
& + F_1\left(\beta^{TS^{-1}}(b)\right)\left(1 - \varphi_2\left(\beta^{TS^{-1}}(b^*)\right)\right)\eta^g v \\
& + \left(1 - \varphi_1\left(\beta^{TS^{-1}}(b)\right)\right)F_1\left(\beta^{TS^{-1}}(b^*)\right)\eta^g \lambda(-v) \\
& + \left(\varphi_1\left(\beta^{TS^{-1}}(b)\right) - F_1\left(\beta^{TS^{-1}}(b)\right)\right)\varphi_2\left(\beta^{TS^{-1}}(b^*)\right)\eta^g \lambda(-v).
\end{aligned}
\tag{103}
$$

The bidding function β^{TS} constitutes a UPE if and only if the utility function $u_i^{TS}(v_i, b|\beta^{TS}(v_i))$ attains its maximum at $b = \beta^{TS}(v_i)$ for all v_i. Differentiating u^{TS} with respect to b and plugging in the equilibrium condition $b = \beta^{FP}(v_i)$ yields the ODE

$$
\begin{aligned}
F_1(s)\,\beta^{TS}(s) + f_1(s)\,\beta^{TS'}(s) = s\Big(& f_1(s) + \eta^g f_1(s)\left[2 - \varphi_1(s) - \varphi_2(s)\right] \\
& + \eta^g \lambda^g\left[F_1(s)\varphi_1'(s) + f_1(s)\varphi_2(s) - \varphi_1'(s)\varphi_2(s)\right]\Big).
\end{aligned}
\tag{104}
$$

It follows that

$$
\begin{aligned}
\beta^{TS}(v) = \frac{1}{F_1(v)}\int_0^v s\Big(& f_1(s) + \eta^g f_1(s)\left[2 - \varphi_1(s) - \varphi_2(s)\right] \\
& + \eta^g \lambda^g\left[F_1(s)\varphi_1'(s) + f_1(s)\varphi_2(s) - \varphi_1'(s)\varphi_2(s)\right]\Big) ds
\end{aligned}
\tag{105}
$$

and

$$
\begin{aligned}
m^{TS}(v) = \int_0^v s \Bigg(& f_1(s) + \eta^g f_1(s)\Big[2 - \varphi_1(s) - \varphi_2(s)\Big] \\
& + \eta^g \lambda^g \Big[F_1(s)\varphi_1'(s) + f_1(s)\varphi_2(s) - \varphi_1'(s)\varphi_2(s)\Big]\Bigg) ds.
\end{aligned}
\tag{106}
$$

□

Proposition 8. *Assume bidders are loss averse in the good domain and assume a general two-stage mechanism that induces* $\varphi_1(s) = \phi_1 \circ F(s)$ *and* $\varphi_2(s) = \phi_2 \circ F(s)$*. Then the expected revenue for the auctioneer is given by*

$$
\begin{aligned}
\mathbb{E}[R] = N \int_0^1 s(1 - F(s)) \Big(& f_1(s) + \eta^g f_1(s)\big[2 - \varphi_1(s) - \varphi_2(s)\big] \\
& + \eta^g \lambda^g \big[F_1(s)\varphi_1'(s) + f_1(s)\varphi_2(s) - \varphi_1'(s)\varphi_2(s)\big]\Big) ds.
\end{aligned}
\tag{107}
$$

Proof. Again, assume the other bidders bid according to an increasing, absolutely continuous bidding function β^{TS} and use the interim results of Proposition 7. Define

$$
\begin{aligned}
\Gamma(s) = & s\Big(f_1(s) + \eta^g f_1(s)\big[2 - \varphi_1(s) - \varphi_2(s)\big] \\
& + \eta^g \lambda^g \big[F_1(s)\varphi_1'(s) + f_1(s)\varphi_2(s) - \varphi_1'(s)\varphi_2(s)\big]\Big).
\end{aligned}
\tag{108}
$$

The expected revenue is given by

$$
\mathbb{E}[R] = N \int_0^1 \int_0^v \Gamma(s) ds \, f(v) dv. \tag{109}
$$

Partial integration yields

$$\int_0^1 \int_0^v \Gamma(s)ds\ f(v)dv = \left[\int_0^v \Gamma(s)ds\ F(v)\right]_{v=0}^{v=1} - \int_0^1 \Gamma(s)\ F(s)ds \tag{110}$$

$$= \int_0^1 \Gamma(s)ds - \int_0^1 \Gamma(s)\ F(s)ds \tag{111}$$

$$= \int_0^1 \Big(1 - F(s)\Big)\Gamma(s)ds. \tag{112}$$

□

Proposition 9 (Optimal two-stage structure)**.** *Assume bidders are loss averse in the good domain. Then the optimal two-stage structure is given by*

Stage 1: With probability $\frac{1}{\lambda}$ *bidders get to the second stage with probability 1. With probability* $\frac{\lambda-1}{\lambda}$ *only the strongest bidder advances to stage 2 and has thus won the auction.*

Stage 2: If bidders got to stage 2 with probability 1, the strongest bidder wins the auction.

Bidders are left unaware whether the branch in which everyone advances to the second stage was selected or if the auction took place in the first stage. The only information they receive is whether they have reached stage two or not and after the second stage, whether they have won the auction or not. The interpretation here is that this mechanism induces just the right amount of risk, a bidder in stage 2 does not know whether he beat his opponents already or if the "real" auction is yet to come. This takes care of lower types who do not need to insure themselves against their expectations by bidding even lower, while it encourages strong bidders to bid even higher.

Proof. The proof is structured in two parts. In a first step we optimize the expected revenue functional for general distribution functions and φ_1

and φ_2. In the second step, we show that the optimal φ_i-functions are equivalent to admissible φ_i, meaning that they satisfy the conditions from section 2.3.2. Assume the other bidders bid according to an increasing, absolutely continuous bidding function β^{TS} and use the interim results of Proposition 7.

We have

$$\mathbb{E}[R] = N \int_0^1 \Big(1 - F(s)\Big)\Gamma(s)ds =: N \int_0^1 J(s, \varphi_1, \varphi_1', \varphi_2)ds, \tag{113}$$

with

$$\begin{aligned}\Gamma(s) =& s\Big(f_1(s) + \eta^g f_1(s)\big[2 - \varphi_1(s) - \varphi_2(s)\big] \\ &+ \eta^g \lambda^g \big[F_1(s)\varphi_1'(s) + f_1(s)\varphi_2(s) - \varphi_1'(s)\varphi_2(s)\big]\Big).\end{aligned} \tag{114}$$

We need to find φ_1 and φ_2 that maximize the functional

$$\int_0^1 J(s, \varphi_1, \varphi_1', \varphi_2)ds. \tag{115}$$

A candidate for the optimal φ_i is given by solving the constrained Euler-Lagrange equations for our functional. We will nonetheless begin with the unconstrained Euler-Lagrange equations,

$$\begin{cases} \dfrac{\partial}{\partial \varphi_1} J(s, \varphi_1, \varphi_1', \varphi_2) - \dfrac{d}{ds}\left(\dfrac{\partial}{\partial \varphi_1'} J(s, \varphi_1, \varphi_1', \varphi_2)\right) = 0 \\ \dfrac{\partial}{\partial \varphi_2} J(s, \varphi_1, \varphi_1', \varphi_2) - \dfrac{d}{ds}\left(\dfrac{\partial}{\partial \varphi_2'} J(s, \varphi_1, \varphi_1', \varphi_2)\right) = 0 \\ \varphi_1(1) = 1 \\ \varphi_2(1) = 1. \end{cases} \tag{116}$$

The initial values of the φ_i are the only natural choice: For reasons of efficiency, the highest possible type should always advance with certainty. The probability that two bidders are of the highest possible type is zero. Prescribing values for $\varphi_i(0)$ could lead to distortions since it might be optimal to have an atom on 0. Note that J does not depend on φ_2', so the Euler-Lagrange equations simplify to

$$\begin{cases} \dfrac{\partial}{\partial \varphi_1} J(s, \varphi_1, \varphi_1', \varphi_2) - \dfrac{d}{ds}\left(\dfrac{\partial}{\partial \varphi_1'} J(s, \varphi_1, \varphi_1', \varphi_2)\right) = 0 & (a_1) \\ \dfrac{\partial}{\partial \varphi_2} J(s, \varphi_1, \varphi_1', \varphi_2) = 0 & (b_1) \\ \varphi_1(1) = 1 & (a_2) \\ \varphi_2(1) = 1. & (b_2) \end{cases} \tag{117}$$

This system of ordinary differential equations is closed-form solvable for general distribution functions. We begin with the initial value problem $(b_1), (a_2), (b_2)$.

$$\begin{cases} s(1-F(s))\Big[-\eta^g f_1(s) + \eta^g \lambda^g\big(f_1(s) - \varphi_1'(s)\big)\Big] = 0 & (b_1) \\ \varphi_1(1) = 1 & (b_2) \\ \varphi_2(1) = 1 & (b_2) \end{cases} \tag{118}$$

$$\Leftrightarrow \quad \begin{cases} \varphi_1'(s) = \dfrac{f_1(s)(\lambda^g - 1)}{\lambda} & (b_1) \\ \varphi_1(1) = 1 & (b_2) \end{cases} \tag{119}$$

$$\Rightarrow \quad \varphi_1(s) = \frac{1 + F_1(s)(\lambda^g - 1)}{\lambda^g}. \tag{120}$$

For the second initial value problem $(a_1), (a_2), (b_2)$, we have

$$\begin{cases} s(1-F(s))\Big[-\eta^g f_1(s) - \eta^g \lambda^g \big(f_1(s) - \varphi_2'(s)\big)\Big] & \\ \qquad -\eta^g \lambda^g \Big(1 - F(s) - sf(s)\Big)\big(F_1(s) - \varphi_2(s)\big) = 0 & (b_1) \\ \qquad\qquad \varphi_1(1) = 1. & (b_2) \\ \qquad\qquad \varphi_2(1) = 1. & (b_2) \end{cases} \tag{121}$$

Note that the ODE only depends on φ_2, as was the case with $(b_1), (a_2), (b_2)$ and φ_1. After rearranging and applying the product rule, we arrive at

$$\varphi_2(s) = F_1(s) - \frac{1}{s(1-F(s))}\int_s^1 \frac{y(1-F(y))f_1(y)}{\lambda^g}dy. \tag{122}$$

This means that for the unconstrained optimization problem, the solution is given by

$$\begin{cases} \varphi_1(s) = \dfrac{1 + F_1(s)(\lambda^g - 1)}{\lambda^g} \\ \varphi_2(s) = F_1(s) - \dfrac{1}{s(1-F(s))}\displaystyle\int_s^1 \frac{y(1-F(y))f_1(y)}{\lambda^g}dy. \end{cases} \tag{123}$$

Note that $\varphi_1(s)\varphi_s(s) \neq F_1(s)$, meaning that these do not satisfy the conditions from section 2.3.2. We now show that choosing $\varphi_1(s)$ and $\varphi_2(s)$ according to the solutions of the unconstrained Euler-Lagrange equations is equivalent to choosing $\varphi_2(s) = \frac{F_1(s)}{\varphi_1(s)}$.

Choosing $\varphi_1(s)$ according to (123), the expressions of $\int_0^1 J(s, \varphi_1, \varphi_1', \varphi_2)ds$ that involve $\varphi_2(s)$ are given by

$$\int_0^1 s(1-F(s))\eta^g\varphi_2(s)\Big[-f_1(s) + \lambda^g f_1(s) - \lambda^g\varphi_1'(s)\Big]ds \tag{124}$$

$$= \int_0^1 s(1-F(s))\eta^g\varphi_2(s)\Big[f_1(s)(\lambda^g - 1) - \cancel{\lambda^g}\frac{f_1(s)(\lambda^g-1)}{\cancel{\lambda^g}}\Big]ds \tag{125}$$

$$= 0. \tag{126}$$

This implies that once we have chosen $\varphi_1(s)$ as the solution of the unconstrained optimization problem and therefore independent of $\varphi_2(s)$, it does not matter which $\varphi_2(s)$ we choose, as long as it remains measurable. Therefore our final φ_i are given by

$$\begin{cases} \varphi_1(s) = \dfrac{1 + F_1(s)(\lambda^g - 1)}{\lambda^g} \\ \varphi_2(s) = \dfrac{\lambda^g F_1(s)}{1 + F_1(s)(\lambda^g - 1)}. \end{cases} \tag{127}$$

$\square$

This two-stage structure optimizes the revenue for the seller. We can even show that bids of *all* types are higher than in the one-stage variants of the mechanism and not just overall revenue.

Proposition 10. *Assume bidders are loss averse in the good domain and consider either the first-price auction, the second-price auction or the all-pay auction. Equilibrium bids in the optimal two-stage structure are higher than in the corresponding one-stage mechanism.*

Proof. First note that replacing the φ_i in Γ by (127) yields

$$\begin{aligned} \Gamma(s) =& s\Big(f_1(s) + \eta^g f_1(s)\big[2 - \varphi_1(s) - \varphi_2(s)\big] \\ &+ \eta^g \lambda^g \big[F_1(s)\varphi_1'(s) + f_1(s)\varphi_2(s) - \varphi_1'(s)\varphi_2(s)\big]\Big) \\ &= s f_1(s)\left(1 + \eta^g\left(2 - \frac{1}{\lambda^g}\right) + \eta^g \frac{(\lambda^g - 1)^2}{\lambda} F_1(s)\right). \end{aligned} \tag{128}$$

Define

$$\gamma^{OS}(s) = s\Big(1 + \eta^g\big(1 - F_1(s)\big) + \eta^g \lambda^g F_1(s)\Big) \tag{129}$$

$$\gamma^{Opt}(s) = s\left(1 + \eta^g\left(2 - \frac{1}{\lambda^g}\right) + \eta^g \frac{(\lambda^g - 1)^2}{\lambda} F_1(s)\right). \tag{130}$$

We have

$$\gamma^{Opt}(s) \overset{!}{\geq} \gamma^{OS}(s) \tag{131}$$

$$\Leftrightarrow \quad 2 - \frac{1}{\lambda^g} + \frac{(\lambda^g - 1)^2}{\lambda} F_1(s) \overset{!}{\geq} 1 - F_1(s) + \lambda^g F_1(s) \tag{132}$$

$$\Leftrightarrow \quad F_1(s) - 1 \overset{!}{\leq} 0, \tag{133}$$

which is always true. This means that the ranking holds for the first-price auction. One can easily compute that in the case of the second-price auction as underlying mechanism, bidding functions are given by

$$\beta^{SP}(v) = \gamma^{OS}(v) \tag{134}$$

$$\beta^{Opt}(v) = \gamma^{Opt}(v). \tag{135}$$

In the case of the all-pay auction, the bidding functions are given by

$$\beta^{SP}(v) = \int_0^v \gamma^{OS}(s) f_1(s) ds \tag{136}$$

$$\beta^{Opt}(v) = \int_0^v \gamma^{Opt}(s) f_1(s) ds. \tag{137}$$

This concludes the proof. $\square$

2.5 Conclusion

In this paper we investigate how a buyer should design her procurement mechanism when bidders are loss averse. Loss aversion implies that the willingness to pay of a bidder depends on the probability he assigns to winning the auction. We show that a simple two-stage mechanism, the tournament, outperforms any one-stage mechanism revenue-wise if bidders are not too loss averse. As a robustness-check, we show that the buyer's revenue is not dependent on the payment rule she implements. Once the structure of the multi-stage mechanism is fixed, a revenue equivalence principle holds. Finally, we derive the optimal, efficient two-stage mechanism. This mechanism is, in contrast to the tournament, dependent on the degree of loss aversion of the bidders and therefore difficult to implement in real-life procurement.

Our analysis opens the door to further research. On the one hand, it might be interesting to investigate whether a buyer could further improve her revenue if she were to implement a three-stage (or even more stages) mechanism. Numerical simulations suggest that the answer is no, but the problem quickly becomes untractable even for a fixed cost distribution like the uniform distribution. On the other hand, one could expand the model to include bidders that are loss averse in the money domain, too. The revenue equivalence principle that we derived fails in that case, as shown by Eisenhuth and Ewers (2012). In their paper, they show that the all-pay auction yields higher revenues than the first-price auction in a setting similar to ours. This implies that the optimal mechanism for two or more stages will depend on the payment rule the buyer implements, making the optimization problem a lot harder.

2.6 Appendix

Mathematica Code

The code takes a starting value an then shoots λ-values until the minimum of the function $Func$ crosses 0.

```
Func[N_, l_] :=
  (1 - x^(N - 1) / 2 - x^(N + 1) / 2 - x^(N) + x^(2 N)) + l * (((N - 1) / (4 N)) * x^(N - 1) +
      x^N / 4 - ((N - 1) / (4 N)) - 1 / 4 + x^(N + 1) / 2 + (x^N) / 2 - x^(2 N))

a = 1;
step = 0.0001;
temp = 0;
startvalue = 2.153;
While[a > 0,
 sumsteps = temp;
 a = FindMinimum[{Func[7, startvalue + sumsteps], 0 < x < .3}, x][[1]];
 temp = sumsteps + step;
 If[a < 0,
  Print["lambda=" <> ToString[NumberForm[startvalue + sumsteps - step, 10]]]]
]
```

3 Motivated Beliefs in Auctions

Abstract

In auctions bidders are usually assumed to have rational expectations with regards to their winning probability. However, experimental and empirical evidence suggests that agent's expectations depend on direct utility stemming from expectations, resulting in optimism or pessimism. Optimism increases ex ante savoring, while pessimism leads to less disappointment ex post. Hence, optimal expectations depend on the time left until the uncertainty is resolved, i.e. the time one can savor ex ante by being (too) optimistic. Applying the decision theory model of Gollier and Muermann (2010) to first price auctions, I show that by decreasing the time between bids and revelation of results, the auctioneer can induce bidders to forego optimism, leading to more aggressive bids and thereby higher revenues for the auctioneer. Finally I test these predictions experimentally, finding no evidence for my theoretical predictions.

3.1 Introduction

When analyzing games with uncertainty, economists usually assume that agents have rational expectations, i.e. correctly infer the probability of all potential outcomes given their actions. In particular, this implies that expectations stay constant over time if agents do not receive new information.

That does not allow for systematic errors of agents confronted with uncertainty, which are however observed in many environments. A large strand of psychological literature finds evidence for an optimism bias, meaning that agents systematically overestimate probabilities of good outcomes and underestimate probabilities of bad outcomes. Interestingly, this bias seems to disappear (or even turn into a pessimism bias) as the moment of truth, i.e. when the uncertainty is resolved, arrives.

This observation is in line with the predictions of motivated beliefs that are caused by ex ante savoring and ex post disappointment: Optimism comes with the benefit of utility gains during the time of optimism. [19] Yet, at the moment of truth agents can insure themselves against their own disappointment aversion by decreasing their expectations. As a result, the closer the temporal distance to the revelation of an uncertainty is, the less optimistic (or more pessimistic) agents tend to be. Or, in other words, when an agent expects the immediate resolution of an uncertainty, he tends to be less optimistic as compared to a situation where the resolution lies in a distant future.

The theoretical and empirical analysis of this behavioral pattern is so far limited to choice models. Clearly systematic errors in probability assessments influence decisions on investments, health outcomes or exam preparations.

However, to the best of my knowledge it has not yet been investigated (i) whether endogenous expectations[20] play a role in strategic games and (ii) what the consequences of this would be. This paper is a first attempt to close this gap by applying endogenous expectations to strategic games with uncertainty. As I will show in the next chapters, an analysis based on endogenous expectations can provide important insights to strategic games. When agents can strategically manipulate the perceived probabilities of good

[19] It is well documented that optimism increases outcomes such as health or general well-being, see e.g. Andersson (1996).

[20] As it is standard in the literature, endogeneous expectations and motivated beliefs are used as synonyms in this work.

or bad outcomes, their optimization problem will change, leading to different equilibria in a certain game (as compared to agents with rational expectations).

A natural choice of a strategic game to apply this framework to are static auctions. On the one hand due to the sheer size of auctions, especially in procurement, where static first-price auctions are the main tool to award suppliers. [21]. On the other hand, in static auctions the auction designer can usually influence the time between bidding and revelation of results. Since, as argued above, this has an influence on bidder´s expectations to win (and thereby on their bidding strategy), the auctioneer has an additional lever to increase or decrease revenue.

In procurement practice, the temporal distance between supplier´s bids and the revelation of the winner of the auction varies by multiple weeks to months. In some procurement projects, suppliers first hand in their final commercial and technical offers, and then the procuring organization analyses the offers in all dimensions. After this elaborate and lengthy analysis, the winning supplier is awarded the business. In other procurement projects, suppliers first hand in their technical offers, then the procuring organization monetarily evaluates all non-commercial differences between suppliers, and then an auction with immediate feedback is conducted.

To summarize, in first price auctions in procurement the time between the final submission of a (commercial) offer and the awarding of the business varies, which, under the assumption of motivated beliefs of bidders, has an effect on the bidding strategies. [22]

[21] Note that procurement makes up 17% of European GDP, see e.g. Internal Market Scoreboard, no19, July 2009 and is even more important in many industries, see https://www.oliverwyman.com/our-expertise/industries/automotive/procurement.html

[22] Note that this is even the case if we assume that the shift in expected winning probabilities is exogenous instead of endogenous, since pessimism per se leads to overbidding in auctions, see e.g. Armantier and Treich (2009)

In this paper I analyze the consequences of a decrease in this temporal distance on estimated winning probabilities and revenues in first-price auctions. Applying a simple framework based on Gollier and Muermann (2010), I show that a low temporal distance between bid and revelation of results leads to more pessimism and thereby to more aggressive bidding. The rationale behind this finding is the following: The longer the time between bidding and revelation of results, the more subjects benefit from being optimistic. When subjects are optimistic, they benefit more from marginally decreasing their bid, as this increases their expected payoff (valuation minus bid multiplied by the expected winning probability) more than that of pessimistic bidders.

In addition to the theoretical analysis I test my main hypothesis experimentally. In two different induced values frameworks I vary the time between bidding and revelation of results. In these experiments I cannot find any effect of an increase in this time on either expected winning probabilities or bidding strategies.

3.2 Related Literature

When it comes to uncertain outcomes, systematic errors in the assessment of probabilities have been well documented. In an extensive study, Weinstein (1980) argues that people are unrealistically optimistic with respect to future life events. While participants correctly estimated probabilities of their peers, they significantly overestimated the chances for own good outcomes (and vice versa underestimated chances for own bad outcomes). Similar patterns have been found for estimates on task completion times (Buehler, Griffin, and Ross (1994)), student debt (Seaward and Kemp (2000)) or success of startups (Baker, Ruback, and Wurgler (2007)).

The economic interpretation behind this is that utility is not only realized at the moment of truth, but also continuously during the time of uncertainty. Being optimistic increases current felicity during this time. The temporal element of utility stemming from anticipation has first been introduced by Loewenstein (1987). Caplin and Leahy (2001) incorporate this formally into an economic model, where anticipatory feelings are caused by exogenous expectations.

The first researchers that modeled agents that can manipulate their expectations were Brunnermeier and Parker (2005). In a portfolio choice model they account for endogenous expectations and current felicity flows and show that in this case investors tend to overestimate their return and have an irrational preference for assets with high variance.

While it seems intuitive that being optimistic has benefits if the revelation of the uncertainty is in the distant future, it becomes less clear as the moment of truth approaches. As introduced by Bell (1985), agents tend to be disappointment averse, i.e. compare outcomes to expected outcomes[23]. With respect to uncertain outcomes, this means that the higher the estimated probability of a good event, the higher the disappointment if the good event does not realize. Hence being pessimistic comes with the benefit of insuring oneself against disappointment. Closing the gap between these two strands of literature, Gollier and Muermann (2010) introduce a choice model that accounts for both ex ante savoring and ex post disappointment.

In line with their model, multiple psychological researchers find that agents have the tendency to abandon optimism (and even become pessimistic) as the moment of truth approaches. In a study by Shepperd,

[23] Disappointment aversion is conceptually very similar to expectations based loss aversion as in Kőszegi and Rabin (2006). The only difference is that here the reference point corresponds to the lottery´s certainty equivalent, while in Kőszegi and Rabin (2006) the reference point is stochastic, i.e. corresponds to the distribution of the lottery.

Ouellette, and Fernandez (1996) college sophomors, juniors and seniors estimated their starting salary in their first post-graduate job at the beginning and end of the semester. As the researchers show, only the seniors significantly decreased their expectations over time. They furthermore argue that the decrease was solely driven by those seniors that were actually about to look for a job. Similarly, when estimating their exam scores multiple times after the exam was written, students abandon their initial optimism in favor of pessimism right before the grades are published (Van Dijk, Zeelenberg, and Van der Pligt (2003)). As Taylor and Shepperd (1998) show, the same logic applies to estimates on health.

Additionally Drobner (2022) conducts a literature review arguing that in experiments subjects update their beliefs optimistically if and only if they expect no immediate resolution of the uncertainty. He confirms this finding in the lab, showing that subjects update their beliefs about an IQ test optimistically if they expect no resolution of the uncertainty, and neutrally if they expect immediate resolution.

In this paper I apply the model of Gollier and Muermann (2010) on first price auctions and show that immediate feedback is favorable for the auctioneer. To the best of my knowledge, this is the first paper to apply a model of endogenous expectations to a settinng that includes strategic interaction. Finally I test my predictions experimentally.

3.3 Model

One indivisible item is to be awarded. There are two bidders with independent private values drawn from a uniform distribution function $U[0, 1]$.

3.3.1 Preferences

I model agent´s preferences based on Gollier and Muermann (2010). There are two dates: At date 1, bidders submit bids. At the same time, they form subjective beliefs about their winning probability. The subjective beliefs can be different from the objective winning probability based on own bid and strategies of competitors. At date 2, i.e. the moment of truth, the winner of the auction is announced. Each bidder generates welfare from anticipatory feelings and the utility generated by the final outcome of the auction. Welfare from anticipatory feelings is weighted with the temporal distance k between now and the moment of revelation. For consumption c_s, subjective probabilities p_s and objective probabilities q_s for different states of the world s, welfare then becomes

$$W = k * \sum_{s=1}^{S} p_s U(c_s, y) + \sum_{s=1}^{S} q_s U(c_s, y) \tag{138}$$

where reference consumption y is defined as expected value given subjective probabilities.

The utility generated by the final outcome of the auction depends on actual consumption x and reference consumption y and is given by[24]

$$U(x, y) = x - \alpha(y - x) \tag{139}$$

where α represents the weight of the utitlity derived from reference depence compared to standard consumption utility.

In first price auctions, welfare then becomes

$$\begin{aligned} W = kpU(v-b, y) + k(1-p)U(0, y) \\ + qU(v-b, y) + (1-q)U(0, y); \\ y = p(v-b) \end{aligned} \tag{140}$$

with p being the subjective winning probability.

The anticipatory utility is represented in the first line of the equation. With subjective probability p the agent expects to win the auction, and receives a utility that accounts for the fact that he expected to receive y. With subjective probability $1-p$ he will not win the auction and will hence receive a (negative) utility that again accounts for the fact that he expected to receive y. All expressions in the first line are of course multiplied by the temporal distance k. Actual consumption utilities are then represented in the second line. These depend on the objective winning probability q and also take into account potential deviations from expected utlity y.

Plugging in $y = p(v - b)$ and the linear utility function from above, this becomes

$$W = p(k - \alpha)(v - b) + q(1 + \alpha)(v - b) \tag{141}$$

[24] To make the analysis tractable, I assume linear utility, resulting in 'no kink' at the point of the reference consumption. Intuitively this means that an agent does not suffer more from a negative surprise than he gains from a positive surprise. The introduction of a kink would however not change the main results, as I will argue in the discussion section.

3.4 Analysis

In contrast to most standard auction models, in this model bidders optimize over 2 variables: Subjective winning probability p and bid b. I begin the analysis with the observation that for all $k < \alpha$, W is strictly decreasing in p, while for all $k > \alpha$, W is strictly increasing in p.[25] As a result, bidders will choose $p = 0$ in the former case, and $p = 1$ in the latter, hence I can make a distinction between these two cases, and the problem becomes a one-dimensional optimization problem in each of the cases.[26]

3.4.1 Small temporal distance: $k < \alpha$

In the case of small temporal distance between bids and publication of results, the welfare of a bidder becomes

$$W_{small} = q(1 + \alpha)(v - b) \tag{142}$$

Assume both bidders bid according to the strictly increasing and differentiable equilibrium bidding strategy $\beta(v)$. The welfare of bidder i bidding b is given by

$$\begin{aligned} W_{small} &= q(1 + \alpha)(v - b) \\ &= Pr\left(b > \beta\left(v\right)\right)(1 + \alpha)(v - b) \\ &= Pr\left(\beta^{-1}\left(b\right) > v\right)(1 + \alpha)(v - b) \\ &= \beta^{-1}\left(b\right)(1 + \alpha)(v - b) \end{aligned} \tag{143}$$

[25] The intuition behind that is the following: When the temporal distance k is high and the weight on reference dependence α is low a bidder benefits from being optimistic, and does not suffer from over-optimism at the time of the revelation. The same logic applies vice versa for low temporal distance k and high weight on reference dependence α.

[26] The fact that agents always choose one of the extremes is caused by the linear utility functions. In the case of non-linear utility functions we would not observe these extremes, but the main results still hold, with the downside that closed-form solutions do not exist. Since the main purpose of the theory in this paper is to motivate my experiments, I decided to take the 'simple' model which however nicely shows the intuition.

Optimize via b:

$$\frac{\partial}{\partial b} W_{small} = \Big(\frac{v-b}{\beta' \left(\beta^{-1}(b) \right)} - \beta^{-1}(b) \Big) (1+\alpha) \tag{144}$$

$$\Big(\frac{v-b}{\beta' \left(\beta^{-1}(b) \right)} - \beta^{-1}(b) \Big) (1+\alpha) \stackrel{!}{=} 0 \tag{145}$$

In equilibrium, $\beta^{-1}(b) = v$.

$$\frac{v - \beta(v)}{\beta'(v)} - v \stackrel{!}{=} 0 \tag{146}$$

$$\frac{\partial}{\partial v} [v\beta(v)] \stackrel{!}{=} v \tag{147}$$

$$\int_0^v \frac{\partial}{\partial y} [y\beta(y)] \, dy \stackrel{!}{=} \int_0^v y dy \tag{148}$$

$$v\beta(v) \stackrel{!}{=} \frac{v^2}{2} \tag{149}$$

Hence, in equilibrium

$$\beta_{small}(v) = \frac{v}{2} \tag{150}$$

Evidently, in the case of a small temporal distance, the equilibrium bidding function corresponds to the bidding function in standard theory. This is due to the fact that ex-ante savoring does not play a role here, since subjects choose a subjective winning probability of zero.

3.4.2 Large temporal distance: $k > \alpha$

In the case of large temporal distance between bids and publication of results, the welfare of a bidder becomes

$$W_{large} = (k-\alpha)(v-b) + q(1+\alpha)(v-b) \tag{151}$$

Assume both bidders bid according to the strictly increasing and differentiable equilibrium bidding strategy $\beta(v)$. The welfare of bidder i bidding b is given by

$$\begin{aligned} W_{large} &= (k-\alpha)(v-b) + q(1+\alpha)(v-b) \\ &= (k-\alpha)(v-b) + Pr\left(b > \beta\left(v\right)\right)(1+\alpha)(v-b) \\ &= (k-\alpha)(v-b) + Pr\left(\beta^{-1}\left(b\right) > v\right)(1+\alpha)(v-b) \\ &= (k-\alpha)(v-b) + \beta^{-1}\left(b\right)(1+\alpha)(v-b) \end{aligned} \tag{152}$$

Optimize via b:

$$\frac{\partial}{\partial b} W_{large} = (\alpha - k) + \left(\frac{v-b}{\beta'\left(\beta^{-1}\left(b\right)\right)} - \beta^{-1}\left(b\right)\right)(1+\alpha) \tag{153}$$

$$\left(\frac{v-b}{\beta'\left(\beta^{-1}\left(b\right)\right)} - \beta^{-1}\left(b\right)\right)(1+\alpha) \overset{!}{=} (k-\alpha) \tag{154}$$

In equilibrium, $\beta^{-1}(b) = v$.

$$\frac{v-\beta(v)}{\beta'(v)} - v \overset{!}{=} \frac{k-\alpha}{1+\alpha} \tag{155}$$

$$v + \frac{\alpha-k}{1+\alpha} * \beta'(v) \overset{!}{=} v * \beta'(v) + \beta(v) \tag{156}$$

$$\frac{\partial}{\partial v}[v\beta(v)] \stackrel{!}{=} v + \frac{\alpha - k}{1+\alpha}\beta'(v) \tag{157}$$

$$\int_0^v \frac{\partial}{\partial y}[y\beta(y)]\, dy \stackrel{!}{=} \int_0^v (y + \frac{\alpha - k}{1+\alpha}\beta'(y))dy \tag{158}$$

$$v\beta(v) \stackrel{!}{=} \frac{v^2}{2} + \frac{\alpha - k}{1+\alpha}\int_0^v (\beta'(y))dy \tag{159}$$

$$v\beta(v) \stackrel{!}{=} \frac{v^2}{2} + \frac{\alpha - k}{1+\alpha}\beta(v) \tag{160}$$

$$\beta(v)(v + \frac{k - \alpha}{1+\alpha}) \stackrel{!}{=} \frac{v^2}{2} \tag{161}$$

Hence, in equilibrium

$$\beta_{large}(v) = \frac{v^2}{2 * (v + \frac{k-\alpha}{1+\alpha})} \tag{162}$$

As we can see, β is increasing in k and decreasing in α, with the following intution: When the temporal distance k is high and the weight on reference dependence α is low, it becomes attractive to (i) be very optimistic and (ii) bid very low, since the bidder benefits strongly from the higher expected gain associated with a high bid and high sibjective winning probability.

3.4.3 Results

Having derived the bidding functions for small and large temporal distances, I can show that the former is always larger than the latter:

Proposition 11. *For all v, bids are strictly higher in the case of small* *temporal distance than in the case of large temporal distance:*

$$\beta_{small}(v) > \beta_{large}(v) \forall v \tag{163}$$

Proof.

$$\beta_{small}(v) = \frac{v}{2} = \frac{v^2}{2 * v} > \frac{v^2}{2 * (v + \frac{k-\alpha}{1+\alpha})} = \beta_{large}(v) \tag{164}$$

□

As intuition suggests, a larger temporal distance leads to more optimism. When slightly decreasing a certain bid, bidders face a tradeoff between higher ex ante savoring (i.e. expecting to win $v-b$) and a lower chance of actually winning the auction. Since for a high temporal distance the bidder benefits from a lower bid longer and with a higher perceived probability, the incentive to slightly decrease the bid is higher than for a short temporal distance, driving my main result.

To test whether the behavioral mechanisms described in the previous chapters are actually relevant for human behavior in auctions, I conducted an experiment.

3.5 Experiment

3.5.1 Experimental Design

The experiment consisted of five bidding rounds. Participants were matched into cohorts of four bidders, that were randomly matched in groups of two in each round.

Auction. Participants were bidding on a coupon, that each participant had a certain valuation for. This valuation was drawn independently from

{0; 2; 4; 6; 8; 11}USD, with each value being equally likely. [27] The bidder submitting the highest bid received the coupon, accordingly his payoff from the auction was valuation minus his bid. The bidder submitting the lower bid received a payoff of zero.

Probability Estimate. In addition to bidding, participants had to provide an estimate on their winning probability given their bid. To do so, they could choose from a set of 'confidence levels', i.e. $\{0\% - 20\%; 20\% - 40\%; 40\% - 60\%; 60\% - 80\%; 80\% - 100\%\}$ that they estimated their winning probability to be within. This estimate was incentivized in the following way: After a cohort finished all 5 rounds, I counted the number of bids (of all other bidders) lower or equal to the respective bid. This number was then divided by 20, i.e. the number of all bids of all other players in this cohort. If the estimate in a given round was corresponding to this probability, the participant received an additional $0.50USD$.

Timing. The timing of the experiment was the following: Participants entered the submission screen, where they were told their valuation for the coupon. On the same screen, participants had to post their offer and their estimate of winning given this offer. To do so, they had 2 minutes. After the 2 minutes, participants in CLOSE were immediately told wether they won the auction and then had to wait 5 minutes for the next round to start. Participants in FAR had to wait 5 minutes for the revelation of the result, and then the next round immediately started. [28] Figure 3 displays

[27] This distribution function was chosen due to its clear theoretical prediction: In the unique RNNE, bidders bid {0; 1; 2; 3; 4; 5}USD respectively.

[28] When designing the experiment, I faced a tradeoff between the amount of data I can collect (i.e. the number of rounds) and the length of the waiting time. In an ideal world, participants would wait for multiple weeks between bidding and revelation, and play the experiment multiple times. This however was not possible due to technical and financial constraints. So I decided to take an approach with a relatively low waiting time in order to let subjects play multiple rounds, since I was not fully convinced that the mechanism I describe also works in a one-shot game.

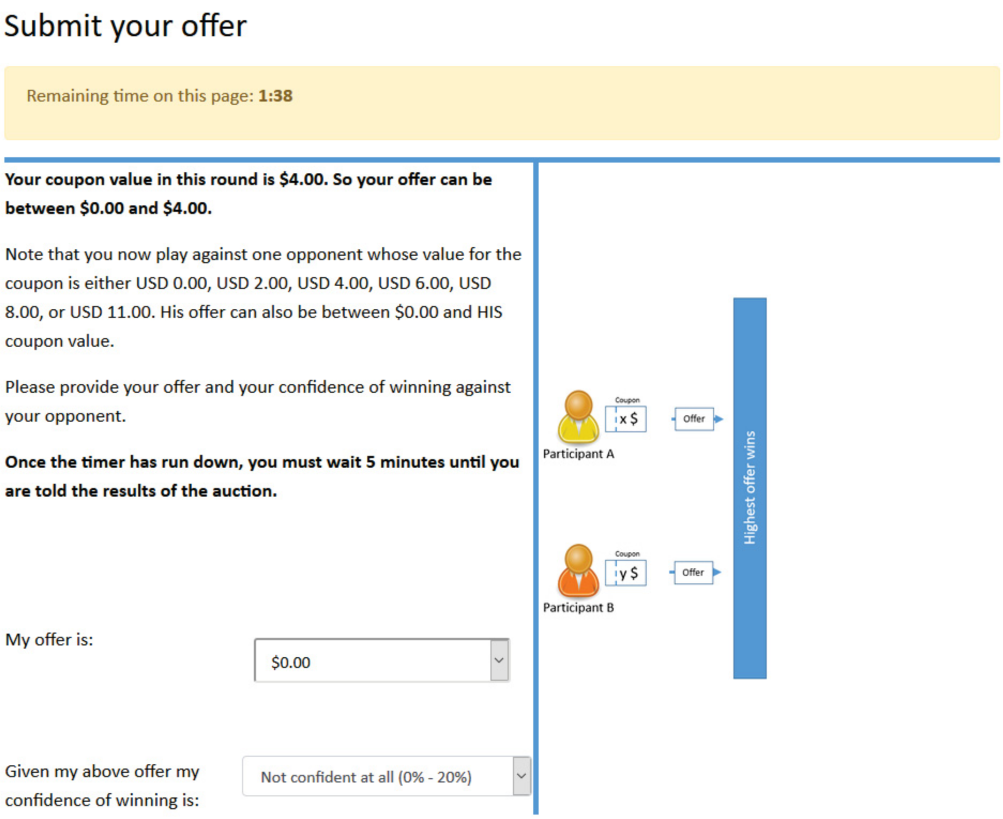


Figure 3: Screenshot of decision situation in FAR

a screenshot of the decision situation that participants were facing in the treatment FAR. Moreover, the full set of screenshots can be found in the appendix.

3.5.2 Hypotheses derived from the model

As shown in the model, bidders choose to be optimistic for high k, and pessimistic for low k. Since the experimental treatments only differ in k[29], I can extract following hypothesis from the model:

Hypothesis 1. *With an increase in temporal distance between bidding and revelation of bids subjects become more optimistic. Hence subjects tend to be more optimistic in FAR than in CLOSE.*

Furthermore, in accordance with Proposition 1 I expect subjects to bid less aggressively when k is high:

Hypothesis 2. *With an increase in temporal distance between bidding and revelation of bids subjects bid less aggressively. Hence subjects tend to bid less aggressively in FAR than in CLOSE.*

3.5.3 Experimental procedures and data sample

The experiments were conducted online and took place on the 14th and 22nd of July 2020. All participants were recruited via Amazon Mechanical Turk, where I published my task at around 4 pm CEST on both days. After choosing my experiment, subjects first received some general information, i.e. on data protection, duration and expected earnings of my experiment.

[29]The hypothesis are based on the assumption that the difference in k between treatments is sufficiently large.

By accepting my terms and conditions, subjects were redirect to the ZEW server, where the actual experiment took place. The whole experiment was computerized using the programming environment oTree (Chen, Schonger, and Wickens, 2016a).

Table 2: Descriptive Statistics

	FAR	CLOSE
Age [Avg]	33.29	33.17
Share of females	0.33	0.35
Share of US citizens	0.65	0.53
Share of College graduates	0.83	0.87
Observations	60	60

To sort out bots and participants with a low level of understanding subjects had to answer 4 comprehension questions after reading the instructions. If a participant answered one of the questions wrongly three times, they got excluded from the experiment.[30] Subjects were then matched into cohorts the following way: On the first day, the first 4 subjects answering the control questions correctly constituted the first cohort in treatment FAR. The next 4 subjects answering the control questions correctly constituted the first cohort in treatment CLOSE etc. On the second day of the experiment I changed this order accordingly.[31]

In total, 120 subjects participated in the experiment, with 60 subjects participating in each treatment. An overview of participant´s characteristics can be found in Table 6.

Payoffs were stated in USD. Participants were paid out by Amazon Me-

[30] I hence had to invite a sufficiently large number of subjects. In my case, I invited 400 subjects in order to get 120 participants that answered all control questions correctly.

[31] At Amazon Mechanical Turk workers do not enter an experiment simultaneously. This kind of matching was hence implemented due to practicial reasons: To avoid long waiting times, that would in turn lead to high drop-out rates.

chanical Turk. The average payoff for the entire experiment was 8.33 USD, including a fixed payment of 0.50 USD and an additional 0.50 USD per control question answered correctly at the first try. The experiment lasted around 45 minutes on average.

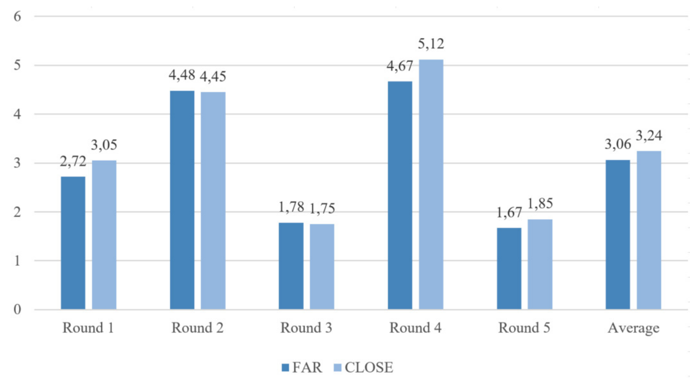
I preregistered the experiment via aspredicted.org, where I stated my research question, the treatments of the experiment and the hypothesis as above. I furthermore predefined the key dependent variables of my analyses: Average estimated winning probability and average bid over the 5 rounds (per cohort and per subject).

3.5.4 Results

In the experiment, behavior does not significantly differ between treatments. Figure 4 and Figure 5 display average values of bids and assessment per round. [32] As can be seen in the figures, average values over all 5 rounds are not substantially different, both for bids and probability assessments. Conducting two-sided Mann-Whitney U-tests of average values per subject, I find no significant difference for either bids or probability assessment between the treatments (the p-values are 0.53 and 0.56 respectively).

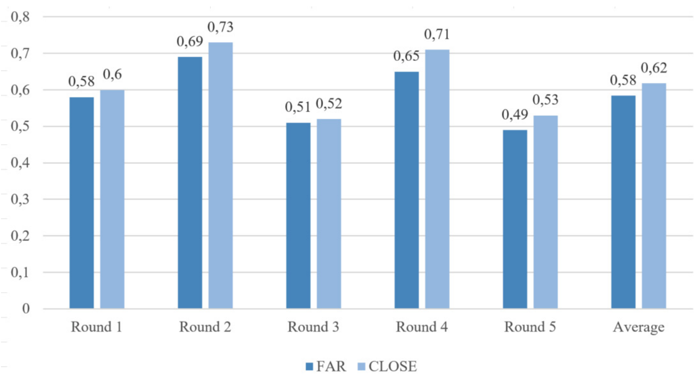
[32] The large variation in average bids over the rounds are due to us drawing valuations upfront and then using the same sets of valuations per cohort.

Figure 4: Average bids per treatment and round



This figure displays the average bid per round submitted by the participants in both treatments, as well as the average over all rounds and subjects.

Figure 5: Average Assessment per treatment and round



This figure displays the average probability assessment per round submitted by the participants in both treatments, as well as the average over all rounds and subjects.

The same is true for parametric analysis of the data taking into account valuations and demographic variables. Table 3 and Table 4 display OLS regressions of average bids and average assessment. As can be seen in the tables, treatment (FAR) is not significant, which does not change with independent variables I add to the model.

Table 3: Regressions: Determinants for bids

Model No.	1	2	3
Dependent Variable	Average Bid	Average Bid	Average Bid
FAR	0.18	0.18	0.115
	[1,02]	[1,02]	[0.73]
Average Valuation		-0,622	-1,161
		[-0,61]	[-1,26]
Male			0,237
			[1,44]
Unknown gender			0,282
			[0,46]
Education			0,0166
			[0,13]
Age (in years)			0,00655
			[0.65]
Constant	3,063**	6,392	9,003
	[24,65]	[1,17]	[1,84]
Model	OLS	OLS	OLS
Observations	120	120	114
Adjusted R-squared	0	-0,005	-0,017

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Regressions: Determinants for assessment

Model No.	1	2	3
Dependent Variable	Average Assessment	Average Assessment	Average Assessment
FAR	0.0353	0.0353	0.0270
	[0.96]	[0.96]	[0.76]
Average Valuation		-0,242	-0,28
		[-1,14]	[-1,35]
Male			0,0385
			[1,04]
Unknown gender			-0,131
			[-0,95]
Education			-0,00821
			[-0,4]
Age (in years)			-0,00219
			[0.97]
Constant	0.583***	1,879	2,183*
	[22,46]	[1,66]	[1,99]
Model	OLS	OLS	OLS
Observations	120	120	114
Adjusted R-squared	-0,001	0,002	-0,005

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

3.5.5 Discussion of results

In the experiment I do not observe any effect of temporal distance on the expected winning probability (and, potentially as a result, also no effect on bidding behavior). This is in stark contrast to the existing literature on endogenous expectations where an increase in the temporal distance to the revelation of an uncertainty usually leads to an increase in optimism.

Importantly, this is the first paper to explore this behavioral mechanism in games with strategic interactions. Hence, an interpretation of the 'zero results' of experiment 1 could be that the behavioral mechanisms described above simply do not play a role in these games.

As a robustness check of this interpretation, and to rule out that the 'zero results' were driven by the low variance in temporal distance (which was only

5 minutes), I conducted a second experiment. This second experiment varies in two main dimensions from the first one: (i) It is a within subject design experiment, where all participants bid exactly twice: Once with immediate feedback and once with delayed feedback. (ii) The variance in the temporal distance is increased to 4 weeks.

In line with the results from experiment 1, I observe no effect of an increase in temporal distance on expectations to win, which gives further evidence for the interpretation that the behavioral mechanisms described above seem to play no role in auctions, even when the time until the resolution of the auction winner is increased to 4 weeks.[33] Furthermore, given that the estimated winning probability does not change, I neither expect nor observe any difference in bidding behavior between treatments.

As a next step it would be interesting to find out if these 'zero results' also hold in other environments. Firstly, researchers should explore if the pattern plays a role for outcomes that are not ego-relevant [34]. If that is positive, it should be examined if the 'zero result' is robust to other strategic games than (first price) auctions.

The detailed description and results of the second experiment are delegated to the appendix.

[33] Alternatively it is possible that the mechanisms do play a role, but only if stakes are 'high'. So far the effect has only been observed in environments where the outcome is of high relevance for the subjects.

[34] One can argue that experimental evidence so far only exists for outcomes that are relevant for ones self-image, since they are all correlated with either health or intelligence.

3.6 Conclusion

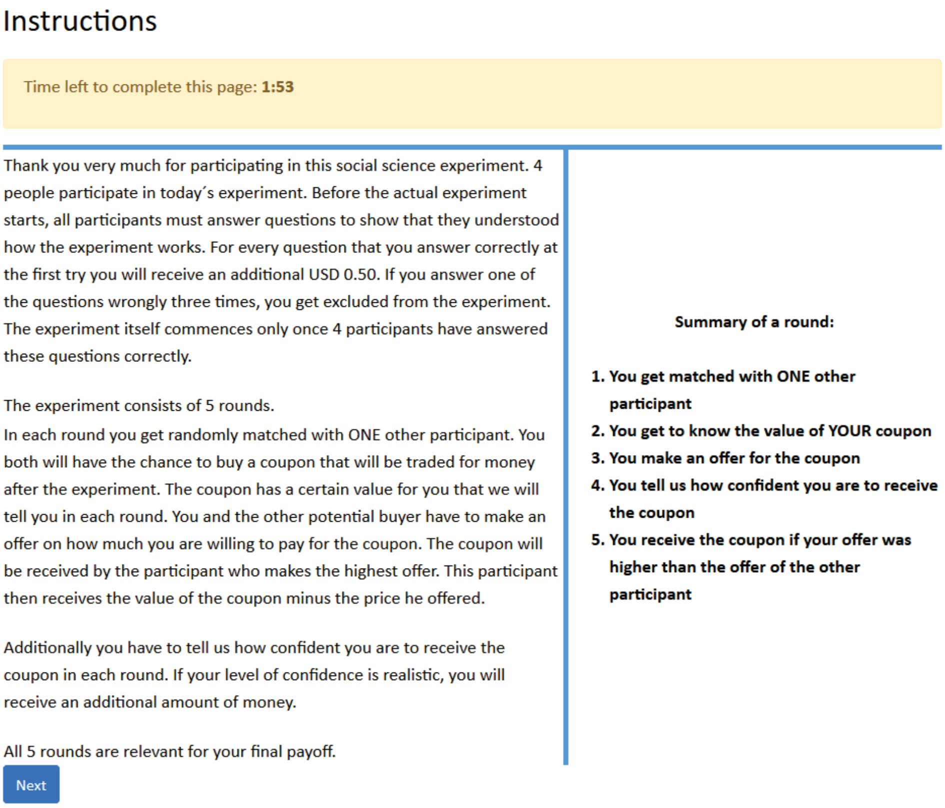
There is ample evidence that agents have systematic biases in their expectations. When the resolution of an uncertainty lies in the distant future, agents can benefit from high subjective winning probabilities, and hence tend to be overly optimistic. When the resolution is imminent, agents want to insure themselves against their own disappointment aversion and therefore forego optimism in favor of a pessimistic bias. In this paper I theoretically analyse the consequences of this pattern in first-price auctions: When the time until the revelation is long, the incentive to increase ones subjective probability is higher (given a fixed bid). Hence, compared to an imminent revelation, agents increase their subjective probability of winning, which in turn leads to higher marginal utility of a decrease in the bid (again given a fixed bid). [35] Based on this theory I hence advise auction designers to minimize the time between bidding and revelation of the winner of the auction.

Finally I test these findings experimentally. In two different standard induced values frameworks I vary the time between bid and revelation of results. This has however no effect on estimated winning probability, and hence also no effect on bidding behavior.

[35] Note that this logic applies independent of a kink in the utility funtion, hence the results will also hold for agents that suffer more from disappointment than they benefit from a positive surprise.

3.7 Appendix

3.7.1 Experimental Instructions



Instructions

Time left to complete this page: **1:53**

Thank you very much for participating in this social science experiment. 4 people participate in today´s experiment. Before the actual experiment starts, all participants must answer questions to show that they understood how the experiment works. For every question that you answer correctly at the first try you will receive an additional USD 0.50. If you answer one of the questions wrongly three times, you get excluded from the experiment. The experiment itself commences only once 4 participants have answered these questions correctly.

The experiment consists of 5 rounds.
In each round you get randomly matched with ONE other participant. You both will have the chance to buy a coupon that will be traded for money after the experiment. The coupon has a certain value for you that we will tell you in each round. You and the other potential buyer have to make an offer on how much you are willing to pay for the coupon. The coupon will be received by the participant who makes the highest offer. This participant then receives the value of the coupon minus the price he offered.

Additionally you have to tell us how confident you are to receive the coupon in each round. If your level of confidence is realistic, you will receive an additional amount of money.

All 5 rounds are relevant for your final payoff.

Next

Summary of a round:

1. **You get matched with ONE other participant**
2. **You get to know the value of YOUR coupon**
3. **You make an offer for the coupon**
4. **You tell us how confident you are to receive the coupon**
5. **You receive the coupon if your offer was higher than the offer of the other participant**

Figure 6: Experimental Instructions

Procedures (1/2): Coupons

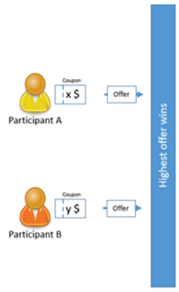
Time left to complete this page: **1:57**

In each round you have 2 minutes to make an offer in USD and provide your level of confidence to receive the coupon given your offer. Should you not specify an offer or not provide information on how confident you are that you receive the coupon, we will regard this as an input of 0 USD (offer) and 0%-20% (confidence level), respectively.

In each round a regular (virtual) dice is tossed independently for each participant to determine that player´s value for the coupon. If the dice shows a 1, the value of your coupon is 0 USD. If the dice shows a 2 (3; 4; 5; 6), the value of your coupon is 2 (4; 6; 8; 11) USD. **Note that the value of your competitor's coupon can be different from the value of your coupon.** The offers are allowed to be between 0 USD and 11 USD in increments of 1 USD, but cannot be higher than the value of your coupon.
The participant making the highest offer receives the coupon. Should both participants offer the same amount of money, a coin flip will determine who receives the coupon.

The payoff of a participant then equals the value of his coupon minus his offer if he receives the coupon, and 0 if he does not receive the coupon.

	Payoff of a participant (Coupon)
Highest offer:	Coupon Value - Offer
Non-highest offer:	0



Next

Figure 7: Experimental Instructions

Procedures (2/2): Estimation

Time left to complete this page: **1:58**

In addition to making an offer each participant has to tell us how confident they are that they made the higher offer. The participant must specify this by telling us if he is "very confident" (80% - 100%), "quite confident" (60% - 80%), "medium confident" (40% - 60%), "not very confident" (20% - 40%) or "not confident at all" (0%-20%) that his offer is higher than the offer of his competitor in this round.

If the participant gives us a realistic level of confidence in a certain round, he receives an additional USD 0.50.

To determine if a level of confidence in a certain round is realistic, we proceed the following way: After the experiment we take all offers from the other participants in this experiment. Then we simply check what share of these offers is lower than (or equal to) your offer in this round.

Example: Assume you make an offer of USD 5.00 in a certain round. During the entire experiment, 70% of the offers of the other participants are lower than USD 5.00, and 30% are higher than USD 5.00. In this case, it would have been realistic if you had been "quite confident", and therefore estimated your confidence to win between 60% and 80%. In this case you would receive the additional USD 0.50.

	Payoff of a participant (estimation)
Realistic level of confidence	USD 0.50
Unrealistic level of confidence	0

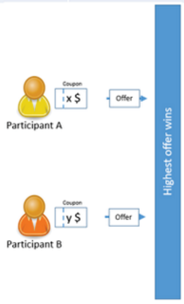


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Figure 8: Experimental Instructions

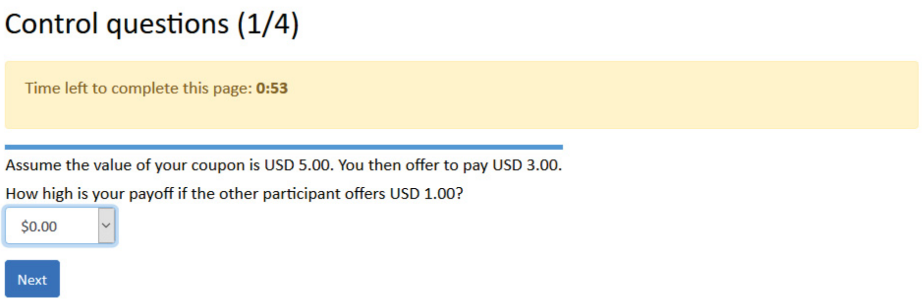


Figure 9: Experimental Instructions

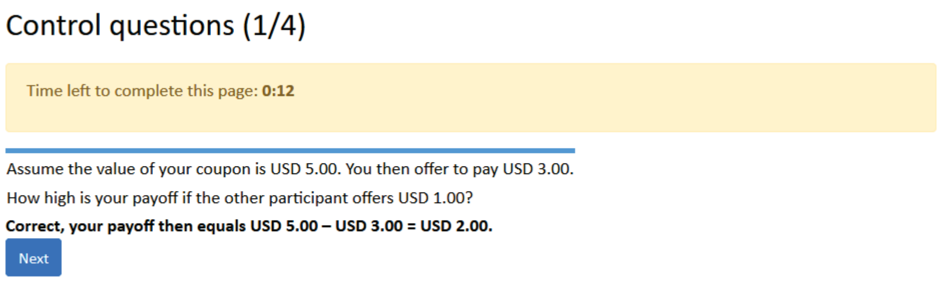


Figure 10: Experimental Instructions

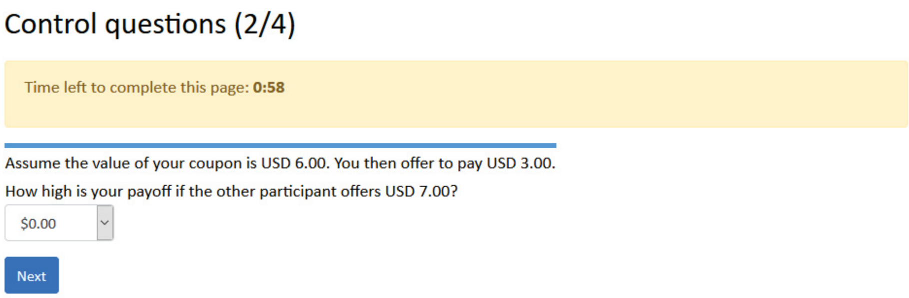


Figure 11: Experimental Instructions

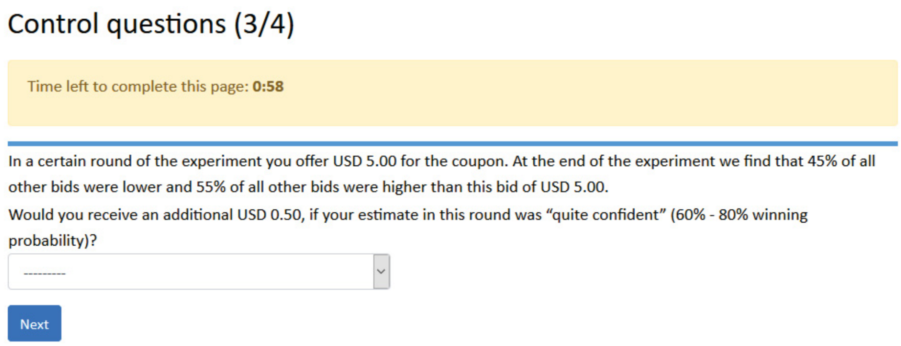


Figure 12: Experimental Instructions

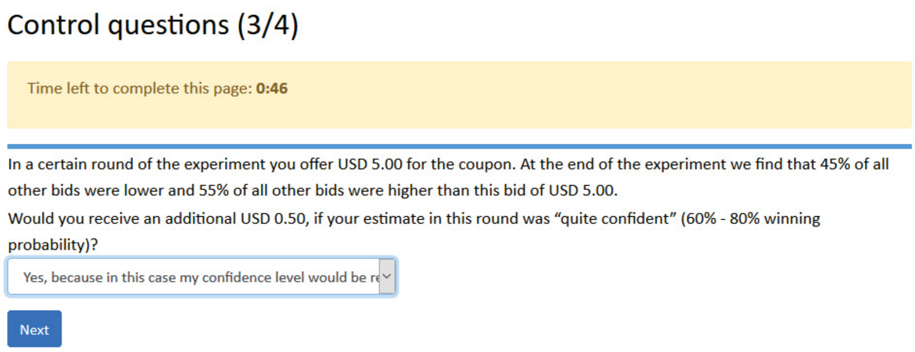


Figure 13: Experimental Instructions

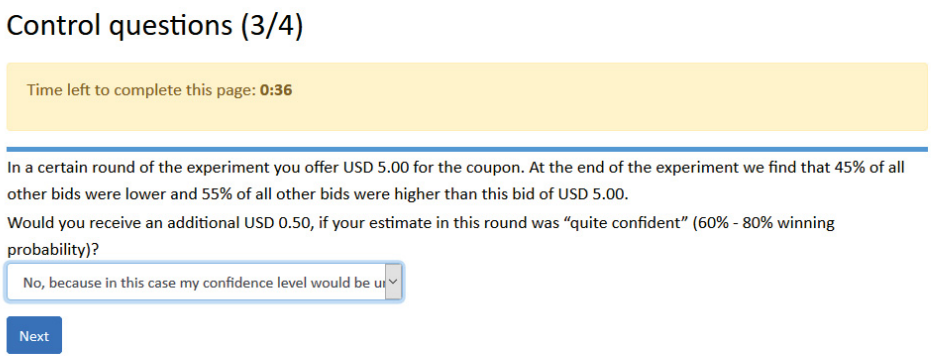


Figure 14: Experimental Instructions

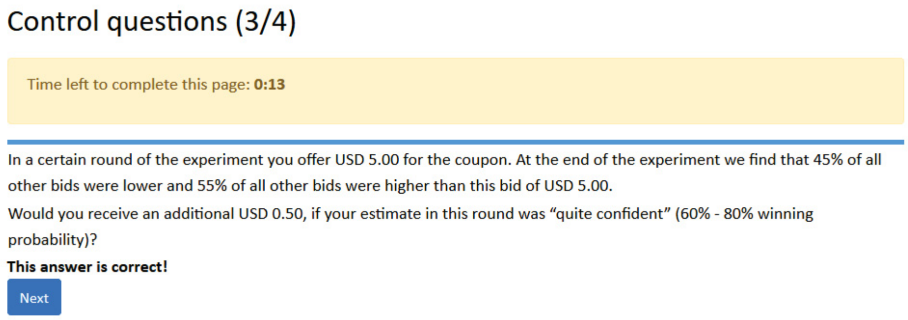


Figure 15: Experimental Instructions

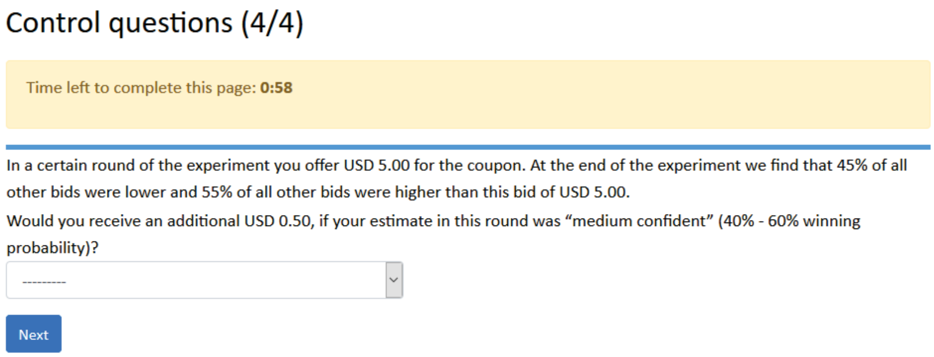


Figure 16: Experimental Instructions

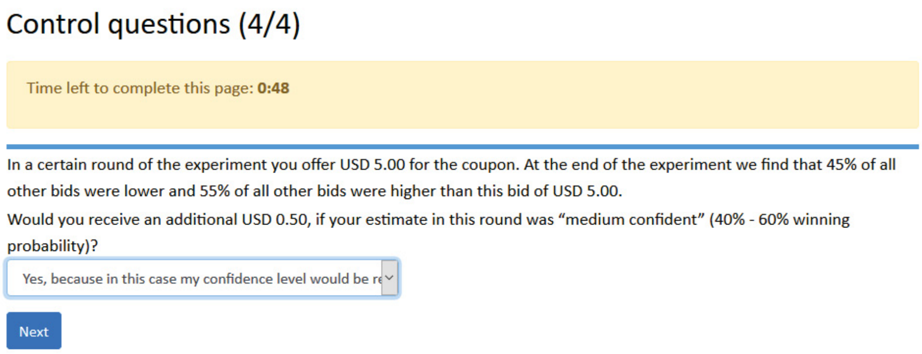


Figure 17: Experimental Instructions

Control questions (4/4)

Time left to complete this page: **0:38**

In a certain round of the experiment you offer USD 5.00 for the coupon. At the end of the experiment we find that 45% of all other bids were lower and 55% of all other bids were higher than this bid of USD 5.00.

Would you receive an additional USD 0.50, if your estimate in this round was "medium confident" (40% - 60% winning probability)?

No, because in this case my confidence level would be u

Next

Figure 18: Experimental Instructions

Control questions (4/4)

Time left to complete this page: **0:13**

In a certain round of the experiment you offer USD 5.00 for the coupon. At the end of the experiment we find that 45% of all other bids were lower and 55% of all other bids were higher than this bid of USD 5.00.

Would you receive an additional USD 0.50, if your estimate in this round was "medium confident" (40% - 60% winning probability)?

This answer is correct!

Next

Figure 19: Experimental Instructions

End of control questions

Time left to complete this page: **1:24**

Thank you very much for answering our control questions. You earned a total of $1.50 with the control questions you answered correctly at the first try.

The experiment will now commence once we have enough players waiting to form a group if all places in the experiment have not been occupied yet. Please click the next button to get in the queue for starting the experiment. In case that you have not been grouped with three other participants after 10 minutes (which might happen if we cannot find enough participants at the moment), you will automatically be redirected to the payments part of the experiment and you will not be able to participate in the remainder of the experiment. You will, however, of course receive your show-up fee of USD 0.50 and the money you earned by correctly answering control questions at the first try even in that case as well as an additional compensation of USD 2.00 for the time you have spent waiting for others.

Next

Figure 20: Experimental Instructions

Information

Remaining time on this page **0:38**

Please take note of the following information: **After having submitted your offer, you must wait 5 minutes until you are told the results of the auction. Once these 5 minutes are over, we inform you whether you have won the auction or not.**

Figure 21: Experimental Instructions

Information

Remaining time on this page **0:38**

Please take note of the following information: **After having submitted your offer, you will be told immediately whether you have won the auction or not. Afterwards you must wait 5 minutes until the next round starts.**

Figure 22: Experimental Instructions

Submit your offer

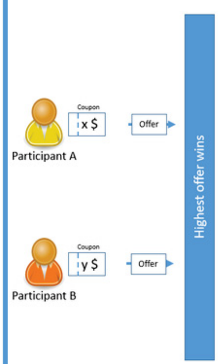
Remaining time on this page: **1:38**

Your coupon value in this round is $4.00. So your offer can be between $0.00 and $4.00.

Note that you now play against one opponent whose value for the coupon is either USD 0.00, USD 2.00, USD 4.00, USD 6.00, USD 8.00, or USD 11.00. His offer can also be between $0.00 and HIS coupon value.

Please provide your offer and your confidence of winning against your opponent.

Once the timer has run down, you must wait 5 minutes until you are told the results of the auction.



My offer is: $0.00

Given my above offer my confidence of winning is: Not confident at all (0% - 20%)

Figure 23: Experimental Instructions

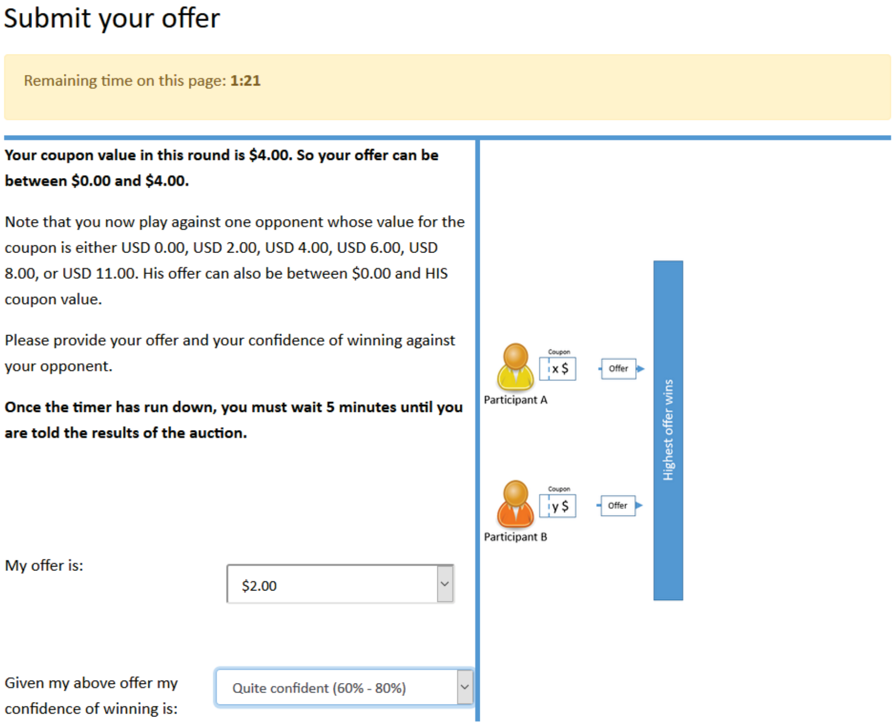


Figure 24: Experimental Instructions

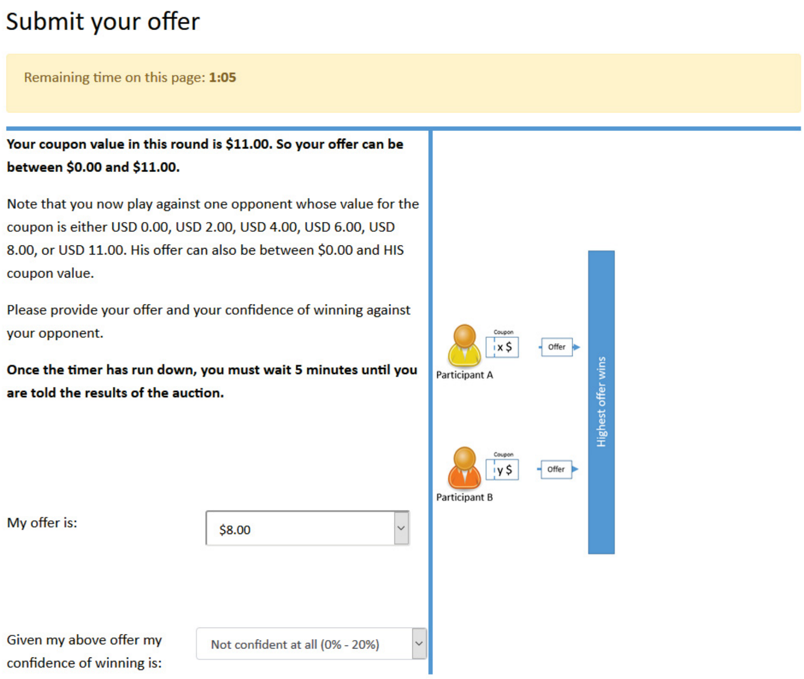


Figure 25: Experimental Instructions

Submit your offer

Remaining time on this page: **0:50**

Your coupon value in this round is $2.00. So your offer can be between $0.00 and $2.00.

Note that you now play against one opponent whose value for the coupon is either USD 0.00, USD 2.00, USD 4.00, USD 6.00, USD 8.00, or USD 11.00. His offer can also be between $0.00 and HIS coupon value.

Please provide your offer and your confidence of winning against your opponent.

Once the timer has run down, you must wait 5 minutes until you are told the results of the auction.

My offer is: $1.00

Given my above offer my confidence of winning is: Very confident (80% - 100%)

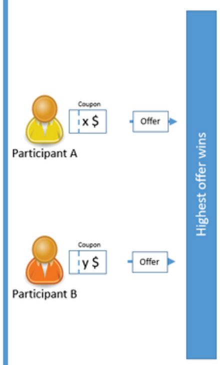


Figure 26: Experimental Instructions

Please wait here

Remaining time on this page: **2:47**

Please wait here for 5 minutes.

Summary of your bid:

In the currently ongoing round, you have offered **$10.00** for the coupon, which you value at **$11.00**.

Given your bid, you have estimated your confidence of winning to be between **80% - 100%**

Figure 27: Experimental Instructions

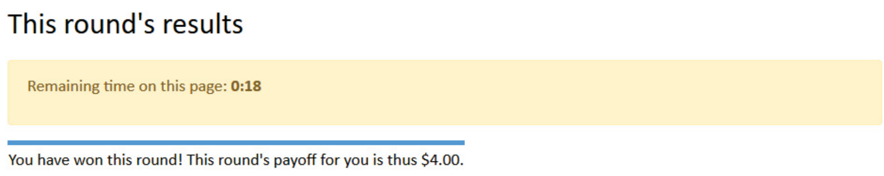


Figure 28: Experimental Instructions

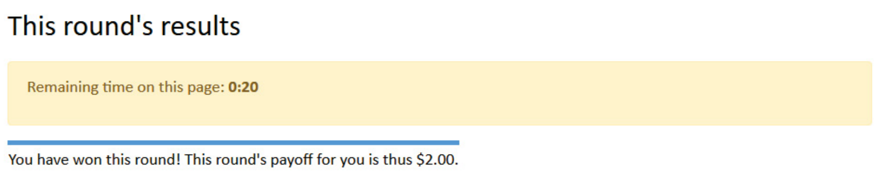


Figure 29: Experimental Instructions

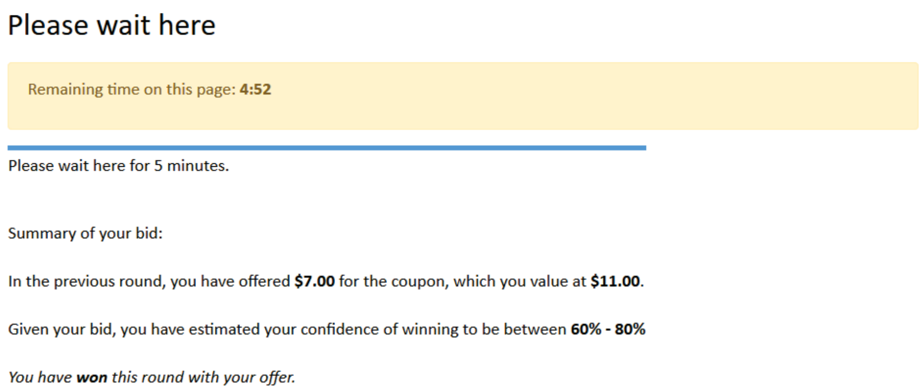
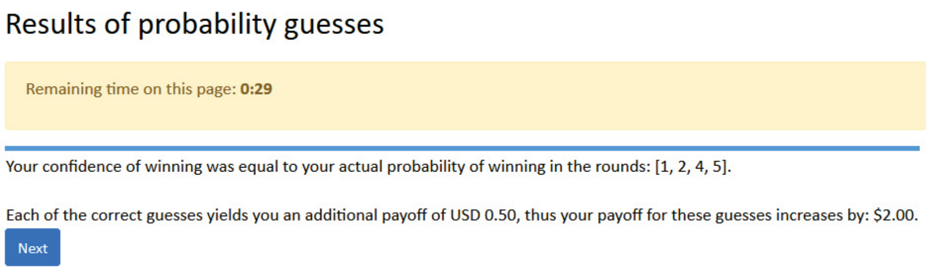


Figure 30: Experimental Instructions



Results of probability guesses

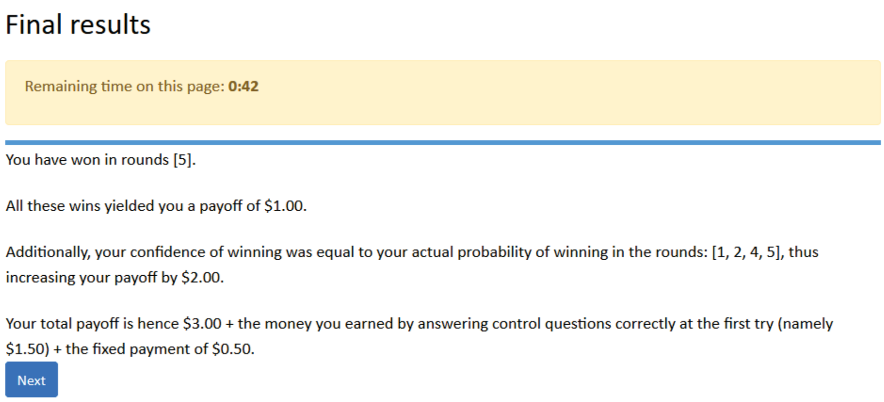
Remaining time on this page: **0:29**

Your confidence of winning was equal to your actual probability of winning in the rounds: [1, 2, 4, 5].

Each of the correct guesses yields you an additional payoff of USD 0.50, thus your payoff for these guesses increases by: $2.00.

Next

Figure 31: Experimental Instructions



Final results

Remaining time on this page: **0:42**

You have won in rounds [5].

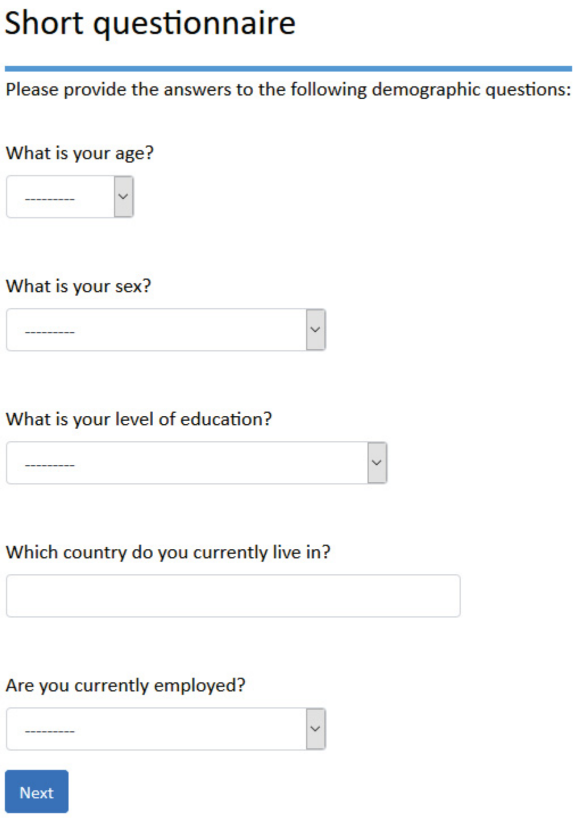
All these wins yielded you a payoff of $1.00.

Additionally, your confidence of winning was equal to your actual probability of winning in the rounds: [1, 2, 4, 5], thus increasing your payoff by $2.00.

Your total payoff is hence $3.00 + the money you earned by answering control questions correctly at the first try (namely $1.50) + the fixed payment of $0.50.

Next

Figure 32: Experimental Instructions



Short questionnaire

Please provide the answers to the following demographic questions:

What is your age?

What is your sex?

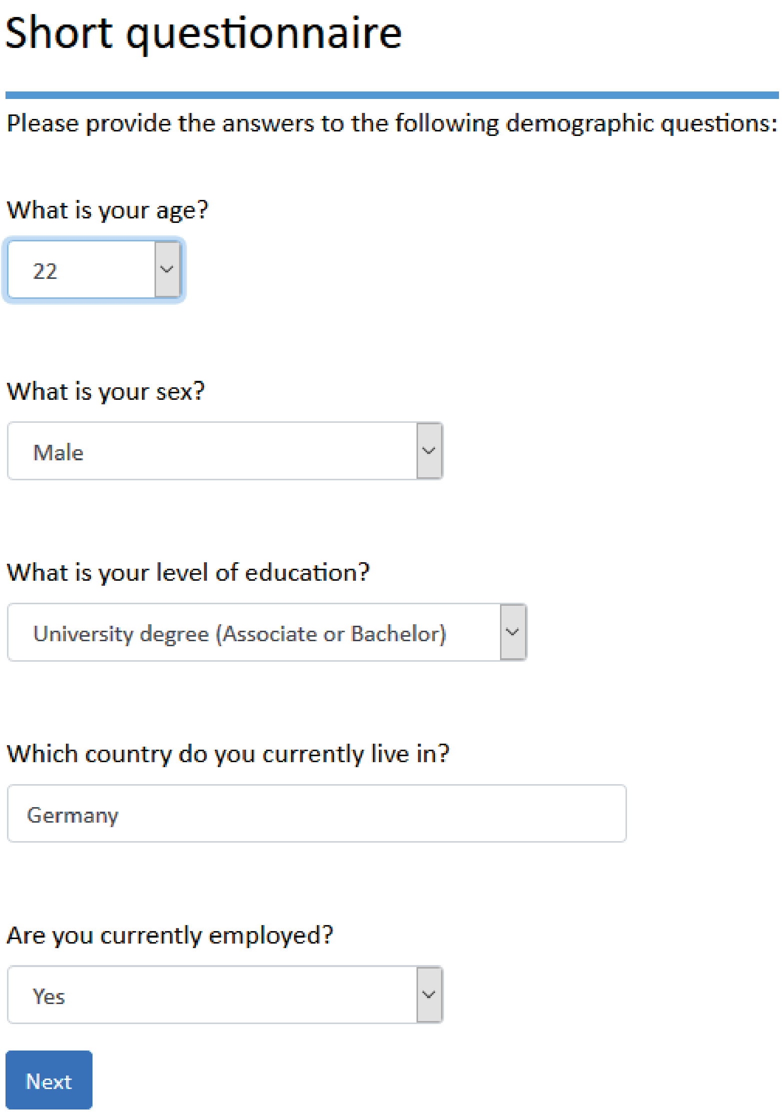
What is your level of education?

Which country do you currently live in?

Are you currently employed?

Next

Figure 33: Experimental Instructions



Short questionnaire

Please provide the answers to the following demographic questions:

What is your age?

22

What is your sex?

Male

What is your level of education?

University degree (Associate or Bachelor)

Which country do you currently live in?

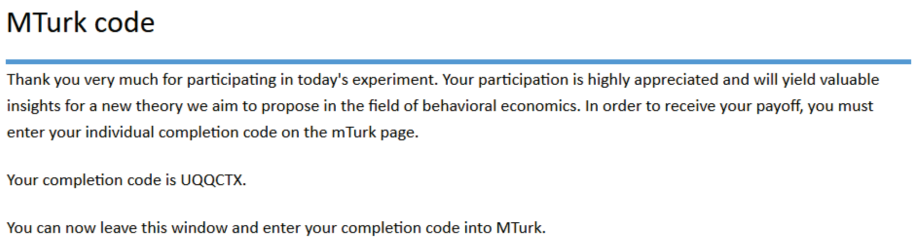
Germany

Are you currently employed?

Yes

Next

Figure 34: Experimental Instructions



MTurk code

Thank you very much for participating in today's experiment. Your participation is highly appreciated and will yield valuable insights for a new theory we aim to propose in the field of behavioral economics. In order to receive your payoff, you must enter your individual completion code on the mTurk page.

Your completion code is UQQCTX.

You can now leave this window and enter your completion code into MTurk.

Figure 35: Experimental Instructions

3.7.2 Experiment 2

Experimental Design The second experiment was a within-subject design experiment and consisted of two auction rounds representing the two treatments of the experiment (FAR and CLOSE): In treatment FAR, they received feedback 4 weeks after the bid, and in treatment CLOSE they received feedback immediately after the bid.

Auction. In both rounds participants were bidding on a coupon, that each participant had a certain valuation for. The valuation of the coupon in a certain round was determined in the following way: At first, subjects independently drew a personal number from 1 to 10, with each value being equally likely. In the two auction rounds, a multiplier equal to 4 Euros and 5 Euros respectively applied to this number. [36] The valuation of a subject was then calculated by multiplying the personal number with the multiplier and was hence correlated between the two rounds. [37] Bidders where then asked to submit any (integer) bid between 0 Euros and their valuation. The bidder submitting the highest bid received the coupon, accordingly his payoff from the auction was valuation minus his bid. The bidder submitting the lower

[36] To sort out sequence effects, participants where randomly selected into one of four treatments, which varied in the sequence of (i) the treatments (FAR - CLOSE vs CLOSE - FAR) and (ii) the multiplier (4 Euros - 5 Euros vs 5 Euros - 4 Euros)

[37] This was done to (i) make the treatments easily comparable and (ii) avoid consistency seeking, i.e. simply bidding the same in both rounds.

bid received a payoff of zero.

Probability Estimate. In addition to bidding, participants had to provide an estimate on their winning probability given their bid. To do so, they could choose from a set of 'confidence values', i.e. $\{0\%; 5\%; ...; 95\%; 100\%\}$ that they estimated their winning probability to be. In experiment 2, this estimate was not incentivized.

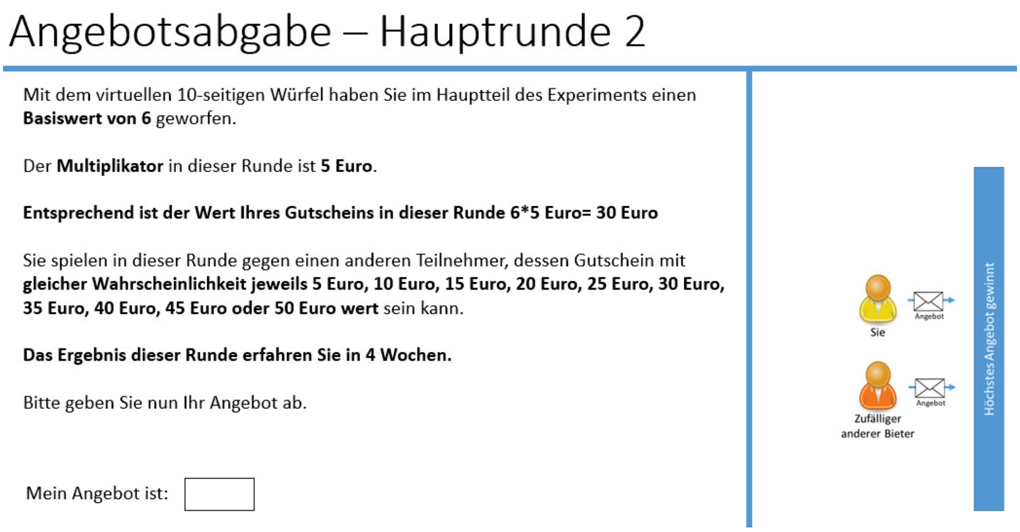


Figure 36: Screenshot of decision situation in FAR

Timing. The timing of the experiment was the following: Participants were matched into one of four treatments: CLOSE-5-FAR-4, CLOSE-4-FAR-5, FAR-4-CLOSE-5 and FAR-5-CLOSE-4. Subjects in CLOSE-5-LONG-4 entered the first submission screen, where they were told their valuation (consisting of their personal number and the multiplier of 5 Euros applying to all bidders in this round) for the coupon. They were then asked to submit a bid, and we told them that they would receive feedback immediately after the second auction round. They then were asked to give us an estimate on their winning probability. On the second submission screen, subjects in CLOSE-5-LONG-4 were again told their valuation (consisting of their personal number and the multiplier of 4 Euros applying to all bidders in this round) for the coupon. They were then again asked to submit a bid, and we told them that they would receive feedback 4 weeks after the experiment., followed by another screen to submit a probability estimate. In the other treatments we proceeded accordingly, varying the sequence of feedback and multiplier. Figure 36 displays a screenshot of the decision situation that participants were facing in the treatment FAR of FAR-5-CLOSE-4. Moreover, the full set of screenshots can be provided on request.

Experimental procedures and data sample The experiments were conducted online and took place on the 24th and 25th of May 2022. Using the recruiting system ORSEE (Greiner, 2015), we invited a random sample of the Cologne Laboratory for Economic Research (CLER) via email, where they received a Zoom link. In the Zoom meeting, subjects where given individual links to the ZEW server, where the experimented was hosted. The whole experiment was computerized using the programming environment oTree (Chen, Schonger, and Wickens, 2016a).

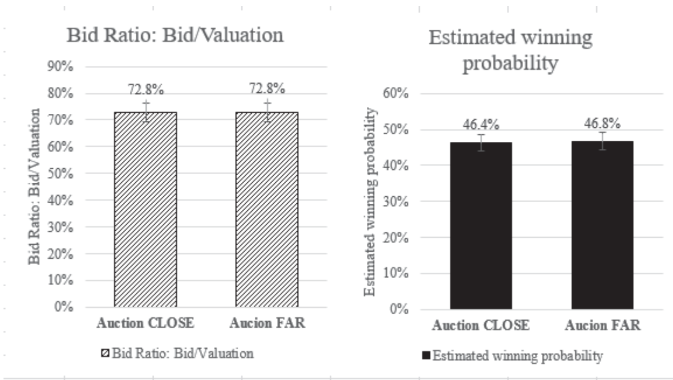
Subjects first received detailled instructions (see Appendix) and then participated in 10 test rounds against a computer to get familiar with the first-price auction.

In total, 81 subjects participated in the experiment, with 20 subjects participating in treatments CLOSE-4-FAR-5, FAR-4-CLOSE-5 and FAR-5-CLOSE-4 and 21 subjects in treatment CLOSE-5-FAR-4.

Payoffs were stated in Euros. Participants were paid out via Paypal 4 weeks after the experiment. The average payoff for the entire experiment was 9 Euros, including a fixed payment of 2 Euros. The experiment lasted around 30 minutes on average.

Results In experiment 2, behavior also does not significantly differ between treatments.

Figure 37: Bid ratio and estimated winning probability



This figure displays the average bid ratios as well as the average estimated winning probability per treatment.

Figure 37 displays average values of bid ratios[38] and assessment for both treatments. As can be seen in the figures, average values are not substantially different, both for bids and probability assessments. Conducting two-sided Mann Whitney U tests, I find no significant difference for either bids or probability assessment between the treatments (the p-values are 0.67 and 0.96 respectively).

[38] As a proxy for 'aggressiveness of bids' I used bid ratios, i.e. bid divided by valuation.

4 Auction Experiments with a Real Effort Task

Abstract

We propose a novel design for auction experiments based on effort and money. Participants bid a number of sliders in order to win a monetary prize. If successful, a participant has to solve a real-effort task, namely the slider task. The design allows us to capture two-dimensional prospect theory and common value effects. In a second step, we test our design in the laboratory. We find evidence for both loss-aversion and common values.

4.1 Introduction

When investigating auctions in the laboratory, economic researchers usually rely on induced values experiments. This means that each participant is assigned a value v for a (hypothetical) good. A participant's payoff associated with getting the good is given by the difference between his induced value v and the price p he has to pay for the good. Induced values experiments grant the researcher a lot of control, which is an advantage when for example hypotheses about a specific bidding function are tested in the laboratory. However, compared to real world auctions, this design choice abstracts from two well-known phenomena that both can potentially limit the external validity of results from the lab: Two-dimensional outcome evaluation and common values. We propose and test a simple experimental design based on money and effort that can account for both these phenomena.

In the vast majority of economic research, agents are assumed to evaluate their outcomes in one dimension. Indeed, assuming a one-dimensional outcome evaluation is without loss of generality if agents have standard preferences, in the sense that they maximize a global utility function over lifetime consumption $U(x|s)$' (DellaVigna, 2009). However, Lange and Ratan (2010) show that theoretical predictions differ between one-dimensional (induced values auctions) and two-dimensional settings (real good auctions), e.g., if agents are loss averse. Furthermore, Abeler, Falk, Goette, and Huffman (2011) provide experimental evidence for a multidimensional evaluation in a setting in which participants perform a real effort task and earn money.

Consider the following situation: You discover that a certain good you always wanted to own is offered in an eBay auction. A day before the auction ends you have determined your willingness to pay and bid exactly that amount. If you have standard preferences and a private valuation for the good, your bid should be equal your willingness to pay. After submitting your bid, you learn that you are currently the highest bidder, which stays the case until one minute before the auction ends. Then you learn that another person outbid you.

If agents have standard preferences, nothing else would happen. Bidding above your predefined private valuation cannot be rationalized by any one-dimensional, standard-preferences model, in which your payoff is simply $v - p$. The same applies to induced values experiments, where paying more than the induced valuation would lead to negative payoffs.

However, if you compare outcomes to expected outcomes in multiple dimensions, you might increase your bid. One minute prior to the end of the auction, your expected outcome is "I will receive the good" in the good dimension, and "I will spend the second-highest bid" in the money dimension. Losing the auction in the last second would imply a large deviation in the good dimension. As a result, you'd rather deviate a little in the money dimension and bid above your valuation.

Kahneman, Knetsch, and Thaler (1990) showed experimentally that the valuations for goods are not exogenous. In line with them, we argue that the willingness to pay for a good depends on the selling mechanism. When you believe the probability of winning a good is high, you become more attached to it, which in turn leads to a higher willingness to pay.

In addition to two-dimensional outcome evaluation, in most real-world auctions bidders are confronted with some common value component in the auctioned good, meaning that there is information on my own valuation in the bids of my competitors. Take again procurement as an example: Suppliers usually have some uncertainty about their actual cost. This might stem from future commodity prices, wages, or changes in the specification after the sourcing process. Hence a very low bid of competitors might mean that I overestimated these future costs. Even when consumption goods are auctioned off, some common value component might be present. Other bidders might e.g. have better (or different) information on the availability and prices of the good in other outlets. In addition, there is a large strand of literature showing that common value auctions lead to different predictions than pure private value auctions (for an extensive review, see Kagel and Levin (2002)).

To summarize, induced values experiments do not account for two-dimensional outcome evaluation and common value components. Since both these phenomena are present in most real world auctions, and both are important drivers of bidding behaviour, one has to be very cautious when giving practitioners advice based on induced values experiments.

We propose a novel design to increase external validity of auction experiments, based on effort and money. In a first step, bidders can familiarize themselves with the real-effort task, the slider task, in an incentivized test round lasting four minutes. In that time, bidders solve as many slider tasks as possible and are remunerated per solved unit. We then let subjects bid on a prize of 10 Euros. We asked participants to submit bids that express the number of slider tasks they would maximally solve in case of winning the auction, i.e. how much effort they are willing to spend in order to receive 10 Euros. We implemented a between-subjects design with a varying number of bidders between treatments ($N = 2$ vs. $N = 8$). Moreover, we chose the second-price auction. It has the desirable property that with standard preferences, the dominant strategy is independent of beliefs about the number of bidders, their valuations, or their strategies. In our design, if subjects were one-dimensional utility maximizers with a purely private valuation, they would determine the level of effort they are maximally willing to spend for 10 Euros, and bid exactly that amount. Based on standard theory and experiments with induced values, we would thus expect no difference in behavior between the treatments. However, as we show in Chapter 2, theoretical predictions differ when agents act according to two-dimensional prospect theory. Bids are higher when the number of bidders is low, as a high winning probability leads to an increased attachment to the prize of 10 Euros. The same applies if there is a common value component in conducting the slider task. When bidding against seven bidders, winning is 'bad news' with a higher probability since seven other bidders estimated a lower common value component.

In line with the reference dependent two-dimensional and common value predictions, we observed significantly higher bids for $N = 2$. On average, subjects were willing to solve roughly 30% more slider tasks when they had one instead of seven opponents. This result is robust to regressions where we control for demographic characteristics as well as participants' test scores, i.e. the amount of sliders they were able to solve in an incentivized test round. We hence argue that (in contrast to induced value experiments) our design enables researchers to increase external validity of auction experiments. Moreover, as pointed out by Gill and Prowse (2019), the slider task allows experimenters to control for participants' abilities, while at the same time having the advantages of real effort tasks.

In addition, we conducted three treatments to investigate the main driver behind our results: To isolate two-dimensional loss aversion from common values, we let bidders bid against computerized competitors. Evidence from these treatments is mixed: On the one hand, we did not observe a significant difference in bids depending on the ex-ante winning probability of bidders bidding against computers. On the other hand, we didn't observe a significant difference between bids against computerized and human competitors, either. While the former result is in favor of common values as main driver, the latter opposes this hypothesis.

Our results are in line with Rosato and Tymula (2019), who investigate bidding behavior in second-price auctions. They auction off several real goods sequentially and find that subjects bid more if they face less competition and hence have a higher probability of getting the good. Banerji and Gupta (2014), find that participants bid less aggressively when they faced stronger computerized competitors. They employ a BDM mechanism in which participants bid against a computerized opponent in a second-price auction.

Notably, compared to real good auctions of Rosato and Tymula (2019), our design has three important advantages: Firstly, we do not observe a concentration of bids at very low values, which is often the case when real goods are sold. Students might have the expectation to leave a laboratory experiment with a certain amount of money, not with a good. Secondly, due to the incentivized test round our design enables researchers to control for valuations of participants, i.e. a participant's pace in solving slider tasks. Thirdly, we argue that experiments with the proposed design are less expensive than real good experiments. In real good experiments all participants are usually endowed with a certain amount of money which at the same time serves as upper bound for bids. In order to allow all participants to express their true willingness to pay for certain goods, these upper bounds need to be quite high. Alternatively, experimenters have to use goods with low values, which in turn aggravates the problem of bid concentration around zero. Using our design, one does not have to define and endow all participants with that artificial upper bound.

Finally, due to remarkable analogies to practices in industry, especially in procurement, our design adds additional realism to the existing experimental literature. When bidding on a procurement contract, suppliers usually have a good idea of their true costs, based on internal calculations and estimations on future developments, e.g. in commodity markets. Furthermore, they tend to have some beliefs about their competitors, i.e. a supplier might know whether they are a high- or a low-cost supplier. Yet they do not know their exact costs, as well as the exact distribution that their competitors draw their costs from. The same holds true for participants in our experiment. They know how the task works and how long it would take them to fulfill a certain amount of tasks given that they keep their initial pace. They also might have an idea on how well they perform, or how high their opportunity costs of staying in the lab are compared to other participants. Yet they are faced with similar uncertainties as suppliers in procurement:

On the one hand, there are uncertainties with regards to the actual costs of effort (resulting from changes in pace or an unexpected evolvement of marginal pain in each slider task) and on the other hand, there is no common distribution function that all bidders draw their valuation from.

4.2 Theory

4.2.1 Model

In this section, we introduce the formal model. We consider $n \geq 2$ bidders competing for one indivisible good in a second-price auction. The value v_i of bidder $i \in \{1, \ldots, n\}$ for the good is privately drawn from a distribution F, $v_i \overset{\text{iid.}}{\sim} F[0,1]$. F is assumed to have a differentiable density f which is strictly positive on its support $[0,1]$. Moreover, f is common knowledge. Analogous to the standard setting, where the value of the good is measured in monetary units, i.e. in the dimension bidders submit their bids, we assume that the value is measured in slider tasks. Hence bidders draw the amount of slider tasks they are willing to solve in order to receive 10 Euros.

Bids are placed after learning the value for the good. The bidder submitting the highest bid is awarded the good and has to pay the second highest bid.

Bidders are assumed to be loss-averse following Kőszegi and Rabin (2006). We assume two distinct dimensions of loss aversion, a currency domain c in which bidders submit their bids, and a prize domain g representing the item the winner of the auction receives. Furthermore, we assume bidders to be narrow-bracketers, following the definition of von Wangenheim (2019). This means that the bidders' gain-loss utility is evaluated separately for each dimension. Summarizing, for outcome $x = (x^c, x^g)$, valuation v for the good, and reference consumptions r^c and r^m, agent's utility is given by

$$u(x|r^g, r^c) = x^c + vx^g + \mu^g(vx^g - vr^g) + \mu^c(x^c - r^c).$$

Following Kőszegi and Rabin (2006), we assume μ^i to be a piecewise linear function with a kink at zero,

$$\mu^g(y) = \begin{cases} \eta^g y & \text{if } y \geq 0 \\ \lambda^g \eta^g y & \text{if } y < 0, \end{cases} \qquad \mu^c(y) = \begin{cases} \eta^c y & \text{if } y \geq 0 \\ \lambda^c \eta^c y & \text{if } y < 0. \end{cases}$$

The μ^i denote the gain-loss utilities in the respective dimension, with $\eta^i > 0$, $\lambda^i > 1$ and $\eta^i(\lambda^i - 1) \leq 1$ for $i \in \{g, c\}$. The interpretation is that bidders perceive, in addition to their classical utility, a feeling of gain or loss, depending on the deviation from their reference consumption.

The reference point in our paper is assumed to be determined by rational expectations following Kőszegi and Rabin (2006).

4.2.2 Equilibrium Concept

We follow Kőszegi and Rabin (2006)'s and von Wangenheim (2019)'s equilibrium concept under uncertainty, according to which bidders form their strategy after learning their valuation. We apply the concept of unacclimated personal equilibria, which is, as argued by Kőszegi and Rabin (2006), the appropriate concept in auction settings. Fixing the opponents' strategies, let $H(b, v_i)$ denote i's payoff distribution given his draw v_i from a continuous distribution $F(v)$ and his bid b. A bid b^* constitutes an unacclimated personal equilibrium (UPE), if for all b

$$U[H(b^*, v_i)|H(b^*, v_i)] \geq U[H(b, v_i)|H(b^*, v_i)].$$

That means, given your reference point is determined by the payoff distribution resulting from an (exogenous) bid b^*, it is a best response to bid b^*.

4.2.3 Analysis

It is well-known that if agents are loss averse only in the prize domain, bidders in second-price auctions bid more aggressively when the number of bidders is low. Yet, in our setting it is arguable that loss aversion in the currency domain, i.e. the amount of slider tasks participants have to solve, also plays a role. Still it seems very plausible that students in the lab are more concerned about receiving money than solving slider tasks, and hence face a higher degree of loss aversion in the prize domain. In this section, we hence derive and analyze bidding behavior in second-price auctions, showing that when agents are more loss averse in the price domain the result above still holds true.

Assume all bidders except bidder i bid according to a strictly increasing bidding function β. Let $G(x) := F^{n-1}(x)$. The utility of bidder with value v, who is loss averse in both the good and the currency domain, bids b and has a reference point of b^*, is given by

$$\begin{aligned}
u_i(v_i, b_i|b^*) = {} & G\Big(\beta^{-1}(b_i)\Big)v - \int_0^{b_i} s\beta(s)dG\big(\beta^{-1}(s)\big) \\
& + G\Big(\beta^{-1}(b_i)\Big)\Big(1 - G\Big(\beta^{-1}(b^*)\Big)\Big)\mu^g(v-0) \\
& + \Big(1 - G\Big(\beta^{-1}(b_i)\Big)\Big)G\Big(\beta^{-1}(b^*)\Big)\mu^g(0-v) \\
& + \int_0^b \Bigg(\int_0^{b^*} \mu^c(t-s)dG\big(\beta^{-1}(t)\big) \\
& \qquad + \int_{b^*}^{\infty} \mu^c(0-s)dG\big(\beta^{-1}(t)\big)\Bigg)dG\big(\beta^{-1}(s)\big) \\
& + \int_b^{\infty} \Bigg(\int_0^{b^*} \mu^c(t-0)dG\big(\beta^{-1}(t)\big) \\
& \qquad + \int_{b^*}^{\infty} \mu^c(0-0)dG\big(\beta^{-1}(t)\big)\Bigg)dG\big(\beta^{-1}(s)\big)
\end{aligned} \tag{165}$$

As shown by von Wangenheim (2019), the equilibrium bidding function for n bidders is given by

$$\begin{aligned}
\beta_n^{II}(v) = {} & \frac{1 + \eta_g + \eta_g\left(\lambda_g - 1\right)F^{n-1}(v)}{1 + \eta_c\lambda_c} v \\
& + \int_0^v \Bigg[\frac{\eta_c\left(\lambda_c - 1\right)\left(1 + \eta_g + \eta_g\left(\lambda_g - 1\right)F^{n-1}(s)\right)}{(1 + \eta_c\lambda_c)^2} s \\
& \qquad \exp\left(\frac{\eta_c\left(\lambda_c - 1\right)}{1 + \eta_c\lambda_c}\Big(F^{n-1}(v) - F^{n-1}(s)\Big)\right)\Bigg]dF(s).
\end{aligned} \tag{166}$$

Theorem 1. *If bidders are loss averse in both the currency (subscript c) and the prize domain (subscript g), and it holds that bidders are more loss averse in the prize domain in the sense that*

$$\lambda_g \geq \lambda_c \frac{\eta_c(1 + \eta_g)}{\eta_g(1 + \eta_c)} + \frac{\eta_g - \eta_c}{\eta_g(1 + \eta_c)}, \tag{167}$$

then $\beta_n^{II}(v) > \beta_m^{II}(v)$ for all v and $n < m$. Sufficient conditions are given *by*

$$\begin{cases} \Lambda_g \geq \Lambda_c & \text{if } \eta_g \leq \eta_c \\ \lambda_g \geq \lambda_c & \text{if } \eta_g > \eta_c. \end{cases} \tag{168}$$

Proof. We need to show that

$$\Delta(v; n, m) := \beta_n^{II}(v) - \beta_m^{II}(v) > 0 \tag{169}$$

if $m > n$. Define

$$a(x, y; n, m) := \exp\left(\tilde{c}\left(x^n - y^n\right)\right) - \exp\left(\tilde{c}\left(x^m - y^m\right)\right) \tag{170}$$

$$b(x, y; n, m) := y^n \exp\left(\tilde{c}\left(x^n - y^n\right)\right) - y^m \exp\left(\tilde{c}\left(x^m - y^m\right)\right), \tag{171}$$

where

$$\tilde{c} := \frac{\eta_c\left(\lambda_c - 1\right)}{1 + \eta_c\lambda_c}. \tag{172}$$

With this, we have

$$\begin{aligned} \Delta(v; n, m) =& \frac{\eta_g\left(\lambda_g - 1\right) v}{1 + \eta_c\lambda_c}\Big(F^{n-1}(v) - F^{m-1}(v)\Big) \\ &+ \int_0^v \frac{\eta_c\left(\lambda_c - 1\right)}{(1 + \eta_c\lambda_c)^2}\Bigg[(1 + \eta_g)a\left(F(v), F(s); n, m\right) \\ &\qquad + \Lambda_g b\left(F(v), F(s); n, m\right)\Bigg] s dF(s) \\ &> \int_0^v \frac{\eta_c\left(\lambda_c - 1\right)}{(1 + \eta_c\lambda_c)^2}\Bigg[(1 + \eta_g)a\left(F(v), F(s); n, m\right) \\ &\qquad + \Lambda_g b\left(F(v), F(s); n, m\right)\Bigg] s dF(s). \end{aligned} \tag{173}$$

A sufficient condition for $\Delta(v; n, m) > 0$ to hold is that

$$(1 + \eta_g)a\left(F(v), F(s); n, m\right) + \Lambda_g b\left(F(v), F(s); n, m\right) > 0. \tag{174}$$

Following the definitions of a and b and because F and exp are strictly increasing, we have, for $s \leq v$

$$(1+\eta_g)a\left(F(v), F(s); n, m\right) + \Lambda_g b\left(F(v), F(s); n, m\right) \overset{!}{>} 0 \tag{175}$$

$$\Leftrightarrow \; (1+\eta_g)a\left(v, s; n, m\right) + \Lambda_g b\left(v, s; n, m\right) \overset{!}{>} 0 \tag{176}$$

$$\Leftrightarrow \; (1+\eta_g)a\left(1, s; n, m\right) + \Lambda_g b\left(1, s; n, m\right) \overset{!}{>} 0. \tag{177}$$

Note that $a\left(1, s; n, m\right) \leq 0$ and $b\left(1, s; n, m\right) \geq 0$ for all s. Also note that $b\left(1, s; n, m\right) > -a\left(1, s; n, m\right)$ for all $s \in (0, 1)$. This means there exist $\tilde{q} \in (0, \infty)$ such that $\tilde{q}\, a\left(1, s; n, m\right) + b\left(1, s; n, m\right) = 0$ for one or multiple $s \in (0, 1)$. Let $q = \min\{\tilde{q}\}$. Then

$$q\, a\left(1, s; n, m\right) + b\left(1, s; n, m\right) \geq 0 \tag{178}$$

for all $s \in [0, 1]$. Let $\tilde{s} \in (0, 1)$ be such that

$$q\, a\left(1, \tilde{s}; n, m\right) + b\left(1, \tilde{s}; n, m\right) = 0. \tag{179}$$

For inequality (174) to hold, it then needs to hold that

$$\frac{1+\eta_g}{\Lambda_g} = \frac{1+\eta_g}{\eta_g(\lambda_g - 1)} \overset{!}{<} q. \tag{180}$$

Rearranging yields

$$\lambda_g \overset{!}{>} \lambda_g^*(\eta_g, q) := \frac{1+\eta_g+\eta_g q}{\eta_g q}. \tag{181}$$

We have that

$$\frac{\partial}{\partial q}\lambda_g^*(\eta_g, q) = -\frac{1+\eta_g}{(\eta_g q)^2} < 0. \tag{182}$$

This means if q increases, the inequality for (181) admits smaller λ_g. The "worst case" to check is therefore the smallest q.

Note that

$$\frac{\partial}{\partial s} q = \frac{\partial}{\partial s} \frac{-b\,(1, s; n, m)}{a\,(1, s; n, m)} < 0. \tag{183}$$

Since $\tilde{s} \in (0, 1)$, and q strictly decreasing in s, we need to check the limit case $s \to 0$,

$$\lim_{s \to 1} q = \frac{1}{\tilde{c}} - 1 = \frac{1 + \eta_c}{\eta_c(\lambda_c - 1)} =: q^*. \tag{184}$$

We can now plug this q^* into λ_g^* from (181), yielding

$$\lambda_g^*(\eta_g, q^*) = \lambda_c \frac{\eta_c(1 + \eta_g)}{\eta_g(1 + \eta_c)} + \frac{\eta_g - \eta_c}{\eta_g(1 + \eta_c)}. \tag{185}$$

Concerning the sufficient conditions, let us first consider the case $\eta_g \leq \eta_c$. Assume it holds that $\Lambda_c < \Lambda_g$, meaning $\eta_c(\lambda_c - 1) < \eta_g(\lambda_g - 1)$. With $\lambda_i > 1$ and $0 < \eta_i < 1$ for $i \in \{g, m\}$, this is equivalent to

$$\lambda_g > \lambda_c \frac{\eta_c}{\eta_g} + \frac{\eta_g - \eta_c}{\eta_g}. \tag{186}$$

For $\eta_g \leq \eta_c$, we have that

$$\begin{aligned} \lambda_c \frac{\eta_c}{\eta_g} + \frac{\eta_g - \eta_c}{\eta_g} - \lambda_c \frac{\eta_c(1 + \eta_g)}{\eta_g(1 + \eta_c)} - \frac{\eta_g - \eta_c}{\eta_g(1 + \eta_c)} \\ = \Big(\lambda_c - 1\Big) \frac{\eta_c(\eta_c - \eta_g)}{\eta_g(1 + \eta_c)} \geq 0. \end{aligned} \tag{187}$$

Therefore it follows that if $\eta_g \leq \eta_c$ and $\Lambda_g \geq \Lambda_c$, then $\lambda_g \geq \lambda_g^*$. For the second case where $\eta_g \geq \eta_c$, we have that

$$\lambda_c > \lambda_c \frac{\eta_c(1 + \eta_g)}{\eta_g(1 + \eta_c)} + \frac{\eta_g - \eta_c}{\eta_g(1 + \eta_c)}, \tag{188}$$

so $\lambda_g > \lambda_c$ is sufficient in the case $\eta_g \geq \eta_c$. $\square$

4.3 Experiment

In this section, we introduce our experimental design and state our hypotheses for the experiment.

4.3.1 Design

In each experimental treatment all subjects participated in a second-price sealed-bid auction. In this auction bidders competed for a fixed payment of 10 Euros and bid how many slider tasks they were willing to solve. The bidder who placed the highest offer won. The number of sliders the winner had to solve was equal to the second highest bid.

After the auction took place the winner had a total of 90 minutes to solve the slider task. Only if the winner managed to solve the required number of sliders the winner received 10 Euros, otherwise the winner received no payment.[39] Losing bidders left the laboratory before winners started to solve the slider tasks.

The auction stage was preceded by a first stage in which participants familiarized with the slider task. In this stage participants had 4 minutes to solve slider tasks. For each slider solved they received 4 Cents. At this point in time they did not yet receive the instructions for the auction stage.

We conducted a total of 5 different treatments. We had 2 treatments in which all bidders were human, in one of the treatments we conducted an auction with 2 bidders (H_2) and in the other treatment we conducted an auction with 8 bidders (H_8). In our 3 treatments with computerized competitors we had one treatment with one computerized competitor (C_2^{2000})

[39] All winners managed to solve the required numbers of sliders.

and one treatment with 7 computerized competitors (C_8^{2000}). In both treatments the bids of the computerized competitors were uniformly distributed between 0 and 2000. In the remaining treatment (C_2^{4000}) participants bid against a single computerized competitor with bids uniformly distributed between 0 and 4000.

Screenshots of the experiment can be found in the appendix.

4.3.2 Organization

The experiments were conducted in the Cologne Laboratory for Economic Research (CLER) at the University of Cologne, Germany. Using the recruiting system ORSEE (Greiner, 2015), we invited a random sample of the CLER's subject pool via email. Our participants were mostly undergraduate students from the University of Cologne, with different beackground with regards to their major. The whole experiment was computerized using the programming environment oTree (Chen, Schonger, and Wickens, 2016b). Upon their arrival at the laboratory, participants were randomly assigned to one of two rooms to either the two-bidder or the eight-bidder treatment. Both treatments were conducted simultaneously and are described in section 4.2. Participants were grouped into cohorts of two and eight respectively. Moreover, participants were seated in visually isolated cubicles and read instructions on their screens (see Appendix 4.5.1) describing the rules of the game.

In total, 112 subjects participated in the experiment, with 48 subjects participating in the two-bidder second-price auctions and 64 subjects participating in the eight-bidder second-price auctions. An overview on participants and their demographics can be found in Table 1.

Payoffs were stated in EUR. Participants were paid out in private after the completion of the experiment. All 112 participants were paid their total net earnings. The average payoff for the entire experiment was 9.59 EUR corresponding to approx. 10.84 USD at the time of the payment.

In order to prevent selection effects as much as possible, we conducted the treatments we primarily want to compare in parallel. Participants were invited to the same experimental session and randomly assigned to one of two treatments that ran simultaneously. Table 5 displays which treatments were conducted in parallel.

Table 5: Experimental sessions

Sessions	Treatment 1	Treatment 2
1	H_2	H_8
2	C_2^{2000}	C_8^{2000}
3	C_2^{2000}	C_2^{4000}

Table 6: Descriptive statistics and summary

	H_2	H_8	C_2^{2000}	C_8^{2000}	C_2^{4000}
Age	24.75	26.25	24	23	24.5
Share of females	0.33	0.32	0.51	0.47	0.41
Lab experience	15 − 20	10 − 15	15 − 20	10 − 15	15 − 20
Observations	48	64	84	47	41
Test score	51.9	50.4	55.1	54.9	63.8
Bid	736	551	784	707	934

4.3.3 Hypotheses

Standard theory predicts that bidders behave the same in both treatments. That is, agents determine their "valuation", i.e. the amount of slider tasks they are maximally willing to solve in order to receive 10 EUR, and then bid exactly that amount. Bidding one's true valuation is a dominant strategy in the second-price auction with private values, independent of risk-aversion or beliefs about others, and therefore the bids should not depend on the number of bidders present in the auction. This leads to the following hypothesis:

Hypothesis 1. *We observe no difference in the bids between the treatments.*

When agents are loss-averse, a relatively high ex ante winning probability leads to a relatively strong attachement to the prize of 10 Euros. A strong attachement to the prize increases agents' willingness to work and hence lets them bid more aggressively as compared to a situation where the ex ante winning probability is low. This leads to the following alternative hypthesis:

Hypothesis 2. *We observe higher bids in the "2 bidder" treatments than in the "8 bidder" treatments.*

4.3.4 Summary

A summary of our data can be found in Table 6. We denote participants experienced if they have participated in more than 10 laboratory experiments. Test score denotes how many sliders the participant solved during the initial, incentivized four-minute test. Participants do not exhibit a significant difference in this score between the two treatments. Bids are distributed between 10 and 4000.

4.3.5 Results

We start the analysis of our experiment by comparing the bidding behavior in the treatments that were conducted in parallel. This is most similar to the analyses conducted by Banerji and Gupta (2014) and Rosato and Tymula (2019). Afterwards, we will also take into consideration data generated in the first part of the experiment, in which participants got used to the slider-task, and demographic information. Since computerized bidders in treatments C_2^{2000} and C_8^{2000} could not bid above 2000, we censored bids at 2000. Six out of 284 bids were larger than 2000.

Result 1. *When two human bidders competed (H_2) they bid more aggressively than in the case in which eight human bidders (H_8) competed (Mann-Whitney-U test, $p = 0.0329$).*

This result is in line with Rosato and Tymula (2019) who find that increasing the number of bidders decreases average bids. Possible explanations are loss-averse bidders or a common-value effect. While the former explanation predicts a similar effect in treatments with computerized competitors, meaning that lower winning probability implies lower bids, the latter explanation implies that no effect should be observable when comparing treatments in which participants bid against computerized competitors.

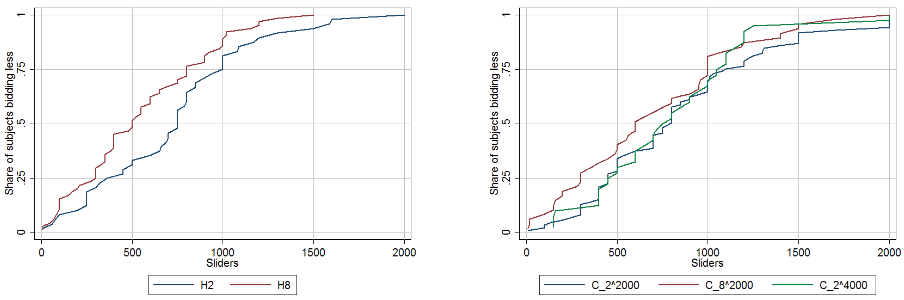
Result 2. *Bids do not differ between C_2^{2000} and C_8^{2000} as well as between C_2^{2000} and C_2^{4000} (MW, $p = 0.4597$ and $p = 0.3590$)*[40].

Looking at the treatments with computerized competitors, we do not find further evidence for loss-aversion. This result is in contrast to Banerji and Gupta (2014) who find that participants bid less aggressively when they faced stronger computerized competitors. Figure 38 displays the cumulative bid distributions for the different treatments.

Table 7 compares bidding behavior in between treatments with human and computerized competitors. Sessions in which competitors were human serve as a baseline. Computer is a dummy variable that is equal to one if the competitors were computerized and zero otherwise. Similarly, Female is a dummy variable indicating the gender of the participant. Age indicates

[40]Significance does not change if we consider all C_2^{2000} sessions.

Figure 38: Cumulative bid distributions



(a) Human competitors (b) Computerized competitors

participants' age and Lab experience how often a subject participated in lab experiments before. The regression shows that the performance in the first part of the experiment is a good predictor of the bid. At the same time we find no evidence that it makes a difference for participants whether they bid against a human or a computerized competitor. In case of a strong common value effect, one would expect a significant difference given that the computer bid is uninformative. Furthermore, demographics have no significant influence on bids.

Table 8 compares bidding behavior in treatments with human competitors taking into account the performance in the first part of the experiment and demographics. The treatment $H2$ serves as a baseline and $H8$ is a dummy variable, being equal to one for the $H8$ treatment and zero otherwise. The analysis confirms the former result, showing that it is not driven by different abilities or demographic factors.

Table 9 compares bidding behavior in treatments with computerized competitors taking into account the performance in the first part of the experiment and demographics. The C_2^{2000} treatment serves as a baseline and C_2^{4000} and C_8^{2000} are dummy variables indicating the treatment. The analysis confirms the former result, showing that the result is not driven by

Table 7: Regression comparing bidding against human and computerized competitors

	(I) Bid	(II) Bid
Test score	18.97***	19.28***
	(11.91)	(11.58)
Computer	59.29	44.93
	(1.09)	(0.81)
Female		-9.380
		(-0.17)
Age		6.330
		(1.92)
Lab experience		-7.648
		(-0.89)
Constant	-319.8***	-452.3**
	(-3.50)	(-3.18)
Observations	284	275[41]

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$

Table 8: Regression comparing in treatments with human competitors

	(I) Bid	(II) Bid
Test score	14.77***	14.56***
	(4.05)	(3.49)
H8	-205.1*	-201.9*
	(-2.35)	(-2.19)
Female		-82.95
		(-0.82)
Age		2.941
		(0.47)
Lab experience		-2.218
		(-0.14)
Constant	216.9	218.3
	(0.90)	(0.63)
Observations	112	110[42]

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$

different abilities or demographic factors. However, it suggests that older participants bid more aggressively.

Table 9: Regression comparing in treatments with human competitors

	(I) Bid	(II) Bid
Test score	19.44***	19.70***
	(11.15)	(10.98)
C_8^{2000}	80.50	103.0
	(0.99)	(1.25)
C_2^{4000}	-73.27	-50.58
	(-0.96)	(-0.65)
Female		10.23
		(0.15)
Age		8.337*
		(2.15)
Lab experience		-16.55
		(-1.60)
Constant	-286.2**	-461.2**
	(-2.69)	(-2.90)
Observations	172	165[43]

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.0001$

4.4 Conclusion

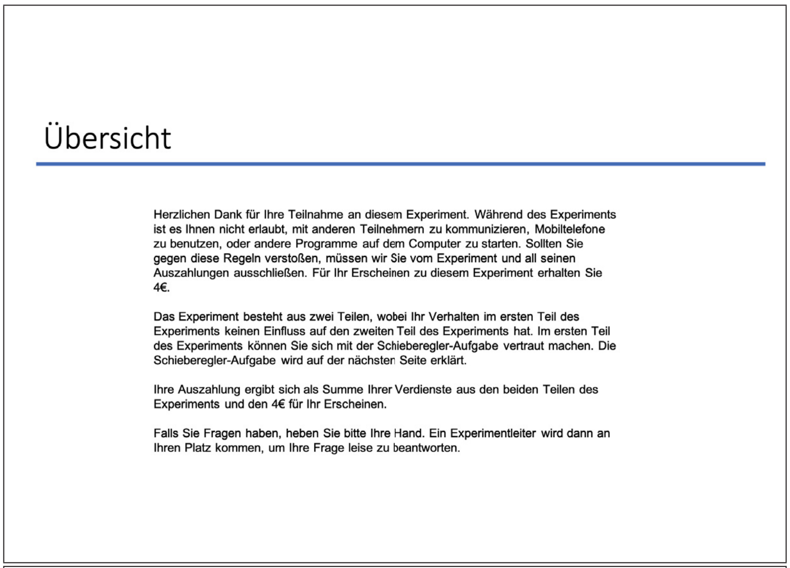
In this paper we propose and test a novel design for auction experiments. In our design, bidders submit bids in terms of slider tasks they are willing to solve in order to receive a certain amount of money. By using different dimensions for bids and good, our design can be exploited to increase external validity of auction experiments. Notably, our design can capture two practically important phenomena that induced values auctions abstract from: Two-dimensional outcome evaluation and common value components. As auction theorists have shown, the existence of either of these two phenomena can lead to qualitatively different predictions as compared to predictions based on induced values experiments (for the former see e.g. Lange and Ratan (2010) and for the latter see e.g. Kagel and Levin (2002)).

Testing our design, we conduct second-price auctions with a varying number of bidders. If agents are either loss-averse and evaluate their outcome in multiple dimensions, or if the auctioned good has a common value component, theory predicts that bids in second-price auctions are decreasing in the number of bidders. This has already been confirmed experimentally Banerji and Gupta (2014) or Rosato and Tymula (2019) in real good experiments. By conducting additional treatments where agents bid against computers, we investigate if our results are mainly driven by two-dimensional loss aversion or common values (which do not play a role when playing against a computer). However, based on these treatments we cannot confirm nor reject common values as a driver behind our results. On the one hand, bids do not differ significantly if the ex-ante probability of winning against a computer is varied, which is in favor of common values as main driver. On the other hand, bids do also not differ significantly between treatments with computerized and human competitors, contradicting the hypothesis of common values as main driver. We however argue that, by manipulating information about the slider task and other bidders, scholars can exploit our design to choose the extent to which common values play a role.

Our contribution is hence that when conducting auction experiments, the design choice should depend on the relevant environment that is investigated. If agents are bidding on objects that have only monetary value to them (e.g. for resale or pure investments), induced values experiments are a natural and appropriate choice. Yet, whenever outcomes are evaluated in multiple dimensions or the auctioned good has a common value component, our design or, if applicable, real good experiments should be preferred.

4.5 Appendix

4.5.1 Instructions



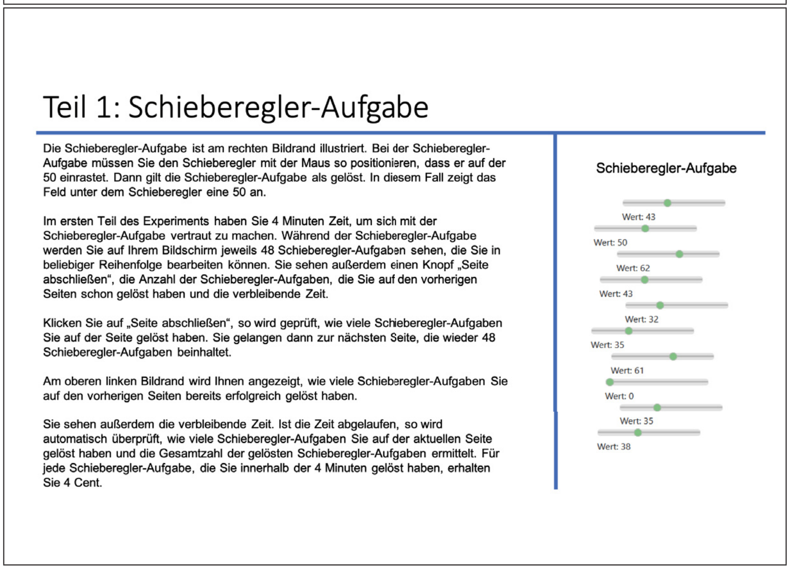


Figure 39: Instructions page 1 and 2 for the H_2 treatment

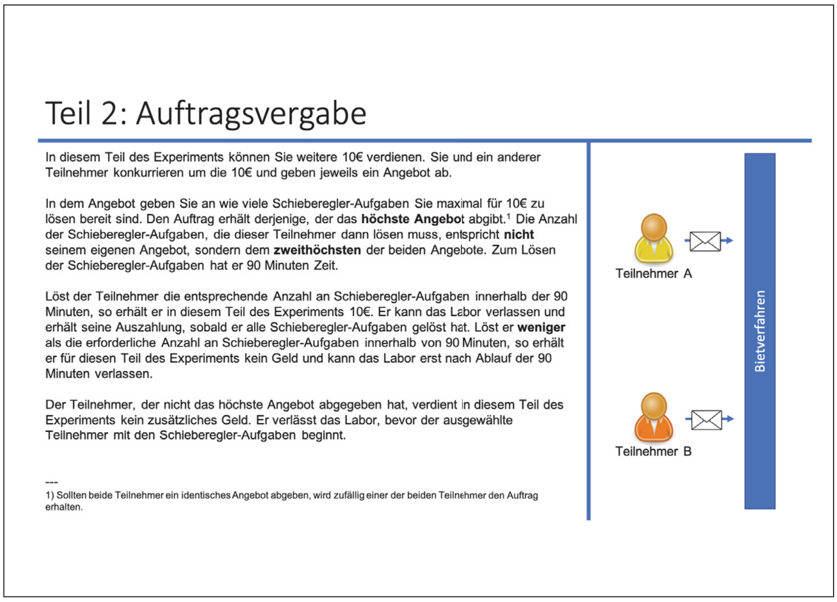
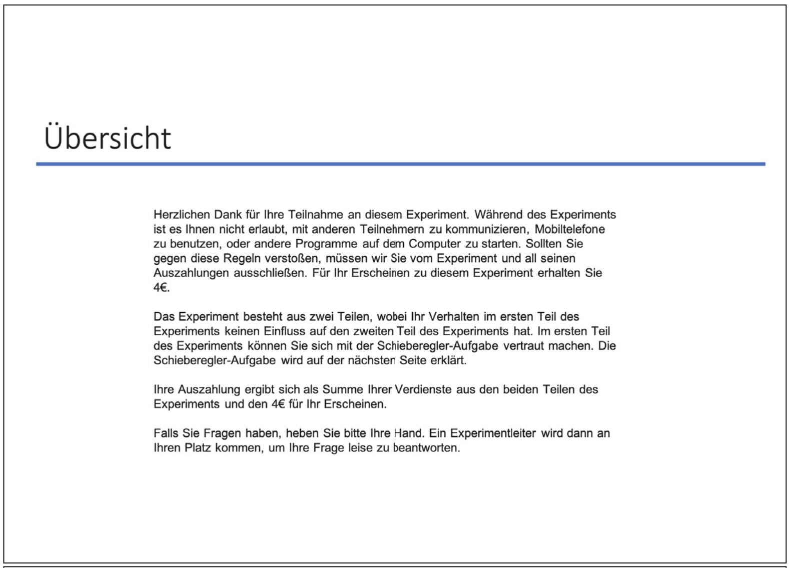


Figure 40: Instructions pages 3 and 4 for the H_2 reatment



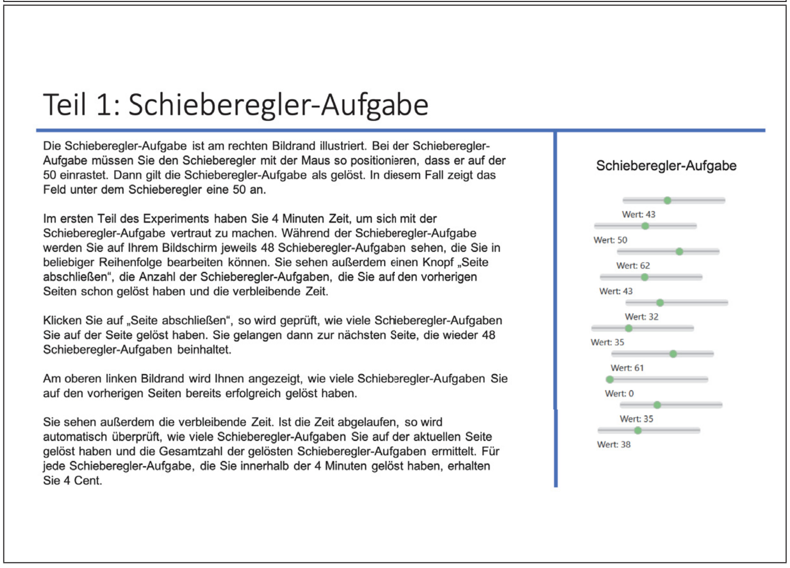


Figure 41: Instructions page 1 and 2 for the H_2 treatment

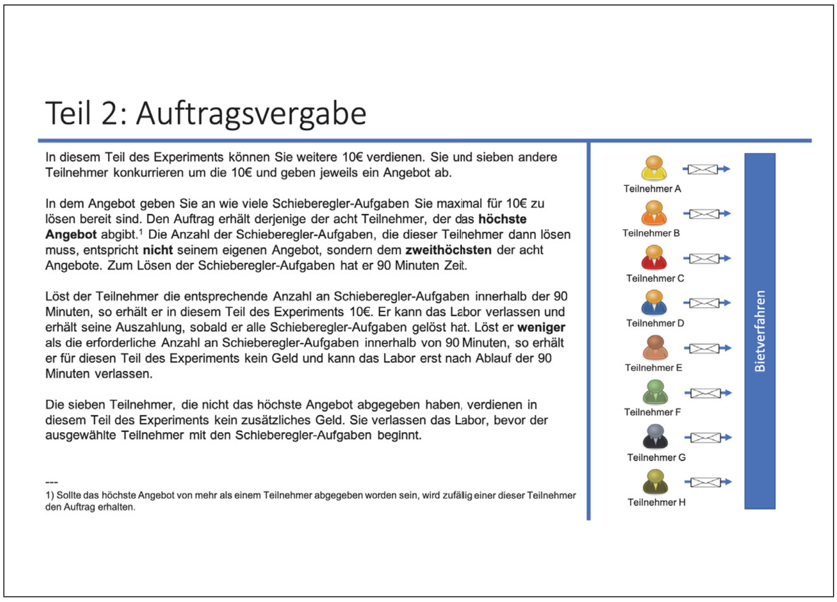


Figure 42: Instructions page 3 for the H_8 reatment

Übersicht

Herzlichen Dank für Ihre Teilnahme an diesem Experiment. Während des Experiments ist es Ihnen nicht erlaubt, mit anderen Teilnehmern zu kommunizieren, Mobiltelefone zu benutzen, oder andere Programme auf dem Computer zu starten. Sollten Sie gegen diese Regeln verstoßen, müssen wir Sie vom Experiment und all seinen Auszahlungen ausschließen. Für Ihr Erscheinen zu diesem Experiment erhalten Sie 4€.

Das Experiment besteht aus zwei Teilen, wobei Ihr Verhalten im ersten Teil des Experiments keinen Einfluss auf den zweiten Teil des Experiments hat. Im ersten Teil des Experiments können Sie sich mit der Schieberegler-Aufgabe vertraut machen. Die Schieberegler-Aufgabe wird auf der nächsten Seite erklärt.

Ihre Auszahlung ergibt sich als Summe Ihrer Verdienste aus den beiden Teilen des Experiments und den 4€ für Ihr Erscheinen.

Falls Sie Fragen haben, heben Sie bitte Ihre Hand. Ein Experimentleiter wird dann an Ihren Platz kommen, um Ihre Frage leise zu beantworten.

Teil 1: Schieberegler-Aufgabe

Die Schieberegler-Aufgabe ist am rechten Bildrand illustriert. Bei der Schieberegler-Aufgabe müssen Sie den Schieberegler mit der Maus so positionieren, dass er auf der 50 einrastet. Dann gilt die Schieberegler-Aufgabe als gelöst. In diesem Fall zeigt das Feld unter dem Schieberegler eine 50 an.

Im ersten Teil des Experiments haben Sie 4 Minuten Zeit, um sich mit der Schieberegler-Aufgabe vertraut zu machen. Während der Schieberegler-Aufgabe werden Sie auf Ihrem Bildschirm jeweils 48 Schieberegler-Aufgaben sehen, die Sie in beliebiger Reihenfolge bearbeiten können. Sie sehen außerdem einen Knopf „Seite abschließen", die Anzahl der Schieberegler-Aufgaben, die Sie auf den vorherigen Seiten schon gelöst haben und die verbleibende Zeit.

Klicken Sie auf „Seite abschließen", so wird geprüft, wie viele Schieberegler-Aufgaben Sie auf der Seite gelöst haben. Sie gelangen dann zur nächsten Seite, die wieder 48 Schieberegler-Aufgaben beinhaltet.

Am oberen linken Bildrand wird Ihnen angezeigt, wie viele Schieberegler-Aufgaben Sie auf den vorherigen Seiten bereits erfolgreich gelöst haben.

Sie sehen außerdem die verbleibende Zeit. Ist die Zeit abgelaufen, so wird automatisch überprüft, wie viele Schieberegler-Aufgaben Sie auf der aktuellen Seite gelöst haben und die Gesamtzahl der gelösten Schieberegler-Aufgaben ermittelt. Für jede Schieberegler-Aufgabe, die Sie innerhalb der 4 Minuten gelöst haben, erhalten Sie 4 Cent.

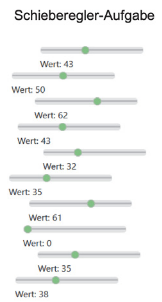


Figure 43: Instructions page 1 and 2 for the C_2^{2000} treatment

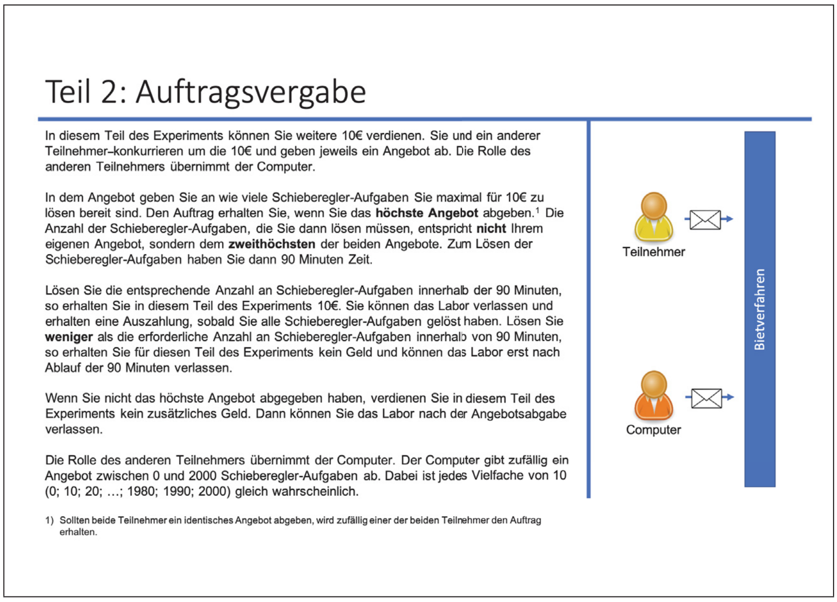


Figure 44: Instructions page 3 for the C_2^{2000} reatment

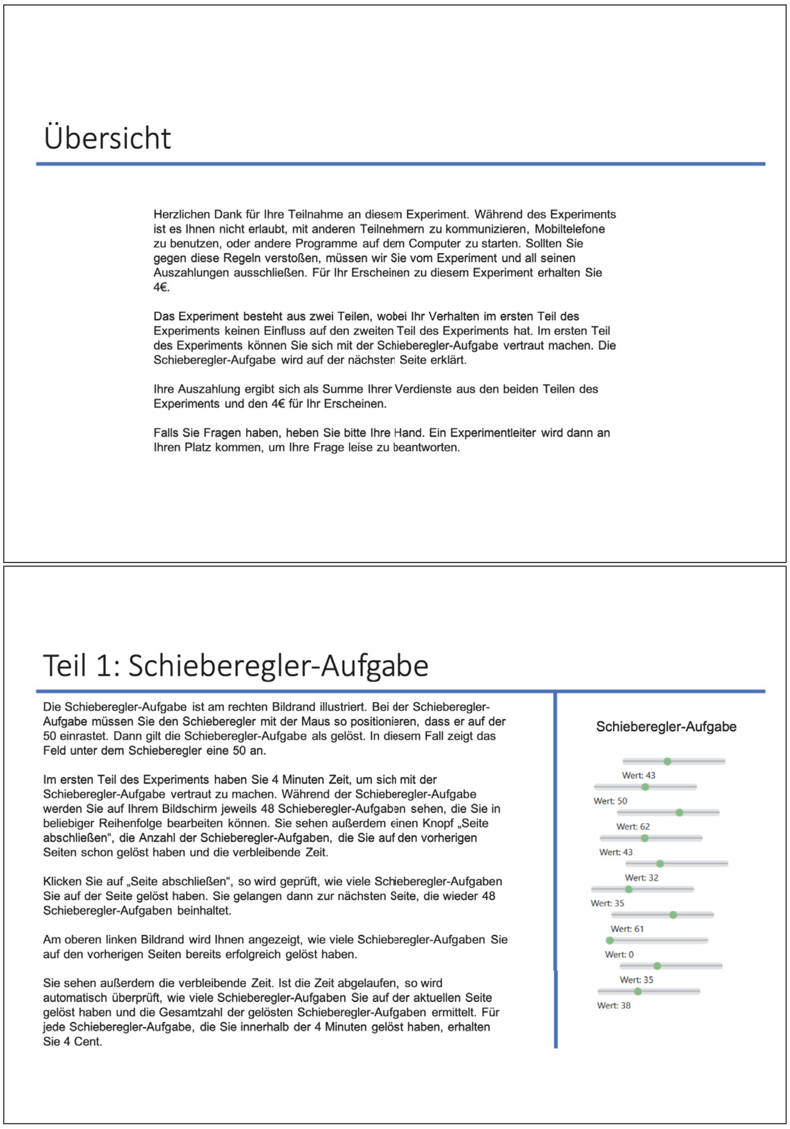


Figure 45: Instructions page 1 and 2 for the C_2^{4000} treatment

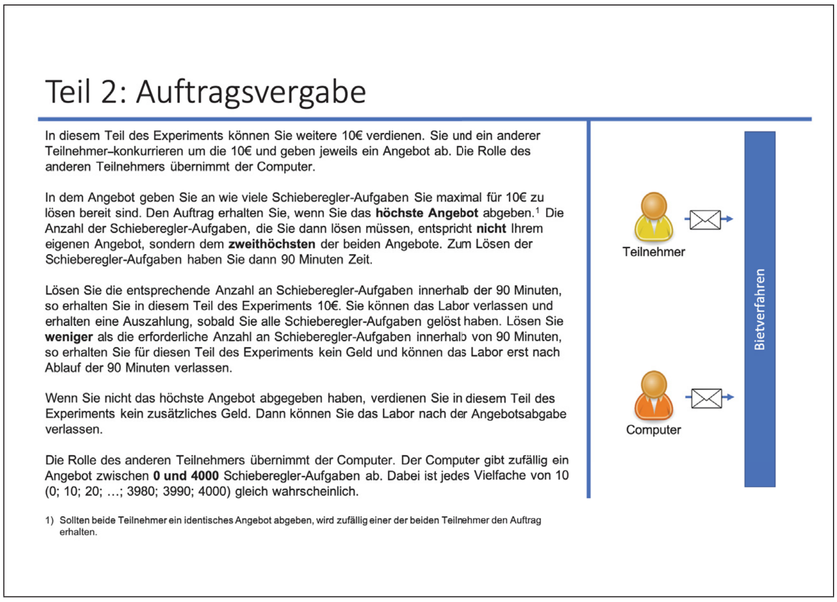


Figure 46: Instructions page 3 for the C_2^{4000} reatment

5 Social Norms, Sanctions, and Conditional Entry in Markets with Externalities: Evidence from an Artefactual Field Experiment

Abstract

In an artefactual field experiment with a large and heterogeneous non-student population sample, we test the implications of social norms for market interactions associated with negative real-world externalities. We run large stylized markets in which sellers and buyers decide whether to enter the market and how much to bid for experimental coupons. Trading leads to profits for sellers and buyers but at the same time destroys donations for a good cause. Calculated over all our treatments, we observe that two-thirds of the participants refuse to trade. Eliciting a controlled measure for conditional moral behavior in one treatment, we find that roughly a quarter of potential traders make their decisions contingent on the decisions of others, indicating that the desire to conform to social norms affects trading decisions in markets with negative externalities. If observers can sanction traders, we find that more than 80% of them are willing to incur personal costs to sanction trading, thus enforcing a social norm for moral behavior.

5.1 Introduction

The presence of negative externalities adds a moral dimension to the buying and selling of goods or services. Many goods differ with regard to the environmental impact arising from their production and transportation (for example, organic versus conventional meat) but also with regard to their social effects (for example, in terms of working conditions). There is an inherent tension between the utility that accrues to the consumer and profit that accrues to the firm and the degree to which consumption or production decisions impose harm on others. In the debate on the importance of moral concerns for market interactions when trading leads to negative externalities, various scholars have argued that market interactions might damage moral values in comparison to non-market transactions (see, for example, Sandel 2012). Based on an artefactual field experiment, this study makes two contributions to the literature on moral behavior, on the interaction between moral behavior and social norms, and the resulting implications for market exchange. First, we provide direct evidence for conditional moral behavior on markets, in line with the notion that the desire to conform to social norms is an important driver of the decision to trade in the presence of negative externalities. Second, we provide evidence for moral behavior and its enforcement in markets using a large and heterogeneous population sample from Germany.

Experimental studies investigating the nature of moral behavior on markets typically define morality in a specific way, and we follow this approach in the present study: moral behavior refers to the decision to forego profits to avert a negative externality for third parties. Our basic decision situation builds on the market settings of previous studies by Falk and Szech (2013), Kirchler, Huber, Stefan, and Sutter (2016), and Sutter, Huber, Kirchler, Stefan, and Walzl (2020) on trading behavior of buyers and sellers in the presence of negative externalities and adjusts them for implementation in a large-scale online setting. We run large stylized markets, one for each of our three experimental treatments, in which sellers and buyers must decide whether to enter the market and, conditional on entering, how much to bid for an experimental coupon. Buying or selling the coupon yields payoffs for the market participants. However, if a coupon is traded, less money will be donated to UNICEF for measles vaccinations (as, for example, in the studies by Kirchler, Huber, Stefan, and Sutter (2016) and Sutter, Huber, Kirchler, Stefan, and Walzl (2020)). We compare a baseline condition with two experimental treatments focusing on the impact of social norms on market exchange and negative externalities. The first treatment allows market participants to condition their market entry on the decisions of other sellers and buyers, directly testing the relevance of conditional moral behavior. In the second treatment, similar to the study by Kirchler, Huber, Stefan, and Sutter (2016), we allow for the (costly) enforcement of a social norm for moral behavior (and thus against trading) by third parties and investigate to what extent potential punishment prevents trading and mitigates externalities.

Our main results are as follows: First, irrespective of the treatment, we find that the majority of sellers and buyers - about two thirds of the participants - act morally. These subjects do not enter the experimental markets at all, and thus forego all monetary payments. Notably, the decision not to enter the market in our experiment is correlated with stated preferences and attitudes such as altruism and the moral perception of trade. Second, we find direct evidence in line with preferences for norm conformity. About a quarter of buyers and sellers make market entry conditional on what other traders do, thus highlighting the potential volatility of moral behavior in markets. In addition, we find that in the treatment with the punishment option, the majority of observers sanction trading behavior at a cost to themselves.

In most related studies - as in the present one - moral behavior in the sense that one should not cause damage to others cannot be distinguished from altruism in the sense that the utility of others directly affects own utility (see, for instance, Fehr and Schmidt (1999), Bolton and Ockenfels (2000), and Andreoni and Miller (2002) for formalizations of altruism and inequality aversion; Fehr and Schmidt (2006) and Cooper and Kagel (2009) survey the literature). Therefore, moral behavior in our setting implicitly incorporates other-regarding concerns. We discuss different mechanisms of moral behavior and present our preferred interpretation based on **?** theoretical framework for the nature of moral preferences and the influence of narratives and imperatives on moral behavior. Moreover, we outline the mechanisms of a stylized model of norm uncertainty and market behavior similar to that of **?**. Our model includes the main characteristics of the market interaction in our experiment and organizes our results concerning conditional moral behavior.

Related literature

Previous studies investigating moral behavior in markets consider student subjects, who might differ significantly in their preferences from other population groups. Therefore, it is essential to test the extent to which behavioral patterns in the presence of negative real-world externalities on markets generalize to subject groups that are more representative of the general population. To the best of our knowledge, no study thus far has measured moral preferences in market interactions within a large population sample. Accordingly, little is known about how decision-makers outside the laboratory trade off their own monetary benefits and negative real-world externalities from market transactions. Moreover, crucial determinants for the establishment of a social norm for moral behavior on markets - that is, the preference of potential traders to act conditionally on the behavior of others as well as the willingness of observers to bear costs to punish immoral trading, and the resulting implications for market outcomes - have so far not been investigated outside the laboratory.

Several studies investigate the prevalence of a wide range of economic preferences in large population samples, such as altruism, inequality aversion, risk and time preferences, and preferences for honesty, as well as their correlations with demographics, socio-economic backgrounds, and stated attitudes (see, for instance, Bellemare, Kröger, and Van Soest (2008), Dohmen, Falk, Huffman, and Sunde (2009), Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011), Falk, Meier, and Zehnder (2013), Abeler, Becker, and Falk (2014), Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018), Riedl, Schmeets, and Werner (2019), Elias, Lacetera, and Macis (2019), and, for a comprehensive study testing a variety of preferences and strategic choices, Snowberg and Yariv (2021)). Our study contributes to this strand of the literature by providing large-scale evidence for the prevalence of moral behavior in markets and its interaction with social norms in an artefactual field experiment with a heterogeneous population sample from Germany.

Furthermore, a growing literature shows the relevance of social norms for altruistic behavior and cooperation (see, for instance, Andreoni and Bernheim (2009), Krupka and Weber (2013), Reuben and Riedl (2013), Kimbrough and Vostroknutov (2016), Dur and Vollaard (2015), Danilov and Sliwka (2017), and Feldhaus, Sobotta, and Werner (2019)). At the same time, the evidence for the influence of social norms on trading patterns and the resulting externalities is not conclusive. Several papers address the determinants of morality in market interactions, focusing on behavioral dynamics and the roles of market institutions and structures (Falk and Szech

(2013), Bartling, Weber, and Yao (2015), Pigors and Rockenbach (2016), Ockenfels, Werner, and Edenhofer (2020), Sutter, Huber, Kirchler, Stefan, and Walzl (2020), Bartling et al. 2021, and Ziegler, Romagnoli, and Offerman (2020)). [44] Other studies provide indirect evidence that social norms may be an important driver of moral behavior in markets - for instance, by documenting significant cross-cultural differences in socially responsible consumption (Bartling, Weber, and Yao (2015)); the effects of introducing costly punishment for market trading patterns (Kirchler, Huber, Stefan, and Sutter (2016)); or the provision of social information about the behavior of other decision-makers on the willingness to impose negative externalities (Kirchler, Huber, Stefan, and Sutter (2016), Irlenbusch and Saxler (2019), and Falk, Neuber, and Szech (2020)).[45]

Our research takes a different approach. We elicit direct information about the norm sensitivity of potential traders in the presence of negative externalities from an ex-ante perspective. In particular, we allow participants to condition their own moral behavior on the moral behavior of others. Potential traders can decide to behave morally by staying out of the market under the condition that a particular minimum share of other participants also refrain from trading. By making their own moral choices dependent on the moral choices of others, participants can conform to the prevalent social norm in the market if they are uncertain about what is considered to be appropriate behavior. This setting allows us to provide direct evidence for

[44]Relatedly, a few studies investigate potential underlying mechanisms for the potential moral decay on markets, such as the diffusion of pivotality among individual traders for the creation of negative externalities (Falk, Neuber, and Szech (2020)) and the replacement excuse existent in markets in the sense that participants who do not engage in trade due to moral concerns are replaced by competitors (Bartling and Özdemir 2021).

[45]The determinants of willingness to pay for socially responsible goods is a focus of several studies (see, for instance, Rode, Hogarth, and Le Menestrel (2008), Engelmann, Friedrichsen, and Kuebler (2018), Friedrichsen and Engelmann (2018), Bartling et al. 2021).

conditional moral behavior and to measure the prevalence of this pattern in a large sample of non-laboratory participants.

Our focus on conditional moral behavior shares a link to research on conditional cooperation. There is an extensive literature showing that the individual's willingness to cooperate if others cooperate as well is an important driver of voluntary contributions in laboratory social dilemmas (see, for instance, Fischbacher, Gaechter, and Fehr (2001), Fischbacher and Gaechter (2010), Chaudhuri 2011, and Thoni and Volk (2018) for evidence from public goods games; Sturm, Pei, Wang, Loeschel, and Zhao (2019) provide evidence for conditional cooperation concerning the purchase of certificates to reduce CO2 emissions). The relevance of conditional cooperation is also observed in field settings. For example, experimentally elicited patterns of conditional cooperation predict the ability of groups to overcome real-world social dilemmas (Rustagi, Engel, and Kosfeld (2010)). Gneezy, Leibbrandt, and List (2016) observe that individuals working in an environment that requires stronger cooperation exhibit more cooperative behavior in various experimental games than individuals working in an environment with weaker cooperative norms. Finally, Nathan, Perez-Truglia, and Zentner (2020) report that citizens who observe a higher average property tax rate in their county are less likely to protest against their own taxes, in line with the notion that citizens tolerate higher tax rates if others pay higher tax rates as well.

However, to the best of our knowledge, there is so far little direct evidence for the relevance of conditional behavior for moral decisions in the context of markets, even though conditional moral behavior might crucially influence the level of negative externalities caused by market exchange. Note that a fundamental difference between the trading decision modeled in our setting and the social dilemma in public goods games relates to the nature of the externality. In public goods games, cooperation implies direct positive effects on the interaction partners due to the efficiency gains associated with contributions that are paid to everyone in the group. In the present setting, the decision to stay out of the market does not positively impact the payoffs within the group (in fact, it even reduces the possibility for other participants to trade profitably) but avoids a negative externality for an uninvolved third party.

5.2 Experimental design and expected behavior

5.2.1 Experimental design

Our experimental decision situation is based on the designs of Falk and Szech (2013), Kirchler, Huber, Stefan, and Sutter (2016), and Sutter, Huber, Kirchler, Stefan, and Walzl (2020), who model the trading behavior of buyers and sellers in the presence of negative externalities. In the market treatments of these experimental designs, the central idea is that (potential) buyers and sellers can decide to trade, engaging in mutually beneficial exchange, while at the same time harming a third party. We take fundamental elements of the market treatments from these studies as the starting point for our study, and we adjust them for implementation in a large-scale online setting. In particular, in each of our treatments, subjects act in a large market consisting of roughly 300 sellers and 300 buyers. As in the original designs, each seller is endowed with a single coupon that she can potentially sell to one of the buyers. Each buyer can buy at most one coupon from one of the sellers. After the experiment, a coupon that is not traded is converted into 50 doses of measles vaccine. To do so, 18 Euros are donated to UNICEF for this particular purpose.[46] A coupon that is traded is converted into 18 Euros, which the buyer receives, determining his valuation for the coupon. From these 18 Euros, buyers have to pay the market price to the seller. Hence, upon trading, a buyer receives 18 Euros minus the market price, and a seller receives the market price. The market price is determined by a uniform pricing rule explained below. Trading is thus associated with monetary profits for buyers and sellers but triggers a negative externality.

[46]UNICEF used the money in 2019 to vaccinate children on the Philippines against measles.

For each trade conducted, no money will be donated to UNICEF.[47]

Our experiment follows the studies by Kirchler, Huber, Stefan, and Sutter (2016) and Sutter, Huber, Kirchler, Stefan, and Walzl (2020) in using donations to UNICEF for measles vaccinations as the negative real-world externality. In our view, this type of externality is well-suited to study moral behavior in markets. As Kirchler, Huber, Stefan, and Sutter (2016) describe in their study, measles still cause a large number of deaths worldwide, mostly among young children. A donation for a vaccination against this disease is, therefore, a life-saving act, and the destruction of the donation constitutes a negative externality (which is also clearly explained to the participants in the previous studies as well as in our design). Therefore, we are confident that the negative externality that trading imposes is sufficiently salient for the participants and is taken into consideration when deciding whether or not to enter the market. Moreover, the negative externality is imposed on a third party outside the experiment, mirroring the negative consequences of trading in markets when externalities are not typically borne by the parties who engage in trading.

Market participants make the following decisions. First, they decide if they are generally willing to enter the market and trade. Second, if so, they are asked to submit an offer. This offer has to be between 0 Euros and 18 Euros. For buyers, the offers reflect the maximum amount they are willing to pay to receive a coupon. For sellers, the offer reflects the minimum amount they want to receive to trade a coupon. If participants decide not to enter

[47] In principle, some participants may doubt the possible positive effect of the vaccination on health. However, we have little indication from free-text answers that a non-negligible share of participants in fact considered these vaccinations as detrimental. Moreover, to the extent that some participants had concerns against measles vaccinations and thus would have no moral objections against trading, our results would actually underestimate the impact of negative externalities on behavior in our experimental markets.

the market, they forego all profits from the experiment.[48]

Our market is cleared with a uniform pricing rule. First, we rank the sellers' offers from lowest to highest. Second, we rank buyers offers from highest to lowest. The market price then equals the lowest offer of a seller that does not exceed the respective offer of a buyer with the same rank.[49] Buyers with offers (weakly) above the market price receive a coupon at the market price. Sellers with offers (weakly) below the market price sell one coupon at the market price. If the number of sellers exceeds the number of buyers willing to trade at the market price, we implement a tie-breaking rule. If n sellers and m buyers are willing to trade at the market price, we randomly choose m - n sellers that do not trade. The case of an excess of buyers is handled in the same manner.

Our experiment implements an abstract and stylized market setting that allows for a controlled analysis of moral behavior under negative externalities and its interaction with social norms. The setting ensures the anonymity of traders as well as a sufficient market size so that the individual trader is unlikely to be pivotal for the price that emerges in equilibrium. Based on this basic market mechanism, we conduct three experimental treatments:

1. **Baseline.** Our baseline treatment (abbreviated as BASE) implements the basic market interaction described above. It allows us to investigate to what extent sellers and buyers are willing to behave morally by not trading or instead engage in trading to attain monetary profits, accepting the negative externality of their actions. As described above, the baseline treatment directly links to the market treatments

[48] Participants should not be able to generate a higher profit from trading than the costs of the vaccinations. Otherwise, participants could create an efficiency gain by trading and donating some of profits to UNICEF.

[49] An example screenshot explaining the pricing mechanism is shown in the Supplementary Material (Figure 54)

in the studies by Falk and Szech (2013), Kirchler, Huber, Stefan, and Sutter (2016), and Sutter, Huber, Kirchler, Stefan, and Walzl (2020).

2. **Conditional entry.** The second treatment (abbreviated as COND) allows for a controlled analysis of the inclination of sellers and buyers to conform to actions of other participants when they are uncertain about the appropriate action. In this treatment, traders have the opportunity to condition their market entry decisions on the behavior of other participants. In addition to unconditionally entering or not entering the market at all (the same options as in BASE), participants have a third option. They can choose a critical threshold X such that they stay out of the market if at least X% of the other participants stay out of the market as well. Hence, subjects can make their choice conditional on the share of other traders in the market who stay out of the market. To determine which participants actually enter the market, we proceed as follows in determining the fixed point for the share of participants who stay out: we choose the maximum of all potential percentage thresholds X such that given X% of all participants would not trade at this threshold, more than X% of all actual participants do not want to enter the market.[50] All participants who enter unconditionally or choose a critical X above the calculated fixed point enter the market, while others do not. We hence take every hypothetical non-entry rate in 10%-steps from 0% to 100% and check how many participants want to stay out of the market given that non-entry rate, combining traders who submitted both conditional and unconditional decisions. The fixed point is then the highest value X such that ac-

[50]Potentially, multiple fixed points could arise. In this case, we take the fixed point with the largest X. However, in the collected data, the fixed point is unique.

tual non-entry exceeds hypothetical non-entry. If, for example, 75% of participants choose a threshold value of 70% or lower (or do not enter unconditionally of other participants), and 78% of participants choose a threshold value of 80% or lower, the fixed point is 70%. This procedure ensures that each participant enters the market if and only if she has stated that she wants to enter given the decisions of all other participants.[51] Importantly, the conditional entry decision in our setting allows participants to act in accordance with the prevailing social norm even if they are uncertain about it. If they are unsure about whether it is appropriate to trade in the market, the procedure ensures that these participants only trade if a sufficient proportion of other participants trade. This treatment thus directly tests whether the share of other traders willing to behave morally is correlated with a subject´s decision to choose the moral action as well. At the same time, a trader who is certain about the prevalent norm for trading or does not care about it can take the unconditional decision to enter the market or stay out.

3. **Punishment.** Similar to the study by Kirchler, Huber, Stefan, and Sutter (2016), our third treatment (abbreviated as PUN) allows for the costly punishment of trading decisions. Here, we test to what extent third-party observers are willing to enforce the social norm of moral behavior among traders, incurring personal costs to sanction the immoral act of trading. Moreover, we investigate whether traders are able to anticipate punishment and how this affects market outcomes. In this treatment, each buyer and seller is randomly assigned to an

[51]Due to the large market size, one´s own action is highly unlikely to influence entry rates, making subjects de-facto norm takers.

observer who is not active in the market, i.e., every trader is matched with one observer. Buyers and sellers interact as in the BASE treatment. The observer can choose to impose (costly) sanctions for the trader matched to herself. Here, punishment is conditional on trading per se but not on the level of profit that the trader achieved. Hence, in our setting, punishment is made conditional on the immoral act rather than on the personal benefit the trader obtained from this immoral act.[52] Observers receive a fixed participation fee of 3 Euros and an additional endowment of 3 Euros. This additional endowment can either be kept or used to decrease the payoff of the respective market participant. Each euro an observer spends decreases the respective buyer´s or seller´s payoff by 3 Euros in the event of trading. Hence, an observer is enabled to impose punishment up to the level of the expected payoffs of a trader in our setting.[53] The endowment not spent on punishment is directly paid out to the observer. Moreover, the observer keeps the entire endowment if the market participant assigned to him does not trade a coupon.

In each treatment, all information provided above is common knowledge among the participants. Due to the online implementation with a large population sample that limits the possible duration and the degree of interactivity, our market treatments are conducted as one-shot decision situations. In contrast, earlier experiments (Falk and Szech (2013), Kirchler, Huber, Stefan, and Sutter (2016), and Sutter, Huber, Kirchler, Stefan, and Walzl (2020)) are conducted as repeated interactive double-auction markets. Nev-

[52]Compared to laboratory studies on punishment (Kirchler, Huber, Stefan, and Sutter (2016) and related settings from the literature on social dilemmas), we implement a simplified punishment technology.

[53]We do not allow for negative payoffs; the buyer´s and seller´s minimum payoff is zero if the amount of punishment exceeds the profits from trade.

ertheless, even in in our non-repeated setting, we expect the effects of social norms and their enforcement. The previous evidence points in this direction: in Kirchler, Huber, Stefan, and Sutter (2016), an effect of (potential) punishment on trading decisions is already visible in the first round of the game, i.e., before the actual punishment is imposed. Hence, a trader's expectation of norm enforcement rather than the actual enforcement seems sufficient to induce more moral behavior. Moreover, as participants can condition their moral behavior ex-ante on the behavior of other potential traders, this allows them to follow the social norm without the need to observe market interactions over a period of time.

5.2.2 Expected behavior

Given our large markets and the uniform pricing rule, neither of the sellers nor buyers should expect to be pivotal for setting the price. In this case, it is optimal for both sellers and buyers to state the true prices at which they are willing to engage in a trade.

If participants do not have preferences for moral behavior and hence disregard the negative externality, buyers would be willing to pay up to 18 Euros. Likewise, sellers would accept any positive price. Consequently, as long as the number of sellers is not lower than the number of buyers, the number of coupons traded would equal the number of buyers in the respective market.[54]

However, suppose some market participants care about the negative externality and experience moral costs. In that case, this could have two implications, both leading to a lower number of traded certificates. They either do not enter the market at all or enter the market and ask for a higher

[54]In our experiment, the number of sellers exceeds the number of buyers in all treatments.

compensation compared to the case without moral costs. The presence of moral costs for triggering the externality lowers the buyers´ willingness to pay and increases costs for the seller, leading to lower bid prices and higher ask prices. If the experienced moral costs are too high, it becomes optimal for these buyers and sellers to stay out of the market. In Section 5, we present different mechanisms of moral behavior that lead to such behavior.

If social norms do not play a role in our setting, the share of other buyers and sellers who are willing to behave in a moral way should be irrelevant for one´s own decision.[55] On the contrary, if some market participants desire to conform to the social norm about trading and are, in addition, uncertain about whether trading is considered appropriate, we expect that in treatment COND, a share of participants condition their market entry on the decisions of other participants. In Section 5, we discuss the framework by **?** to argue how norm uncertainty leads to conditional behavior and discuss alternative interpretations.

Finally, in the PUN treatment, profit-maximizing observers will refrain from sanctioning since it is associated with costs. At the same time, an extensive experimental literature (see, for example, Fehr and Gaechter (2000), Fehr, Fischbacher, and Gaechter (2002), Herrmann, Thoni, and Gachter (2008), Chaudhuri (2011), and Balafoutas, Nikiforakis, and Rockenbach (2014) and Balafoutas, Nikiforakis, and Rockenbach (2016)) provides evidence that decision-makers are willing to incur non-negligible costs to sanction inappropriate behavior - for example, in dilemma games, but also in natural field settings. Hence, we expect to observe positive punishment

[55]We make the implicit assumption that moral costs only arise if a trade is executed. Entering the market does not impose a moral cost per-se. Thus, absent any entry costs, the decision to enter the market does not depend on the probability of trade once in the market. In particular, such an assumption together with the uniform pricing implies that entry decisions are independent of the "competition" in the market.

levels on average and - to the extent that sellers and buyers foresee the punishment for engaging in trade - less frequent market entries compared to the control condition.

5.3 Experimental procedures and data sample

We conducted our experiment in cooperation with Infratest dimap, a German institute for political and electoral research. Infratest recruits participants from the Payback Panel. The Payback Panel consists of 115,000 Payback customers recruited by Payback, Germany´s largest retail rebate program, with around 30,000,000 customers.[56] Members of the Payback Panel regularly participate in online surveys.[57] Given that we implement an abstract decision situation with a clear set of imposed rules as in the laboratory, but within a non-standard subject pool, our study belongs to the group of artefactual field experiments, according to the classification of Harrison and List (2004).

We conducted our study as an online experiment. Subjects were invited to participate via email. In the solicitation email, subjects learned that they receive a participation fee of 200 Payback points (equivalent to 2 Euros) and that they have the chance to earn an additional amount during the experiment.

Upon entering the experimental website, participants saw the instructions for the decision situation on the screen.[58] To facilitate understanding of the decision situation, parts of the experiment were explained with the help of illustrations. In the next step, participants had to answer a control question verifying their understanding of the experiment´s basic market mechanism. In this question, we hypothetically asked buyers/sellers

[56]Several large retail chains offer "Payback points" for making purchases at their stores. Payback points can be converted into Euros or used as a rebate for future purchases. Hence, transaction costs for obtaining the payoffs from the experiment were minimized for the participants.

[57]Thanks to the collection of demographic data on all panel members, Payback guarantees large sample heterogeneity with respect to gender, age and education within each survey, as subjects with certain characteristics are invited in a gradual manner.

[58]Instructions for the experimental decision situation can be found in the Supplementary Material to our paper.

(and their observers) regarding the consequences of an offer above/below equilibrium market price. Participants could choose between two potential answers, i.e., whether or not they would trade in this particular scenario. If they provided the wrong answer, the correct one was explained on the screen in the next step.

After the participants had made their decisions in the experiment, they had to answer additional questions to elicit several social preferences and attitudes (e.g., measures for general altruism and the importance attached to ethical consumption) as well as the moral evaluation of trading behavior in the experimental market. The decisions and answers to the survey questions were matched to data on demographics and socioeconomic characteristics from the Payback panel in a way that preserved the anonymity of the subjects. Table 11 in the Appendix lists and explains the variables that we use in our study.

The field period was from November 30, 2018, to December 14, 2018. Since there was no direct interaction between participants, all decisions were collected until the end of the field period and matched thereafter. A total of 2,576 participants finished the experiment and answered all the questions.

We calculate descriptive statistics of the participants' demographic and socioeconomic factors across the roles in the experimental treatments as well as the probability of observing respective distributions under the assumption of independence (resulting from Kruskal-Wallis equality-of-populations rank tests). We observe small but statistically significant differences in age and the number of persons in the household between roles. For all other variables, our treatments do not differ with respect to demographic and socioeconomic factors. An overview of the descriptive statistics related to our sample can be found in Tables 12 and 13 in the Appendix.

We observe slight differences in attrition rates between treatments (21.2% of the participants in BASE and 27.5% of the participants in COND and PUN quit the experiment before finalizing it, p = 0.003, and p = 0.001 two-sided two-sample tests of proportions comparing COND and PUN with the BASE treatment). This difference is likely due to the fact that, compared to BASE, the decision situations in COND and PUN include additional elements and, as the result, the experimental instructions were longer in these treatments.[59] At the same time, the lack of differences in most demographic and socioeconomic factors across treatments and roles makes us confident that the differences in attrition do not systematically influence our results. Moreover, we include controls for all demographic and socioeconomic factors in our parametric analyses.

On average, participants spent 16 minutes on the experiment (standard deviation: 7 minutes) and earned 4.37 Euros (standard deviation 3.26 Euros), including the participation fee of 2 Euros. As we will see below, this average payment includes a substantial share of participants who did not receive any payoffs from the experimental decision at all because they decided against trading. As a result of the participants´ decisions in the experiment, altogether 14,472 Euros were transferred to UNICEF as a donation, resulting in 40,200 doses of measles vaccine.

[59]In COND there are 2 additional screens, and in PUN there are 3 additional screens as compared to BASE. While we cannot track at which point participants dropped out exactly in the experiment, we know that 97% of those who dropped out did so before making any decision and before they were asked the question concerning the understanding of the market mechanism. In fact, only 25 participants who started our experiment (5 in BASE, 6 in COND und 14 in PUN, no significant differences between treatments, as two-sided two-sample tests of proportions indicate) did not finalize it. It thus seems reasonable to assume that the somewhat higher dropout rates in COND and PUN are related to the difference in the length of the instructions.

5.4 Results

Our analyses reported in the following refer to the entire sample of 2,576 participants. In total, 378 out of these 2,576 participants (14.7%) did not answer the control question correctly. Importantly, participant groups do not differ in their understanding of the control question if we compare the shares of participants per role and treatment who answered the control question incorrectly ($p = 0.23$, Chi-squared test). Furthermore, our qualitative conclusions do not change if we repeat our main analyses, considering only subjects who answered the control question correctly. These analyses can be found in the Supplementary Material to this article.

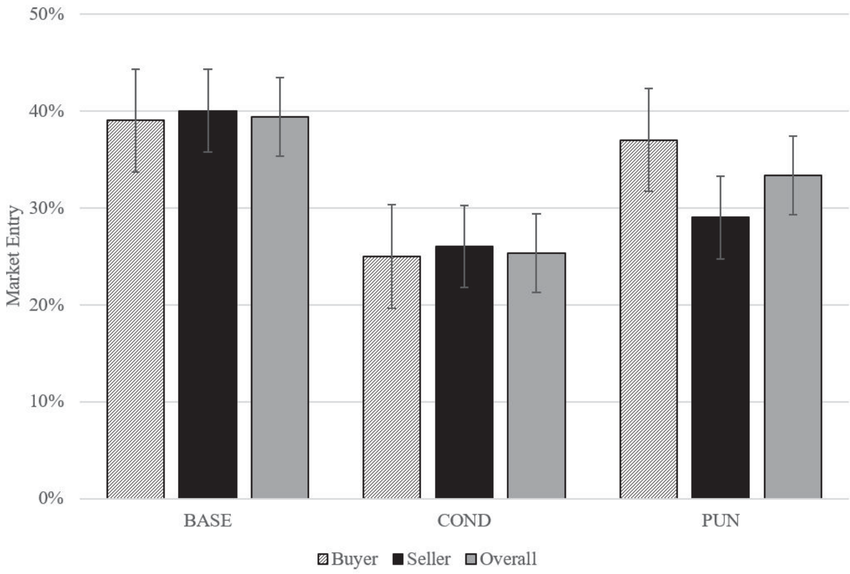
5.4.1 Decisions of sellers and buyers

Entry rates We start our analysis with the share of traders willing to enter the market despite the negative externality. In our setting, this decision is the clearest indication for moral concerns of subjects against trading. Refraining from entering the market at all is the only way to make sure that a participant does not cause a negative externality. Moreover, by not entering the market, a participant maximizes the expected amount donated to UNICEF (18 Euros). For these reasons, we use the decision to stay out of the market as our main proxy for the moral behavior of participants in the role of traders.

Result 1. *Over all treatments, a majority of 67% of agents does not enter the market.*

We find substantial evidence for moral behavior in all treatments. Calculated over all participants, we observe a share of market entry of only 33%. In turn, this means that about two-thirds of the experimental participants forego all monetary payoffs in order to avoid eliminating the donation.

Figure 47: REALIZED MARKET ENTRY PER ROLE AND TREATMENT



Notes: This figure displays the share of participants entering the market per treatment and role and respective 95% confidence intervals. The graph is based on 324 sellers and 321 buyers in BASE, 318 sellers and 317 buyers in COND, and 320 sellers and 316 buyers in PUN.

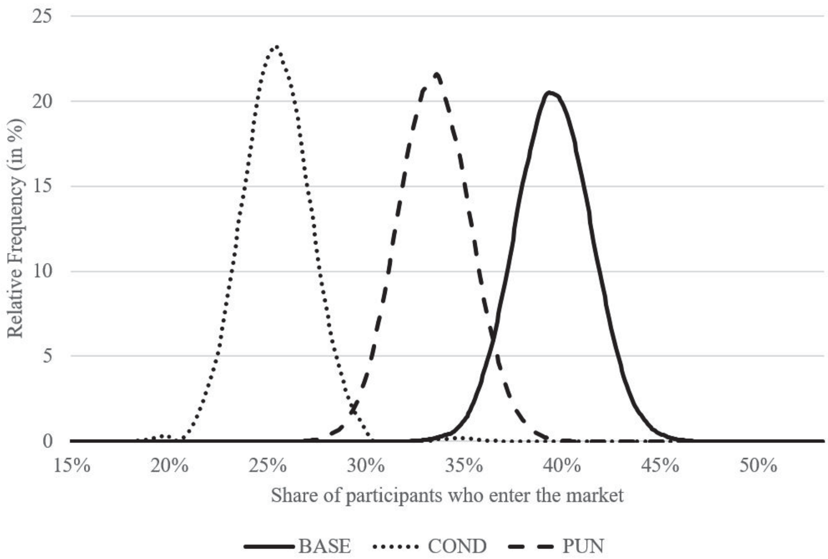
Figure 47 displays the share of participants entering the market per role and treatment. For the COND treatment, the figure refers to the actually realized entries, taking into account both unconditional and conditional decisions. In the baseline treatment, 39% of buyers and 40% of sellers enter the market. In COND, realized entry rates are only 25% and 26%, respectively. Market entry in PUN accounts for 37% in the case of buyers and 29% in the case of sellers.

Result 2. *In COND and PUN, the market entry rate is significantly lower than in BASE.*

Comparing overall entry rates between PUN and BASE, we find a significantly lower likelihood to enter in the former (p = 0.03, two-sample tests of proportions). Moreover, the lower entry rate in PUN is driven mainly by sellers. We observe a significant difference in entry rates between PUN and BASE for sellers (p ¡ 0.01, two-sample tests of proportions) but not for buyers (p = 0.68, two-sample tests of proportions). Hence, in the PUN treatment, the possibility of enforcing a no-trading norm via punishment is associated with less frequent market entry, similar to the observation by Kirchler, Huber, Stefan, and Sutter (2016). In our case, it seems that this deterrence effect is driven predominantly by the participants in the role of sellers who seem to react more strongly to the threat of punishment than buyers (p = 0.03, two-sample tests of proportions). As we show later in the paper, one reason for the lower probability of sellers entering the market in PUN may be differences in the moral evaluations of buyer and seller decisions, as suggested by results from the post-experimental survey.

Moreover, we find significantly lower entry rates for buyers and sellers in COND than in BASE (both two-sample tests of proportions yield p-values of p ¡ 0.01). However, a direct comparison of entry rates between COND and BASE is technically not entirely appropriate since realized entries in COND are interdependent by construction. If a trader decides to enter conditionally, the realized entry depends on the decisions of the other market participants. To consider this interdependence, we conduct simulations based on our data. For each treatment, we randomly generate 100,000 bootstrap samples of the same size as the original sample by drawing decisions from the original sample with replacement. For example, we have 318 buyers and 317 suppliers in the original COND sample. A bootstrap sample for the COND treatment then contains 318 draws from the buyer sample and 317 draws from the supplier sample. For each bootstrap sample, we then calculate the realized fixed point for the COND treatment and the realized entry rates for the BASE, COND, and PUN treatments.

Figure 48: RELATIVE FREQUENCIES OF ENTRY SHARES PER TREATMENT



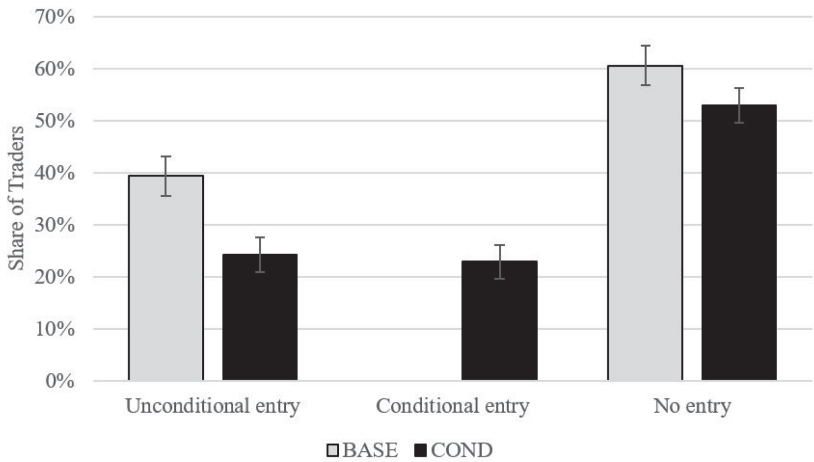
Notes: This figure displays the relative frequencies of entry shares resulting from simulations. For each treatment, we randomly generate 100,000 bootstrap samples of the same size as the original sample by drawing decisions from the original sample with replacement. For each bootstrap sample from the COND treatment, we then calculate the realized fixed point and the entry rates following from these fixed points. For each bootstrap sample from the BASE and PUN treatments we directly calculate the realized entry rates. As can be seen in the figure, the majority of resulting entry shares for COND is between 20% and 30%, the majority of entry shares for PUN is between 30% and 40%, and the majority of entry shares for BASE is between 35% and 45%. The size of the original sample consists of 324 sellers and 321 buyers in BASE, 320 sellers and 316 buyers in PUN, and 318 sellers and 317 buyers in COND.

Figure 48 shows the distributions of entry rates across the treatments based on the results of these simulations, with entry rates on the horizontal and the respective frequencies of these entry rates per treatment on the vertical axis. The simulations show that the observation of a lower realized entry rate in COND compared to BASE displayed in Figure 47 is not a coincidence caused by the interdependency of decisions in the COND treatment. On the contrary, a pairwise comparison of the simulated entry rates in COND and BASE shows that the former is larger in more than 99.9 percent of cases. Hence, we conclude that allowing for conditional moral behavior systematically lowers market entry in our setting.

Conditional moral behavior The previous analyses show that the possibility of making market entry contingent on the decisions of others leads to substantially less entry in our setting. Participants uncertain about the appropriateness of entering the markets can rule out a social-norm violation by entering the market conditional on the share of others who enter. To obtain more insights into the drivers behind this result, we focus on traders' conditional and unconditional entry choices in the next step.

Result 3. *In COND, 23% of subjects choose conditional entry, which could, in principle, result in higher or lower entry rates as compared to BASE.*

Figure 49: TRADER DECISIONS IN BASE AND COND



Notes: This figure displays entry decisions in BASE (where traders could only decide between unconditional entry and no entry) and COND (where traders had the additional choice to stay out of the market conditional on the behavior of others), and respective 95% confidence intervals. The graph is based on 645 participants in BASE and 635 participants in COND.

In the COND treatment, about a quarter of the traders (23%) decide to make the market entry conditional on the decisions of other traders. At the same time, 24% of subjects enter unconditionally, while 52% refrain from entering independent of the decision of others in the COND treatment.

The substantial share of the traders who condition their market entry on others provides evidence in line with the relevance of the desire to conform to social norms in our setting. Nevertheless, the comparison with the unconditional entry and no-entry decisions in the BASE treatment in Figure 49 also highlights that the effect of norm compliance for trading activities on markets can go in either direction. If all conditional traders stayed out, we would observe substantially less market entry than in BASE. If, however, all conditional traders entered the market, the entry rate would be higher than in BASE. This indicates the importance of the specific social norm for moral behavior in markets. Decreasing uncertainty about the existing norm can either improve or impair moral outcomes depending on the particular market environment. More generally, the relatively large share of conditional entries in our setting may explain the heterogeneity of moral behavior in different market settings - the actual willingness to create negative externalities through trading may depend on the participants´ belief about the prevalent social norm.

Looking at the thresholds required by conditional entrants, we find that a majority of 76% indicate a preference for non-entry when 60% or fewer traders exhibit moral behavior and refrain from trading. About half of the conditional traders state thresholds of 50% or 60%, suggesting a focus on majority decisions. (For more details, please see Figure 55 in the Supplementary Material showing the distributions of the thresholds.)[60] The combination of a relatively high share of unconditional non-entrants and the moderate threshold values required by conditional entrants to refrain from entry results in a fixed-point threshold of 70% and a share of 75% non-entrants.[61] Looking at the simulations reported above, we find that the thresholds differ from 70% in less than 1% of the simulated markets. Hence, the endogenous threshold of 70% can be interpreted as a "natural" threshold in our setting, meaning that it would be the result of similar (conditional) markets in almost all cases.

Result 4. *Changes in unconditional trader decisions have spillover ef-*

[60] One could hypothesize that some traders may state motivated beliefs about the required shares of other participants who stay out of the market. One example for such a pattern would be to state a very high threshold that the trader does not genuinely believe to be achieved. While we generally cannot rule out such motivated beliefs, we note that the share of very high required thresholds (80% or 90%) stated by the experimental traders is only marginal in our setting (less than 5%).

[61] In our case, 75% of entrants do not want to enter with a hypothetical non-entry rate of 70%, and with a hypothetical non-entry rate of 80%, 76% of entrants do not want to enter.

fects on norm conformists that significantly affect the overall degree of moral behavior in the market.

Finally, we conduct an additional analysis to better understand the impact of conditional entrants on the realized market outcome. In particular, we investigate how the market outcome in COND would change in different scenarios where certain shares of unconditional market entrants are turned into unconditional non-entrants and vice versa. As a baseline, we consider our population in COND, where 24.3% are unconditional entrants, 52.9% are unconditional non-entrants, and 22.8% are conditional entrants. In scenario (i), we assume that 5% of the population switch from unconditional non-entrants to unconditional entrants, implying that the population consists of 29.3% unconditional entrants, 47.9% unconditional non-entrants, and 22.8% conditional entrants. In scenario (ii), we assume that 10% of the population are turned from unconditional non-entrants to unconditional entrants. In scenarios (iii) and (iv), 5% and 10%, respectively, of the population are assumed to switch from unconditional entrants to unconditional non-entrants.

For each scenario, we simulate overall market outcomes as in the previous section (again with 100,000 repetitions) and calculate the effect on realized market entry. The results are summarized in Table 10. We observe that an increase in the unconditional entry rate by 5 (10) percentage points would have substantial implications on the entry decisions of conditional traders and increase the entry rate by 7.53 (17.42) percentage points. Here, each unconditional non-entrant that becomes an unconditional entrant causes, on average, another 0.51 (0.74) conditional entrants to enter the market. In contrast, a decrease in the unconditional entry rate by 5 (10) percentage points would have a weaker effect, decreasing the market entry rate by 5.67 (11.04) percentage points. Put differently, each unconditional entrant that becomes an unconditional non-entrant leads, on average, to another 0.13 (0.10) conditional entrants who do not enter the market either. Hence, we observe an asymmetric effect of shifts in unconditional moral/immoral behavior on realized market entry in our data, given the existence of conditional market participants. As described above, the relatively high share of unconditional non-entrants and the moderate share of non-entry required by conditional market entrants to stay out already leads to a generally low realized entry rate. Hence, starting from the prevalence of conditional and unconditional moral behavior in our setting, the potential to decrease market entry further is limited. At the same time, our simulations show that if immoral behavior is relatively more important in the market, the positive spillover effects of turning unconditional entrants into non-entrants can be sizable: starting from the realized market outcome in Scenario (ii) with an equilibrium entry rate of 42.77%, convincing ten unconditional entrants to stay out of the market would result in up to seven additional conditional entrants not entering.

Table 10: SPILLOVER EFFECTS OF CONDITIONAL ENTRY

	Baseline	Scenario (i)	Scenario (ii)	Scenario (iii)	Scenario (iv)
Unconditional entrants	24.3%	29.3%	34.3%	19.3%	14.3%
Unconditional non-entrants	52.9%	47.9%	42.9%	57.9%	62.9%
Conditional entrants	22.8%				
Direct effect on equilibrium entry rate		+5.00%	+10.00%	-5.00%	-10.00%
Indirect effect on equilibrium entry rate		+2.53%	+7.42%	-0.67%	-1.04%
Multiplier		1.51	1.74	1.13	1.10

Notes: This table displays simulated entry rates in 5 different scenarios. Compared to the Baseline Scenario based on the observed data in the COND treatments, in Scenario (i) to Scenario (iv) we turn a share of unconditional entrants to unconditional non-entrants (or vice versa), and simulate market outcomes resulting from this 'manipulation' 100,000 times per scenario. We then calculate the difference to entry in Baseline, and decompose this into the direct effect, i.e., how many unconditional types we manipulated, and the indirect effect, i.e., how many conditional types would change their decision based on this manipulation. Finally, the multiplier expresses how many entries (non-entries) are induced by each unconditional non-entrant (entrant) turned into an unconditional entrant (non-entrant) on average. Hence the multiplier equals the ratio between the difference to the entry rate in Baseline (line 5 in the table) and the direct effect (line 6 in the table).

Compensation for trade and moral assessments As argued above, the second possible response of traders who experience moral costs related to the destruction of the donation is to ask for monetary compensation for the moral costs associated with trading.[62] On average, sellers who enter the market ask for higher compensation than buyers.[63] In particular, buyers (sellers) on average require 8.61 Euros (10.14 Euros) to be willing to trade,

[62]Cumulative distributions of sellers´ and buyers´ bids and the resulting equilibria per treatment can be found in the Supplementary Material. Note that the monetary compensation requested by sellers equals their bid, while the monetary compensation requested by buyers equals 18 minus their bid.

[63]For a detailed analysis of required compensations between treatments and trader roles, please see Appendix A.2.

and this difference is significant ($p<0.01$, two-sided MWU comparing buyers and sellers across all treatments). The difference in requested compensation might be due to an endowment effect (Kahneman, Knetsch, and Thaler (1991)) in the sense that assigning the coupon to the seller creates a sense of ownership for which the seller has to be additionally compensated. At the same time, the higher required compensation might reflect higher moral costs associated with the act of trading.

Our setting does not allow us to distinguish between these two possible mechanisms. However, the data from the survey answers point towards the second interpretation: As part of our study, we elicit the moral perception of sellers and buyers who trade on our market after the experimental decision to rule out that subjects are primed on the immorality of trading prior to their trading and punishment decisions. The questionnaire asks all subjects how immoral they perceive the trading of buyers and sellers, ranging from 1 (not immoral at all) to 7 (very immoral). Interestingly, we find that irrespective of the role of the experimental participant who evaluates the morality, selling is considered to be somewhat less moral than buying, and the difference is statistically significant: While the average level of the immorality of buyers who trade accounts for 3.63, the same value for sellers is 3.99 ($p<0.01$, two-sided Wilcoxon matched-pairs signed-ranks tests for all groups of participants).[64] However, this difference in moral perception accounts for 0.21 standard deviations and is thus relatively small. At the same time, the observation that trading by sellers is generally viewed as less morally appropriate suggests that moral costs are at least partially responsible for the differences in the required compensation for trading by buyers and sellers.

[64]For a more detailed analysis of the moral perception of trades between roles, please see Appendix A.3

5.4.2 Heterogeneity analysis of sellers and buyers

Next, we focus on the heterogeneity of potential traders concerning stated attitudes and preferences and investigate if and how they correlate with moral behavior on our experimental markets. In particular, we check whether the following variables are correlated with the decision to trade: *Altruism* (a combined measure of altruism taken from Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018) based on a general willingness to give money to charity and the amount a participant would donate to charity if he/she unexpectedly wins 1000 Euros), *Ethical consumption* (a categorical variable indicating the frequency of buying socially responsible products, ranging from 1: never; to 5: always), *Voluntary work* (a variable capturing the number of hours per month the participant engages in unpaid work for a good cause, taken also from Falk, Becker, Dohmen, Enke, Huffman, and Sunde (2018)), and *Average Morality* (the average value for the moral assessment of buyers and sellers who trade, ranging from 1: not immoral at all; to 7: very immoral). Figure 50 depicts binned scatterplots of these four variables.

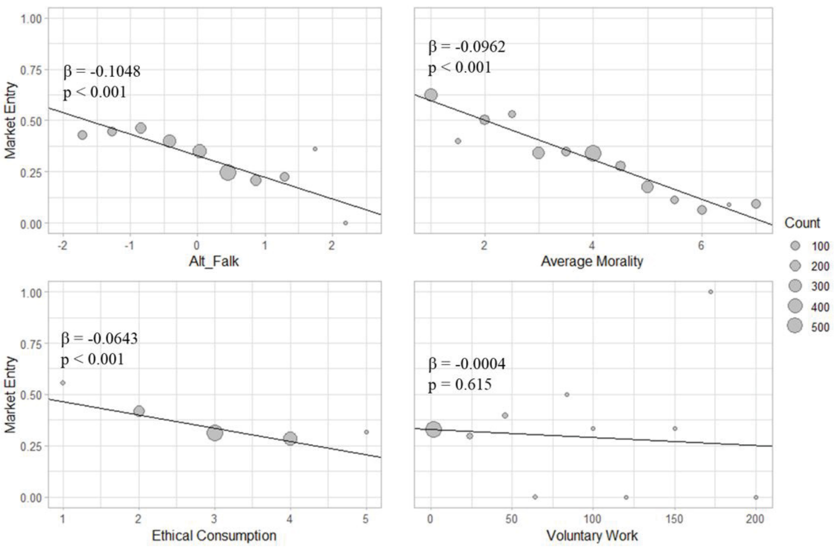
Result 5. *More altruistic participants, participants who attach higher importance to ethical consumption, and those who assign a higher degree of immorality to trading are less likely to enter the market.*

Apart from *hours of voluntary work*, all variables correlate with entry behavior in the intuitive direction: (i) more altruistic participants, (ii) participants who attach higher importance to ethical consumption, and (iii) those who assign a higher degree of immorality to trading are less likely to enter.[65] The effect size is also substantial: for the most altruistic subjects,

[65] The coefficients (and standard errors) resulting from simple linear regressions of entry separately on the four variables are: Altruism: -0.1048 (0.0131); Average Morality: -0.0962 (0.0061); Ethical Consumption: -0.0643 (0.0132); Voluntary Work: -0.0004 (0.0008), resulting in p-values of p¡0.001 for all variables except for Voluntary Work, which has a p-value of 0.615.

the probability of entering is about half of the probability of the least altruistic ones (22% for participants with a combined score above 1.2 versus 44% for participants with a combined score below -1.2). A similar pattern can be observed for the participants who most frequently buy ethical products as compared to participants who do not buy ethical products at all (32% versus 55%). For *Average Morality*, the entry rate declines from 62% (for the subjects with the lowest moral concerns) to 9% (for the subjects with the highest moral concerns). Therefore, the actual moral behavior of the traders in our experiment reasonably correlates with stated attitudes related to pro-sociality and morality. Moreover, our results align with findings from student samples that attitudes related to altruism and responsible consumption are linked to ethical behavior in laboratory settings (Engelmann, Friedrichsen, and Kuebler (2018), Sutter, Huber, Kirchler, Stefan, and Walzl (2020)).

Figure 50: RELATION BETWEEN MARKET ENTRY, ATTITUDES AND PREFERENCES



Notes: This figure features binned scatterplots of the relationship between market entry and stated attitudes and preferences elicited in a post-experimental survey. In each subfigure, participants are grouped based on their stated attitudes and preferences. The size of each bubble is proportional to the group size. The center of each bubble refers to the average statement within the group (x coordinate) and the average entry rate (y coordinate) within the group. For "Altruism" and "Voluntary Work", we divide subjects according to their stated attitudes into ten groups by determining ten equidistant intervals of the potential values of the variable. For "Average Morality" and "Ethical Consumption" we take the actual values instead of intervals, since these are discrete variables with 13 ("Average Morality") and 5 ("Ethical Consumption") potential values. The lines result from linear regressions with market entry as the dependent variable and the respective attitude or preference as the (sole) independent variable. Each subfigure displays the value for β (the regression coefficient of the attitude/preference variable) as well as its significance level.

In the next step, we extend our analysis of demographic and socio-economic characteristics as well as expressed preferences and attitudes of the participants and their correlation with the decision to trade. For this purpose, we estimate a probit model based on actual entry decisions with a binary dependent variable equal to one if the participant entered the market and zero otherwise.

We find robust effects of gender and age on market entry, i.e., older people and women tend to enter the market less frequently. This observation is in line with previous findings that older decision-makers and women seem to behave more altruistically, although the evidence is not conclusive (see, for example, Sutter and Kocher (2007); Bellemare, Kröger, and Van Soest (2008); Croson and Gneezy (2009); Engel (2011); Matsumoto, Yamagishi, Li, and Kiyonari (2016); Kagel and Roth (2020), Bilen, Dreber, and Johannesson (2021) and the references cited therein). It also aligns with the finding from laboratory data by Deckers, Falk, Kosse, and Szech (2016) that female participants are more likely to behave morally than men. Moreover, in line with the results from Figure 50, we find that altruism and the moral perception of trade are robustly linked to market entry.[66] Finally, as an indicator for the link between general cooperativeness and market behavior we find that non-voters are significantly more likely to enter the experimental markets.[67] Details about the variables included in the model and the estimation results can be found in Table 14 in the Appendix.

Here, we also report the results of a linear regression with the compensation in Euros requested by market entrants as the dependent variable. Sellers and older participants ask for significantly higher amounts. In addition, the compensation subjects request is lower for more altruistic persons and higher for persons with more hours spent on voluntary work. Given that altruism is also associated with lower market entry, the first result might seem surprising. However, altruism could also be directed toward the trading partner. Among traders who enter the market and therefore accept

[66] In addition, sellers and high earners tend to be less likely to enter the market ($p = 0.070$ for sellers and $p=0.069$ for high earners).

[67] Previous research identified a positive correlation between an experimental cooperativeness measure and the likelihood of participating in a national election, which can be interpreted as a public good (Barr, Packard, and Serra (2014)). Moreover, non-voting has been found to be negatively correlated with solidarity preferences in a large population sample from the Netherlands (Riedl, Schmeets, and Werner (2019)).

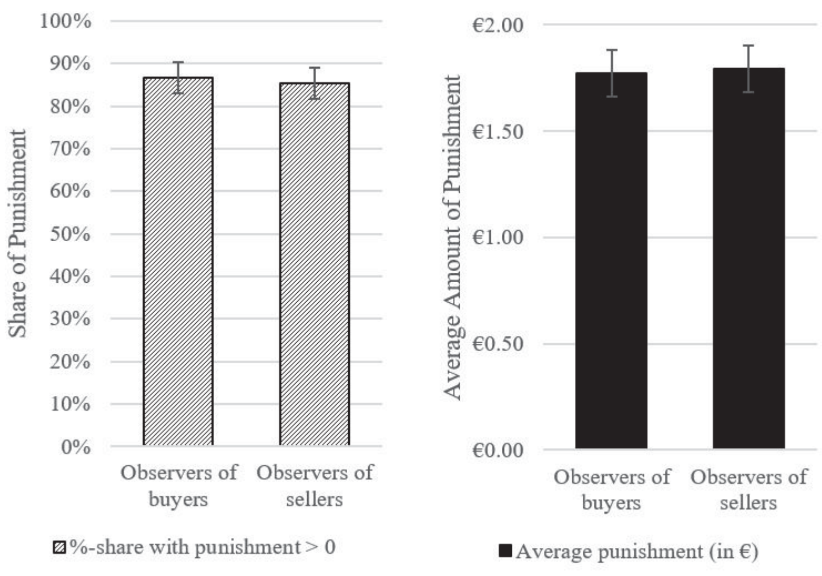
the negative externality, those with higher altruism might demand less from the trading surplus to be willing to engage in trade.

5.4.3 Decisions of observers

In the next step of our analysis, we focus on the willingness of observers to impose costly punishment on sellers and buyers who trade. We consider the share of observers who choose a positive amount of punishment (left part of Figure 51) and the amount observers are willing to spend on punishment (right part of Figure 51).

Result 6. *About 86% of all observers are willing to punish trading. The average observer spends more than half of the budget on punishment.*

Figure 51: SHARE AND AMOUNT OF PUNISHMENT PER OBSERVER



Notes: This figure displays the share (left) and amount of punishment (right) that observers in PUN impose on their respective counterpart, and 95% confidence intervals. The graph is based on 331 observers of buyers and 329 observers of sellers.

Figure 51 shows that most observers (around 86%) choose costly punishment. Moreover, on average, observers spend more than half of their extra budget of 3 Euros on punishment. Thus, we find strong evidence for a willingness to sanction the immoral action of trading in our setting. Interestingly, although the perceived immorality of trading elicited in the survey is somewhat higher for sellers, observers do not differentiate between buyers and sellers. In fact, observers of buyers and sellers do not differ in the punishment probability (87% vs. 85%, $p = 0.63$, two-sample test of proportions) and in the average amount spent on punishment (1.77 Euros vs. 1.79 Euros, $p = 0.78$, MWU).

We observe a higher frequency and a higher level of punishment than in, for example, the laboratory market experiment by Kirchler, Huber, Stefan, and Sutter (2016). Moreover, the share of observers of buyers and sellers who opt for punishment is somewhat higher than the share of participants not entering the market in our experiment in the PUN treatment, some 63% (71%) of buyers and sellers stay out. The latter result might seem surprising at first glance, as one could expect that, if the distribution of moral concerns is similar for the groups of traders and observers, the shares of non-entry and punishment would also be similar. Yet this is not necessarily the case, as we explain in the next section: one factor that might contribute to the high willingness to punish in our setting is that observers have to state their decisions about punishment prior to becoming informed about the actual decisions of traders and unconditional on the realized profit from trade. Moreover, punishment and the associated costs for the observers are only implemented when the assigned seller or buyer actually traded; otherwise, observers keep their entire budget. This insurance against wasteful punishment might increase the willingness to punish on the observers´ side. Section 5 discusses a unifying theoretical framework and places this argument within the framework.[68]

Finally, we conduct a heterogeneity analysis of observers, running similar regression models as in the case of traders. Here, we find that age and the proxy variable for altruism are significant predictors of positive punishment levels, with older and more altruistic participants being more likely to sanction trading. The detailed results can be found in Table 15 in the Appendix.

[68]Moreover, the high share of punishment rates might be related to the fact that we allowed only for a blanket punishment that could not be tailored towards the profit of the seller.

5.5 Mechanisms of moral behavior

There are several potential mechanisms driving our results. In this section, we present our preferred interpretation of social norm concerns and show how it can explain conditional market entry as well as costly sanctions on trading before we discuss alternative explanations.

Social norm interpretation

Our preferred interpretation is that market participants are driven by the desire to adhere to social norms about the moral appropriateness of trading, and that these norms are uncertain. **?** conceptualize such norms by assuming that the utility of an agent has two parts.[69] The first is the profit of an action minus the private cost from taking this action, which depends on the morality-cost type of the agent. Second, there is negative image concern that depends on what the action taken by the agent reveals about her type relative to the distribution of morality types in society. The second part can be interpreted as how the agent is perceived by others or as a self-image concern as to how the agent views her own decision. In particular, the agent's decision (in our case, the decision to enter the market and to bid) depends on the distribution of morality types in the society. Suppose the distribution of morality types is uncertain. That is, a priori, several distributions are feasible, thus creating uncertainty as to whether trading is considered to be relatively appropriate or inappropriate. Agents with a high morality (cost) type will always abstain from trading, irrespective of the distribution of morality types, as abstaining is optimal for most feasible distributions. Agents with a low morality (cost) type will always enter the market, as

[69]The model is also used, among others, by Benabou, Falk, and Tirole (2018) and Bénabou, Falk, and Tirole (2018)).

entering is optimal for most feasible distributions. However, agents with an intermediate morality (cost) type can benefit from conditional entry as the optimality of their decision is sensitive to the actual distribution of morality types. In equilibrium, those agents can set entry thresholds such that if the actual distribution places more weight on low-morality types, i.e., if the society is relatively immoral, they will enter the market. If the actual distribution places more weight on high-morality types, thus being relatively moral, they will abstain from entry.

In the Supplementary Material, we apply a model similar to **?** model to precisely demonstrate the effects of norm uncertainty on the BASE and COND treatment. As in **?**, the agent's utility has two parts. The first is the profit from trading minus a private moral cost of trading, which depends on the morality type of the agent. Second, there is a negative image concern that depends on how the morality type of the agent relates to the distribution of morality types in the market. We assume that the distribution is uncertain such that two different distributions are feasible. One distribution places more weight on low-morality types (immoral society), and another distribution places more weight on high-morality types (moral society). We demonstrate that for the BASE treatment, the price carries no information about the morality of the society. The argument is similar to the theoretical considerations and experimental results of Sutter, Huber, Kirchler, Stefan, and Walzl (2020), who vary the degree of competition between sellers and buyers on markets with and without externalities and show that moral concerns are reflected in the trading volume, but that the price is determined mainly by competitive forces - the ratio between sellers and buyers in these markets. In large markets, such as ours, uniform pricing implies that both buyers and sellers are price takers. Thus, if the market consists of a similar number of buyers and sellers, the market price is expected at half the coupon's value. Differences in morality change the marginal morality type who is willing to trade and thereby the trading volume but not the price.

We show that agents with intermediate morality types can benefit from setting a conditional entry threshold in the COND treatment. The equilibrium threshold is such that agents enter the market if the society turns out to be immoral and stay out of the market if the society turns out to be moral. Intuitively, if the society is moral, there are fewer agents who are willing to enter unconditionally. Thus, the entry rate falls below the equilibrium threshold, and the conditional entrants stay out of the market. If society is immoral, more agents enter unconditionally. Thus, the entry rate falls above the threshold and conditional entrants enter the market.

The social norm interpretation is consistent with the results in the PUN treatment. Applying the model of **?** to observers yields a utility that again consists of two parts. The first part refers to the private moral benefit from sanctioning an immoral decision of a trader minus the associated monetary cost. Second, there is a positive image concern that depends on the distribution of morality types in society. Sanctioning immoral behavior at a personal cost reveals a high moral type, from which agents gain more in a moral society. Thus, depending on the moral type, observers are willing to sacrifice monetary profit to punish a market participant. As buyers and sellers anticipate such behavior, they adjust their entry decisions and price offers.

Applying the model of **?** also explains the high punishment rates we observe in our data. As the decision to punish is taken ex-ante in our setting, the positive effect of punishment for the observer's image concern for the observers is realized independent of the actual implementation of the decision. Put differently, if an observer ex-ante decides to punish, but her market participant does not trade, she still enjoys a positive utility from her decision to punish, but at the same time does not incur the costs associated with the punishment. Thus, if the trading rate is low and, hence, the probability that the punishment is implemented decreases, the incentive to punish increases. This observation explains the high punishment rates in our data compared to the study by Kirchler, Huber, Stefan, and Sutter (2016), which implements ex-post punishments, that is, punishments after the third party has observed immoral behavior.

For the decision to enter the market, the distinction between traders´ (conditional) preferences for moral behavior and beliefs about the moral behavior of others is important. One advantage of our model and the model of **?** is that one can distinguish between preferences about moral behavior and beliefs about what the society perceives as moral. Thus, the model can be applied to situations in which agents are systematically wrong about the morality of society. The judgment of an agent on how her moral type relates to the morality in the society is encoded in the distribution of moral types in the society. When evaluating their image concerns, agents can hold different subjective beliefs about this distribution. In particular, they may over- or underestimate the morality of the society. However, the decision of whether to enter the market in the model not only depends on the beliefs but also on the realized moral-cost type. Thus, the entry decisions of all agents are informative of the actual distribution of moral types, even if all agents hold different beliefs. For example, agents with high morality types stay out of the market and agents with low morality types enter the market, irrespective of their beliefs. Conditional market entry allows agents with intermediate moral types to "correct" their subjective beliefs. By setting an entry threshold, an agent can ensure that they stay out of the market if the actual distribution is more moral than her subjective beliefs indicated or enter the market in the converse case. Thus, conceptually, the same patterns of behavior would emerge as in a case with a common but uncertain distribution of morality types.

Alternative interpretations

We cannot fully isolate the mechanisms behind moral behavior in our setting. As we describe in the introduction, our setting is not designed to distinguish between moral behavior in the sense that morally undesirable actions should be avoided per se irrespective of their outcomes and other-regarding behavior, such as altruism, which takes the outcomes imposed on others as the result of one's actions into account. In a next step, it would thus be interesting to investigate how behavior in our markets changes when the third party affected by the externality is modified. For example, it might be possible that the general willingness to trade increases when the harm is imposed on a private company or a public or political institution rather than a charity, as in the present case. Such controlled variation in the harmed party would allow us to better distinguish between altruism and morality as potential motives behind the decision to refrain from trade.

Linked to the previous point, in our setting, we consider only one specific tradeoff between personal gains and a fixed negative externality. Hence, our design does not allow us to gain insights into the rate at which individual decision-makers trade off their own profits against the damage done to third parties.[70] It would thus be worthwhile for further studies in similar

[70]In our case, traders receive 9 Euros in expectation for causing an externality of 18 Euros. A potential trader who weighs the negative externality half as high as her own monetary payoff would thus be indifferent between participating and not participating.

contexts to elicit participants' willingness to cause negative externalities for personal profit, given a variety of potential externality sizes. This would make it possible to gain an understanding of the empirical distributions of the underlying individual tradeoffs of market participants.

Finally, conditional moral behavior in our setting could also be driven by an aversion to inequality (Fehr and Schmidt (1999), Bolton and Ockenfels (2000). Participants might only be willing to stay out of the market and give away their payoff from trading (thus acting morally) if a sufficiently high number of other participants are willing to do so as well. Hence, other-regarding preferences might not only be important for the decision to impose harm on third parties but also for how to share payoffs between traders. Preliminary indication of this fact is provided by the results from our regression analyses, which showed that altruism is negatively correlated with a trader's requested compensation, as reported in the previous section. Moreover, depending on the beliefs about the surplus that a buyer or seller generates from trading (up to 18 Euros), inequality aversion might also motivate observers who receive relatively low endowments (3 Euros for punishment plus 3 Euros fixed) to reduce the traders´ payoff. At the same time, our experimental design does not allow us to clearly distinguish between concerns for the social appropriateness of trading and aversion toward inequality between traders, on the one hand, and between traders and observers, on the other hand. Accordingly, it would be interesting for further studies to isolate and compare the impact of other-regarding preferences concerning traders and parties harmed by market activities.

5.6 Discussion and conclusion

We conducted an artefactual field experiment to investigate moral behavior in markets with negative externalities as well as how this behavior interacts with social norms in a large population sample from Germany. We find that qualitative patterns of trading and sanctioning found in laboratory studies are confirmed in our heterogeneous non-student sample. In our setting, the absolute level of moral behavior - that is, the willingness to trade and the likelihood of sanctioning trading - seems to be relatively high, with more than half of participants completely refraining from entering the market and the large majority of observers sanctioning trading activities. However, while we caution that our experiment and previous laboratory studies are not directly comparable due to important differences in their designs, the observation that moral behavior is strongly pronounced within our sample of German citizens seems similar to the results of previous studies, which have found that non-student subjects tend to behave in a more pro-social way than student subjects (see, for example, Falk et al. 2013, Belot, Duch, and Miller (2015), and Snowberg and Yariv (2021)).

From a policy perspective, our study provides several important insights into how governments should approach markets in which trading is associated with negative externalities. First, the observation that the majority of participants are willing to forego profits in order to avoid negative externalities would suggest that in some domains, governments might not need to impose regulations on markets in the form of taxes or prohibitions on certain activities if market participants are able to establish a reduction in negative externalities based on moral concerns. Moreover, due to moral concerns regarding the conduct of certain firms, market participants might be inclined to change their purchase decisions, which could culminate in consumer boycotts. A recent study by Bartling, Valero, Weber, and Yao (2020) provides evidence that market participants can achieve more moral outcomes on their own. The authors find that public discourse - that is, the discussion between market actors about the potential harm created by trade - can significantly shift the social norm against harmful products and increase the share of fair product choices across different experimental conditions and across subject pools in Switzerland and China.

Second, the observation that a non-negligible share of the traders in our setting behave in a "conditionally moral" way suggests that social-norm interventions in markets with externalities may play an important role from a policy perspective for facilitating the coordination of market participants along moral lines. In particular, the existence of conditional moral behavior implies that the decisions of traders in markets can be shifted in the direction of more moral behavior by adequate interventions that signal the appropriateness of taking negative externalities into account. For instance, related to our setting, emphasizing that the participation in our experimental markets is damaging to children and thus highlighting its inappropriateness might be effective for inducing more moral behavior. In general, the provision of social information and appeals to social norms of cooperation have been effective in engendering more cooperative and pro-social behavior in a variety of domains. For example, social-norm messages and moral appeals have been found to increase overdue tax payments (Hallsworth, List, Metcalfe, and Vlaev (2017)) and self-declared foreign income (Bott et al. 2020). Furthermore, social information has been shown to foster environmentally friendly behavior - for instance, related to the consumption of energy (see Allcott (2011), Allcott and Rogers (2014), Ito, Ida, and Tanaka (2018), Brandon, List, Metcalfe, Price, and Rundhammer (2019)) and water (Ferraro and

Price (2013)).[71]

Among conditionally moral market participants, subjective beliefs about the moral perception of others play an important role, and entry decisions will be based on these beliefs. This may lead to a coordination problem: if beliefs are too pessimistic, this might lead to a market outcome with high externalities and low moral behavior, although a substantial share of traders would, in principle, be willing to cooperate. [72] From the perspective of a policy-maker who wants to reduce externalities under budget constraints, the provision of social information might be particularly effective in such cases as a means of inducing greater cooperation. For example, the study by Nathan, Perez-Truglia, and Zentner (2020) reported above shows that fairness perceptions of property taxes play an important role for the decision to protest against taxes and providing the information to citizens that their property tax rate is lower than the average increases the feeling of fairness and reduces the probability of protests. Moreover, Andre, Boneva, Chopra, and Falk (2021) measure climate preferences by letting participants allocate money between themselves and a charity that finances projects to mitigate the negative effects of climate change. The authors find that partic-

[71]More generally, providing social information and appeals to social norms have been effective for enhancing cooperation and pro-social behavior - for instance, regarding contributions to online communities (Chen, Harper, Konstan, and Li (2010)), reducing violations of traffic laws (Chen, Lu, and Zhang (2017)), for increasing charitable donations (for example, Frey and Meier (2004) and Shang and Croson (2009)), and for increasing voluntary payments (Pruckner and Sausgruber (2013), Feldhaus, Sobotta, and Werner (2019)).

[72]This coordination problem is mitigated in our specific experimental setting because the conditional entry decision is made before one knows the actual degree of moral behavior in the market. Here, traders can make moral behavior ex-ante contingent on a certain share of other moral market participants. We acknowledge that our experimental design does not allow us to identify partial free-riding strategies: that is, potential traders who care in principle about the externality may only enter when they think that many other participants stay out of the market, thus ensuring a high level of realized vaccinations, and stay out when the expectation is that only few other traders refrain from trading. Investigating to what extent this reasoning is a motivation behind conditional entries in markets would be an interesting avenue for further research.

ipants, on average, significantly underestimate both the prevalent behavior and norms concerning activities to fight climate change within the US population. Social norm interventions presenting participants with accurate statistics significantly increase donations, an effect driven by the positive responses of participants with initially too pessimistic beliefs.

Finally, this finding is also relevant with a view to the capacity of markets to self-govern. In principle, social media have the potential to serve as a coordination device in markets by reducing uncertainty about the moral decisions of a consumer's peers. For example, social media can increase the likelihood of a successful consumer boycott, as consumers might not be willing to boycott a product on their own, but may do so if they see that many others are abstaining from purchase.

At the same time, the success of social norm interventions might crucially depend on their specific designs and the environments in which they are implemented. For example, Fellner, Sausgruber, and Traxler (2013) find that neither moral appeals nor social information have a significant aggregate effect on the evasion of TV license fees, and also provide indications that the effect of social information may depend on beliefs about the compliance of others. Also, Ito, Ida, and Tanaka (2018) and Bott et al. (2020) observe that the positive effect of moral appeals may not be persistent over time. Therefore, from our perspective, more systematic research is needed. First, research that tests the effectiveness of specific types of interventions related to social information and moral appeals in market settings. Second, research that provides insights into the factors that determine the success and failure of these interventions in promoting moral behavior.

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5.7 Appendix

Table 11: VARIABLES

Variable	Description
PUN	Dummy variable equal to one if treatment is PUN
COND	Dummy variable equal to one if treatment is COND
Seller	Dummy variable equal to one if participant is seller
Female	Dummy variable that is equal to one if participant identifies as female
Age	Age of a participant in years
High School	Dummy variable indicating if a participant has the general qualification for university entrance. In Germany this is a requirement to study at a university. Around 32% of the German population are in possession of this qualification. (https://www.destatis.de/DE/Presse/Pressemitteilungen/2019/02/PD19_055_213.html)
High Earner	Dummy variable indicating that a participant has a monthly net household income above €2500
No Income Info	Dummy variable indicating a participant has not given us information on their income
Persons Household	Number of persons living in the participant's household
Ethical Consumption	A categorical variable indicating the frequency of buying socially responsible products, ranging from 1: never; to 5: always
Voluntary Work	Number of hours per month the participant engages in unpaid work for a good cause (Falk et al. 2018)
Average Morality	The average of how a trader assesses buyers who trade and sellers who trade, ranging from 1: not immoral at all; to 7: very immoral
Non-Voter	Dummy variable indicating if a participant has stated that she would not vote or vote in an invalid way in the next election
Altruism	A combined measure of altruism taken from Falk et al. (2018) based on the general willingness to give money to charity without expecting compensation in return, and the amount a participant would donate to charity if he/she surprisingly wins €1000. It is defined as 0.6350048 times the z value (i.e. the amount of standard deviations above average) of the former variable plus 0.3649952 times the z value of the latter variable.

5.7.1 Descriptive Statistics

Table 12: DESCRIPTIVE STATISTICS-RANDOMIZATION CHECK (PART 1)

Treatment (role)	Participants	Age, mean (min. – max.)	Female (share)	High School (share)	Persons Household (mean)
BASE (buyer)	321	51.4 (19 – 90)	0.48	0.35	2.33
BASE (seller)	324	52.3 (19 – 85)	0.52	0.29	2.20
COND (buyer)	317	50.5 (19 – 82)	0.52	0.34	2.33
COND (seller)	318	52.3 (19 – 85)	0.48	0.33	2.21
PUN (buyer)	316	48.4 (19 – 95)	0.51	0.31	2.28
PUN (seller)	320	52.6 (20 – 93)	0.51	0.30	2.08
PUN (obs. buyer)	331	51.1 (19 – 86)	0.53	0.25	2.26
PUN (obs. seller)	329	51.0 (19 – 90)	0.54	0.32	2.42
p-values (Kruskal Wallis rank test)		0.037	0.889	0.446	0.012

Notes: This table displays descriptive statistics of the participants' demographic and socioeconomic factors across the roles in the experimental treatments as well as p-values resulting from Kruskal Wallis rank testing if the samples of all eight roles originate from the same distribution.

Table 13: DESCRIPTIVE STATISTICS-RANDOMIZATION CHECK (PART 2)

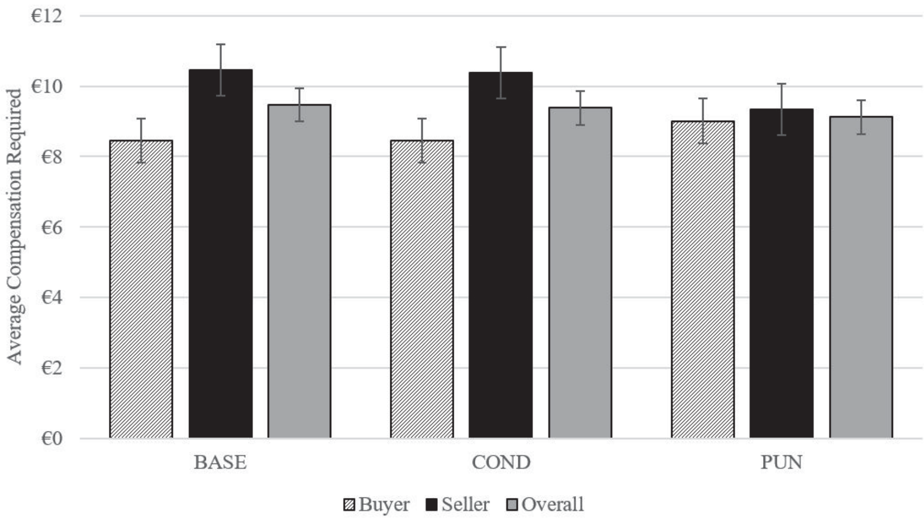
Treatment (role)	Participants	High Earner (share)	Frequency of Ethical Consumption (mean)	Voluntary Work (mean)	Non-Voter (share)
BASE (buyer)	321	0.61	3.15	5.71	0.08
BASE (seller)	324	0.55	3.14	4.21	0.04
COND (buyer)	317	0.57	3.13	3.97	0.07
COND (seller)	318	0.53	3.09	4.63	0.07
PUN (buyer)	316	0.56	3.14	4.74	0.07
PUN (seller)	320	0.56	3.19	5.31	0.05
PUN (obs. buyer)	331	0.53	3.22	5.45	0.08
PUN (obs. seller)	329	0.59	3.09	3.90	0.07
p-values (Kruskal Wallis rank test)		0.61	0.473	0.308	0.994

Notes: This table displays descriptive statistics of the participants' demographic and socioeconomic factors across the roles in the experimental treatments as well as p-values resulting from Kruskal Wallis rank testing if the samples of all eight roles originate from the same distribution.

5.7.2 Compensations required by sellers and buyers

As illustrated in Figure 52, sellers generally request higher monetary compensation than buyers on average. This difference is significant in BASE, where buyers (sellers) ask for 8.45 Euros (10.46 Euros, $p<0.01$, two-sided Mann-Whitney U-test [MWU] comparing buyers and sellers), and in COND, where buyers (sellers) ask for 8.45 Euros (10.38 Euros, $p<0.01$, two-sided MWU). In contrast, it is not significant in PUN (9.01 Euros vs. 9.34 Euros, $p = 0.86$, two-sided MWU). At the same time, when comparing the distribution of required compensations between treatments jointly for both roles, we do not observe significant differences. [73]

Figure 52: AVERAGE MONETARY COMPENSATIONS ASKED BY PARTICIPANTS, PER TREATMENT AND ROLE



Notes: This figure displays the average monetary compensation asked by participants per treatment and role, and respective 95% confidence intervals. The graph is based on 129 sellers and 125 buyers in BASE, 146 sellers and 153 buyers in COND and 94 sellers and 118 buyers in PUN.

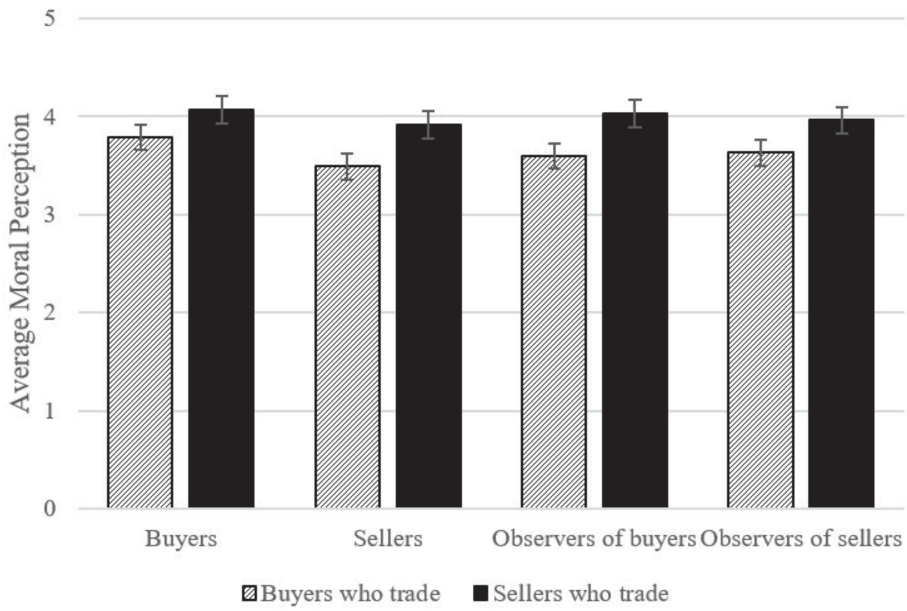
5.7.3 Moral perception of sellers and buyers

Figure 53 breaks down the morality perception separately for the role of the trader. The light bars display how immoral buyers, sellers, and their respective observers perceive buyers who trade, while the black bars do the same for sellers who trade.

The figure shows that irrespective of the role of the experimental participant who evaluates the morality, selling is considered to be somewhat less moral than buying, and the difference is statistically significant ($p<0.01$, two-sided Wilcoxon matched-pairs signed-ranks tests for all groups of participants).

[73] Comparing BASE and PUN results in a p-value of 0.41 (two-sided MWU), and comparing BASE and COND results in a p-value of 0.98 (two-sided MWU).

Figure 53: AVERAGE PERCEPTION OF THE IMMORALITY OF TRADE



Notes: This figure displays the average moral perception of buyers who trade and sellers who trade per treatment and role, and respective 95% confidence intervals. Moral evaluations of buyers and sellers who trade were elicited on a scale ranging from 1 (not immoral at all) to 7 (very immoral). The graph is based on 954 buyers, 962 sellers, 331 observers of buyers, and 329 observers of sellers.

Interestingly, sellers seem to assess the moral burden of trading in a self-serving manner: sellers perceive trading (of both sellers and buyers) as generally less problematic than all other roles do (two-sided MWU tests comparing moral assessments of sellers to moral assessments of all other participants yield $p = 0.06$ for buyers who trade and $p<0.01$ for sellers who trade.). Moreover, the moral self-perceptions of buyers who trade (3.79) and sellers who trade (3.91) do not differ significantly ($p= 0.13$, two-sided MWU test).

5.7.4 Simulations and regressions

Table 14 reports the results of a probit regression of actual market entry decisions with the binary dependent variable equal to one if the participant entered the market and zero otherwise (column 1). In addition, the table reports the results of a linear regression with the compensation in Euros requested by market entrants as the dependent variable (column 3). The regressions are based on our experimental data and contain controls for treatments, the role of the participant in the experiment, demographic background, socio-economic background, and attitudes and preferences. Descriptions of all variables included in the models can be found in Table 11.

Concerning the compensation that market entrants request once they enter the market, we observe, in line with our previous results, that sellers ask for significantly higher amounts. Moreover, the requested compensation increases with age. [74] We do not find significant effects of our treatments for the compensation level. In addition, the required compensation is negatively (positively) correlated with altruism (hours spent on voluntary work).

The observations for realized entry in the COND treatment are interdependent by construction. Hence, the estimates from regressions reported in columns 1 and 3 might not be appropriate. Similar to our simulation approach described in Section 4.1.1, we draw 100,000 bootstrap samples and conduct the same regressions on each of these samples. We report the average coefficient estimates and standard errors in columns 2 (for market entry) and 4 (for requested compensation), respectively. Comparing the coefficient estimates and standard errors, we find virtually no differences between regressions on actual and simulated data.

[74] There is an indication that female participants seem to ask for higher compensations in order to be willing to trade, but the coefficient fails to reach significance (p = 0.198).

Table 14: DETERMINANTS OF ENTRY AND MONETARY COMPENSATIONS-IMPACT OF SOCIOECONOMIC BACKGROUND AND STATED ATTITUDES: REGRESSIONS ON EXPERIMENTAL DATA

	1	2	3	4
Dependent Variable	Market Entry - Yes/No	Market Entry - Yes/No	Requested Compensation	Requested Compensation
Sample	Experiment Data	Simulated Data	Experiment Data	Simulated Data
COND	-0.458***	-0.461***	-0.009	-0.011
	[0.078]	[0.083]	[0.331]	[0.331]
PUN	-0.133**	-0.134**	-0.056	-0.054
	[0.076]	[0.076]	[0.362]	[0.355]
Seller	-0.116*	-0.117*	1.566***	1.569***
	[0.064]	[0.065]	[0.282]	[0.281]
Female	-0.278***	-0.280***	0.380	0.378
	[0.065]	[0.065]	[0.295]	[0.292]
Age	-0.008***	-0.008***	0.029***	0.029***
	[0.002]	[0.002]	[0.009]	[0.009]
High School	0.061	0.061	0.109	0.115
	[0.072]	[0.071]	[0.311]	[0.308]
Persons Household	0.024	0.024	-0.005	-0.007
	[0.031]	[0.031]	[0.130]	[0.123]
High Earner	-0.140*	-0.141*	-0.037	-0.036
	[0.077]	[0.078]	[0.337]	[0.329]
No Income Info	-0.020	-0.021	-0.141	-0.135
	[0.090]	[0.092]	[0.403]	[0.416]
Altruism	-0.133***	-0.134***	-0.438**	-0.436**
	[0.045]	[0.044]	[0.200]	[0.204]
Ethical Consumption	-0.024	-0.024	0.186	0.181
	[0.043]	[0.044]	[0.185]	[0.184]
Voluntary Work	0.001	0.001	0.031***	0.031***
	[0.002]	[0.002]	[0.010]	[0.009]
Average Morality	-0.285***	-0.287***	-0.073	-0.075
	[0.021]	[0.021]	[0.097]	[0.098]
Non-Voter	0.310**	0.311**	0.233	0.237
	[0.127]	[0.132]	[0.505]	[0.492]
Constant	1.405 ***	1.417 ***	5.997***	6.008***
	[0.221]	[0.224]	[0.954]	[0.964]
Model	Probit	Probit	Linear	Linear
# of Observations	1,916	1,916	765	765
# of Simulations	-	100,000	-	100,000

Notes: Column 1 reports the results of a probit regression of Market Entry (1 in case of entry, 0 in case of no entry) based on our observed data. Similarly, column 2 reports the average coefficients and standard errors (in brackets) of 100,000 probit regressions based on bootstrap samples of our observations.

In the next step, we conduct a probit regression to better understand the drivers of sanctioning behavior. As independent variables, we include the same variables as in the models of trading behavior listed above. The results of the model are listed in Table 15 below. From the demographic variables, we find that only age is a significant predictor of punishment, with older participants being more likely to punish trading. In contrast, all other demographic characteristics are insignificant. [75] Moreover, among stated attitudes and preferences, only the proxy for altruism is positively significantly related to punishment.

[75] In addition, there is a weakly significant positive correlation between the number of persons in the observer's household and the probability of sanctioning trading.

Table 15: DETERMINANTS OF PUNISHMENT-IMPACT OF SOCIOECONOMIC BACKGROUND AND STATED ATTITUDES

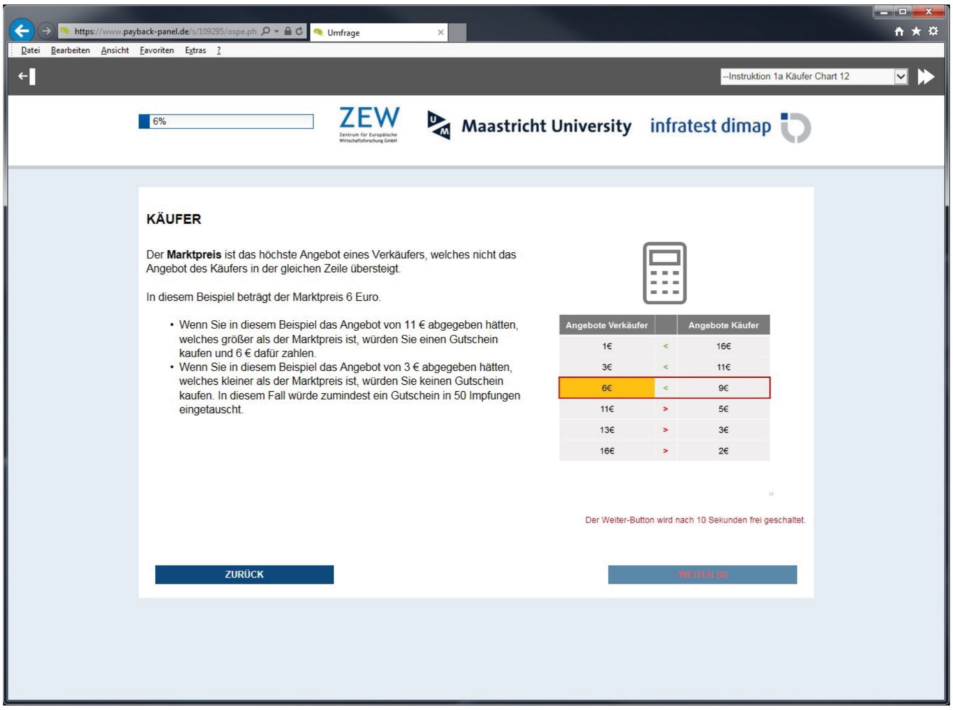
Model No.	1
Dependent Variable	Punishment – Yes/No
Seller	-0.048
	[0.126]
Female	0.041
	[0.132]
Age	0.010**
	[0.004]
High School	-0.039
	[0.149]
Persons Household	0.118*
	[0.063]
High Earner	-0.015
	[0.152]
No Income Info	0.129
	[0.184]
Altruism	0.178**
	[0.082]
Ethical Consumption	0.099
	[0.082]
Voluntary Work	0.009
	[0.007]
Average Morality	-0.040
	[0.044]
Non-Voter	-0.061
	[0.231]
Constant	0.175
	[0.411]
Model	Probit
Observations	660

Notes: Model 1 is a probit specification that uses a dummy dependent variable equal to one if the observer decided to punish the trader. Standard errors are given in brackets. *, ** and *** denominate significance at the 10%, 5% and 1% levels, respectively.

5.8 Supplementary Material

5.8.1 Example Price Determination

Figure 54: SCREENSHOT INSTRUCTIONS PRICE DETERMINATION



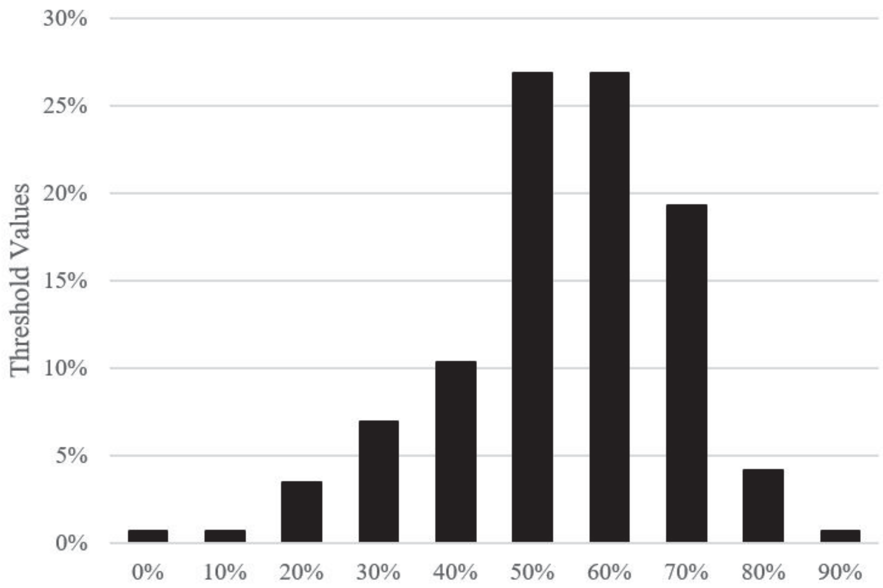
Notes: This figure is a screenshot of the instructions that all participants received. Seller´s offers (on the left) are ranked from lowest to highest, and buyer's offers (on the right) from highest to lowest. The market price then equals the lowest offer of a seller that does not exceed the respective offer of a buyer with the same rank. In this case, a market price of 6 Euros is realized, and a total of 3 coupons are traded.

5.8.2 Additional analyses

5.8.3 Supply and Demand

This section illustrates the realized market equilibria in the three treatments. For each price between 0 Euros and 18 Euros, Figures 56 to 58 show how many buyers and sellers are willing to trade. It hence shows the cumulative distribution of supply and demand. As a result of our market-clearing rule,

Figure 55: THRESHOLD VALUES FOR SHARES OF PARTICIPANTS WHO STAY OUT OF THE MARKET REQUIRED BY CONDITIONAL ENTRANTS IN COND



Notes: This figure displays the distribution of threshold values for non-entry that conditional entrants in COND require to also stay out of the market. E.g., 27% of conditional entrants stated that prefer not entering the market if at least 50% of the other participants do not enter the market. The graph is based on 145 conditional entrants in COND.

the market price was 10 Euros in BASE and COND, and 9 Euros in PUN.[76]

[76] According to our market clearing rule, the market price is the lowest price p such that the number of sellers willing to trade at p exceeds the number of buyers willing to trade at p+1.

Figure 56: SUPPLY AND DEMAND BASE

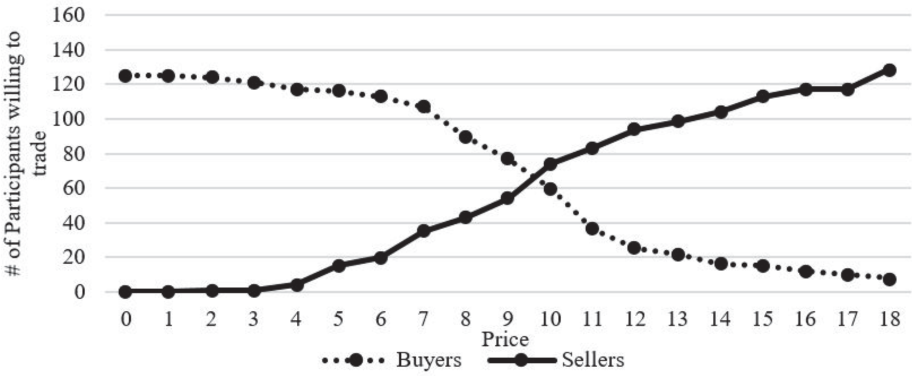


Figure 57: SUPPLY AND DEMAND PUN

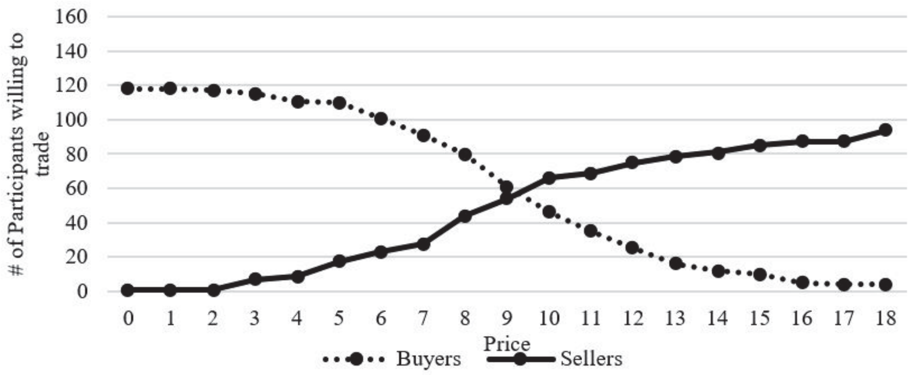
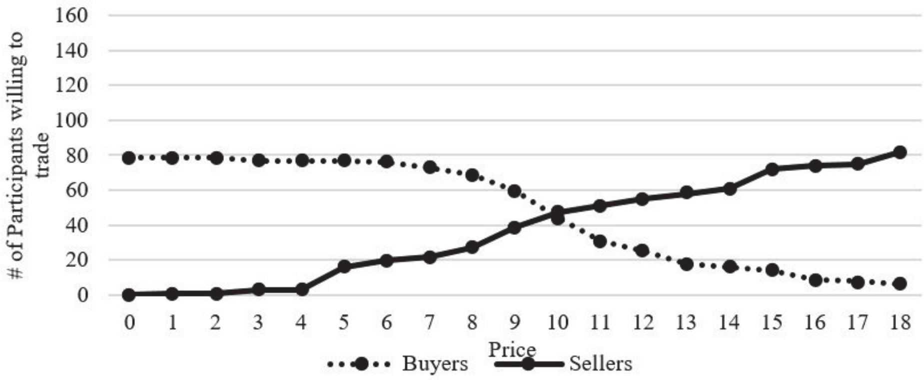


Figure 58: SUPPLY AND DEMAND COND

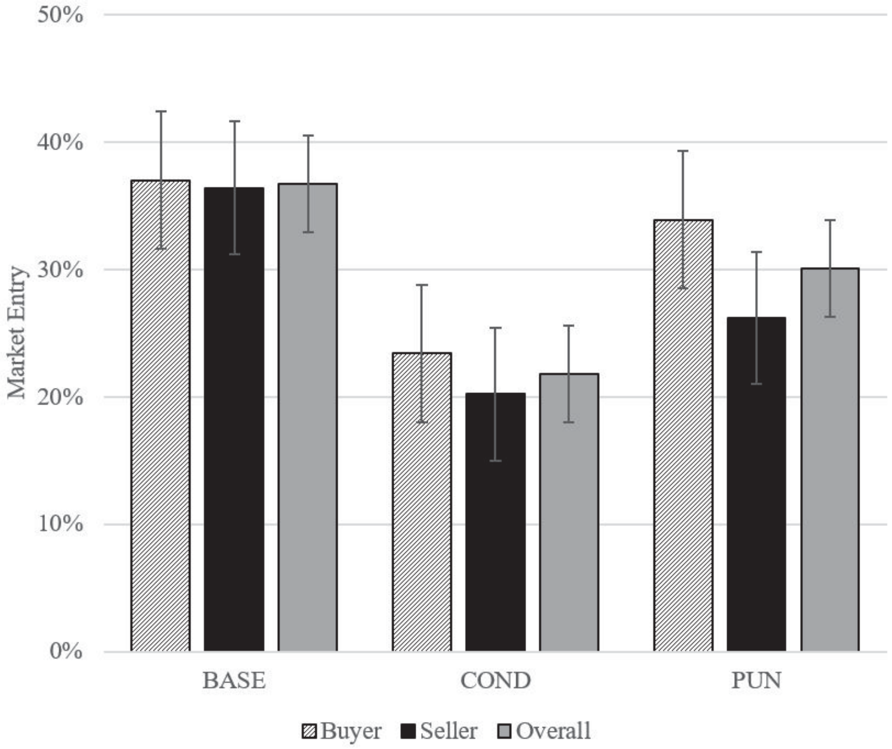


Notes: These figures display cumulative distributions of supply and demand in BASE, COND, and PUN. The figures are based on 324 sellers and 321 buyers in BASE, 318 sellers and 317 buyers in COND, and 320 sellers and 316 buyers in PUN.

5.8.4 Analyses without participants answering the control question incorrectly

In this section we report additional analyses that exclude participants who answered the control question incorrectly.

Figure 59: REALIZED MARKET ENTRY PER ROLE AND TREATMENT (CONTROL)

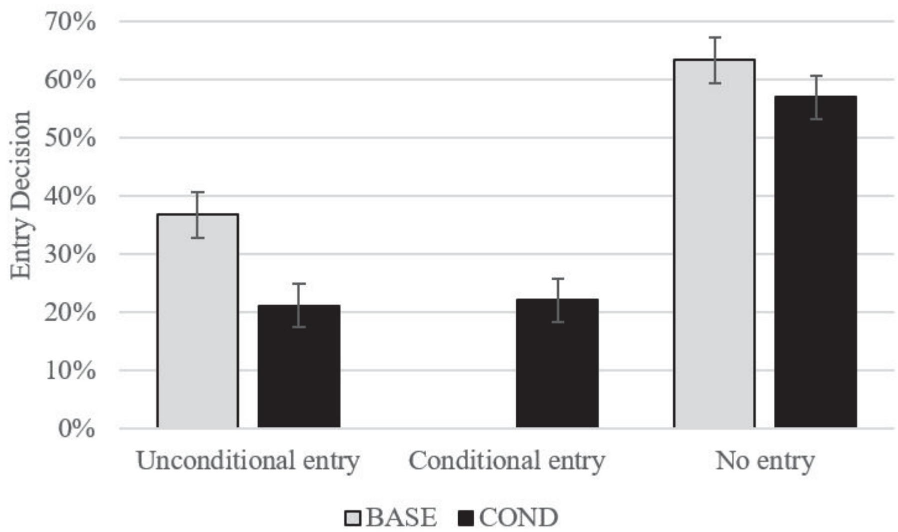


Notes: This figure displays the share of participants entering the market per treatment and role and respective 95% confidence intervals. The graph is based on 280 sellers and 281 buyers in BASE, 272 sellers and 278 buyers in COND, and 271 sellers and 271 buyers in PUN answering the control question correctly.

Figure 59 displays the share of participants entering the market per role and treatment. In BASE, 37% of buyers and 36% of sellers enter the market. In COND, realized entry rates are 23% and 20%, respectively. Market entry in PUN accounts for 34% in the case of buyers and 26% in the case of sellers. The share of participants entering the market in BASE significantly exceeds the share of participants entering the market in PUN ($p = 0.02$, two-sample tests of proportions). Furthermore, we find a significant difference in entry rates between PUN and BASE for sellers ($p = 0.01$, two-sample tests of proportions), but not for buyers ($p = 0.45$, two-sample tests of proportions).

Sellers seem to react more strongly to the threat of punishment than buyers (p = 0.05, two-sample tests of proportions).

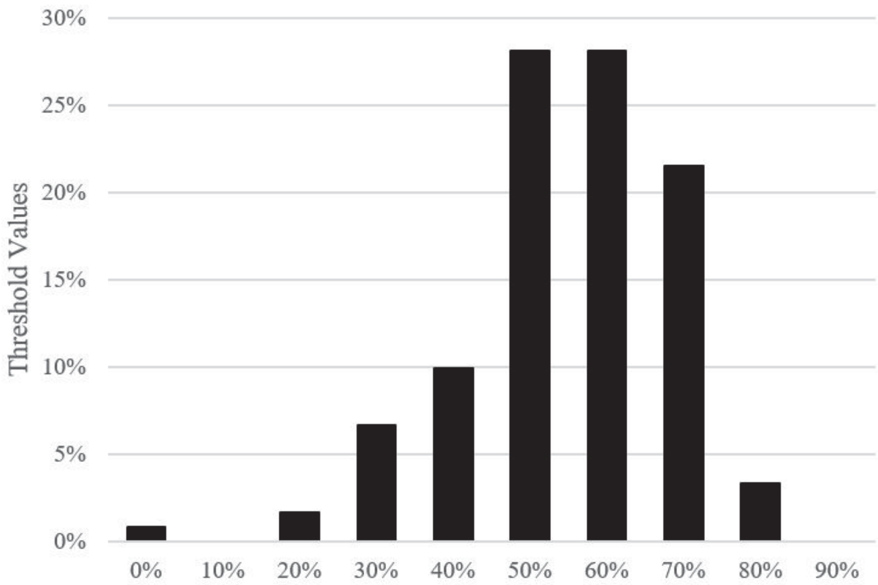
Figure 60: TRADER DECISIONS IN BASE AND COND (CONTROL)



Notes: This figure displays entry decisions in BASE (where traders could only decide between unconditional entry and no entry) and COND (where traders had the additional choice to enter the market conditionally), and respective 95% confidence intervals. The graph is based on 561 participants in BASE and 550 participants in COND answering the control question correctly.

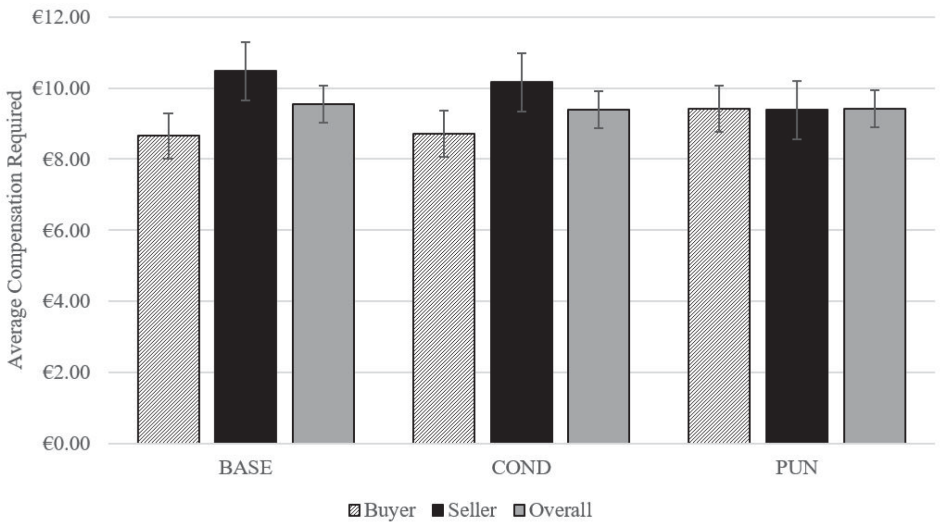
Figure 60 displays entry decisions in BASE and COND. In COND, 22% of the traders decide to make the market entry conditional on the decisions of other traders. Moreover, 21% of subjects enter unconditionally, while 57% do not enter independent of the decision of others in the COND treatment.

Figure 61: THRESHOLD VALUES FOR SHARES OF PARTICIPANTS WHO STAY OUT OF THE MARKET REQUIRED BY CONDITIONAL ENTRANTS IN COND (CONTROL)



Notes: This figure displays the distribution of threshold values for non-entry that conditional entrants in COND require to also stay out of the market. E.g., 28% of conditional entrants stated that prefer not entering the market if at least 50% of the other participants do not enter the market. The graph is based on 121 conditional entrants in COND answering the control question correctly.

Figure 62: AVERAGE MONETARY COMPENSATIONS ASKED BY PARTICIPANTS, PER TREATMENT AND ROLE (CONTROL)

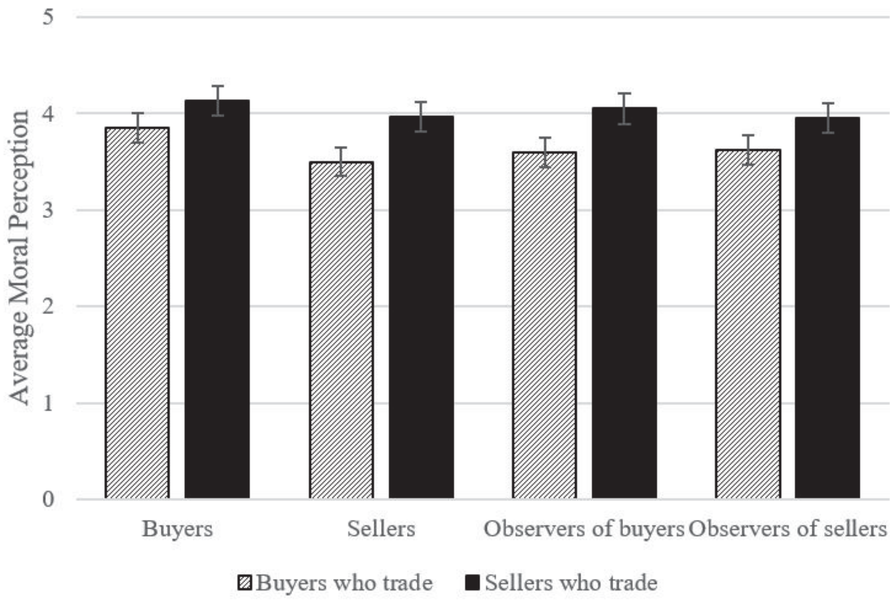


Notes: This figure displays the average monetary compensation asked by market entrants per treatment and role, and respective 95% confidence intervals. The graph is based on 104 sellers and 102 buyers in BASE, 127 sellers and 110 buyers in COND and 92 sellers and 71 buyers in PUN who answered the control question correctly.

As can be seen in Figure 62, sellers generally request higher monetary compensations than buyers on average. This difference is significant in BASE, where buyers (sellers) ask for 8.65 Euros (10.48 Euros, p ¡ 0.01, two-sided Mann-Whitney U-test (MWU) comparing buyers and sellers), and in COND, where buyers (sellers) ask for 8.72 Euros (10.17 Euros, p = 0.02, two-sided MWU), but not in PUN (9.43 Euros vs. 9.39 Euros, p = 0.42, two-sided MWU). In contrast, we do not observe significant differences between treatments when comparing the distribution of required compensations jointly for both roles. [77]

[77] Comparing BASE and PUN results in a p-value of 0.79 (two-sided MWU), and comparing BASE and COND results in a p-value of 0.80 (two-sided MWU).

Figure 63: AVERAGE PERCEPTION OF THE IMMORALITY OF TRADE (CONTROL)

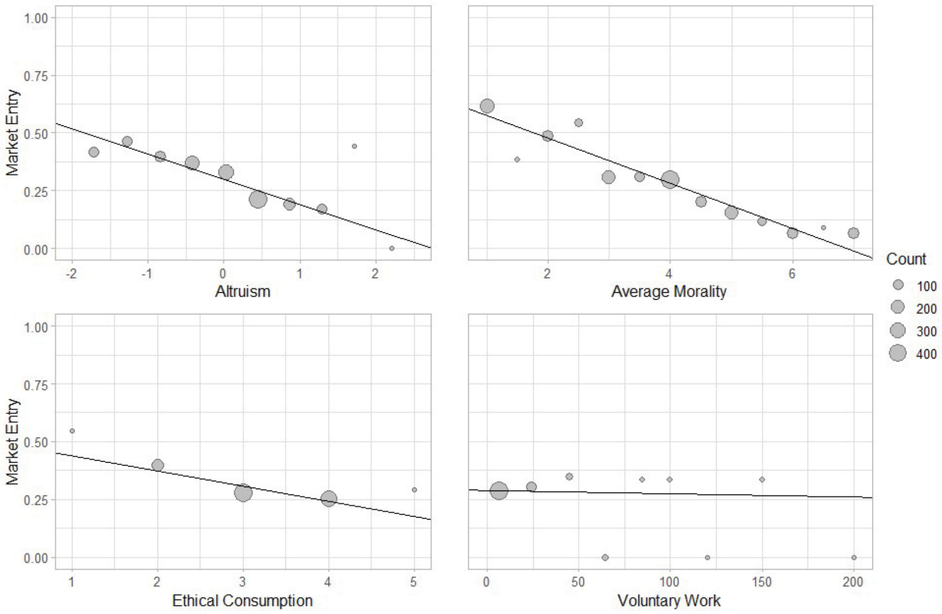


Notes: This figure displays the average moral perception of buyers who trade and sellers who trade per treatment and role, and respective 95% confidence intervals. Moral evaluations of buyers and sellers who trade were elicited on a scale ranging from 1 (not immoral at all) to 7 (very immoral). The graph is based on 830 buyers, 823 sellers, 280 observers of buyers, and 265 observers of sellers who answered the control question correctly.

Figure 63 illustrates that independent of the role of the experimental participant who evaluates the morality, selling is considered to be less moral than buying ($p<0.01$, two-sided Wilcoxon matched-pairs signed-ranks tests for all groups of participants). While the average level of the immorality of buyers who trade accounts for 3.66, the same value for sellers is 4.04.[78]

[78]Sellers perceive trading (of both sellers and buyers) as generally less problematic than all other roles do, and this difference is significant for the moral assessment of selling (two-sided MWU tests comparing moral assessments of sellers to moral assessments of all other participants yield $p = 0.11$ for buyers who trade and $p<0.01$ for sellers who trade). Also, the moral self-perceptions of buyers who trade (3.85) and sellers who trade (3.97) do not differ significantly ($p= 0.11$, two-sided MWU test).

Figure 64: RELATION BETWEEN MARKET ENTRY; ATTITUDES AND PREFERENCES (CONTROL)

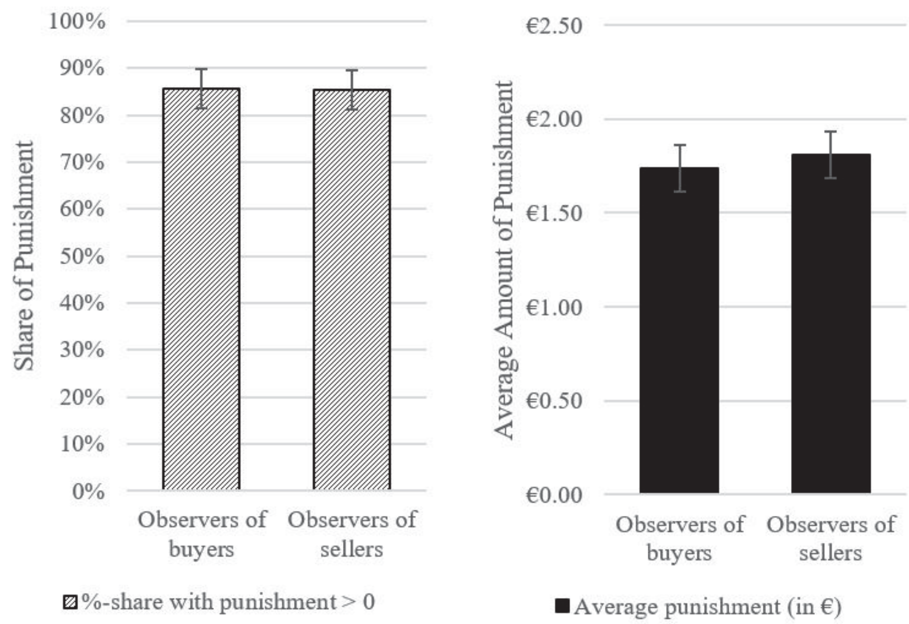


Notes: This figure features binned scatterplots of the relationship between market entry and stated attitudes and preferences we elicited in a post-experimental survey. In each subfigure, participants who answered the control question correctly are grouped based on their stated attitudes and preferences. The size of each bubble is proportional to the group size. The center of each bubble refers to the average statement within the group (x coordinate) and the average entry rate (y coordinate) within the group. For "Altruism" and "Voluntary Work", we divide subjects according to their stated attitudes into ten groups by determining ten equidistant intervals of the potential values of the variable. For "Average Morality" and "Ethical Consumption" we take the actual values instead of artificial intervals, since these are discrete variables with 13 ("Average Morality") and 5 ("Ethical Consumption") potential values. The lines result from linear regressions of market entry and the respective attitude or preference.

Figure 64 shows the relationship between market entry and stated attitudes and preferences we elicited in a post-experimental survey. Aside from *hours of voluntary work*, all variables correlate with entry behavior in the expected direction: (i) more altruistic participants, (ii) participants who attach higher importance to ethical consumption, and (iii) who assign a higher degree of immorality to trade are less likely to enter. [79]

[79] The coefficients (and standard errors) resulting from simple linear regressions of entry

Figure 65: SHARE AND AMOUNT OF PUNISHMENT PER OBSERVER



Notes: This figure displays the share (left) and amount of punishment (right) that observers in PUN impose on their respective counterpart, and 95% confidence intervals. The graph is based on 280 observers of buyers and 265 observers of sellers who answered the control question correctly.

Figure 65 illustrates that most observers (around 86%) choose costly punishment. In addition, on average observers spend more than half of their extra budget of 3 Euros for punishment. Observers of buyers and sellers do not differ in the punishment probability (86% vs. 85%, p = 0.886, two-sample test of proportions) and in the average amount spent for punishment (1.74 Euros vs. 1.81 Euros, p = 0.39, MWU).

on the four variables are: Altruism: -0.1089 (0.0142); Average Morality: -0.0978 (0.0063); Ethical Consumption: -0.0650 (0.0142); Voluntary Work: -0.0007 (0.0008), resulting in p-values of $p<0.001$ for all variables except for Voluntary Work, which has a p-value of 0.368.

Table 16: DETERMINANTS OF ENTRY AND MONETARY COMPENSATIONS-IMPACT OF SOCIOECONOMIC BACKGROUND AND STATED ATTITUDES: REGRESSIONS ON EXPERIMENTAL DATA (CONTROL)

Dependent Variable	Market Entry - Yes/No	Requested Compensation
Sample	Experiment Data	Experiment Data
COND	-0.508***	-0.200
	[0.087]	[0.363]
PUN	-0.120	-0.041
	[0.084]	[0.399]
Seller	-0.205***	1.231***
	[0.071]	[0.313]
Female	-0.217***	0.070
	[0.073]	[0.325]
Age	-0.008***	0.026**
	[0.002]	[0.010]
High School	0.096	0.149
	[0.079]	[0.340]
Persons Household	0.001	-0.054
	[0.035]	[0.148]
High Earner	-0.055	-0.360
	[0.086]	[0.376]
No Income Info	-0.064	-0.138
	[0.099]	[0.438]
Altruism	-0.153***	-0.216
	[0.049]	[0.230]
Ethical Consumption	-0.039	0.049
	[0.049]	[0.210]
Voluntary Work	0.000	0.023**
	[0.003]	[0.011]
Average Morality	-0.307***	0.021
	[0.023]	[0.108]
Non-Voter	0.229	-0.090
	[0.142]	[0.572]
Constant	1.513 ***	7.821***
	[0.248]	[1.067]
Model	Probit	Linear
# of Observations	1653	606
# of Simulations	-	-

Notes: Column 1 reports the results of a probit regression of Market Entry (1 in case of entry, 0 in case of no entry) based on our observed data of participants who answered the control question correctly. Column 2 reports the results of a linear regression based on participants who answered the control question correctly that uses the required compensation of traders as the dependent variable. PUN and COND are binary dummy variables for the respective treatments PUN and COND (the reference condition is BASE). *, ** and *** denominate significance at the 10%, 5% and 1% levels, respectively.

Table 17: DETERMINANTS OF PUNISHMENT-IMPACT OF SOCIOECONOMIC BACKGROUND AND STATED ATTITUDES (CONTROL)

Model No.	1
Dependent Variable	Punishment - Yes/No
Seller	-0.016
	[0.137]
Female	0.068
	[0.143]
Age	0.010**
	[0.004]
High School	-0.002
	[0.160]
Persons Household	0.069
	[0.066]
High Earner	0.027
	[0.165]
No Income Info	0.070
	[0.202]
Altruism	0.156*
	[0.093]
Ethical Consumption	0.085
	[0.090]
Voluntary Work	0.009
	[0.008]
Average Morality	-0.018
	[0.047]
Non-Voter	-0.076
	[0.249]
Constant	0.137
	[0.442]
Model	Probit
Observations	545

Notes: Model 1 is a probit specification that uses a dummy dependent variable equal to one if the observer decided to punish the trader based on our observed data of participants who answered the control question correctly. Standard errors are given in brackets. *, ** and *** denominate significance at the 10%, 5% and 1% levels, respectively.

5.8.5 Experimental Instructions

In the following, a translation of the experimental instructions and decision situation of sellers in COND is displayed. The other treatments and roles were given similar instructions, which will be provided on request. In addition, all participants filled in a survey on demographics, opinions, and other outcome variables, which will also be provided on request.

Page 1

Welcome to a new survey in the PAYBACK Online Panel.

Thank you very much for your willingness to participate in this scientific experiment, which we are conducting on behalf of **infratest dimap**. The experiment was designed by a research team led by Prof. Vitali Gretschko (Centre for European Economic Research in Mannheim) and Prof. Peter Werner (University of Maastricht in the Netherlands) and will subsequently be evaluated by them.

The participation takes about 20 minutes. You will be credited **200 Payback points** for fully answering today's survey.

In this study, you have the **opportunity to earn additional money**. The amount depends, among other things, on how you decide during the experiment. About three weeks after the end of the study, you will receive information as to whether and how much additional money you have earned. You can transfer the additional money you have earned to your bank account or have it paid out in PAYBACK points.

PLEASE NOTE: The participation via PC, Laptop, or Tablet is clearly more comfortable.

Your decisions and answers will, of course, be evaluated anonymously. Your possible payoffs will not be communicated to any other participant.

Likewise, you will not be informed of any payoffs made by other participants. Your decisions and answers will be anonymously linked with demographic data (e.g., gender or marital status) and socio-economic data (e.g., occupation or income). Thereby, it can be used to investigate whether there are differences between decisions and responses from different groups of participants.

No personal information is passed on to third parties, and it is not possible to identify people at any time during the statistical evaluation.

Thank you very much for your support and enjoy filling out the questionnaire. Your PAYBACK Online Panel Team

Page 2

This study is an experiment in which you participate either as a buyer or as a seller. As a result of the experiment, you can either earn additional money or ensure that children in developing countries are vaccinated against measles.

On the following pages, the rules of the experiment are explained. It is determined by chance whether you belong to the group of buyers or sellers. All information is true, and all decisions are implemented exactly as described. After the experiment, you will receive proof of the money paid for measles vaccinations upon request. All participants receive exactly the same information about how this experiment works.

Please read the descriptions carefully and do not proceed with the study until you have understood everything. The Continue button will be activated after 10 seconds.

Page 3 The experiment is about **vaccinations against measles**.

Measles are highly contagious and spread rapidly, especially in overcrowded shelters and refugee camps. In case of weakened children, the infectious disease is often fatal. Vaccinations offer reliable protection against measles. Especially after natural disasters or in crisis regions, UNICEF organises large vaccination campaigns that reach millions of children. (Source: UNICEF)

Page 4

You are a **seller** in this experiment.

In this experiment, a large number of buyers and sellers (more than 100 each) face each other on a market.

Sellers have coupons and can decide whether they want to keep them or sell them.

Buyers can decide whether they want to buy coupons or not.

You are one of those sellers who each has a coupon.

Page 5

The decisions of buyers and sellers have the following consequences:

1. If the coupon remains in the seller's possession, it will be exchanged for 50 vaccinations against measles at the end of the experiment. For this purpose, 18 Euro will be donated to UNICEF.

2. If the coupon is bought by a buyer at market price, it will be exchanged for 18 Euro after the experiment. Then the seller receives the market price in Euro, and the buyer receives 18 Euro minus the market price.

The payoffs are then:

- Payoff seller = market price in Euro

- Payoff buyer = 18 Euro - market price in Euro

Page 6

You and the other sellers face a large number of potential buyers.

As a seller, you now have two options, which you can make dependent on how other participants behave on the market:

1. You are not trading. Thus, at least your coupon is not traded and is exchanged accordingly in 50 vaccinations against measles. You will then not receive any payment in Euro.
2. You are trying to sell a coupon and thereby receive a payment in Euro.

Page 7

If you want to sell the coupon, you have to make an offer between 0 and 18 Euros. The offer is the **minimum** amount you would like to receive for the coupon.

Page 8

Besides you, there are other sellers who make offers on the market; there is a market for sellers and buyers. The buyers, in turn, make offers on how much money they want to spend maximally for one coupon (0 to 18 Euros).

Page 9

After sellers and buyers have submitted their offers, the **market price** is determined: Therefore, the sellers' offers are sorted from the smallest to the largest and the buyers' offers from the largest to the smallest.

Page 10

The **market price** is the highest bid of a seller which does not exceed the buyer's bid in the same row.

In this example, the market price is 6 Euros.

- In this example, if you offered 3 Euros, which is less than the market price, you would sell your coupon and receive 6 Euros.
- In this example, if you offered 11 Euros, which is greater than the market price, you would keep your coupon. In this case, your coupon would be exchanged for 50 vaccinations.

Page 11

You can only sell your coupon if your offer is **not above** the determined market price. If there are more sellers than buyers who want to trade at this market price, it is randomly determined which sellers are trading.

Page 12

If you trade, you sell your coupon to a buyer and receive the market price in Euro. The buyer then receives the difference between 18 Euro and the market price.

Page 13

If your offer is **above** the determined market price, you will not sell your coupon and will not receive money. In this case, your coupon will be exchanged for 50 vaccinations against measles.

Page 14

If you additionally would like to make your participation in the market dependent on how other market participants behave, you have the following options:

You can specify what percentage of other market participants would have to forego trading in order for you to also forego trading.

Based on the information provided by the other participants, we then evaluate whether or not you forego trading.

Page 15

Example:

You indicate that you would forego trading if at least 60% of the other market participants did the same. Now there are two possibilities:

1. At least 60% of the other participants answered the question with a value of 60% or less or in principle forego trading. In this case, you and these participants will not trade.

2. Less than 60% of the other participants answered the question with a value of 60% or less or in principle forego trading. In this case, you will trade.

Page 16

We would like to ask you now a comprehension question about the experiment we just described: What happens if you submit an offer of 10 Euros, thus demand at least 10 Euros for your coupon, and the market price determined at the end is 9 Euros?

a) I sell my coupon at the market price of 9 Euro

b) I do not buy my coupon and my coupon is exchanged for 50 measles vaccinations

Page 17

Please indicate if you want to make an offer to sell a coupon or if you do not wish to trade.

a) I would not like to trade

b) I would like to forego trading if at least {0;10;...;100} % of other market participants decide that way.

c) I would like to make an offer to sell the coupon in any case.

Please submit your offer now. Your offer is the minimum amount you would like to receive for the coupon: 0 Euros - 18 Euros.

Page 18

You require at least 9 Euros for your coupon.

1. If the market price determined at the end is smaller than 9 Euros or at least 30% of the other market participants forego trading, you do not trade. One coupon will be exchanged for 50 vaccinations against measles.

2. If the market price determined at the end is 9 Euros or more, you would like to trade and therefore forego a donation if not at least 30% of the other market participants do not trade.

a) Confirm the offer

b) Change the offer

Page 19 (only if the participant indicated that she wants to change the offer)

Please indicate under which conditions you would like to make an offer to sell the coupon. You will not be able to change this offer afterward. Please enter only whole numbers and tens steps for the percentage (0, 10, 20, 30, etc.).

a) I would like to forego trading if at least {0;10;...;100}% of other market participants decide that way.

b) I would like to make an offer to sell the coupon in any case. Please submit your modified offer now. Your offer is the maximum amount you would like to spend on the coupon. You cannot change this offer afterward.

5.8.6 A simple model of norm conformity

The model's primary purpose is to provide a simple analytical framework of norm uncertainty that includes the main characteristics of the market interaction in our experiment and can organize our results concerning conditional conformity behavior.

The model Consider a continuous society of agents. Here, society may reflect, for example, the group of potential market participants in our experiment. The agents of the society trade in a double auction market with a uniform pricing rule. Half of the agents are sellers, and half are buyers. Offers from sellers are ranked from lowest to highest. Offers from buyers are ranked from highest to lowest. Pick the lowest offer of a seller that does not exceed the respective offer of a buyer with the same rank. The market price is the average of the offers of this seller and this buyer. [80] Buyers with offers (weakly) above the market price buy at the market price. Sellers with offers (weakly) below the market price sell at the market price. Each buyer´s valuation of the good is $v \in \mathbb{R}_+$, each seller´s cost is zero. The trade of the good induces an externality normalized to 1. Agents differ in the extent to which they consider externalities they generate by trade immoral. That is, each agent is represented by a (morality-)type θ. Sellers and buyers are uniformly distributed across society. For each given agent θ it is equally likely that this agent is a seller or a buyer. Society is either "immoral" or "moral". If the society is 'immoral', each agent is represented by a morality type $\theta \in [0, b]$. If the society is "moral", each agent is represented by a morality type $\theta \in [a, c]$, with $0 < a < b < c$. Hence, we define morality within society as the distribution of moral concerns; the "moral"

[80] For convenience of notation, this is a different pricing rule than in the experiment. However, with a continuous population every uniform pricing rule yields the same results.

society here consists of a larger proportion of agents who experience relatively high moral costs due to the externality. Agents are ex-ante uncertain in which society they live, and both societies are equally likely. A graphical illustration of the model can be found in Figure 66 below.

Observation 1. *Agents with types strictly below a learn from observing their type that the society is "immoral". Agents with types strictly above b learn that the "society" is "moral". Agents with types between a and b are uncertain about society. Our model reflects that market participants with low morality concerns believe that society is less concerned with the externality. If the morality type increases, so does the perception of morality in society. Our model is a simple way to incorporate such dynamics.*

To simplify notation, we define $\mu_\theta(x)$ *as the density of the morality distribution in the society from the point of view of agent* θ*. That is, for agents with* $\theta < a$, $\mu_\theta(x)$ *(x) is* $1/b$ *for* $0 < x < b$ *and zero otherwise. For agents with* $\theta > b$, $\mu_\theta(x)$ *is* $1/(c-a)$ *for* $a < x < c$ *and zero otherwise. For agents with* $a < \theta < b$, $\mu_\theta(x)$ *is* $0.5/c$ *for* $0 < x < c$ *and zero otherwise.*

Agents do not only care about their own perception of whether trade is immoral but also about the average perception of all other agents in society. The relative importance of the society's types is measured by $\gamma > 0$*. The willingness to pay for the good of a buyer is*

$$v - \theta - \gamma \int_{x \in [0,c]} x\mu_\theta(x)dx \tag{189}$$

and the willingness to accept of a seller x is

$$\theta + \gamma \int_{x \in [0,c]} x\mu_\theta(x)dx. \tag{190}$$

Each agent cares about her own externality-type and the average type in the society and experiences disutility both from causing the externality and *deviating from the average morality in society. We denote by*

$$\mathbb{E}(\theta) = \int_{x\in[0,c]} x\mu_\theta(x)dx. \tag{191}$$

the expected average morality type in the society for each type θ. Our goal is to organize the results from the COND treatment along the lines of a simple model. Thus, we make the following assumption to keep the exposition as clear as possible.

Assumption 1. *The market is covered and morality is relevant. That is, $b+\gamma\frac{(a+c)}{2} > v > a+\gamma\frac{b}{2}$.*

This assumption guarantees that all low morality types enter the market (the market is covered), while all high morality types do not enter (morality is relevant).

Assumption 2. *The market is symmetric. That is, $a = c - b$.*

Assuming symmetry greatly simplifies exposition without influencing main intuitions.

Unconditional market entry Consider the setup of the BASE treatment. Each agent decides whether to enter the market and which price to bid conditional on entry. The following proposition summarizes equilibrium bidding.

Proposition 12. *Entering the market whenever $\theta \leq \tilde{\theta} = v - \gamma\frac{(a+b+c)}{4}$, bidding*

$$p(\theta) = \begin{cases} v - \gamma\frac{b}{2} - \theta & \theta < a \\ v - \gamma\frac{a+b+c}{4} - \theta & a < \theta < b \end{cases} \tag{192}$$

for buyers, and bidding

$$p(\theta) = \begin{cases} \gamma\frac{b}{2} + \theta & \theta < a \\ \gamma\frac{a+b+c}{4} + \theta & a < \theta < b \end{cases} \tag{193}$$

for sellers constitutes a Bayes-Nash equilibrium of the double auction with unconditional entry.

Proof. Due to the continuum of agents, each agent has a weight of zero and her bid does not change the price. Therefore, it is optimal to (i) enter whenever a positive gain from trade is possible and (ii) bid the price at which an agent is indifferent between trading and not trading considering the information about the society contained in the price.

That is, a buyer bids

$$v - \theta - \gamma\mathbb{E}(\theta|p_\theta) = p_\theta \tag{194}$$

and a seller bids

$$\theta_x + \gamma\mathbb{E}(\theta|p_\theta) = p_\theta \tag{195}$$

With $\mathbb{E}(\theta|p)$ denoting the conditional expectation of the morality in the society of type θ given the equilibrium price p. As the demand of the buyers is symmetric to the supply of the sellers, the equilibrium price is $v/2$ almost surely. That is, in the situation at hand, the equilibrium price contains no information with probability one. To see this more formally, pick the lowest offer of a seller that does not exceed the offer of the buyer with the same rank. Denote the offer of this seller by s^* and the offer of the respective buyer by b^*. As the society is continuous and each type is equally likely to be a seller or a buyer, it holds that the probability of the event $b^* - s^* < \epsilon$ is one for all $\epsilon > 0$. From the proposed bidding functions, it follows that for the type of the buyer $\theta_{(b^*)}$ and for the type of the seller $\theta_{(s^*)}$, it holds $\theta_{(s^*)} - \theta_{(b^*)} < \epsilon$ with probability one for all $\epsilon > 0$.

The price is determined by

$$0.5(v - \theta_{(b^*)} - \gamma\frac{b^*}{2}) + 0.5(\theta_{(s^*)} + \gamma\frac{b}{2}) = p. \tag{196}$$

or

$$0.5(v - \theta_{(b^*)} - \gamma\frac{a+b+c}{4}) + 0.5(\theta_{(s^*)} + \gamma\frac{a+b+c}{4}) = p. \tag{197}$$

As $\theta_{(s^*)} - \theta_{(b^*)} < \epsilon$ with probability one for all $\epsilon > 0$, both equations reduce to p=v/2 with probability one. Given that the price contains no information, a buyer bids $p_\theta = v - \theta - \gamma\mathbb{E}(\theta)$ and a seller $p_\theta = \theta + \gamma\mathbb{E}(\theta)$. For agents with types below a, $\mathbb{E}(\theta) = b/2$, for types between a and b, $\mathbb{E}(\theta) = (a + b + c)/4$. Types above b never enter due to Assumption 1. This yields the bidding functions from Proposition 1. The cut-off type θ_α, who is indifferent between entering and not entering, is determined by $\theta_\alpha = v - \gamma\mathbb{E}(\theta)$. Due to Assumption 1, substituting $\mathbb{E}(\theta) = \frac{(a+b+c)}{4}$ into the bids and the cut-off type yields the remaining result.

□

Proposition 1 reflects that a single agent is not pivotal for setting the price in a uniform price auction with many agents. Thus, sellers offer their willingness to accept and buyers bid their willingness to pay given their information. The bidding functions reflect the moral concerns: buyers and sellers have to be compensated both for their personal moral costs associated with the externality and for the disutility caused by deviating from the social norm. As the demand of the buyers is symmetric to the supply of the sellers, the price does not carry any information about the morality of society. Agents, therefore, bid according to their prior. Agents with low types know that they live in an "immoral" society. Thus, they bid more aggressively than agents who are uncertain.

Conditional market entry Consider the set-up of the COND treatment. Each market participant decides whether she wants to enter the market unconditionally, whether she wants to not enter the market unconditionally, or whether she wants to condition her market-entry on the decisions of other agents. If she decides to make a conditional decision, she can choose a critical threshold α such that she foregoes entering the market if at least α of the other participants do not enter the market either. To determine which participants then actually enter the market, a fixed point α^* is calculated such that given α^* of all participants do not trade, more than α^* of all participants do not want to trade. If more than one such fixed point exists, take the maximum α^*. All participants that enter unconditionally or choose a critical α larger than α^* enter the market, while all other participants do not enter.

Proposition 13. *The following constitutes a Bayes-Nash equilibrium of the double auction with conditional entry. All types $\theta \leq v - \gamma\frac{a+c}{2}$ enter unconditionally. All types $\theta \geq v - \gamma\frac{b}{2}$ stay out of the market unconditionally. All types $\theta \in (v - \gamma\frac{a+c}{2}, v - \gamma\frac{b}{2})$ choose*

$$\alpha = \frac{b - v + \gamma\frac{a+c}{2}}{b}. \tag{198}$$

Buyers entering unconditionally bid

$$p(\theta) = \begin{cases} v - \gamma\frac{b}{2} - \theta & \theta < a \\ v - \gamma\frac{a+b+c}{4} - \theta & a < \theta \end{cases} \tag{199}$$

Sellers entering unconditionally bid

$$p(\theta) = \begin{cases} \gamma\frac{b}{2} + \theta & \theta < a \\ \gamma\frac{a+b+c}{4} + \theta & a < \theta \end{cases} \tag{200}$$

Buyers entering conditionally bid

$$p(\theta) = v - \gamma\frac{b}{2} - \theta. \tag{201}$$

Sellers entering conditionally bid

$$p(\theta) = \gamma\frac{b}{2} + \theta_x. \tag{202}$$

Proof. We start with the observation that by choosing $\alpha = \frac{b-v+\gamma\frac{a+c}{2}}{b}$ all conditional types make sure that they enter if and only if the society is "moral". This choice of α equals the total share of conditional entrants and unconditional non-entrants if the society is "moral". Thus, it is smaller than the total share of conditional entrants and unconditional non-entrants in case the society turns out to be "immoral".

An agent is indifferent between entering unconditionally and entering conditionally if her expected gains from trade are the same for conditional and unconditional entry. Hence, the cut-off type $\underline{\theta}$ is determined by $v - \gamma\frac{a+b+c}{4} - \theta_\beta = \frac{1}{2}(v - \gamma\frac{b}{2} - \theta_\beta)$. An agent is indifferent between entering conditionally and not entering if her expected gain from (conditional) trade equals zero. That is, the cut-off type $\bar{\theta}$ is determined by $\frac{1}{2}(v - \gamma\frac{b}{2} - \theta_\delta) = 0$.

As in the proof of Proposition 1, once entered, there is no additional information contained in the equilibrium price. Thus, agents bid according to their expected gains from trade (conditional on trading). Simple calculations then yield the remaining results of Proposition 2.

$\square$

With conditional entry, the agents who are uncertain about the morality of the society can make sure that they enter only when it is socially appropriate to do so, i.e., if and only if the society is "immoral". If the society is "moral", there are no agents with types below a who enter no matter what. However, there are agents with types above b who stay out no matter what. Thus, uncertain agents can choose a threshold such that they stay out whenever enough agents also stay out, i.e., the morality types above b.

We now compare the cut-off types with conditional market entry to the cut-off type of the unconditional market. We illustrate that allowing for conditional market entry draws some types who entered in the unconditional market and some types who stayed out in the unconditional market.

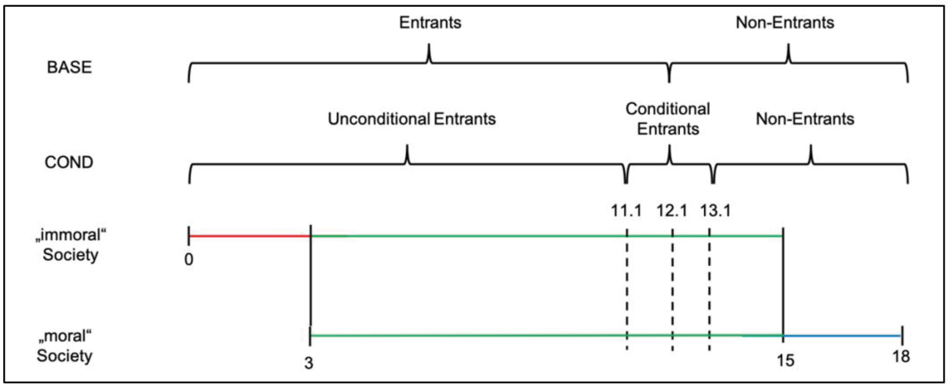
Corollary 3. *Allowing for conditional entry draws morality type who stay out and morality types that enter the market in an unconditional market. That is,* $\underline{\theta} < \tilde{\theta} < \bar{\theta}$.

Proof. Observe that $\underline{\theta} = v - \gamma\frac{a+c}{2} < v - \gamma\frac{c}{2}$. Due to symmetry $v - \gamma\frac{c}{2} = v - \gamma\frac{a+b+c}{4} = \tilde{\theta}$. Moreover, $v - \gamma\frac{a+b+c}{4} = \tilde{\theta} < v - \gamma\frac{b}{2} = \bar{\theta}$. This yields the result.

$\square$

Our simple model organizes the results of the experiment well. Corollary 1 is in line with the observation that the share of entrants in BASE exceeds the share of unconditional entrants in COND, and the share of non-entrants in BASE exceeds the share of unconditional non-entrants in COND. Or, in other words, there exist types that enter in BASE and enter conditionally in COND, as well as types that do not enter in BASE and enter conditionally in COND. If the society turns out to be "moral", however, the realized entry is lower in the COND treatment as in the BASE treatment. A specific example is illustrated in Figure 66.

Figure 66: EXAMPLE FOR THE MODEL WITH V=18, a=3, b=15, c=18, γ=0.65



Notes: This figure shows a specific example for our model with v=18,a=3,b=15,c=18, and γ=0.65. In this case, in the unconditional market, all types below 12.1 enter the market, and the rest stays out. In the conditional market, agents with relatively low moral costs (all types below 11.1) enter unconditionally, whereas relatively moral agents (all types above 12.75) stay out unconditionally. All types with intermediate moral costs (in this example between 11.1 and 13.1) stay out of the market conditionally and set a threshold of α=0.3.

References

Abeler, J., A. Becker, and A. Falk (2014): "Representative evidence on lying costs," *Journal of Public Economics*, 113, 96–104.

Abeler, J., A. Falk, L. Goette, and D. Huffman (2011): "Reference points and effort provision," *American Economic Review*, 101(2), 470–92.

Allcott, H. (2011): "Social norms and energy conservation," *Journal of public Economics*, 95(9-10), 1082–1095.

Allcott, H., and T. Rogers (2014): "The short-run and long-run effects of behavioral interventions: Experimental evidence from energy conservation," *American Economic Review*, 104(10), 3003–37.

Andersson, G. (1996): "The benefits of optimism: A meta-analytic review of the Life Orientation Test," *Personality and Individual Differences*, 21(5), 719–725.

Andre, P., T. Boneva, F. Chopra, and A. Falk (2021): "Fighting climate change: The role of norms, preferences, and moral values," .

Andreoni, J., and B. D. Bernheim (2009): "Social image and the 50–50 norm: A theoretical and experimental analysis of audience effects," *Econometrica*, 77(5), 1607–1636.

Andreoni, J., and J. Miller (2002): "Giving according to GARP: An experimental test of the consistency of preferences for altruism," *Econometrica*, 70(2), 737–753.

Armantier, O., and N. Treich (2009): "Subjective probabilities in games: An application to the overbidding puzzle," *International Economic Review*, 50(4), 1079–1102.

Baker, M., R. S. Ruback, and J. Wurgler (2007): “Behavioral corporate finance,” in *Handbook of empirical corporate finance*, pp. 145–186. Elsevier.

Balafoutas, L., N. Nikiforakis, and B. Rockenbach (2014): “Direct and indirect punishment among strangers in the field,” *Proceedings of the National Academy of Sciences*, 111(45), 15924–15927.

——— (2016): “Altruistic punishment does not increase with the severity of norm violations in the field,” *Nature communications*, 7(1), 1–6.

Banerji, A., and N. Gupta (2014): “Detection, identification, and estimation of loss aversion: Evidence from an auction experiment,” *American Economic Journal: Microeconomics*, 6(1), 91–133.

Barr, A., T. Packard, and D. Serra (2014): “Participatory accountability and collective action: Experimental evidence from Albania,” *European Economic Review*, 68, 250–269.

Bartling, B., V. Valero, R. A. Weber, and L. Yao (2020): “Public discourse and socially responsible market behavior,” *University of Zurich, Department of Economics, Working Paper*, (359).

Bartling, B., R. A. Weber, and L. Yao (2015): “Do markets erode social responsibility?,” *The Quarterly Journal of Economics*, 130(1), 219–266.

Bell, D. E. (1985): “Disappointment in decision making under uncertainty,” *Operations research*, 33(1), 1–27.

Bellemare, C., S. Kröger, and A. Van Soest (2008): “Measuring inequity aversion in a heterogeneous population using experimental decisions and subjective probabilities,” *Econometrica*, 76(4), 815–839.

Belot, M., R. Duch, and L. Miller (2015): "A comprehensive comparison of students and non-students in classic experimental games," *Journal of Economic Behavior & Organization*, 113, 26–33.

Benabou, R., A. Falk, and J. Tirole (2018): "Eliciting moral preferences," *Unpublished manuscript. https://scholar. princeton. edu/sites/default/files/rbenabou/files/moral_preferences_august_9_snd. pdf.*

Bénabou, R., A. Falk, and J. Tirole (2018): "Narratives, imperatives, and moral reasoning," Discussion paper, National Bureau of Economic Research.

Bilen, D., A. Dreber, and M. Johannesson (2021): "Are women more generous than men? A meta-analysis," *Journal of the Economic Science Association*, 7(1), 1–18.

Bolton, G. E., and A. Ockenfels (2000): "ERC: A theory of equity, reciprocity, and competition," *American economic review*, 90(1), 166–193.

Brandon, A., J. A. List, R. D. Metcalfe, M. K. Price, and F. Rundhammer (2019): "Testing for crowd out in social nudges: Evidence from a natural field experiment in the market for electricity," *Proceedings of the National Academy of Sciences*, 116(12), 5293–5298.

Brunnermeier, M. K., and J. A. Parker (2005): "Optimal expectations," *American Economic Review*, 95(4), 1092–1118.

Buehler, R., D. Griffin, and M. Ross (1994): "Exploring the" planning fallacy": Why people underestimate their task completion times.," *Journal of personality and social psychology*, 67(3), 366.

Caplin, A., and J. Leahy (2001): "Psychological expected utility theory and anticipatory feelings," *The Quarterly Journal of Economics*, 116(1), 55–79.

Chaudhuri, A. (2011): "Sustaining cooperation in laboratory public goods experiments: a selective survey of the literature," *Experimental economics*, 14(1), 47–83.

Chen, D. L., M. Schonger, and C. Wickens (2016a): "oTree - An open-source platform for laboratory, online, and field experiments," *Journal of Behavioral and Experimental Finance*, 9, 88–97.

Chen, D. L., M. Schonger, and C. Wickens (2016b): "oTree—An open-source platform for laboratory, online, and field experiments," *Journal of Behavioral and Experimental Finance*, 9, 88 – 97.

Chen, Y., F. M. Harper, J. Konstan, and S. X. Li (2010): "Social comparisons and contributions to online communities: A field experiment on movielens," *American Economic Review*, 100(4), 1358–98.

Chen, Y., F. Lu, and J. Zhang (2017): "Social comparisons, status and driving behavior," *Journal of Public Economics*, 155, 11–20.

Cooper, D. J., and J. H. Kagel (2009): "Other regarding Preferences: A selective survey...," .

Croson, R., and U. Gneezy (2009): "Gender differences in preferences," *Journal of Economic literature*, 47(2), 448–74.

Danilov, A., and D. Sliwka (2017): "Can contracts signal social norms? Experimental evidence," *Management Science*, 63(2), 459–476.

Deckers, T., A. Falk, F. Kosse, and N. Szech (2016): "Homo moralis:

Personal characteristics, institutions, and moral decision-making," *Institutions, and Moral Decision-Making (March 10, 2016)*.

DellaVigna, S. (2009): "Psychology and economics: Evidence from the field," *Journal of Economic literature*, 47(2), 315–72.

Dohmen, T., A. Falk, D. Huffman, and U. Sunde (2009): "Homo reciprocans: Survey evidence on behavioural outcomes," *The Economic Journal*, 119(536), 592–612.

Dohmen, T., A. Falk, D. Huffman, U. Sunde, J. Schupp, and G. G. Wagner (2011): "Individual risk attitudes: Measurement, determinants, and behavioral consequences," *Journal of the european economic association*, 9(3), 522–550.

Drobner, C. (2022): "Motivated beliefs and anticipation of uncertainty resolution," *American Economic Review: Insights*, 4(1), 89–105.

Dur, R., and B. Vollaard (2015): "The power of a bad example: A field experiment in household garbage disposal," *Environment and Behavior*, 47(9), 970–1000.

Ehrhart, K., and M. Ott (2014): "Reference-dependent bidding in dynamic auctions," Discussion paper, Mimeo.

Eisenhuth, R., and M. Ewers (2012): "Auctions with loss averse bidders," Discussion paper, Citeseer.

Elias, J. J., N. Lacetera, and M. Macis (2019): "Paying for kidneys? A randomized survey and choice experiment," *American Economic Review*, 109(8), 2855–88.

Engel, C. (2011): “Dictator games: A meta study,” *Experimental economics*, 14(4), 583–610.

Engelbrecht-Wiggans, R., and E. Katok (2007): “Regret in auctions: theory and evidence,” *Economic Theory*, 33(1), 81–101.

Engelmann, D., J. Friedrichsen, and D. Kuebler (2018): “Fairness in markets and market experiments,” Discussion paper, WZB Discussion Paper.

Falk, A., A. Becker, T. Dohmen, B. Enke, D. Huffman, and U. Sunde (2018): “Global evidence on economic preferences,” *The Quarterly Journal of Economics*, 133(4), 1645–1692.

Falk, A., S. Meier, and C. Zehnder (2013): “Do lab experiments misrepresent social preferences? The case of self-selected student samples,” *Journal of the European Economic Association*, 11(4), 839–852.

Falk, A., T. Neuber, and N. Szech (2020): “Diffusion of being pivotal and immoral outcomes,” *The Review of Economic Studies*, 87(5), 2205–2229.

Falk, A., and N. Szech (2013): “Morals and markets,” *science*, 340(6133), 707–711.

Fehr, E., U. Fischbacher, and S. Gaechter (2002): “Strong reciprocity, human cooperation, and the enforcement of social norms,” *Human nature*, 13(1), 1–25.

Fehr, E., and S. Gaechter (2000): “Cooperation and punishment in public goods experiments,” *American Economic Review*, 90(4), 980–994.

Fehr, E., and K. M. Schmidt (1999): “A theory of fairness, competition, and cooperation,” *The quarterly journal of economics*, 114(3), 817–868.

——— (2006): “The economics of fairness, reciprocity and altruism–experimental evidence and new theories,” *Handbook of the economics of giving, altruism and reciprocity*, 1, 615–691.

Feldhaus, C., T. Sobotta, and P. Werner (2019): “Norm uncertainty and voluntary payments in the field,” *Management Science*, 65(4), 1855–1866.

Fellner, G., R. Sausgruber, and C. Traxler (2013): “Testing enforcement strategies in the field: Threat, moral appeal and social information,” *Journal of the European Economic Association*, 11(3), 634–660.

Ferraro, P. J., and M. K. Price (2013): “Using nonpecuniary strategies to influence behavior: evidence from a large-scale field experiment,” *Review of Economics and Statistics*, 95(1), 64–73.

Fischbacher, U., and S. Gaechter (2010): “Social preferences, beliefs, and the dynamics of free riding in public goods experiments,” *American economic review*, 100(1), 541–56.

Fischbacher, U., S. Gaechter, and E. Fehr (2001): “Are people conditionally cooperative? Evidence from a public goods experiment,” *Economics letters*, 71(3), 397–404.

Frey, B. S., and S. Meier (2004): “Social comparisons and pro-social behavior: Testing” conditional cooperation” in a field experiment,” *American economic review*, 94(5), 1717–1722.

Friedrichsen, J., and D. Engelmann (2018): “Who cares about social image?,” *European Economic Review*, 110, 61–77.

Gächter, S., E. J. Johnson, and A. Herrmann (2007): "Individual-level loss aversion in riskless and risky choices," .

Gill, D., and V. Prowse (2019): "Measuring costly effort using the slider task," *Journal of Behavioral and Experimental Finance*, 21, 1–9.

Gneezy, U., A. Leibbrandt, and J. A. List (2016): "Ode to the sea: Workplace organizations and norms of cooperation," *The Economic Journal*, 126(595), 1856–1883.

Gollier, C., and A. Muermann (2010): "Optimal choice and beliefs with ex ante savoring and ex post disappointment," *Management Science*, 56(8), 1272–1284.

Greiner, B. (2015): "Subject pool recruitment procedures: organizing experiments with ORSEE," *Journal of the Economic Science Association*, 1(1), 114–125.

Hallsworth, M., J. A. List, R. D. Metcalfe, and I. Vlaev (2017): "The behavioralist as tax collector: Using natural field experiments to enhance tax compliance," *Journal of public economics*, 148, 14–31.

Harrison, G. W., and J. A. List (2004): "Field experiments," *Journal of Economic literature*, 42(4), 1009–1055.

Heffetz, O., and J. A. List (2014): "Is the endowment effect an expectations effect?," *Journal of the European Economic Association*, 12(5), 1396–1422.

Herrmann, B., C. Thoni, and S. Gachter (2008): "Antisocial punishment across societies," *Science*, 319(5868), 1362–1367.

Herweg, F., D. Müller, and P. Weinschenk (2010): "Binary payment schemes: Moral hazard and loss aversion," *American Economic Review*, 100(5), 2451–77.

Horowitz, J. K., and K. E. McConnell (2003): "Willingness to accept, willingness to pay and the income effect," *Journal of Economic Behavior & Organization*, 51(4), 537–545.

Irlenbusch, B., and D. J. Saxler (2019): "The role of social information, market framing, and diffusion of responsibility as determinants of socially responsible behavior," *Journal of Behavioral and Experimental Economics*, 80, 141–161.

Ito, K., T. Ida, and M. Tanaka (2018): "Moral suasion and economic incentives: Field experimental evidence from energy demand," *American Economic Journal: Economic Policy*, 10(1), 240–67.

Kagel, J. H., and D. Levin (2002): *Common value auctions and the winner's curse*. Princeton University Press.

Kagel, J. H., and A. E. Roth (2020): *The handbook of experimental economics, volume 2*. Princeton university press.

Kahneman, D., J. L. Knetsch, and R. H. Thaler (1990): "Experimental tests of the endowment effect and the Coase theorem," *Journal of political Economy*, 98(6), 1325–1348.

——— (1991): "Anomalies: The endowment effect, loss aversion, and status quo bias," *Journal of Economic perspectives*, 5(1), 193–206.

Kimbrough, E. O., and A. Vostroknutov (2016): "Norms make preferences social," *Journal of the European Economic Association*, 14(3), 608–638.

Kirchler, M., J. Huber, M. Stefan, and M. Sutter (2016): "Market design and moral behavior," *Management Science*, 62(9), 2615–2625.

Kőszegi, B., and M. Rabin (2006): "A model of reference-dependent preferences," *The Quarterly Journal of Economics*, 121(4), 1133–1165.

Krishna, V. (2009): *Auction theory*. Academic press.

Krupka, E. L., and R. A. Weber (2013): "Identifying social norms using coordination games: Why does dictator game sharing vary?," *Journal of the European Economic Association*, 11(3), 495–524.

Lange, A., and A. Ratan (2010): "Multi-dimensional reference-dependent preferences in sealed-bid auctions–How (most) laboratory experiments differ from the field," *Games and Economic Behavior*, 68(2), 634–645.

Loewenstein, G. (1987): "Anticipation and the valuation of delayed consumption," *The Economic Journal*, 97(387), 666–684.

Maskin, E., and J. Riley (1984): "Optimal Auctions with Risk Averse Buyers," *Econometrica*, 52(6), 1473–1518.

Matsumoto, Y., T. Yamagishi, Y. Li, and T. Kiyonari (2016): "Prosocial behavior increases with age across five economic games," *PloS one*, 11(7), e0158671.

Nathan, B. C., R. Perez-Truglia, and A. Zentner (2020): "My Taxes are Too Darn High: Why Do Households Protest Their Taxes?," Discussion paper, National Bureau of Economic Research.

Ockenfels, A., P. Werner, and O. Edenhofer (2020): "Pricing externalities and moral behaviour," *Nature Sustainability*, 3(10), 872–877.

Pigors, M., and B. Rockenbach (2016): “Consumer social responsibility,” *Management Science*, 62(11), 3123–3137.

Pruckner, G. J., and R. Sausgruber (2013): “Honesty on the streets: A field study on newspaper purchasing,” *Journal of the European Economic Association*, 11(3), 661–679.

Reuben, E., and A. Riedl (2013): “Enforcement of contribution norms in public good games with heterogeneous populations,” *Games and Economic Behavior*, 77(1), 122–137.

Riedl, A., H. Schmeets, and P. Werner (2019): “Preferences for solidarity and attitudes towards the dutch pension system: Evidence from a representative sample,” *NETSPAR Design Paper*, 128.

Rode, J., R. M. Hogarth, and M. Le Menestrel (2008): “Ethical differentiation and market behavior: An experimental approach,” *Journal of Economic Behavior & Organization*, 66(2), 265–280.

Rosato, A., and A. A. Tymula (2019): “Loss aversion and competition in Vickrey auctions: Money ain’t no good,” *Games and Economic Behavior*, 115, 188–208.

Rustagi, D., S. Engel, and M. Kosfeld (2010): “Conditional cooperation and costly monitoring explain success in forest commons management,” *science*, 330(6006), 961–965.

Seaward, H. G., and S. Kemp (2000): “Optimism bias and student debt,” *New Zealand Journal of Psychology*, 29(1), 17.

Shang, J., and R. Croson (2009): “A field experiment in charitable contribution: The impact of social information on the voluntary provision of public goods,” *The economic journal*, 119(540), 1422–1439.

Shepperd, J. A., J. A. Ouellette, and J. K. Fernandez (1996): "Abandoning unrealistic optimism: Performance estimates and the temporal proximity of self-relevant feedback.," *Journal of Personality and Social Psychology*, 70(4), 844.

Snowberg, E., and L. Yariv (2021): "Testing the waters: Behavior across participant pools," *American Economic Review*, 111(2), 687–719.

Sturm, B., J. Pei, R. Wang, A. Loeschel, and Z. Zhao (2019): "Conditional cooperation in case of a global public good–Experimental evidence from climate change mitigation in Beijing," *China Economic Review*, 56, 101308.

Sutter, M., J. Huber, M. Kirchler, M. Stefan, and M. Walzl (2020): "Where to look for the morals in markets?," *Experimental Economics*, 23(1), 30–52.

Sutter, M., and M. G. Kocher (2007): "Trust and trustworthiness across different age groups," *Games and Economic behavior*, 59(2), 364–382.

Taylor, K. M., and J. A. Shepperd (1998): "Bracing for the worst: Severity, testing, and feedback timing as moderators of the optimistic bias," *Personality and Social Psychology Bulletin*, 24(9), 915–926.

Thoni, C., and S. Volk (2018): "Conditional cooperation: Review and refinement," *Economics Letters*, 171, 37–40.

Van Dijk, W. W., M. Zeelenberg, and J. Van der Pligt (2003): "Blessed are those who expect nothing: Lowering expectations as a way of avoiding disappointment," *Journal of Economic Psychology*, 24(4), 505–516.

von Wangenheim, J. (2019): "English versus Vickrey Auctions with Loss Averse Bidders," Discussion paper, CRC TRR 190 Rationality and Competition.

Weinstein, N. D. (1980): "Unrealistic optimism about future life events.," *Journal of personality and social psychology*, 39(5), 806.

Ziegler, A., G. Romagnoli, and T. Offerman (2020): "Morals in multi-unit markets," Discussion paper, Tinbergen Institute Discussion Paper.