Behavioral and financial change

Essays in market design

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This thesis consists of three essays in the realm of market design covering two topics: incentives for behavioral change and allocation mechanisms in reward-based crowdfunding. In the first essay, I use theoretical analysis and a field experiment to investigate whether introducing a betting market can help people to follow through with their plans to lead a healthier life. In the second and third essay, I use theory and laboratory experiments to examine whether a new allocation mechanism can improve reward-based crowdfunding practice.

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Behavioral and Financial Change – Essays in Market Design Andrej Woerner

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Behavioral and Financial Change – Essays in Market Design

Andrej Woerner

Universiteit van Amsterdam

BEHAVIORAL AND FINANCIAL CHANGE – ESSAYS IN MARKET DESIGN

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BEHAVIORAL AND FINANCIAL CHANGE – ESSAYS IN MARKET DESIGN

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prof. dr. ir. K.I.J. Maex

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Andrej Woerner

Munich, August 2021

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Chapter 1

Introduction

This thesis consists of three chapters in the realm of market design. While traditional fields of economics are more concerned with understanding the outcomes of existing markets and mechanisms, the field of market design focuses on improving or creating new markets. Despite its relative novelty, the market design literature has already left a prominent real-world impact in various areas such as environmental regulation, organ transplantation and spectrum allocation.[1]

The idea to develop new markets and mechanisms to improve real-world outcomes also serves as the underlying motivation of this thesis. I study two important areas that so far have been somewhat neglected in the market design literature: behavioral and financial change. In Chapter 2, I investigate whether introducing a betting market can help people to follow through with their plans to lead a healthier life. In Chapters 3 and 4, I examine whether a new allocation mechanism can improve reward-based crowdfunding practice.

[1] See Kominers et al. (2017) for an overview. Early seminal work in market design has led to Nobel Memorial Prizes in Economic Sciences to Alvin Roth and Lloyd Shapley in 2012 *for the theory of stable allocations and the practice of market design* and Paul Milgrom and Robert Wilson in 2020 *for improvements to auction theory and inventions of new auction formats.*

When designing mechanisms to improve or create new markets, theory and experiments are closely intertwined. Theory allows to narrow down one's search among the infinite set of possible mechanisms to those with desirable properties. Experiments then test which of the theoretically promising mechanisms also work in practice. Acknowledging this complementary relationship, my thesis combines theoretical analysis with empirical evidence from field and laboratory experiments.

Thesis Overview

In Chapter 2, titled **Overcoming Time Inconsistency with a Matched Bet: Theory and Evidence from Exercising**, I introduce, theoretically analyze, and experimentally test a new mechanism that helps people overcome their time inconsistency issues.

Many people struggle to follow through with their plans to lead a healthy life. They fall short of their exercising goals, or fail to lose weight and quit smoking. These behavioral problems can result in severe consequences both for the individual and for society. This study introduces and tests an ex-post strictly budget-balanced mechanism, the matched bet, that helps people overcome their time inconsistency issues.

I first introduce a three-period model inspired by DellaVigna and Malmendier (2004) to analyze the effects of a matched bet on individual and social welfare. The model allows agents to have private and individual-specific degrees of time inconsistency, overconfidence, health benefits and effort costs. I show that it is sufficient to know agents' expected baseline investment frequencies to offer a Pareto improving matched bet. My theoretical analysis predicts that participating in a matched bet increases an agent's expected investment frequency. I derive a condition under which an agent is strictly better off. Agents with a high degree of time inconsistency benefit the most from a matched bet. I discuss the different rationale between sophisticated and naive procrastinators to take up a bet. Sophisticated procrastinators use the matched bet as a costless commitment device. In contrast, naive procrastinators (erroneously) expect to win money with it.

In a field experiment on exercising at the University of Amsterdam gym I test whether the matched bet is also a promising device in practice. I use 601 gym members who completed a short online survey and randomize them into two groups. I compare the gym attendance during and after a four-week intervention period between the treatment and control group. In the treatment group, subjects are offered to participate in a matched bet. Participation in the bet is voluntary. Bet participants are grouped with all other participants who attended the gym equally often in the four weeks preceding the intervention. Bet participants earn €5 from their grouped partners for each day they visit the gym (up to the 8th time) within the four-week intervention period. In exchange, participants have to pay the average earnings of their grouped partners.

The experimental results confirm the theoretical predictions. Offering a matched bet has a significantly positive effect on gym attendance. Subjects who were offered to participate in the bet recorded on average 0.87 more gym visits than subjects in the control group. This implies a 38% (0.34 standard deviations) increase in gym attendance. The effect is larger both in absolute and relative terms for people who reported to have procrastinated exercising in the past. The bet take-up rate is 25%. I find that self-reported procrastination issues and low past exercising frequency outside the university gym have a significant positive effect on bet take-up. This suggests that people who benefit the most from taking up a matched bet are also those most likely to participate.

Overall, the matched bet proves a promising mechanism to help people overcome time inconsistency issues, both in theory and in practice. The matched bet could also be applied to other areas in which people exhibit time-inconsistent behavior, such as academic performance, weight loss and smoking cessation.

The third and fourth chapter are about reward-based crowdfunding. Crowdfunding is omnipresent. The rise of the internet and the explosion of social media have made it an important source of funds for, i.a., charities, musicians and startups. Yet, it has received remarkably little attention in the economics literature. In particular, the allocation mechanisms used by reward-based crowdfunding platforms remain under-studied. I aim to fill this gap with the studies in Chapters 3 and 4, which are both based on joint work with Sander Onderstal and Arthur Schram.

In Chapter 3, titled **Comparing Crowdfunding Mechanisms: Introducing the Generalized Moulin-Shenker Mechanism**, we introduce a new, strategy-proof crowdfunding mechanism, the Generalized Moulin-Shenker mechanism (GMS), which generalizes Moulin and Shenker's (1992) serial cost sharing mechanism. We distinguish between a sealed-bid (sGMS) and a dynamic (dGMS) version. The latter is reminiscent of the Japanese auction and is obviously strategy-proof in the sense of Li (2017). We theoretically and experimentally compare sGMS and dGMS to the prevailing All-or-Nothing (AON) mechanism.

We first present a simple model in which the producer can develop an indivisible and excludable public good at fixed costs in order to maximize profits or funding success probability. As is standard in crowdfunding practice, the producer chooses a fundraising threshold and a reservation price, whereas consumers, who have private values for the good, report individual bids. We characterize equilibrium bidding behavior and optimal producer behavior in AON and GMS. We further show that for a sufficiently large crowd of consumers, both sGMS and dGMS perform better than AON in terms of expected profit and success probability; both also outperform AON in terms of aggregate surplus when the producer aims to maximize the likelihood of success.

We test our theoretical predictions in a laboratory experiment. This experiment varies the mechanism between subjects, and the producer objective and production costs within subjects, and thereby allows us to draw conclusions about crowdfunding behavior and outcomes over a wide range of possible scenarios. To capture that crowdfunding typically involves many consumers, we use comparatively large groups with 15 consumers each. We computerize producer choices such that thresholds and reservation prices are automatically set as predicted by theory.

In line with our theoretical predictions, dGMS performs better than sGMS. It also outperforms AON when the producer's objective is to maximize funding success. In contrast to our predictions, however, the performance ranking between AON and sGMS is ambiguous. We show that this can be attributed to the observation that consumers tend to underbid in sGMS.

Chapter 4, titled **Reservation Prices and Thresholds: Producer Behavior in Crowdfunding**, builds on Chapter 3 but focuses on producer behavior. Producers in crowdfunding face a difficult optimization problem and their decisions may strongly impact the outcome of their crowdfunding campaign. Moreover, errors in setting parameters may differentially affect the outcome of distinct mechanisms and may therefore also affect the relative performance of AON, sGMS and dGMS.

In this chapter, we conduct a laboratory experiment that introduces producer decisions. The experimental design closely resembles that used in Chapter 3. Again, we vary the mechanism between subjects, and the producer objective and production costs within subjects. Further, we again use groups of 15 consumers, adding one active producer. However, in contrast to the previous chapter, the producers now decide on the fundraising thresholds and reservation prices. This design allows us to explore the extent to which suboptimal producer behavior explains crowdfunding failures and to check whether, in the case of human producers, dGMS is as promising as the experiment in Chapter 3 suggests.

Contrary to theoretical predictions, we find that AON weakly outperforms both versions of GMS. Even though producer decisions deviate substantially from the theoretical predictions in all three mechanisms, producer payoffs are comparatively robust to these deviations only in AON. In all three mechanisms, producers typically set reasonable thresholds but poor reservation prices.

Our experimental results of Chapters 3 and 4 contribute to explaining why AON is the prevalent reward-based crowdfunding mechanism in practice. Further, our results suggest that the current standard of financing projects when producers aim to maximize funding success probability could be improved upon by implementing a crowdfunding mechanism that is similar to dGMS.

Chapter 2

Overcoming Time Inconsistency with a Matched Bet: Theory and Evidence from Exercising

2.1 Introduction

Many people struggle to follow through on their best intentions. They start with ambitious goals for improving their lifestyle but end up falling short of their exercising, studying and saving goals, or fail to lose weight and

This chapter is based on Woerner (2021). I would like to thank my advisors Sander Onderstal and Arthur Schram for their many helpful comments and suggestions. I would also like to thank Pol Campos-Mercade, Gary Charness, Uri Gneezy, Ben Greiner, Taisuke Imai, Timo Klein, David K. Levine, Michel Maréchal, Heather Royer, Joep Sonnemans, Simon ter Meulen, Leonard Treuren and Max van Lent. The chapter has also greatly benefitted from seminar presentations at the University of Amsterdam, European University Institute and UC San Diego, as well as from conference presentations at IMEBESS, the ESA world meeting, and Advances with Field Experiments Conference. I am grateful to the University Sports Center Amsterdam for their willingness to cooperate in the field experiment, and in particular to Maurice Maas for his administrative support. Financial support from the Research Priority Area Behavioral Economics of the University of Amsterdam is gratefully acknowledged.

quit smoking. These behavioral problems can result in severe consequences both for the individual and for society, and have motivated a rich literature in economics aimed at better understanding time-inconsistent behavior.[1] In recent years, the focus of the literature has shifted towards testing behavioral interventions that could help people overcome time inconsistency issues.[2] Unfortunately, effective interventions tend to be costly, while low-cost interventions tend to be ineffective.

This chapter tries to resolve the trade-off between costs and effectiveness and presents a new mechanism, the matched bet. The matched bet is an easily applicable and strictly budget-balanced mechanism that aims to help people overcome time-inconsistent behavior. In a simple model, I show that the matched-bet mechanism has desirable theoretical properties. In a field experiment on exercising, I show that the matched bet is also an effective mechanism in practice.

The matched bet works as follows: People are offered to participate in a matched bet with a given monetary bet stake. Bet participants are grouped with other participants who are expected to be equally likely to reach a prespecified target. Bet participants obtain a reward equal to the bet stake if they reach the target. In exchange, they have to pay the average reward of their grouped partners.

To illustrate the rules of the matched bet, consider the following simple example: Assume that Anne, Bob and Claire choose to participate in a matched bet on exercising with a bet stake of \$6. Suppose they are grouped together, because they are expected to exercise equally likely. Consider three possible scenarios. In scenario 1, Anne exercises and both Bob and Claire do not exercise. The resulting bet payoffs are \$6 – \$0 = \$6 for Anne

[1] See e.g. Strotz (1955); Laibson (1997); O'Donoghue and Rabin (1999).

[2] See e.g. Charness and Gneezy (2009) and Royer et al. (2015) on exercising, Bachireddy et al. (2019) and Aggarwal et al. (2020) on walking, Fryer Jr (2011) and Lusher (2017) on academic performance, Thaler and Benartzi (2004) and Ashraf et al. (2006) on saving, Burger and Lynham (2010) and Augurzky et al. (2018) on weight loss, and Giné et al. (2010) and Halpern et al. (2015) on smoking cessation.

and \$0 − \$3 = −\$3 for Bob and Claire each. In scenario 2, both Anne and Bob exercise, and Claire does not. The bet payoffs are then \$6 − \$3 = \$3 for both Anne and Bob and \$0 − \$6 = −\$6 for Claire. In scenario 3, Anne, Bob and Claire all exercise, which results in bet payoffs of \$6 − \$6 = \$0 for each.

The matched-bet mechanism has two attractive properties: it is ex-post strictly budget balanced and it is strategically straightforward in that it has an equilibrium in dominant strategies. Note that in all three scenarios, the bet payoffs sum up to zero. This is a property of the matched-bet mechanism: the reward paid to a bet participant is exactly refinanced by the payments obtained from her grouped partners. The matched-bet mechanism is thus ex-post strictly budget-balanced. For this reason, a budget-constrained policy maker can offer a matched bet repeatedly to achieve persistent behavioral change. Comparing scenarios 1 and 2, we observe that Bob increases his bet payoff by \$6 (from −\$3 to \$3) if he exercises. Similarly, comparing scenarios 2 and 3, we observe that Claire increases her bet payoff by \$6 (from −\$6 to \$0) if she exercises. The matched bet thus provides participants with an extra monetary incentive to reach the target. Note that this extra incentive is always equal to the bet stake, so that it does not depend on the behavior of a participant's grouped partners.

Because participants are grouped with other participants who are expected to be equally likely to reach the target, the expected participation costs are zero in equilibrium, which renders participation attractive. Time-inconsistent bet participants can use the extra monetary incentive to counterbalance their present bias. They can do so at zero cost in expectation, because the matching ensures that they are grouped with participants who are expected to be equally likely to reach the prespecified target. Without matching, time-inconsistent people might refrain from taking up a bet. To illustrate, imagine Anne, Bob and Claire knew that they would be grouped also with Arnie and his bodybuilder friends. If Anne, Bob and Claire are prone to procrastinate exercising, they might then reject this unmatched bet to prevent losing too much money in expectation. In contrast, Arnie and his bodybuilder friends, who have no need for more exercise, would not take up a matched bet, but might take up an unmatched bet to win money. Matching is thus crucial to ensure that the 'right' people self-select into the bet. While there exist a few papers that use bets for behavioral change (Halpern et al., 2015; Lusher, 2017), this study is the first to analyze and test a bet mechanism in which participants are grouped based on how likely they are expected to reach a prespecified target.

This chapter tries to answer whether the matched-bet mechanism is effective in helping people overcome time-inconsistent behavior. I introduce a three-period model inspired by DellaVigna and Malmendier (2004) to analyze the effects of a matched bet on individual and social welfare. In period 0, agents decide whether to participate in a matched bet. In period 1, agents decide whether to invest in an investment good such as exercising, studying or saving. If they do, they incur immediate costs. Bet participants are paid depending on their bet outcome. In period 2, agents who invested obtain benefits. I assume agents' time preferences can be expressed by a quasi-hyperbolic discounting model (Phelps and Pollak, 1968; Laibson, 1997; O'Donoghue and Rabin, 1999). Agents who are time-inconsistent undervalue future benefits and thus underinvest in the baseline. My model allows agents to have private and individual-specific degrees of time inconsistency, naiveté, benefits and costs.

I show that it is sufficient to know agents' expected baseline investment frequencies to offer a Pareto improving matched bet. My theoretical analysis predicts that participating in a matched bet increases an agent's expected investment frequency. I show that the matched bet features favorable self-selection into the bet. The more present-biased an agent is, the more likely she is to take up the matched bet. Time-consistent agents do not take up the matched bet. The rationale why time-inconsistent people do take up a matched bet depends on their degree of naiveté. Sophisticated procrastinators, i.e. time-inconsistent agents who are aware of their time inconsistency, use the matched bet as a costless commitment device. In contrast, naive procrastinators, i.e. time-inconsitent agents who are unaware of their time inconsistency, take up the matched bet because they (erroneously) expect to win money with it. Agents with a high degree of time inconsistency benefit most from the matched-bet mechanism. As the matched bet perfectly aligns individual and social welfare, the matched-bet mechanism also increases investment efficiency. I present numerical examples showing that the matched bet is more efficient that an unmatched bet, a subsidy, and a commitment contract.

In a field experiment at a university gym, I test whether the matched bet is also a promising device in practice. I study 601 gym members and randomize them into a treatment and control group. In the treatment group, subjects are *offered* to participate in a matched bet. Participation in the bet is voluntary. Bet participants are grouped with all other participants who attended the gym equally often in the four weeks preceding the intervention. Bet participants earn €5 from their grouped partners for each day they visit the gym (up to the 8th time) within the four-week intervention period. In exchange, participants have to pay the average earnings of their grouped partners. Subjects in the control group are not informed about the matched bet. I compare the gym attendance between the treatment and control group during and after a four-week intervention period.

The experimental results confirm the theoretical predictions. Offering a matched bet has a significant positive effect on gym attendance. Subjects who were offered to participate in the bet recorded on average 0.87 more gym visits than subjects in the control group. This implies a 38% (0.34 standard deviations) increase in gym attendance. The effect is larger both in absolute and relative terms for people who reported to have procrastinated exercising in the past. The bet take-up rate is 25%. I find that self-reported procrastination and low past exercising frequency outside the university gym have a significant positive effect on bet take-up. This suggests that people who benefit the most from taking up a matched bet are also the most likely to participate. Overall, the matched bet proves a promising mechanism to help people overcome time inconsistency issues, both in theory and in practice.

The chapter proceeds as follows: Section 2.2 discusses the related literature. Section 2.3 theoretically analyzes the matched-bet mechanism. Section 2.4 describes the experimental design. Section 2.5 presents the experimental results. Section 2.6 compares the matched bet to existing mechanisms. It also discusses practical challenges and points out other areas in which the matched bet could be applied. Finally, Section 2.7 concludes.

2.2 Related Literature

This section discusses the related literature, with a focus on monetary incentive schemes for behavioral change. The literature on monetary incentives has predominantly studied subsidies, also referred to as conditional cash transfers. With a subsidy, a policy maker pays participants if they reach a prespecified target. Subsidies have been implemented in various areas such as exercising, studying, weight loss and smoking cessation (see e.g. Charness and Gneezy, 2009; Fryer Jr, 2011; Halpern et al., 2015; Rohde and Verbeke, 2017; Augurzky et al., 2018; Aggarwal et al., 2020; Campos-Mercade and Wengström, 2020). Most papers find that subsidies increase participants' desired behavior. Evidence suggests that the effect size positively depends on how well participants can control reaching the target (Gneezy et al., 2011).

When applied to exercising, several field experiments at university or company gyms have found that subsidies increase gym attendance during the intervention period (see e.g. Charness and Gneezy, 2009; Pope and Harvey-Berino, 2013; Acland and Levy, 2015; Cappelen et al., 2017; Arada et al., 2020; Carrera et al., 2020). Perhaps not surprisingly, participants attend the gym more often the more they get paid for attendance. Studies with only modest incentives yield only small increases in gym attendance (Carrera et al., 2018a; Rohde and Verbeke, 2017). The literature also finds an increase in gym attendance after the intervention period, which suggests that people form a habit of exercising. It thus seems that the monetary incentives do not crowd out participants' intrinsic motivation to exercise. The positive post-intervention effects are limited in size and duration, however, and often decay after a quasi-exogenous negative shock on gym attendance due to holidays (Acland and Levy, 2015). This implies that it is not sufficient to pay people once over a short period of time to achieve persistent behavioral change. As subsidies impose high costs on the policy maker, repeated rounds of subsidies might prove too costly to solve time inconsistency issues.

In the pursuit of a cost-effective way to solve time inconsistency issues, the literature has also looked at commitment contracts (see Bryan et al., 2010 for a review). With commitment contracts, participants either restrict their future choice set or put their own money at stake, which they lose if they fail to reach a prespecified target. Just like a matched bet, a budget-constrained policy maker can thus offer a commitment contract repeatedly. Evidence shows that offering commitment contracts increases the desired behavior, but often only to a small margin. Typically, only a minority of people is willing to take up a commitment contract. In particular, pure monetary commitment contracts have low take-up rates (Giné et al., 2010; Royer et al., 2015). The literature finds higher take-up rates when the commitment contract restricts participants' future choice sets (Ashraf et al., 2006; Milkman et al., 2014; Beshears et al., 2020) or merely threatens to decrease a positive payoff to participants (John et al., 2012; Kaur et al., 2015; Exley and Naecker, 2016; Schilbach, 2019). Laibson (2015) argues that the low take-up rate is due to two reasons. First, naive procrastinators (erroneously) perceive that they do not need commitment. Second, commitment contracts can become quite costly due to the possible loss in flexibility or money. Sadoff and Samek (2019) argue that naive procrastinators might learn about the value of commitment over time. They provide evidence that externally imposed experience with commitment contracts increases voluntary take-up later on.

Behavioral interventions that neither restrict participants' future choice sets nor provide monetary incentives often fail to change subjects' behavior. For instance, neither helping people with planning exercising sessions (Carrera et al., 2018b), nor informing people about how often their peers exercise (Beatty and Katare, 2018) increased gym attendance. In contrast, Calzolari and Nardotto (2016) show that weekly reminders can be effective in increasing gym attendance.

A few papers have investigated the effects of offering bets on changing people's behavior. Halpern et al. (2015) compare the effect of a one-sided bet on smoking cessation to a subsidy and control group. They find that both the subsidy and bet significantly increase abstinence rates, though the subsidy does so to a larger extent. My study is most closely related to Lusher (2017), who analyzes the effects of a parimutuel betting market on academic performance of university students. In parimutuel betting, participants' bet stakes are placed in a bet pool, which is then shared by all winning participants. Lusher implements a bet without matching. He offers a bet with a modest bet stake and a binary target to increase one's GPA. He finds that participation in the bet increases the likelihood to increase one's GPA. Especially low-achieving students benefit from the bet; they are also the most likely to participate. My study differs from Lusher's in the investigated bet mechanism (matched bet vs. unmatched bet) and application (exercising vs. academic performance).

2.3 Theory

This section theoretically analyzes the effects of offering a matched bet to help people overcome time-inconsistent behavior in a model inspired by DellaVigna and Malmendier (2004). The section serves two purposes. First, it demonstrates that a matched bet has desirable theoretical properties, making it a device worth studying in practice. Second, the theoretical results propose specific hypotheses that are subsequently tested in a field experiment.

2.3.1 Model

Consider a setting with a set of N agents labeled $i = 1, ..., N$. Agents decide whether to invest in an investment good.[3] More specifically, agents make a binary investment decision $\mathcal{I}_i = \{0, 1\}$ where $\mathcal{I}_i = 1$ if agent i invests and $\mathcal{I}_i = 0$ if agent i does not invest.[4]

Matched Bet. A matched bet with monetary bet stake $m > 0$ specifies the (possibly negative) monetary transfer T_i to bet participant i as follows

$$T_i = \mathcal{I}_i m - \frac{1}{|S_i|} \sum_{j \in S_i} \mathcal{I}_j m, \tag{2.1}$$

where S_i denotes the set of i's grouped partners (excluding herself) and $|S_i|$ denotes the number of i's grouped partners. Transfer T_i thus equals the difference of a bet participant's own and her partners' average investment frequencies, multiplied by the bet stake.

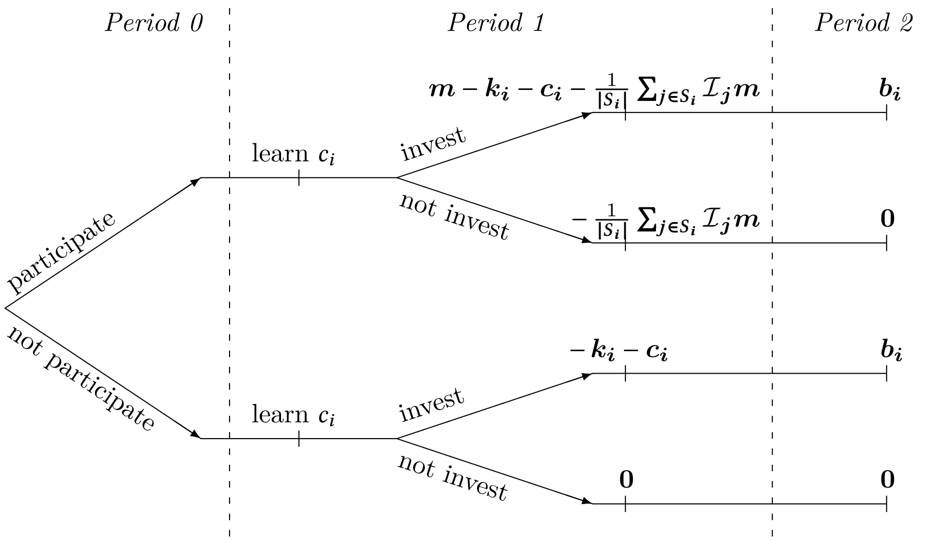
Timing of Events. I assume a three-period model. In period 0, agents are offered an opportunity to participate in a matched bet with monetary

[3] Examples of such investment decisions concern exercising, studying, saving, eating healthily and having medical check-ups.

[4] I assume binary investment decisions as these are sufficient to distill the mechanism's main properties. Generalizing the model to a larger set of possible investment decisions would complicate the analysis substantially without offering much additional insight.

bet stake m, and each agent i decides whether to participate ($\mathcal{P}_i = 1$) or not ($\mathcal{P}_i = 0$). In period 1, agents learn about their opportunity costs c_i and then make a binary investment decision $\mathcal{I}_i = \{0, 1\}$. If an agent invests ($\mathcal{I}_i = 1$), she incurs immediate effort costs $k_i \geq 0$ and opportunity costs $c_i \geq 0$, but later obtains (expected) benefits $b_i > 0$ in period 2. If an agent does not invest ($\mathcal{I}_i = 0$), both her costs and benefits are equal to zero. Furthermore, there are (possibly negative) monetary transfers T_i, as specified in (2.1), to bet participants in period 1 depending on their bet outcome. Figure 2.1 illustrates the timing of events for agent i.

Figure 2.1: Timing of Events



Notes: The figure depicts the timing of events, agent i's choice set and resulting payoffs (highlighted in bold).

Agents. Benefits b_i and costs $k_i + c_i$ may vary across agents. The costs of investing consist of deterministic effort costs k_i and stochastic opportunity costs $c_i \in [0, \bar{c}]$ with $\bar{c} > 0$. At period 0, agents know their own non-monetary benefits b_i, their own effort costs k_i and the common distribution $F(\cdot)$ from which their own opportunity costs c_i are drawn from. The distribution $F(\cdot)$

is differentiable and strictly increasing. The corresponding density function $f(\cdot)$ is weakly decreasing on $[0, \overline{c}]$. At the start of period 1, agents learn about their own opportunity costs c_i.

Agents are risk-neutral and may have time-inconsistent preferences. I assume agents' time preferences can be expressed by a quasi-hyperbolic discounting model, also known as the β-δ model (Phelps and Pollak, 1968; Laibson, 1997; O'Donoghue and Rabin, 1999). More precisely, an agent's direct utilities in period 0 and period 1 are given by

$$U_i^0 = \beta_i \delta_i \left[(\delta_i b_i - k_i - c_i)\mathcal{I}_i + \mathcal{P}_i T_i \right] \tag{2.2}$$

and

$$U_i^1 = (\beta_i \delta_i b_i - k_i - c_i)\mathcal{I}_i + \mathcal{P}_i T_i, \tag{2.3}$$

where $\delta_i \leq 1$ denotes agent i's long-run discount factor, and $\beta_i \leq 1$ indicates agent i's short-run discount factor.

Further, $\hat{\beta}_i$ indicates agent i's perceived short-run discount factor, i.e. agent i's belief in period 0 about her short-run discount factor in period 1. An agent's present bias is defined as $1-\beta_i$, and an agent's perceived present bias is defined as $1-\hat{\beta}_i$. I allow agents to underestimate their degree of time inconsistency, which implies $\beta_i \leq \hat{\beta}_i$. The difference between an agent's true and perceived present bias describes an agent's degree of naiveté $\hat{\beta}_i - \beta_i$. An agent's perceived direct utility in period 0 equals

$$\hat{U}_i^0 = \beta_i \delta_i \left[(\delta_i b_i - k_i - c_i)\hat{\mathcal{I}}_i + \mathcal{P}_i \hat{T}_i \right], \tag{2.4}$$

where $\hat{\mathcal{I}}_i$ captures the agent's belief in period 0 about her investment decision in period 1. Similarly, $\hat{T}_i$ captures the agent's belief in period 0 about the resulting monetary transfer to her in period 1.

Following O'Donoghue and Rabin (1999), three special types are worth mentioning: *rational* agents who are time-consistent ($\beta_i = \hat{\beta}_i = 1$), *sophis-*

ticated agents who are time-inconsistent and aware of it ($\beta_i = \hat{\beta}_i < 1$), and *naive* agents who are time-inconsistent but completely unaware of it ($\beta_i < \hat{\beta}_i = 1$). While (partially) naive agents believe that their present bias will be lower in period 1 than it is in period 0, I assume that all agents (correctly) believe that the other agents' present biases are constant over time.[5]

As agents' preferences may be time-inconsistent, welfare depends on which preferences capture an agent's true preferences. As is standard in the literature, I assume that an agent's welfare depends on her long-run (time-consistent) preferences (O'Donoghue and Rabin, 2001; DellaVigna and Malmendier, 2004; Galperti, 2015). Note that an agent's long-run preferences coincide, up to the multiplicative constant β_i, with the agent's preferences in period 0. An agent's individual welfare in period 0 is thus given by

$$U_i^W = \delta_i \left[(\delta_i b_i - k_i - c_i)\mathcal{I}_i + \mathcal{P}_i T_i \right]. \tag{2.5}$$

leading to the following definition of efficient investment.

Definition 2.1 *Let $\mathcal{I}_i(c_i)$ be agent i's investment strategy. Agent i is said to invest efficiently if $\mathcal{I}_i(c_i) = 1$ if and only if $c_i \leq \delta_i b_i - k_i$.*

An agent who invests efficiently obtains $\mathbb{E}[U_{i,\mathit{eff}}^W]$. To rule out trivial cases, I assume $k_i < \delta_i b_i < k_i + \bar{c}$ for all agents. These conditions ensure that investing is not always nor never efficient. To guarantee accurate matching, I further assume $k_i < \beta_i \delta_i b_i$ for all agents. This condition ensures that, in the baseline (pre-bet) case, all agents invest with strictly positive probability. In the baseline, an agent invests if and only if $c_i \leq \beta_i \delta_i b_i - k_i$, so that an agent's expected baseline investment frequency equals $F(\beta_i \delta_i b_i - k_i)$.

Matching. Bet participants are grouped with all other participants who

[5] This modeling assumption is in line with experimental evidence in Fedyk (2018), who finds that people anticipate present bias in others.

have the same expected baseline investment frequency. Recall that S_i denotes the set of i's grouped partners and $|S_i|$ denotes the number of grouped partners. In a matched bet, the set S_i includes all bet participants who have the same expected baseline investment frequency as participant i excluding herself, thus

$$S_i \equiv \{j \neq i | \mathcal{P}_j = 1, F(\beta_j \delta_j b_j - k_j) = F(\beta_i \delta_i b_i - k_i)\}. \tag{2.6}$$

I assume $|S_i| \geq 1 \ \forall \ i : \mathcal{P}_i = 1$. This implies that the market is sufficiently thick to ensure that a bet participant always has at least one viable partner to be matched with. The matching assumes that an agent's expected baseline investment frequency can be identified, possibly because there is sufficient information about her past investment behavior.[6] An agent's underlying parameters β_i, $\hat{\beta}_i$, δ_i, b_i, k_i and $F(\cdot)$, however, are assumed to be private information. One example where reality approaches this informational setting are gyms. Gyms typically record each member's gym attendance. The information about past gym attendance can be used to predict a member's future attendance quite accurately in spite of the fact that gyms are ignorant about the underlying preferences of their members.[7]

2.3.2 Analysis

In this section, I explore the properties of the matched-bet mechanism in the framework laid out in the previous subsection.

Budget. Before I analyze agents' behavior, note that the reward paid to a bet participant is always exactly refinanced by the payments obtained from

[6]Appendix 2.A.1 shows that the performance of the matched-bet mechanism is robust to imperfect matching.

[7]Not surprisingly, additional information about underlying parameters might improve the matched-bet mechanism's performance. Appendix 2.A.3 shows that the matched-bet mechanism can achieve the first best if also β_i, δ_i and b_i can be identified.

her grouped partners. Summing up all transfers to agents (2.1) yields

$$\sum_i \mathcal{P}_i T_i = \sum_i \mathcal{P}_i \mathcal{I}_i m - \sum_i \mathcal{P}_i \frac{1}{|S_i|} \sum_{j \in S_i} \mathcal{I}_j m = \sum_i \mathcal{P}_i \mathcal{I}_i m - \sum_j \mathcal{P}_j \mathcal{I}_j m = 0.$$

which leads to the following proposition.

Proposition 2.1 (Budget Balancedness) *A matched bet is ex-post strictly budget-balanced.*

The ex-post property makes the matched bet robust to common investment frequency shocks. The strict budget balancedness allows a budget-constrained policy maker to offer matched bets over extended periods of time, which might be necessary to induce long-run behavioral change.

I now turn to the analysis of agents' behavior. Every agent faces two binary decisions: a bet participation decision in period 0 and an investment decision in period 1. The analysis employs a Perfect Bayesian Nash equilibrium concept. I thus solve using backward induction and first focus on the investment decision, taking the earlier bet participation decision as given. Throughout the chapter, I assume, without loss of generality, that agents participate when indifferent between participating and not participating, and invest when indifferent between investing and not investing.

Investment Decision. An agent's investment decision in period 1 depends on the agent's preferences in period 1. Substituting (2.1) into (2.3) and rearranging, we obtain the maximization problem

$$\max_{\mathcal{I}_i \in \{0,1\}} (\beta_i \delta_i b_i - k_i - c_i + \mathcal{P}_i m)\mathcal{I}_i - \mathcal{P}_i \frac{1}{|S_i|} \sum_{j \in S_i} \mathcal{I}_j m. \tag{2.7}$$

Note that the second term in the above expression does not depend on agent i's investment strategy. An agent thus maximizes her utility by investing if and only if

$$c_i \leq \beta_i \delta_i b_i - k_i + \mathcal{P}_i m. \tag{2.8}$$

In other words, an agent invests in period 1 if and only if her realized opportunity costs are sufficiently low. In period 0, when opportunity costs have not yet realized, an agent's expected investment frequency thus equals $F(\beta_i \delta_i b_i - k_i + \mathcal{P}_i m)$. This leads to

Proposition 2.2 (Bet Effect)

(i) Without a matched bet, present-biased agents underinvest.

(ii) Participating in a matched bet increases an agent's expected investment frequency.

(iii) If agent i participates in a matched bet, she invests efficiently if $m = (1 - \beta_i)\delta_i b_i$, underinvests if $m < (1 - \beta_i)\delta_i b_i$ and overinvests if $m > (1 - \beta_i)\delta_i b_i$.

(iv) An agent who participates in a matched bet has a dominant investment strategy.

Proof (i) It follows from Definition 2.1 that efficient investment involves a frequency of $F(\delta_i b_i - k_i)$. Without a matched bet, agent i invests if and only if $c_i \leq \beta_i \delta_i b_i - k_i$, so that her expected investment frequency without the bet equals $F(\beta_i \delta_i b_i - k_i)$. Because $F(\beta_i \delta_i b_i - k_i) < F(\delta_i b_i - k_i)$ for all agents with $\beta_i < 1$, all present-biased agents underinvest without a matched bet. The inefficiency increases in the agent's present bias. (ii) Taking up a matched bet increases an agent's investment frequency as $F(\beta_i \delta_i b_i - k_i + m) > F(\beta_i \delta_i b_i - k_i)$. (iii) If agent i participates in a matched bet, she invests efficiently if and only if her expected investment frequency equals her expected efficient frequency, i.e. if and only if $F(\beta_i \delta_i b_i - k_i + m) = F(\delta_i b_i - k_i)$.

The condition is satisfied only if $m = (1-\beta_i)\delta_i b_i$. If $m < (1-\beta_i)\delta_i b_i$, $F(\beta_i\delta_i b_i - k_i + m) < F(\delta_i b_i - k_i)$, so that agent i underinvests. In contrast, if $m > (1-\beta_i)\delta_i b_i$, $F(\beta_i\delta_i b_i - k_i + m) > F(\delta_i b_i - k_i)$, so that agent i overinvests. (*iv*) A bet participant's investment strategy equals $\mathcal{I}_i(c_i) = 1$ if and only if $c_i \leq \beta_i\delta_i b_i - k_i + m$. Clearly, the strategy does not depend on the behavior of other participants. Bet participants thus have a dominant investment strategy. An agent's belief about other agent's behavior is only relevant for the bet participation but not for the investment decision. ■

Note that parts one to three of above proposition together imply that, even though an agent still underinvests when participating in a matched bet with $m < (1-\beta_i)\delta_i b_i$, she does so to a lesser extent than without the bet.

Bet Participation Decision. In period 0, an agent makes a bet participation decision that depends on the agent's preferences in period 0 as well as her *perceived* investment strategy in period 1. Given opportunity costs c_i, an agent's perceived utility in period 0 equals

$$\begin{aligned} &\beta_i\delta_i\left[(\delta_i b_i - k_i - c_i + \mathcal{P}_i m)\hat{\mathcal{I}}_i - \mathcal{P}_i\frac{1}{|S_i|}\sum_{j\in S_i}\mathcal{I}_j m\right] \\ \textit{with}\quad &\hat{\mathcal{I}}_i(c_i) = 1 \iff c_i \leq \hat{\beta}_i\delta_i b_i - k_i + \mathcal{P}_i m, \\ &\mathcal{I}_j(c_j) = 1 \iff c_j \leq \beta_j\delta_j b_j - k_j + m \quad \forall\ j \in S_i. \end{aligned} \tag{2.9}$$

Recall that an agent might have incorrect beliefs about her own investment strategy (as $\beta_i \leq \hat{\beta}_i$), but is assumed to have accurate, i.e. consistent with equilibrium, beliefs about her grouped partners' investment strategies. As opportunity costs have not yet materialized in period 0, agents maximize their perceived expected utility $\mathbb{E}[\hat{U}_i^0]$ as follows

$$\max_{\mathcal{P}_i \in \{0,1\}} \beta_i \delta_i \left[\int_0^{\hat{\beta}_i \delta_i b_i - k_i + \mathcal{P}_i m} (\delta_i b_i - k_i - c_i + \mathcal{P}_i m) f(c_i) dc_i \right] - \beta_i \delta_i \left[\mathcal{P}_i \frac{1}{|S_i|} \sum_{j \in S_i} \int_0^{\beta_j \delta_j b_j - k_j + m} m f(c_j) dc_j \right].$$

Recall that since bet participants are grouped with all other participants who have the same expected baseline investment frequency, $S_i \equiv \{j \neq i | \mathcal{P}_j = 1, F(\beta_j \delta_j b_j - k_j) = F(\beta_i \delta_i b_i - k_i)\}$. Thus, $\beta_j \delta_j b_j - k_j + m = \beta_i \delta_i b_i - k_i + m \; \forall \; j \in S_i$, which simplifies the agent's maximization problem to

$$\max_{\mathcal{P}_i \in \{0,1\}} \beta_i \delta_i \left[\int_0^{\hat{\beta}_i \delta_i b_i - k_i + \mathcal{P}_i m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i \right] + \beta_i \delta_i \left[\mathcal{P}_i \int_{\beta_i \delta_i b_i - k_i + m}^{\hat{\beta}_i \delta_i b_i - k_i + m} m f(c_i) dc_i \right]. \tag{2.10}$$

The first term of the expression above quantifies the perceived non-monetary payoff from investing while the second term quantifies the perceived monetary payoff from participating in the matched bet. As an agent's bet participation decision is binary, we can rewrite the agent's maximization problem as the bet participation constraint $\mathbb{E}[\hat{U}^0_{i,\mathcal{P}_i=1}] - \mathbb{E}[\hat{U}^0_{i,\mathcal{P}_i=0}] \geq 0$, which is given by

$$\underbrace{\int_{\hat{\beta}_i \delta_i b_i - k_i}^{\hat{\beta}_i \delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i}_{\text{Incentive Value}} + \underbrace{\int_{\beta_i \delta_i b_i - k_i + m}^{\hat{\beta}_i \delta_i b_i - k_i + m} m f(c_i) dc_i}_{\text{Monetary Value}} \geq 0. \tag{PC}$$

The first term on the left-hand side describes the (possibly negative) incentive value, i.e. the extra net benefits an agent expects to obtain from the increase in her investment frequency when participating in the bet. Without the bet, an agent expects to invest only if $c \leq \hat{\beta}_i \delta_i b_i - k_i$. With a matched bet, an agent expects to invest also if $\hat{\beta}_i \delta_i b_i - k_i < c_i \leq \hat{\beta}_i \delta_i b_i - k_i + m$.

The second term describes the monetary value, i.e. the monetary amount an agent expects to win with the bet. The rationale for why agents might take up the bet depends on their degree of naiveté $\hat{\beta}_i - \beta_i$. Sophisticated agents ($\beta_i = \hat{\beta}_i < 1$) do not expect to win money with the bet. If they take up the bet, they do so because their incentive value is positive. Sophisticated agents acknowledge their time inconsistency and use the matched bet as a costless incentive device to invest more efficiently. In contrast, naive agents ($\beta_i < \hat{\beta}_i = 1$) do not recognize a bet's incentive value and even expect to invest less efficiently with a bet. They erroneously expect to invest efficiently without a matched bet and expect to overinvest with a matched bet. Inserting $\hat{\beta}_i = 1$ into the participation constraint shows that the incentive value is always negative for naive agents as $\int_{\delta_i b_i - k_i}^{\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i < 0$. Even though naive agents expect to invest less efficiently with a matched bet, they might take up the bet because they erroneously expect to win a sufficient amount of money. A combination of the reasons stated above holds true for partially naive agents ($\beta_i < \hat{\beta}_i < 1$). Naiveté thus yields two opposing effects. It decreases the perceived incentive value but increases the perceived monetary value.

Analyzing the comparative statics of the participation constraint yields the following proposition that describes the take-up of a matched bet.

Proposition 2.3 (Bet Take-up)

(i) *There exists an $\overline{m}_i$ such that an agent participates in the matched bet if and only if $m \leq \overline{m}_i$.*

(ii) *There exists a $\overline{\beta}_i$ such that an agent participates in the matched bet if and only if $\beta_i \leq \overline{\beta}_i$.*

(iii) *There exists a $\overline{\hat{\beta}}_i$ such that an agent participates in the matched bet if and only if $\hat{\beta}_i \leq \overline{\hat{\beta}}_i$.*

Proof See Appendix 2.B

Proposition 2.3 shows that an agent will participate in the matched bet if and only if the monetary bet stake is sufficiently small, the agent is sufficiently present-biased, and the agent's perceived present bias is sufficiently large.

The participation constraint is never fulfilled for time-consistent agents. Inserting $\beta_i = \hat{\beta}_i = 1$ into (PC) yields a negative incentive value and a monetary value of zero. This implies

Corollary 2.1 *Time-consistent agents do not take up a matched bet.*

Proof See Appendix 2.B

Time-consistent agents invest efficiently without a matched bet. With a matched bet, they would overinvest. Time-consistent agents therefore negatively value the bet's commitment aspect. As they expect to break even with a matched bet, they reject it. The matched bet thus features favorable self-selection. Time-inconsistent agents might participate in the bet while time-consistent agents do not participate.[8]

Welfare. I now consider the effects of offering a matched bet on individual and social welfare. Substituting (2.1) into (2.5) yields an agent's utility in period 0 given opportunity costs c_i:

$$\begin{aligned} U_i^W &= \delta_i \left[(\delta_i b_i - k_i - c_i + \mathcal{P}_i m)\mathcal{I}_i - \mathcal{P}_i \frac{1}{|S_i|} \sum_{j \in S_i} \mathcal{I}_j m \right] \\ \textit{with} \quad \mathcal{I}_i(c_i) = 1 &\iff c_i \leq \beta_i \delta_i b_i - k_i + \mathcal{P}_i m, \\ \mathcal{I}_j(c_j) = 1 &\iff c_j \leq \beta_j \delta_j b_j - k_j + m \quad \forall\ j \in S_i. \end{aligned} \tag{2.11}$$

Taking expectations as opportunity costs have not yet materialized in

[8]Note that matching is crucial for favorable self-selection into the bet as shown in Section 2.6.1.

period 0 yields

$$\mathbb{E}[U_i^W] = \delta_i \left[\int_0^{\beta_i \delta_i b_i - k_i + \mathcal{P}_i m} (\delta_i b_i - k_i - c_i + \mathcal{P}_i m) f(c_i) dc_i \right] - \delta_i \left[\mathcal{P}_i \frac{1}{|S_i|} \sum_{j \in S_i} \int_0^{\beta_j \delta_j b_j - k_j + m} m f(c_j) dc_j \right]$$

which can be simplified to

$$\mathbb{E}[U_i^W] = \delta_i \left[\int_0^{\beta_i \delta_i b_i - k_i + \mathcal{P}_i m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i \right] \tag{2.12}$$

as $\beta_j \delta_j b_j - k_j + m = \beta_i \delta_i b_i - k_i + m \;\forall\; j \in S_i$. Because of matching, bet participants are expected to break even with the bet. The size of the bet stake thus only influences an agent's investment efficiency. One obtains an agent's individual welfare by combining (2.12) with the participation constraint (PC) leading to the following proposition that shows that offering a matched bet does not harm any agent.

Proposition 2.4 (Individual Welfare)

(i) Compared to the baseline, the matched-bet mechanism makes all agents weakly better off in expectation.

(ii) Compared to the baseline, the matched-bet mechanism makes all agents for whom $m \leq (2 - \hat{\beta}_i - \beta_i)\delta_i b_i$ strictly better off in expectation.[9]

Proof See Appendix 2.B

Only agents who are better off in expectation with a matched bet participate in it. The Pareto improvement trivially holds for sophisticated agents because their perceived utility equals their true utility. It also holds for naive agents who maximize their perceived rather than their true utility.

[9]Note that in the special case of $c \sim U[0, \bar{c}]$ with $\bar{c} \geq (2 - \beta_i)\delta_i b_i - k_i$ the inequality is strict for sophisticated agents.

One could imagine naive agents to participate in a matched bet with a bet stake that is much too high, erroneously expecting to earn money with the bet, and thereby overinvesting. It turns out that this is not the case. Whenever an agent would be worse off taking up the bet, she does not take it up.

The second part of the above proposition provides a sufficient condition for when agents are strictly better off with a matched bet. Sophisticated agents are for sure better off in expectation if $m \leq 2(1-\beta_i)\delta_i b_i$, i.e. if the bet stake is at most double the optimal, efficiency-inducing, bet stake of $m = (1-\beta_i)\delta_i b_i$. Naive agents are for sure better off in expectation if the bet stake is at most equal to the optimal bet stake.

I now derive the effect of the matched bet on efficiency. Even though agents' welfare and investment efficiency are closely related, they are not equivalent. An agent might participate in a mechanism that makes her better off but induces her to invest less efficiently, for example, if the mechanisms subsidizes investment of time-consistent agents, which induces them to overinvest (see Section 2.6.1). With a matched bet, however, individual and social welfare are perfectly aligned.

Proposition 2.5 (Social Welfare)

(i) All agents who take up a matched bet increase their investment efficiency compared to the baseline.

(ii) The fraction of prevented investment efficiency loss for an agent who takes up the bet is

$$\frac{\mathbb{E}[U^W_{i,\mathcal{P}_i=1}] - \mathbb{E}[U^W_{i,\mathcal{P}_i=0}]}{\mathbb{E}[U^W_{i,eff}] - \mathbb{E}[U^W_{i,\mathcal{P}_i=0}]} \geq \max\left[1-\left(1-\frac{m}{(1-\beta_i)\delta_i b_i}\right)^2, 0\right] \tag{2.13}$$

(iii) For agents with $\hat{\beta}_i = \beta_i$, the matched-bet mechanism maximizes investment efficiency among all take-it-or-leave-it mechanisms that provide

agents with a dominant investment strategy.

Proof See Appendix 2.B

The first part of the above proposition implies that social welfare never decreases with a matched bet. Matching is crucial for this result. Without matching, some agents might participate in a bet that induces them to actually invest less efficiently because this effect is overcompensated by a positive expected bet payoff (see Section 2.6.1).

The second part of the above proposition shows that the matched bet is robust to deviations from the optimal bet stake $m = (1 - \beta_i)\delta_i b_i$. For instance, an agent who participates in a matched bet with a bet stake that is half its optimal level already prevents at least 75% of the initial efficiency loss.

The intuition is as follows. If costs are considerably lower than benefits, not investing yields a high efficiency loss. In contrast, if costs are only slightly lower than benefits, not investing yields only a small efficiency loss. This implies that a small bet stake, which prevents situations when the agent would incur a high efficiency loss, may already prevent most of the efficiency loss that occurs without a bet. The argument is analogous for a suboptimally high bet stake with one caveat. As agents' willingness to participate in a matched bet decreases in the size of the bet stake, a suboptimally high bet stake might make naive agents erroneously reject the matched bet. Because of this, a benevolent policy maker offering a matched bet should lean to setting an overall conservative bet stake. This way, the policy maker ensures a high take-up rate and exploits the mechanism's robustness in efficiency to suboptimally small bet stakes.

The third part of Proposition 2.5 states that for sophisticated agents the matched bet is the optimal mechanism among all take-it-or-leave-it mechanisms that provide agents with a dominant investment strategy. The intuition is straightforward. With a matched bet, an agent is better off if and only if the agent exercises more efficiently, because matching ensures an expected bet payment of zero. Sophisticated agents who take up a matched bet whenever it makes them better off, thus take up a matched bet whenever they invest more efficiently with it. Note that potentially other mechanisms might yield a higher efficiency for (partially) naive agents as these agents might not take up a matched bet even though it would be beneficial for them to do so. Numerical solutions suggest, however, that these inefficiencies are minor. In Section 2.6.1, I compare the matched-bet mechanism to a subsidy, monetary commitment contract and unmatched bet, and show that the matched-bet mechanism yields the highest overall efficiency. This result is robust to the chosen bet stake and cost distribution.

From Theory to Experiment. Based on Propositions 2.3.ii and 2.2.ii, I formulate the following hypotheses that I can test in the experiment on exercising.

Hypothesis 2.1 *Time inconsistency has a positive effect on the likelihood of taking up the matched bet.*

Hypothesis 2.2 *Offering a matched bet increases gym attendance.*

2.4 Experimental Design

Recruitment. The experiment was conducted in collaboration with the university sports center (USC) of the University of Amsterdam in November and December 2017. I invited 1477 eligible gym members to participate in the experiment. All eligible members had a running student fitness membership at the USC in the period from October 16th (start of the matching period) to December 17th 2017 (end of the bet period). To target non-frequent gym attendees, only members who attended the gym on at most four days during the four-week matching period were invited.

Subjects were randomized into a control and treatment group. All subjects had to complete a short baseline survey. Completion of the survey was incentivized by a one-month extension of the fitness membership. The median person took about five minutes to complete the survey. In total, 629 subjects completed the baseline survey out of which 601 subjects were eligible for the analysis (206 subjects in a control group and 395 subjects in a treatment group).[10] The uneven group sizes were chosen to increase statistical power.

Procedure. Table 2.1 presents the timeline of the experiment.[11] Eligible gym members were contacted via e-mail by the university sports center on November 14th 2017. They were asked to click on a link which forwarded them to an online survey that they could complete until November 19th 2017. A reminder e-mail was sent on November 17th 2017.

The first part of this baseline survey included questions about demographics as well as past exercising behavior and future exercising beliefs. Subsequently, subjects were randomized into two groups, control and treatment. Only subjects in the treatment group continued with the second part of the survey, which introduced subjects to the matched bet and then offered them to participate in it.

The four-week bet period started on November 20th and lasted until December 17th 2017. Bet participants were reminded of the beginning of the bet period and the rules on November 20th 2017 via e-mail. They were reminded that the bet period had ended on December 18th 2017 also via e-mail. Bet participants received another e-mail on December 20th with a link to a one-page follow-up survey.[12] The links were valid until December

[10] I excluded 28 subjects as they erroneously received incorrect information about their past gym attendance in the baseline survey.

[11] Prior to the main experiment, I conducted a trial round in May and June 2017. Appendix 2.C presents details about the design of the trial round.

[12] Subjects who did not participate in the matched bet also received a link to a follow-up survey. As their response rate was only 21%, I do not use these data.

31st 2017. Directly after the one-page follow-up survey, bet participants were informed about their bet results and payment details.

Table 2.1: Timeline of Experiment

Date	Event
Sep 18, 2017 - Oct 15, 2017	Pre-matching period (pre-MP)
Oct 16, 2017 - Nov 12, 2017	Matching period (MP)
Nov 14, 2017 - Nov 19, 2017	Baseline survey
Nov 20, 2017 - Dec 17, 2017	Bet period (BP)
Dec 20, 2017 - Dec 31, 2017	Follow-up survey
Dec 18, 2017 - May 6, 2018	Post-bet period (post-BP)

Data. This study combines data from two sources. It uses administrative data from the university sports center (USC) of the University of Amsterdam and survey data from the baseline and follow-up surveys.

The administrative data contains information about each member's subscription and sports center attendance record. Members' visits are registered via finger scanners at the entry gates of all five USC gym locations. The attendance data thus provides precise information about where and when a member entered a USC gym.

The second source of data stems from the baseline and follow-up surveys. Both asked subjects about personal characteristics and exercising behavior. Appendix 2.D gives the survey questions. In the baseline survey, subjects self-report the extent to which they agree with a set of statements. Responses are given on a 7-point Likert-scale from 'strongly disagree' to 'strongly agree'. Statements addressed a subject's fitness level, motivation to exercise, satisfaction with exercising frequency, past and expected future procrastination of exercising sessions, willingness to take risks, competitiveness, healthy lifestyle and overall life happiness. Subjects were also asked about past and expected future exercising behavior. Questions asked about their average exercising duration at the USC and their exercising frequency outside the USC during the four-week matching period prior to the survey. Subjects also had to report on their exercising frequency goals and expectations about exercising at the USC in the coming four weeks. In addition, subjects answered demographic questions about gender, age, height, weight and weight goal. Bet participants were asked about their exercising frequency expectations given their bet participation and the (possibly negative) monetary net payoff they expect from the bet.

The follow-up survey was a shorter, non-incentivized version of the baseline survey except that bet participants were additionally asked how likely it is that they would take up a matched bet again.

Matched Bet Treatment. In the treatment group, subjects are *offered* to participate in a matched bet. Bet participants earn €5 from their grouped partners for each day they visit the university sports center (up to the 8th time) within the four-week bet period. In exchange, bet participants have to pay the average earnings of their grouped partners.

Bet participants were paid a constant reward of €5 for each visit up to a cap of 8 visits. The matched bet thus implements a stepwise incentive scheme. This is in contrast with most other related papers where participants are either fully paid or not at all. The advantage of rewarding each visit is that participants continue to have marginal monetary incentives to exercise even if it has become unfeasible for them to reach the cap. The cap itself yields bet participants more control over their bet outcome. Participants can ensure to at least break-even by visiting the gym 8 times or more during the bet period. About two thirds of the subjects reported a goal of 8 or more gym visits. I chose a comparatively low reward of €5 per gym visit because Propositions 2.3.i and 2.5.ii together suggest that a policy maker should lean to a conservative bet stake to maximize exercising efficiency.

Bet participants were anonymously grouped with participants who visited the sports center equally often in the four-week matching period. I chose this matching criterion because it predicts future attendance well while being easy to understand. In fact, past gym attendance is a better predictor of future gym attendance than subjects' own expectation about their future gym attendance.[13] More elaborate matching procedures might predict future attendance even better and thus make the matching more precise. However, the performance of a matched bet is robust to imperfect matching as shown in Appendix 2.A.1. Also, for the matched-bet mechanism to work in practice, it is not important whether participants are actually grouped fairly; it matters more whether they perceive it as such. To increase participation rates, bet participants were grouped with all rather than a subset of their viable bet partners. Risk- and loss-averse people would prefer to be grouped with more bet partners, because the variance of the average earnings of one's grouped partners decreases in the number of partners.

Bet participants were told that their workout needed to last at least 30 minutes to have it count for the bet. This is only partly verifiable as members only need to scan their fingers at the entry gates but not at the exit gates of the university sports center. For safety reasons, it is not possible to require members to scan their fingers to exit the sports areas. Aside from duration issues, a member might also spend time in the sports area without exercising at all. The gym staff was told to look out for 'suspicious' behavior, e.g. members scanning their fingers and leaving immediately afterwards, or occupying themselves with clearly non-exercising related activities in the sports area. They did not report seeing any such behavior. To enforce payments of bet participants who lost money, the accounts of participants who did not pay their bet losses on time were put on hold five and a half weeks after the end of the bet period. This prevented them from doing any

[13]For subjects in the control group, regressing gym attendance during the bet period on gym attendance during the matching period yields $R^2 = 0.139$, while a corresponding regression on subjects' expected gym visits during the bet period only gives $R^2 = 0.104$.

sports at the university sports center until they had paid their bet losses.[14]

The matched bet was framed as a fitness challenge rather than a bet. The reason is that survey answers of the trial round in which the matched bet was framed as a bet suggested that a non-negligible number of subjects perceived the bet as gambling and rejected it for moral or religious reasons. In contrast, the survey answers of the main experiment suggest that subjects did not relate the matched bet to gambling.

Sample. Table 2.2 depicts the summary statistics. The first column shows the mean of baseline characteristics for all subjects. Columns 2 and 3 show the means for the control and treatment group. Subjects were on average 23 years old. There were slightly more women (59%) than men in the sample. About 16% of the subjects reported a BMI above 25 and are classified as overweight. Subjects recorded on average 1.8 gym visits at the USC during the four-week matching period. For this period, they self-reported on average 4.9 exercising sessions outside the USC. Subjects aimed to record on average 8.9 gym visits at the USC during the bet period, and expected to record 6.7.[15] To ease interpretation, subjects' answers to Likert-scale statements were converted into binary variables and coded as 1, if the subject answered 'slightly agree', 'agree' or 'strongly agree', and 0, otherwise. 62% of the subjects reported to have procrastinated exercising sessions during the matching period and 34% expected to procrastinate exercising sessions during the bet period. Even though 75% of the subjects stated that they

[14] Despite this, 8 out of 40 bet losers did not pay. In total, the payment default equaled €118. This suggests that a stronger enforcement mechanism is needed to prevent payment default. Alternatively, one could request bet participants to pay an amount upfront (as e.g. successfully implemented by Lusher, 2017).

[15] Subjects in the control group turned out to record only 2.7 gym visits during the bet period. They thus greatly overestimate their future gym attendance, in line with the literature (Garon et al., 2015). Next to overestimation, there is also evidence for overplacement in the data. Even though bet payoffs sum up to zero by construction, bet participants expected to win on average €7.93. 70% of the bet participants expected to win money, 21% to break-even, and only 9% to lose money with the bet. Interestingly, participants' expected bet payoffs do not significantly predict their actual bet payoffs (regression of bet payoffs on expected bet payoffs, $p = 0.727$).

were motivated to exercise, only 35% of the subjects were satisfied with their exercising frequency at the university gym.

Table 2.2: Summary Statistics

	(1) Overall	(2) Control	(3) Treat-ment	(4) p-value (2) vs. (3)	(5) Bet Re-jecters	(6) Bet Partici-pants	(7) p-value (5) vs. (6)
Female (0/1)	0.586	0.549	0.605	0.182	0.608	0.596	0.831
Age	23.448	23.660	23.337	0.294	23.149	23.899	0.047
International (0/1)	0.293	0.330	0.273	0.147	0.250	0.343	0.071
Overweight (0/1)	0.163	0.180	0.154	0.428	0.149	0.172	0.582
Duration of gym contract	11.087	11.126	11.066	0.774	11.189	10.697	0.081
Gym visits in pre-MP	2.877	2.874	2.878	0.984	2.851	2.960	0.737
Gym visits in MP	1.767	1.704	1.800	0.439	1.767	1.899	0.434
Avg. duration of exercise	60.780	61.544	60.382	0.533	59.878	61.889	0.416
Exercise outside USC in MP	4.905	5.267	4.716	0.260	5.159	3.394	0.005
Exp. gym visits in BP	6.691	7.083	6.486	0.078	6.264	7.152	0.042
Exp. gym visits in BP for €5	8.471	8.597	8.405	0.689	8.115	9.273	0.068
Gym visits goal in BP	8.867	9.330	8.625	0.049	8.463	9.111	0.160
Procrastinated in MP (0/1)	0.621	0.631	0.615	0.703	0.571	0.747	0.002
Expects to procr. in MP (0/1)	0.343	0.330	0.349	0.637	0.324	0.424	0.071
Motivated (0/1)	0.749	0.738	0.754	0.657	0.757	0.747	0.853
Competitive (0/1)	0.744	0.767	0.732	0.346	0.723	0.758	0.501
Willing to take risks (0/1)	0.696	0.709	0.689	0.611	0.669	0.747	0.144
Fewer gym visits in MP (0/1)	0.720	0.738	0.711	0.493	0.696	0.758	0.241
More gym visits in MP (0/1)	0.087	0.102	0.078	0.332	0.084	0.061	0.445
Fit (0/1)	0.784	0.786	0.782	0.907	0.787	0.768	0.684
Satisfied with exercise (0/1)	0.346	0.325	0.357	0.438	0.355	0.364	0.873
Happy (0/1)	0.842	0.864	0.830	0.283	0.848	0.778	0.107
Healthy lifestyle (0/1)	0.571	0.558	0.577	0.656	0.578	0.576	0.973
Exp. gym visits in BP with bet						8.899	
Exp. bet earnings in €						7.929	
F-statistic (p-value)				0.815			
Observations	601	206	395		296	99	

Notes: Column 1 is the overall mean, columns 2 and 3 are the means of the control resp. treatment group. Columns 5 and 6 are the means of bet rejecters resp. bet participants. Columns 4 resp. 7 give the p-value of the differences in means between control and treatment resp. bet rejecters and participants from t-tests or tests of proportions. F-statistic to test joint significance. pre-MP = pre-matching period, MP = matching period, BP = bet period.

As one would expect from randomization, subjects in the control and treatment group are not significantly different from each other. A regression of the treatment assignment on the baseline characteristics shows that the characteristics cannot predict assignment to the treatment group as they are not jointly significant (p-value of F-statistic = 0.82). Only 1 out of 19 variables, gym visits goal during the bet period, is significantly different at the 5%-significance level. As the average gym visits goal is higher for the control group, and as gym visits goal is positively correlated with gym visits during the bet period, the treatment effect estimate will, if at all, be downward biased.

2.5 Experimental Results

This section presents the experimental results. Section 2.5.1 examines predictors of bet take-up. Section 2.5.2 presents the main treatment effects of offering as well as of taking up a matched bet on gym attendance. Section 2.5.3 analyzes heterogeneity in the effect of offering a matched bet. Section 2.5.4 presents the effect of offering a matched bet on post-intervention gym attendance. Finally, Section 2.5.5 provides evidence that the increase in gym attendance of bet participants led to an increase in participants' welfare.

2.5.1 Bet Participation

In order to test whether the matched bet features favorable self-selection not only in theory but also in practice, this section investigates who participates in a matched bet. In total, 99 out of 395 subjects (25%) that were offered the matched bet chose to participate. Columns 5 to 7 of Table 2.2 compare characteristics of bet rejecters and bet participants. Age, expected gym visits during the bet period and procrastination of exercising sessions during the matching period are significantly positively correlated with bet take-up, while exercising sessions outside the university gym is significantly negatively correlated. There is no significant gender difference in the bet take-up rate.

The results of the univariate analysis are supported by a multivariate analysis. Table 2.3 shows marginal effects of probit regressions aimed at explaining bet take-up. Column 1 shows the take-up rates depending on gym visits during the matching period. Zero visits during the matching period serves as the reference group. Subjects who visited the gym at least once during the matching period are more likely to take up the bet than subjects who recorded zero visits. A probit regression of bet take-up on an indicator variable specifying whether a subject visited the gym at least once during the matching period yields that this increases the bet take-up rate by 9.5 percentage points ($p = 0.036$). While subjects with a strictly positive gym attendance during the matching period reveal to be at least somewhat interested in going to the gym, some subjects with zero visits might have lost interest in doing so. Indeed, subjects with at least one visit are significantly more motivated to exercise (test of proportions, $p < 0.001$). Conditional on at least one visit, however, participation decreases in past gym attendance.

Column 2 shows the results of a regression of bet take-up on past gym attendance and demographic variables. This regression serves as an indication of how well a policy maker could predict who will take up a matched bet. Note that the variables can only explain about 5% of the variation in the bet take-up decision. The only significant variables are age and duration of gym contract. Being older and having a 3-month rather than a 12-month gym contract makes subjects more likely to take up the bet.

Column 3 includes only variables that are usually unknown to a policy maker. There are three variables with a significant effect on bet take-up. One extra exercising session outside the USC during the matching period significantly decreases bet take-up by 1.1 percentage points ($p = 0.009$). An

Table 2.3: Predictors of Bet Take-up

	(1)	(2)	(3)	(4)
Mean take-up rate	0.251	0.251	0.251	0.251
1 gym visit in MP (0/1)	0.144* (0.075)	0.145* (0.076)		0.134* (0.073)
2 gym visits in MP (0/1)	0.133* (0.076)	0.109 (0.078)		0.091 (0.077)
3 gym visits in MP (0/1)	0.079 (0.068)	0.066 (0.070)		0.049 (0.066)
4 gym visits in MP (0/1)	0.068 (0.076)	0.059 (0.085)		0.026 (0.078)
Gym visits in pre-MP		0.002 (0.009)		0.001 (0.009)
Female (0/1)		-0.006 (0.045)		0.016 (0.045)
Age		0.013** (0.006)		0.012** (0.006)
International (0/1)		0.064 (0.050)		0.039 (0.048)
Overweight (0/1)		0.024 (0.062)		0.025 (0.061)
3-month gym contract		0.286** (0.122)		0.244** (0.120)
6-month gym contract		-0.019 (0.073)		-0.015 (0.068)
Exercise outside USC in MP			-0.011*** (0.004)	-0.009** (0.004)
Expected gym visits in BP			0.012** (0.006)	0.011* (0.006)
Procrastinated in MP (0/1)			0.111** (0.047)	0.112** (0.045)
Expects to procr. in BP (0/1)			0.064 (0.051)	0.064 (0.050)
Motivated (0/1)			0.036 (0.049)	0.026 (0.051)
Competitive (0/1)			0.037 (0.046)	0.042 (0.046)
Willing to take risks (0/1)			0.066 (0.044)	0.045 (0.044)
Observations	395	395	395	395
(Pseudo-) R^2	0.012	0.041	0.057	0.089

Notes: The table shows marginal effects of probit regressions. The dependent variable indicates whether a subject participated in the matched bet. MP = matching period, BP = bet period. Omitted: 0 visits in MP (0/1) and 12-month gym contract. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

explanation for this finding is that people who already exercise outside the USC often do not need to increase their gym attendance at the USC to stay fit and healthy, and thus do not participate in the matched bet. Bet take-up increases by 1.2 percentage points for every day subjects expect to visit the USC gym during the bet period ($p = 0.035$). Having procrastinated exercising sessions during the matching period significantly increases bet take-up by 11.1 percentage points ($p = 0.018$). The estimated effect of 6.4 percentage points of expecting to procrastinate exercising sessions during the bet period on bet take-up is positive, but not statistically significant

(p = 0.204).

If we denote subjects who reported past or future procrastination as self-reported procrastinators, we find that being a procrastinator increases the bet take-up rate by 13.4 percentage points (p = 0.003). This confirms Hypothesis 2.1, which states that time inconsistency has a positive effect on the likelihood of taking up a matched bet. There is thus evidence for favorable self-selection into the matched-bet mechanism.

Result 2.1 *Subjective time inconsistency has a positive effect on the likelihood of taking up a matched bet.*

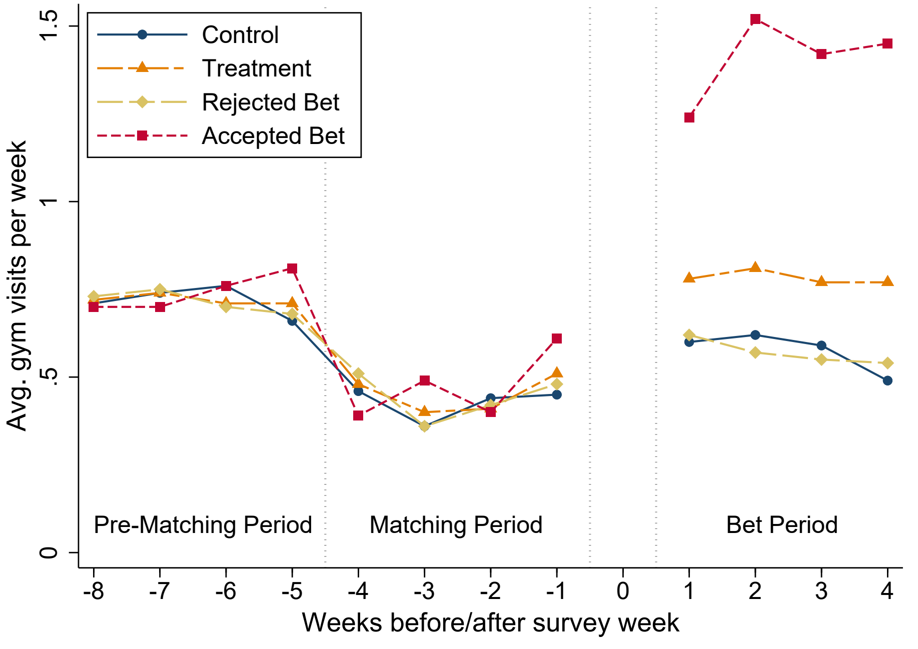
The sizes of the effects of past and future procrastination hardly change depending on whether past gym attendance data and demographic variables are included or not (columns 3 vs. 4). This suggests that a policy maker cannot easily identify time-inconsistent people and has to rely on people's self-selection into the bet. Motivation to exercise, competitiveness, willingness to take risks and expected procrastination in the future all have a positive but insignificant effect on bet take-up. In total, all variables explain only about 9% of the variation in the bet take-up decision.

2.5.2 Main Effects

This section analyzes the main treatment effects. I first graphically show the effect of a matched bet on gym attendance and then provide regression results. Figure 2.2 depicts the average gym visits per week for different groups over time for the pre-matching period (week -8 to -4), matching period (week -4 to week -1) and bet period (week 1 to week 4). Week 0 is the survey week.

Recall that subjects learned about the upcoming matched bet only in the survey week. The lower average gym attendance during the matching period is because I restricted the sample to gym members who visited the

Figure 2.2: Average Weekly Gym Visits over Time by Groups



Notes: The figure shows the average weekly gym visits over time by different groups. It shows averages for the control group (continuous blue line) and treatment group (long-short-dashed orange line). Splitting up the treatment group shows average visits over time for subjects who rejected the bet (long-dashed golden line) and who accepted the bet (short-dashed red line). Weeks -8 to -4 constitute the pre-matching period, weeks -4 to -1 constitute the matching period, week 0 constitutes the survey week, and weeks 1 to 4 constitute the bet period.

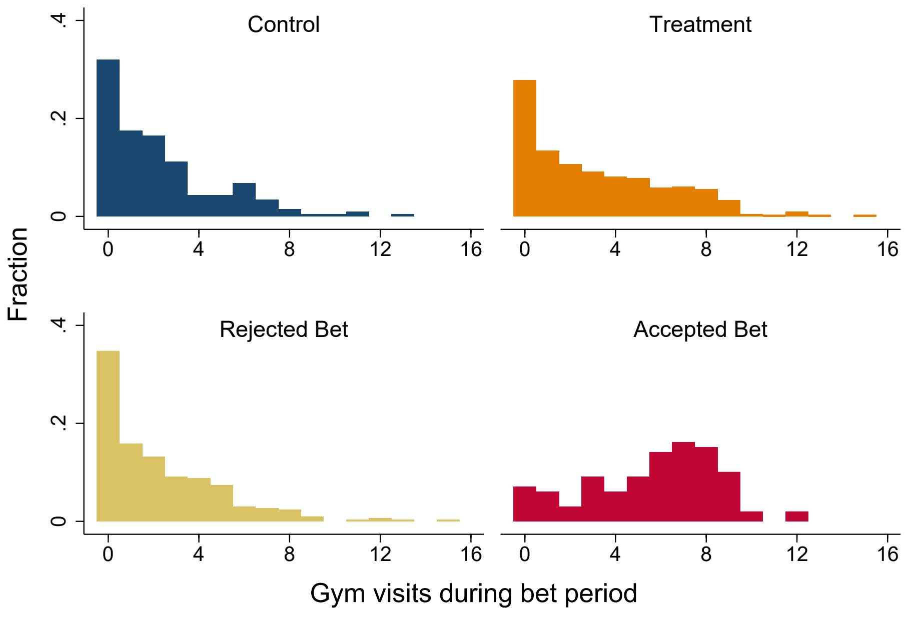
gym on at most four days during the matching period, but did not put any restrictions on gym attendance before and after the matching period.

As expected by randomization, average gym attendance of the treatment and control group is very similar during the pre-matching and matching periods. During the bet period, subjects in the bet treatment visited the gym more often than subjects in the control treatment over all four weeks of the bet period. The difference increases slightly over time from 0.18 weekly visits in the first week to 0.28 in the last week of the bet period.

Out of the 395 subjects in the bet treatment 99 accepted and 296 rejected the bet, which yields a take-up rate of just over 25%. Both groups visit the gym similarly often during the pre-matching and matching periods. During the bet period bet participants continuously visit the gym much more often than bet rejecters. The latter have a weekly gym attendance similar to that of the control group.

Figure 2.3 shows the distributions of gym visits for various groups during the bet period. The top row depicts the distributions for the control and treatment group (offered bet). The bottom row splits up the treatment group and shows the distributions for subjects who rejected and who accepted the matched bet.

Figure 2.3: Distributions of Gym Visits during Bet Period by Groups



Notes: The figure presents the distributions of gym visits during the bet period by different groups. It shows the distribution for the control group (top left) and treatment group (top right). Splitting up the treatment group shows the distributions for subjects who rejected the bet (bottom left) and who accepted the bet (bottom right).

We observe a similar gym attendance distribution of the control and bet treatment. Both empirical distributions are shaped like an exponential distribution with zero-attendance subjects being overrepresented. The bet treatment distribution first-order dominates the control treatment distribution and a Wilcoxon rank-sum test shows that the two distributions are not equal ($p = 0.002$).

The frequency distribution of gym visits of bet participants looks distinctly different from the control group and from the subjects that rejected the bet. The distribution has a mode of 7 visits. Even though the matched bet monetarily incentivized gym visits up to the 8th visit, about 14% of the bet participants registered more than 8 gym visits during the bet period.

Table 2.4 shows results of regressing the number of gym visits on the treatment variable. Columns 1 and 2 show results without resp. with controls. Offering a matched bet increases gym attendance by 0.87 visits during the bet period (column 1).[16] The effect is highly significant ($p < 0.001$). With an average gym attendance of 2.26 of the control group, this translates into a 38% increase in gym attendance. The treatment effect equals 0.34 standard deviations.

The effect size is robust to including some control variables; here the treatment effect is estimated at 0.93 extra gym visits (column 2). This gives the following result, which confirms Hypothesis 2.2.

Result 2.2 *Offering a matched bet increases gym attendance.*

Columns 3 in Table 2.4 shows the treatment effect on recording at least one gym visit during the bet period. Offering the matched bet does not significantly increase the proportion of people that record at least one gym visit during the bet period ($p = 0.284$). This finding is robust to including

[16]To test the effect of the matched bet, one needs to compare all participants who were offered the bet to the control group. A simple comparison between bet participants and non-participants would be biased due to self-selection.

Table 2.4: Treatment Effect of Offering Bet

	Gym visits in BP		1+ gym visits in BP (0/1)	
	(1)	(2)	(3)	(4)
Mean of control group	2.257	2.257	0.680	0.680
Treated (0/1)	0.867***	0.928***	0.042	0.043
	(0.235)	(0.203)	(0.040)	(0.034)
Gym visits in MP		0.460***		0.108***
		(0.074)		(0.012)
Gym visits in pre-MP		0.254***		0.027***
		(0.047)		(0.008)
Expected gym visits in BP		0.179***		0.011***
		(0.033)		(0.004)
Observations	601	601	601	601
(Pseudo-) R^2	0.020	0.269	0.002	0.203

Notes: The table shows OLS estimates in (1) and (2) and marginal effects of probit regressions in (3) and (4). The dependent variable in (1) and (2) is the number of gym visits during the (four-week) bet period. The dependent variable in (3) and (4) indicates whether a subject recorded at least one gym visit during the bet period. The treatment variable indicates whether a subject was offered to participate in the matched bet. The control variables are the numbers of gym visits during the (four-week) matching and pre-matching periods, and the self-reported expected number of gym visits during the bet period. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

some control variables (column 4). The matched bet thus shows no significant effect at the extensive margin. This finding is in contrast to Royer et al. (2015) who find significant effects at the extensive margin of existing gym members when a subsidy is used to incentivize exercising. One explanation for these different findings could be that a subsidy 'forces' monetary incentives on unmotivated subjects who would reject imposing monetary incentives on themselves through a bet.

The analysis so far has focused on the effect of *offering* the matched bet on gym attendance, which is crucially influenced by the take-up rate. The remainder of this subsection presents the effect of *taking up* the matched bet, which corrects for the take-up rate and thus directly estimates the behavioral change due to the monetary incentives. This analysis relies on the assumption that offering the bet has no direct effect on gym attendance except to cause some subjects to actually take up the bet, a condition typically referred to as the exclusion restriction. If the exclusion restriction holds, one can use the random treatment assignment as an instrument for bet take-up to estimate the treatment effects on the treated, depicted in Table 2.5.

Table 2.5: Treatment Effect of Accepting Bet (IV)

	Gym visits in BP		1+ gym visits in BP (0/1)	
	(1)	(2)	(3)	(4)
Mean of control group	2.257	2.257	0.680	0.680
Accepted Bet (0/1)	3.458***	3.650***	0.167	0.151
	(0.891)	(0.750)	(0.156)	(0.138)
Gym visits in MP		0.437***		0.113***
		(0.068)		(0.012)
Gym visits in pre-MP		0.260***		0.022***
		(0.044)		(0.006)
Expected gym visits in BP		0.153***		0.011***
		(0.030)		(0.004)
Observations	601	601	601	601
R^2	0.181	0.405	0.041	0.246

Notes: The table shows OLS estimates. The dependent variable in (1) and (2) is the number of gym visits during the bet period. The dependent variable in (3) and (4) indicates whether a subject recorded at least one gym visit during the (four-week) bet period. The treatment variable indicates whether a subject participated in the matched bet. Its estimation uses the random treatment assignment as an instrument for bet take-up. The control variables are the numbers of gym visits during the (four-week) matching and pre-matching periods, and the self-reported expected number of gym visits during the bet period. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Column 1 shows that taking up a matched bet increases gym attendance by 3.46 visits during the bet period. The effect is highly significant ($p < 0.001$) and robust to including some control variables (column 2). With an average gym attendance of 2.26 of the control group, this translates into a 153% increase in gym attendance. The effect equals 1.36 standard deviations. The magnitude of the increase in weekly gym attendance (0.87) due to taking up the bet is in line with the literature: Charness and Gneezy (2009) and Acland and Levy (2015) find larger effects of about 1.5 extra weekly visits during their intervention period with higher monetary incentives, while Rohde and Verbeke (2017) and Carrera et al. (2018a) find lower effects of about 0.2 extra weekly visits with lower monetary incentives than provided with the matched bet in this experiment.

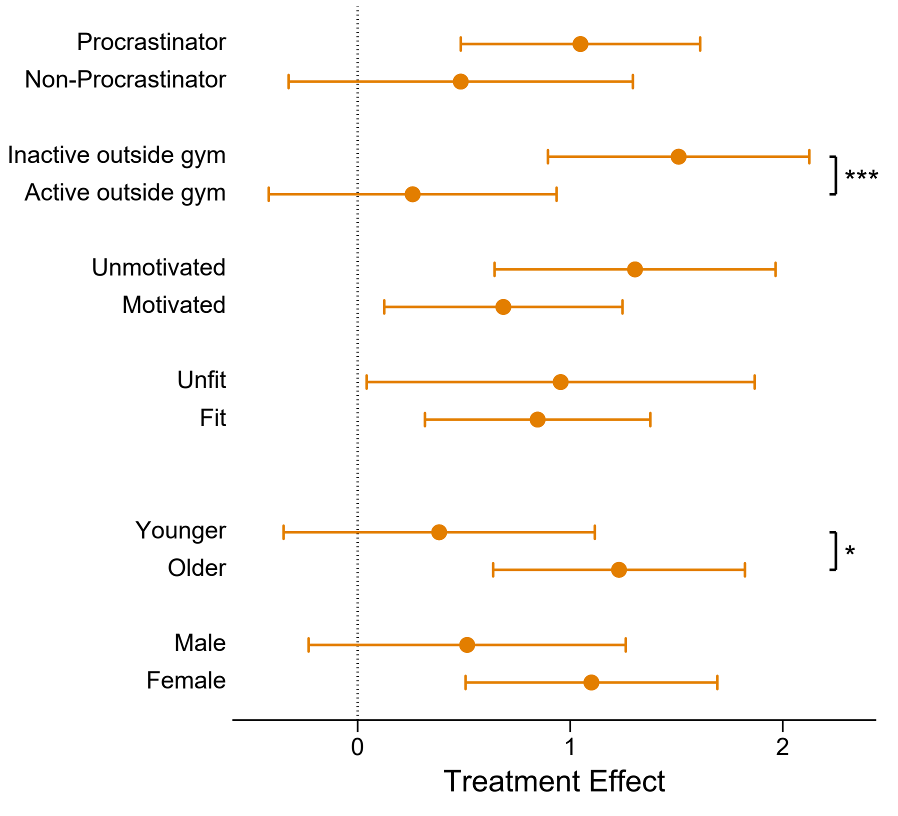
Column 3 shows that taking up a matched bet increases the likelihood to record at least one gym visit during the bet period by 16.7 percentage points. This increase is robust to including some control variables (column 4), but is not significant ($p = 0.285$).

2.5.3 Heterogeneous Treatment Effects

Offering a matched bet increases gym attendance in the aggregate. This section analyzes potential heterogeneity in the treatment effect by splitting up the treatment and control group in various ways. Figure 2.4 shows the effects of offering the matched bet on gym attendance along four behavioral and two demographic dimensions.

We observe that the treatment effect is about double the size for self-reported procrastinators compared to non-procrastinators, which can be explained by the higher bet take-up rate of procrastinators (30% vs. 16%; test of proportions, $p = 0.002$). However, regressing gym attendance during the bet period on treatment, self-reported procrastination and their respective interaction term reveals that the treatment effects are not statistically significantly different from each other ($p = 0.261$). In contrast, the treatment effect is significantly larger for subjects who reported fewer than the median number of exercising sessions outside the university gym during the matching period than for subjects who reported a number equal or above

Figure 2.4: Heterogeneous Treatment Effects



Notes: The figure shows differences in the effect of offering the matched bet on gym attendance during the (four-week) bet period by splitting up the subject pool into self-reported procrastinators vs. non-procrastinators, subjects who reported less vs. equal or more exercising sessions than the median outside the university gym during the (four-week) matching period, self-reported unmotivated vs. motivated subjects, self-reported unfit vs. fit subjects, male vs. female subjects, and into subjects who have below vs. equal or above median age. Error bars indicate ninety-five percent confidence intervals. *** $p < 0.01$, * $p < 0.1$

the median (p = 0.007). While subjects below the median are marginally more likely to take up the matched bet (29% vs. 21%; p = 0.098), those that accept also increase their gym attendance significantly more than subjects above the median (p = 0.030). An explanation for this finding is that participants who do not regularly exercise outside the university gym find it easier to increase their gym attendance as additional gym visits do not interfere with their other sports activities. We further observe that the treatment effect is larger, albeit insignificantly so, for unmotivated compared to motivated subjects ($p = 0.159$). As the take-up rates for unmotivated and motivated subjects are very similar, the larger treatment effect for unmotivated subjects suggests that unmotivated bet participants tend to react more strongly to the monetary incentive, which might act as a substitute for their lack of intrinsic motivation. There is no notable difference in the treatment effects for self-reported unfit and fit subjects ($p = 0.839$).

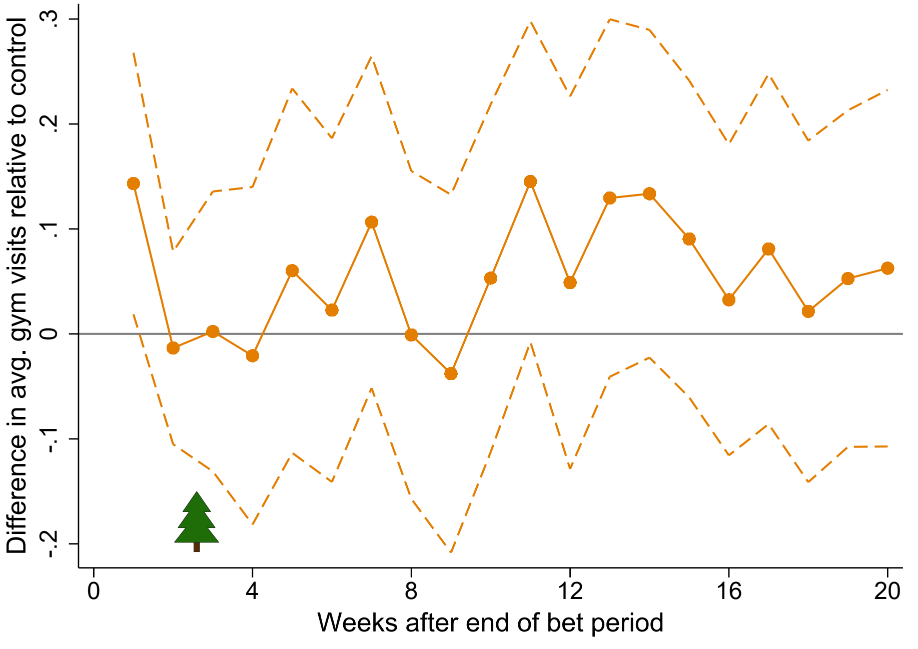
Figure 2.4 also depicts the effect of offering a matched bet on gym attendance along two demographic dimensions, age and gender. There is a marginally significantly larger treatment effect for subjects that are equal or older than the median in the sample (age 23 or older) compared to subjects that are below the median ($p = 0.077$). There is no significant difference in the treatment effect by gender ($p = 0.227$).

2.5.4 Long-Run Effects

This section analyzes the long-run effects of offering a matched bet. Figure 2.5 depicts the weekly effect of offering the matched bet on gym attendance up to 20 weeks after the end of the bet period.

Subjects in the treatment group continued to visit the gym significantly more often than subjects in the control group in the first week after the end of the bet period ($p = 0.024$). From the second week onward, the weekly treatment effects – though mostly positive – are statistically insignificant. This could be partly explained by the two-week Christmas break starting one week after the end of the bet period, during which gym attendance is overall low. The quasi-exogenous negative attendance shock might have broken some of the just newly formed exercising habit. This finding is in line with the literature (Acland and Levy, 2015). Over the course of the 20-week

Figure 2.5: Long-Run Treatment Effects



Notes: The figure shows the difference in average weekly gym visits over time after the end of the bet period of the treatment relative to the control group. The dashed lines represent ninety-five percent confidence intervals using robust standard errors. The Christmas tree denotes the two-week Christmas break at the University of Amsterdam in the second and third week after the end of the bet period.

post-bet period, subjects in the treatment group recorded 1.11 (10% resp. 0.10 standard deviations) more gym visits than subjects in the control group (12.10 vs. 10.99). The difference is not significant (regression of gym visits during 20-week post-bet period on treatment, $p = 0.269$). Per week, the point estimate for the post-bet period is about one fourth of the treatment effect estimated for the bet period. This ratio is about double the size found in Acland and Levy (2015)[17], close to the one in Royer et al. (2015), and slightly more than half the size found in Charness and Gneezy (2009). Note that, unlike for a subsidy, the cost-effectiveness of the matched bet does not

[17]See März (2019) for a correction of their post-intervention estimates.

rely on post-intervention effects. Due to its budget balancedness, matched bet rounds could be continuously offered (see Section 2.6.2).

2.5.5 Welfare Effects

The matched bet increases participants' gym attendance. But do bet participants also exercise more efficiently with a matched bet? It could be the case that the extra monetary incentive makes participants visit the gym too often. While a participant's efficient exercising level is not observable, the survey results provide evidence that the bet does indeed increase efficiency.

First, bet participants visited the gym less often than they initially aimed and expected. Bet participants recorded on average 5.64 visits during the bet period. However, prior to learning about the matched bet, they aimed and expected to visit the gym on 9.11 resp. 7.15 days. Only 18% of bet participants recorded more visits than they initially aimed for. In general, it thus seems that the matched bet did not induce bet participants to overexercise, but instead helped them decrease the extent of underexercising.

Second, bet participants were more satisfied with their exercising frequency at the USC and procrastinated exercising sessions less during the bet period than before. Table 2.6 shows a before-after comparison of several outcome measures. As there was some attrition in the follow-up survey, columns 1 and 2 show the difference assuming attrition was random, while columns 3 to 5 provide bounds on the difference. Assuming random attrition, the satisfaction of bet participants increased by 18 percentage points (McNemar's test, $p = 0.005$) and self-reported procrastination of exercising sessions decreased by 32 percentage points ($p < 0.001$), both of which are highly significant. There seems to be no effect on participants' self-reported fitness, lifestyle and overall happiness. Given the short span of the intervention, these null results might not be surprising; other papers with a longer time horizon have found positive effects on fitness and lifestyle (see e.g. Charness and Gneezy, 2009).

Table 2.6: Welfare Effects of Offering Bet

	Random attrition		Manski Bounds		
	Baseline	Δ	Baseline	Lower Δ	Upper Δ
Satisfied with exercise (0/1)	0.356	0.178	0.364	0.121	0.212
	(0.051)	[0.005]	(0.049)		
Procrastinated in prior 4 weeks (0/1)	0.756	-0.322	0.747	-0.354	-0.263
	(0.046)	[0.000]	(0.044)		
Fit (0/1)	0.789	-0.033	0.768	-0.081	0.010
	(0.043)	[0.664]	(0.043)		
Healthy lifestyle (0/1)	0.600	0.078	0.576	0.040	0.131
	(0.052)	[0.265]	(0.050)		
Happy (0/1)	0.800	-0.022	0.778	-0.071	0.020
	(0.042)	[0.832]	(0.042)		
Observations	90	90	99	99	99

Notes: The binary variables indicate self-reported satisfaction with one's exercising frequency at the university sports center, self-reported procrastination of exercising sessions at the university sports center in the prior four weeks, self-reported fitness, self-reported healthy lifestyle, and self-reported happiness. Δ denotes the difference between the follow-up and baseline survey. Manski bounds give the lower and upper bound of the difference. The lower bound assigns a 0, the upper bound a 1 to all missing variables in the follow-up survey. Standard errors are in parentheses, p-values from McNemar's tests are in brackets.

Third, 72 out of 90 bet participants who completed the follow-up survey stated they would likely participate in a matched bet again in the future. Most participants thus perceive the matched bet as welfare-enhancing.

Fourth, there seems little substitution in exercising behavior. Bet participants reported an almost identical (Wilcoxon signed-rank test, $p = 0.976$) average duration of their gym visits before (62.8 minutes) and during the bet period (63.0 minutes). They also reported a similar ($p = 0.209$) number of exercising sessions outside the USC before (3.2 sessions) and during the bet period (2.9 sessions).

In summary, participants came closer to their desired exercising frequency, were more satisfied with their exercising behavior, procrastinated less and did not report significant substitution of exercising behavior. Also, most of the bet participants stated they would likely take up a matched bet again in the future. Together, these findings suggest that the matched bet indeed increased participants' welfare.

2.6 Discussion

The results of the theoretical analysis and the field experiment on exercising show that the matched bet is a promising mechanism to help people overcome time inconsistency. In Section 2.6.1, I show that the matched bet is theoretically superior to three commonly-used mechanisms. In Section 2.6.2, I discuss practical challenges to the implementation of the matched-bet mechanism. In Section 2.6.3, I discuss opportunities to apply the matched bet in other areas, such as academic performance, weight loss and smoking cessation.

2.6.1 Relative Performance of the Matched-Bet Mechanism

This section compares the matched-bet mechanism to a subsidy, a monetary commitment contract and an unmatched bet. I discuss each mechanism's required budget and theoretically compare the mechanisms' induced behavioral change and overall efficiency under the assumption that the monetary stakes are the same across mechanisms.

With a subsidy, a policy maker pays a participant a monetary reward if she reaches a prespecified target. In contrast, with a commitment contract, a participant has to pay a monetary fine to the policy maker if she fails to reach the target. An unmatched bet works similarly to the matched bet. They differ in that an unmatched bet groups bet participants with all other participants, and thus not just participants that are equally likely to reach the target.[18]

[18] Formally (cf. (2.1)), the monetary transfers to a participant in a subsidy, monetary commitment contract and unmatched bet are specified by $T_i^{Su} = \mathcal{I}_i m$, $T_i^{Co} = \mathcal{I}_i m - m$, and $T_i^{Un} = \mathcal{I}_i m - \frac{1}{|S_i'|} \sum_{j \in S_i'} \mathcal{I}_j m$ with set $S_i' \equiv \{j \neq i | \mathcal{P}_j = 1\}$, and $|S_i'|$ denoting the number of agents in S_i'.

Budget. The mechanisms differ in their required budget. Offering a subsidy requires a positive budget to finance the rewards paid to participants that reach the target. The size of the required budget positively depends on the size of the monetary reward, as well as on how likely participants reach the target on average. In contrast, offering a matched bet or unmatched bet does not require a positive budget. Like a matched bet, an unmatched bet is ex-post strictly budget-balanced. The reward paid to a participant is exactly refinanced by the payments obtained from her grouped partners. With a commitment contract, a policy maker either breaks even (if all participants reach the target) or makes a positive profit (if at least one participant fails to reach the target). This implies that a commitment contract is ex-post weakly budget-balanced.

Behavioral Change. The matched bet, subsidy, unmatched bet and commitment contract also differ in how they change people's behavior. Potentially, the mechanisms might differ in who participates and by how much participants change their behavior. However, theory suggests that differing effects are only due to differing participation decisions. The reason is that all four mechanisms provide participants with the same extra incentive, equal to the monetary stake, to reach the target. All four mechanisms thus change participants' behavior to the same extent. In contrast, the mechanisms differ in how much participants have to pay if they fail to reach the target. The less they have to pay, the more attractive it is for people to participate.

The participation rate is highest for a subsidy; everyone participates because participants can only win but never lose money. Full participation ensures that all time-inconsistent people are more likely to engage in the targeted behavior compared to the baseline. On the downside, all time-consistent people, who already behave efficiently, overengage in the targeted behavior.

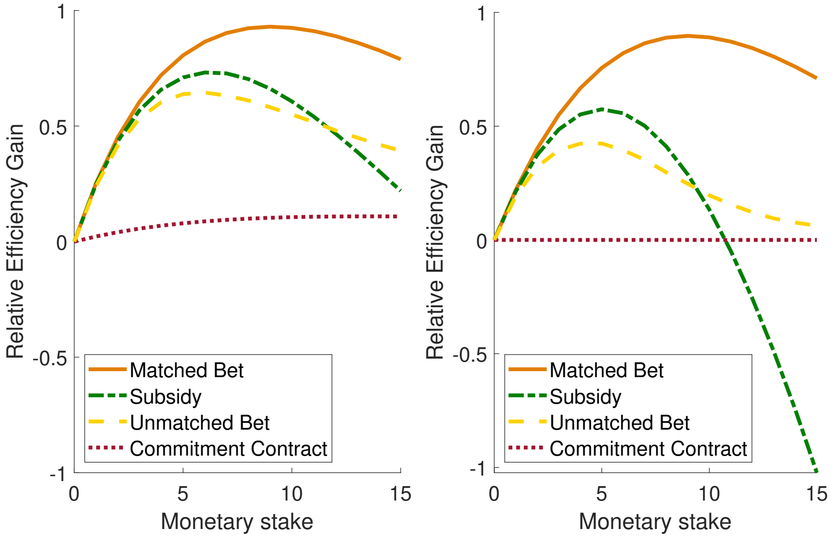
The participation rates are lower for a matched and unmatched bet. If a bet participant does not reach the target, she needs to pay an amount equal to the average reward of her grouped partners, which makes it less attractive to participate in a bet than in a subsidy. The theoretical analysis and the field experiment establish that the matched bet features favorable self-selection: the participation rate in a matched bet positively depends on the degree of one's time-inconsistency. In contrast, the participation rate in an unmatched bet only depends on one's *perceived* time-inconsistency. It follows that, ceteris paribus, naive procrastinators and time-consistent people do not differ in their participation decision. Further, the lack of matching decreases the participation rate of sophisticated procrastinators that are unlikely to reach the target. Even though they are well aware that an unmatched bet might help them behave more efficiently, they might refrain from participating to prevent losing too much money in expectation. On the other hand, some time-consistent people that are likely to reach the target participate in the unmatched bet, as their expected bet earnings overcompensate their efficiency loss from overengaging in the targeted behavior.

The participation rate is lowest for a commitment contract. As participants cannot win money with a commitment contract, naive procrastinators and time-consistent people never participate. Many sophisticated procrastinators also decide against taking up a commitment contract as its induced behavioral change rarely outweighs the expected monetary loss.

Efficiency. I now compare the mechanisms in terms of social welfare. Figure 2.6 compares the relative efficiency gain of the matched-bet mechanism to a subsidy, unmatched bet and commitment contract for various monetary stakes. A mechanism's relative efficiency gain denotes the increase in social welfare from offering this mechanism divided by the difference in social welfare between the first best, i.e. the efficient outcome, and the baseline.

The figure depicts performance when people are likely (left graph) and unlikely to reach the target. I rely on numerical solutions as results are not analytically tractable.[19]

Figure 2.6: Efficiency of Mechanisms



Notes: The figure shows the relative efficiency gain of the matched bet, subsidy, unmatched bet and commitment contract by size of the monetary stake m. Variables are calibrated in the following way: benefits $b_i \sim \text{U}[15, 25]$, effort costs $k_i \sim \text{U}[0, 5]$, stochastic opportunity costs $c_i \sim \text{Exp}(10)$ for left graph and $c_i \sim \text{Exp}(30)$ for right graph, short-run discount factor $\beta_i \sim \min\{\text{U}[\frac{1}{3}, \frac{4}{3}], 1\}$, perceived short-run discount factor $\hat{\beta}_i \sim \text{U}[\beta_i, 1]$, long-run discount factor $\delta_i = 1$.

We observe that the matched-bet mechanism is close to the first best for a medium-sized monetary stake. The matched-bet mechanism achieves a higher relative efficiency gain than a subsidy, unmatched bet and commitment contract over all monetary stakes. For a low monetary stake, a matched bet increases relative efficiency only marginally more than a subsidy and unmatched bet. The difference in efficiency increases in the mon-

[19]The calibration of time preferences is based on the empirical literature (see e.g. Augenblick et al., 2015; Augenblick and Rabin, 2019). The results, however, are robust to the chosen parameters.

etary stake. The reason is that the matched-bet mechanism is more robust to setting suboptimally high monetary stakes than the other mechanisms. With a subsidy, a high monetary stake induces a considerable number of people to overengange in the targeted behavior. The right graph depicts that overall efficiency even drops below the baseline for a sufficiently high stake. For an unmatched bet, a high monetary stake amplifies the negative effect of grouping people unfairly. The difference in efficiency between a matched bet and a commitment contract is large, irrespective of the monetary stake and how likely people reach the target. Even if people are likely to reach the target (left graph), commitment contracts prevent only a small share of the initial efficiency loss. If people are unlikely to reach the target (right graph), commitment contracts become too costly in expectation and all agents are unwilling to participate; a commitment contract then does not increase efficiency over the baseline.

2.6.2 Challenges

The experiment shows that offering a matched bet increases participants' gym attendance during the intervention period to a statistically and economically significant extent. Challenges remain with respect to increasing the bet take-up rate and establishing positive long-run effects.

Take-Up Rate. The experiment featured a bet take-up rate of 25%. This is about double the take-up rate observed in experiments with 'pure' deposit commitment contracts.[20] Given that 62% of the subjects self-identified as procrastinators, however, the efficient bet take-up rate is likely to be higher than 25%. This suboptimally low rate limits the matched bet's effectiveness. There could be several reasons why many subjects rejected the matched bet. In the baseline survey, the most commonly stated reasons to reject

[20] Royer et al. (2015) and Giné et al. (2010) find take-up rates of 12% for commitment to exercise and 11% to stop smoking.

the matched bet were: being too busy with studying, being afraid of losing money and opposing linking exercising to money. While study obligations are an understandable reason to refrain from committing oneself to exercise, recent studies suggest that there is no actual trade-off between academic performance and exercising. Cappelen et al. (2017) and Fricke et al. (2018) provide evidence that exercising has a considerable and positive effect on academic performance. In order to also attract subjects who are comparatively busy in the first few weeks of the bet period, one might offer the matched bet with a longer bet period of several months. The longer bet period might also mitigate people's fear of losing money, as a longer period diminishes the effect of potential negative exercising frequency shocks such as injuries or sickness.

A straightforward alternative for a less budget-constrained policy maker to mitigate people's fear of losing money and thereby increasing bet take-up is to offer a subsidized matched bet. One way to implement a subsidized bet is to offer a matched bet with a participation bonus. The magnitude of this bonus should depend on the policy maker's budget, the current underparticipation in the matched bet and possible externalities of the incentivized behavior. The overall utility from exercising, for example, includes the utility for the individual and the utility for employers and society due to lower health costs. This implies that even when the matched bet helps bet participants to achieve their maximal utility from exercising, participants might still exercise at inefficiently low frequencies from the point of view of the employer or society. In such cases, adding a participation bonus to the matched bet can increase social welfare.

A minority of subjects refrained from taking up the matched bet because they opposed linking exercising to money. For these people offering a bet with a non-monetary bet stake might be more suitable. One could, for example, bet for duration of gym contract days (exercising) or grade points (studying). Non-monetary bet stakes could also be a viable alternative if monetary bets cannot be implemented for other, e.g. legal, reasons.

Long-Run Effects. The second challenge concerns the lack of statistically significant positive long-run effects of the matched bet in the experiment. While offering the bet still has a significantly positive effect on gym attendance in the first week after the end of the bet period, the weekly effects – though mostly positive – are statistically insignificant from the second week onward. As explained above, this might be partly due to the Christmas break starting one week after the end of the bet period. A different timing of the intervention might have yielded more persistent effects. Nevertheless, it could be that many bet participants need to participate in a matched bet not only once but repeatedly to continue visiting the gym on a more regular basis. As the matched bet is strictly budget-balanced, offering repeated bet rounds does not run into financing issues (as might be the case with a subsidy).

Note though that bet participants need to be willing to repeatedly participate in matched bet rounds. While whether they do so is an empirical question that calls for future studies, in this study at least 73% of bet participants find it likely that they would take up a matched bet again.[21] Not surprisingly, interest in future bet rounds is highly and positively correlated with a bet participant's increase in gym attendance during the bet period (corr. = 0.42).

Offering the matched bet on a regular basis introduces an obstacle, the so called ratchet effect. Once potential participants know about an upcoming bet round, they might be inclined to 'trick' the matching system by deliberately exercising rarely during the matching period. In this way they can ensure to be grouped with partners with a lower expected exercising frequency, which translates into an increase in their expected bet payoff.

[21] 72 out of 90 (80%) responding bet participants stated in the follow-up survey that they would likely take up a matched bet again. The share drops to 73% if we assume that all 9 non-responding bet participants would not take up a matched bet again.

To prevent such behavior, the deliberately foregone exercising benefit during the matching period needs to outweigh the expected monetary gain due to an easier matching group. Two possible solutions are to either set the bet stake sufficiently low or to have a comparatively long matching period.

2.6.3 Applying the Matched Bet in Other Areas

The matched bet is not limited to exercising only, but can be readily applied to other areas such as academic performance, weight loss and smoking cessation. The matched bet is especially promising if a large proportion of the targeted population exhibits time-inconsistent behavior, participants' target behavior is easily observable, and accurate matching is possible.

The more people of the targeted population exhibit time-inconsistent behavior, the more the matched bet can help people behave more efficiently. The matched bet shares the requirement that participants' target behavior is easily observable or estimable with other incentive schemes such as subsidies and commitment contracts. In many cases, however, target behavior is not easily observable. Then, the matched-bet mechanism might still work if there exists a sufficiently good and easily observable proxy to estimate the target behavior. For example, gym attendance is a proxy for overall exercise, the target behavior. Proxies can be input- or output-driven. Ceteris paribus, input-driven proxies seem preferable as people can better control their input than their output (Gneezy et al., 2011). However, input-driven proxies are not always available, they might lead to inefficient substitution or make it difficult to accurately match bet participants. If a policy maker can neither easily observe input-driven nor output-driven proxies, a centralized version of the matched bet is not possible. In this case, one might turn to a decentralized version of the matched bet where agents directly bet with each other and choose the bet stake themselves. An outline of this alternative mechanism is given in Appendix 2.A.2.

The matched bet requires that accurate matching is possible. If matching is not possible, one can only offer an unmatched bet. Section 2.6.1 shows the effects of a bet without matching. The matching instrument needs to be predictive of behavior during the bet period. Often, past behavior is a good predictor of future behavior. As previously discussed, however, past behavior might be prone to manipulation.

Given the three requirements, academic performance, weight loss and smoking cessation seem to be promising new areas of application. In all three areas many people exhibit time-inconsistent behavior. Grades are a good proxy for study effort, BMI is a good proxy for excessive body fat and cotinine tests are a good indicator of smoking behavior. Past grades in related courses should be a good matching instrument, as is current BMI for weight loss and current cotinine levels for smoking behavior.

2.7 Conclusion

In this chapter, I introduce, theoretically analyze and experimentally test the matched-bet mechanism. The matched bet is an easily applicable, strictly budget-balanced and strategically straightforward mechanism that aims to help people overcome time-inconsistent behavior.

In a theoretical model inspired by DellaVigna and Malmendier (2004), I show that the matched-bet mechanism helps both sophisticated and naive procrastinators to reduce time-inconsistent behavior. In a model that allows agents to have private and individual-specific degrees of time inconsistency, naiveté, investment benefits and effort costs, I find that it is sufficient to know agents' expected baseline investment frequencies to offer a Pareto improving matched bet.

In a field experiment at a university gym, I observe that the matched bet also proves a promising device in practice. Subjects who were offered to participate in the matched bet recorded on average 38% more gym visits (an increase of 0.34 standard deviations) during the bet period than subjects in the control group. Self-reported procrastinators were significantly more likely to take up the matched bet, confirming favorable self-selection into the bet. Further evidence suggests that the matched bet increased participant's welfare.

Overall, the matched-bet mechanism is a promising mechanism to help people overcome time-inconsistent behavior, both in theory and in practice. Unlike existing mechanisms such as subsidies, monetary commitment contracts, and unmatched bets, the matched bet is both low-cost and effective. For future research, it would be interesting to investigate whether the matched-bet mechanism can induce persistent behavioral change through repeated bet rounds, and whether the matched bet would also prove to be an effective mechanism in other areas such as academic performance, weight loss and smoking cessation.

2.A Theoretical Extensions

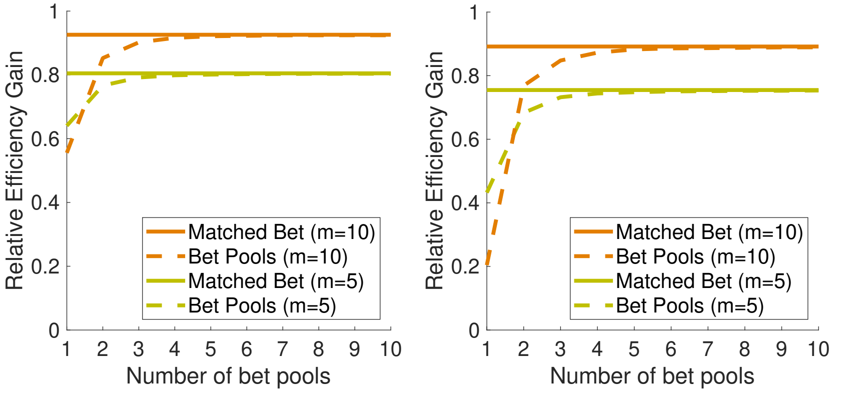
This section discusses three extensions to the theoretical analysis. First, it shows that the matched-bet mechanism is robust to imperfect matching. Second, it discusses a decentralized version of the matched bet. And third, I analyze a setting in which the underlying parameters of each agent are known.

2.A.1 Robustness towards Imperfect Matching

In my theoretical analysis of the matched-bet mechanism, I assume perfect matching, i.e. bet participants are grouped with other participants that have the same expected investment frequency. In reality, perfect matching is generally not possible. This raises the question how robust the matched-bet mechanism is to imperfect matching. Figure 2.A1 shows the prevented share of efficiency loss dependent on the number of bet pools using the same calibration as in Section 2.6.1. Given a number of bet pools n, bet participants are grouped with other participants whose ranks in terms of expected investment frequency in the population of N agents fall in the same interval of $(0, \frac{N}{n}], (\frac{N}{n}, \frac{2N}{n}], ..., (\frac{(n-1)N}{n}, N]$ as their own. Note that an unmatched bet is equivalent to one bet pool, while a matched bet is equivalent to an infinite number of bet pools.

The figure shows that the relative efficiency gain increases concavely in the number of bet pools. With one bet pool, i.e. an unmatched bet, efficiency is considerably lower than with a matched bet. There is a steep increase in efficiency when bet participants are divided into two bet pools according to their expected investment frequency. Efficiency with two bet pools is already closer to efficiency with an infinite number of bet pools, i.e. a matched bet, than with one bet pool. This finding is irrespective of low (left graph) or high expected investment costs (right), and a low (olive) or high (orange) bet stake. For a moderate number of bet pools, efficiency

Figure 2.A1: Robustness of Matched Bet towards Imperfect Matching



Notes: The figure shows the relative efficiency gain of the matched bet in comparison to an imperfectly matched bet with various numbers of bet pools. Variables are calibrated in the following way: $b_i \sim \mathrm{U}[15, 25]$, $k_i \sim \mathrm{U}[0, 5]$, $c_i \sim \mathrm{Exp}(10)$ for left graph and $c_i \sim \mathrm{Exp}(30)$ for right graph, $\beta_i \sim \min\{\mathrm{U}[\frac{1}{3}, \frac{4}{3}], 1\}$, $\hat{\beta}_i \sim \mathrm{U}[\beta_i, 1]$, $\delta_i = 1$, $m = 5$ (olive) and $m = 10$ (orange).

with an imperfectly matched bet already closely approaches efficiency with a matched bet. The figure thus illustrates that the matched bet is robust to imperfect matching.

2.A.2 Decentralized Matched Bet

The main text analyzes a centralized version of the matched-bet mechanism. The policy maker acts as a central institution that offers the bet, observes agents' decisions and enforces monetary transfers. In some cases the central institution might not be necessary and agents could directly bet with each other. In this decentralized version, agents choose their bet stakes themselves. The matched-bet mechanism then requires that bet participants group with other participants who prefer the same bet stake and have the same expected investment frequency.

An agent chooses the bet stake m_i^* that she expects to maximize her utility. Formally, an agent's maximization problem becomes

$$\max_{m_i} \beta_i \delta_i \left[\int_0^{\hat{\beta}_i \delta_i b_i + m_i - k_i} (\delta_i b_i - k_i - c_i) f(c_i) dc_i + \int_{\beta_i \delta_i b_i + m_i - k_i}^{\hat{\beta}_i \delta_i b_i + m_i - k_i} m_i f(c_i) dc_i \right]. \tag{2.A1}$$

Agents choose a bet stake m_i^*, which can be implicitly defined by

$$m_i^* = (1 - \hat{\beta}_i)\delta_i b_i \frac{f(\hat{\beta}_i \delta_i b_i - k_i + m_i^*)}{f(\beta_i \delta_i b_i - k_i + m_i^*)} + \frac{F(\hat{\beta}_i \delta_i b_i - k_i + m_i^*) - F(\beta_i \delta_i b_i - k_i + m_i^*)}{f(\beta_i \delta_i b_i - k_i + m_i^*)} \tag{2.A2}$$

For sophisticated agents ($\beta_i = \hat{\beta}_i$) the equation above simplifies to $m_i^* = (1 - \beta_i)\delta_i b_i$, which yields the following proposition.

Proposition 2.A1 (Decentralized Matched Bet) *Sophisticated agents take up a decentralized matched bet. They choose the optimal bet stake $m_i^* = (1 - \beta_i)\delta_i b_i$, and thereby invest efficiently.*

Proof See Appendix 2.B

Sophisticated agents thus self-select into the matched bet contract that maximizes their utility. Partially naive agents take up a decentralized matched bet choosing $m_i^* \leq (1 - \beta_i)\delta_i b_i$. Time-consistent agents do not take up a matched bet. The welfare comparison between a centralized and decentralized matched-bet mechanism is ambiguous. While the decentralized version is always better for sophisticated agents, the centralized version might be better for partially naive agents.

The desirable theoretical results of a decentralized matched bet raise the question why we do not regularly observe it in the real world. There are several reasons that make it difficult to implement a decentralized matched bet in practice. First, choosing a bet stake is difficult if one lacks experience with monetary incentives for changing one's own behavior. In the trial round, bet participants could choose between a bet stake of €3 and €5 (see

Appendix 2.C). Theory predicts that participants with a higher degree of time inconsistency will opt for a higher bet stake. Participants' selection did not seem to be driven by their degree of time inconsistency, however, but seemed to be affected more by the participant's inclination to bet and compete. Second, fair decentralized matching is difficult to achieve. It would require a considerable amount of effort to find other people who want to take up a matched bet with the same bet stake and also have the same expected investment frequency as oneself. Third, it is difficult to enforce a monetary transfer from a matched bet without a central authority. This restricts possible partners to trustworthy people. And fourth, it might be socially not acceptable to claim money from bet partners, especially if one is sufficiently close to trust them (i.e. family or friends). The centralized version does not have these issues and is thus more easily implementable.

2.A.3 Full Information

The theoretical model in the main text assumes that each agent's expected baseline investment frequency $F(\beta_i\delta_i b_i - k_i)$ is common knowledge, but each agent's long-run discount factor δ_i, present bias β_i, benefits b_i, effort costs k_i and cost distribution function $F(\cdot)$ are private. This implies that the take-it-or-leave-it offer of the matched bet cannot be customized to every agent's need. The offered bet stake might be too low or too high for some agents.

It turns out that the matched bet is a more effective mechanism if each agent's long-run discount factor, present bias and benefits are known. In fact, the matched bet can then even make all agents invest efficiently as stated in the proposition below.

Proposition 2.A2 (First Best) *Assume that each agent's long-run discount factor δ_i, present bias $1 - \beta_i$, benefits b_i and expected baseline investment frequency $F(\beta_i\delta_i b_i - k_i)$ are observable. By offering each agent a* *matched bet with bet stake* $m_i = (1-\beta_i)\delta_i b_i$*, every agent participates in the bet and invests efficiently.*

Proof See Appendix 2.B

Note that while information about each agent's long-run discount factor, present bias, benefits and expected investment frequency is a strong requirement, the result does not require information about agents' perceived present bias, effort costs and cost distribution function.

Under the information structure of Proposition 2.A2, the first best outcome for all agents could also be achieved with a subsidy. This would, however, cost the policy maker $\sum_i Pr\{\mathcal{I}_i = 1\}m_i = \sum_i F(\delta_i b_i - k_i)(1-\beta_i)\delta_i b_i$ in total. With a matched bet, the efficient outcome can be achieved at zero costs to the policy maker.

2.B Proofs

Proof of Proposition 2.3 ←

(i) An agent's willingness to participate in a matched bet decreases in the size of the offered bet stake m. Define

$$\mathbb{E}[\hat{G}_i^0] \equiv \mathbb{E}[\hat{U}^0_{i,\mathcal{P}_i=1}] - \mathbb{E}[\hat{U}^0_{i,\mathcal{P}_i=0}] = \beta_i\delta_i \int_{\hat{\beta}_i\delta_i b_i - k_i}^{\hat{\beta}_i\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i + \beta_i\delta_i \int_{\beta_i\delta_i b_i - k_i + m}^{\hat{\beta}_i\delta_i b_i - k_i + m} m f(c_i) dc_i.$$

Taking the derivative of $\mathbb{E}[\hat{G}_i^0]$ w.r.t. m yields

$$\frac{\partial \mathbb{E}[\hat{G}_i^0]}{\partial m} = \beta_i[\delta_i F(\hat{\beta}_i\delta_i b_i - k_i + m) - \delta_i F(\beta_i\delta_i b_i - k_i + m)] + \beta_i[(1-\hat{\beta}_i)\delta_i^2 b_i f(\hat{\beta}_i\delta_i b_i - k_i + m) - \delta_i m f(\beta_i\delta_i b_i - k_i + m)].$$

Bounding this expression from above yields

$$\frac{\partial \mathbb{E}[\hat{G}_i^0]}{\partial m} \leq \beta_i[(\hat{\beta}_i - \beta_i)\delta_i^2 b_i f(\beta_i\delta_i b_i - k_i + m) + (1-\hat{\beta}_i)\delta_i^2 b_i f(\beta_i\delta_i b_i - k_i + m)] - \beta_i[\delta_i m f(\beta_i\delta_i b_i - k_i + m)]$$

$$\frac{\partial \mathbb{E}[\hat{G}_i^0]}{\partial m} \leq \beta_i[[(1-\beta_i)\delta_i b_i - m]\delta_i f(\beta_i\delta_i b_i - k_i + m)]$$

Therefore, $\frac{\partial \mathbb{E}[\hat{G}_i^0]}{\partial m} \leq 0$ if $m \geq (1-\beta_i)\delta_i b_i$. Now, note that $\mathbb{E}[\hat{G}_i^0] \geq 0$ if $m \leq (1-\beta_i)\delta_i b_i$ as

$$\begin{aligned}\mathbb{E}[\hat{G}_i^0] &= \beta_i\delta_i \int_{\hat{\beta}_i\delta_i b_i - k_i}^{\hat{\beta}_i\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i + \beta_i\delta_i \int_{\beta_i\delta_i b_i - k_i + m}^{\hat{\beta}_i\delta_i b_i - k_i + m} m f(c_i) dc_i \\ &= \beta_i\delta_i \int_{\hat{\beta}_i\delta_i b_i - k_i}^{\hat{\beta}_i\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i + m) f(c_i) dc_i + \beta_i\delta_i \int_{\beta_i\delta_i b_i - k_i + m}^{\hat{\beta}_i\delta_i b_i - k_i} m f(c_i) dc_i \\ &\geq 0\end{aligned}$$

for $m \leq (\hat{\beta}_i - \beta_i)\delta_i b_i$. Also,

$$\begin{aligned}
\mathbb{E}[\hat{G}_i^0] &= \beta_i\delta_i \int_{\hat{\beta}_i\delta_i b_i - k_i}^{\hat{\beta}_i\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i + \beta_i\delta_i \int_{\beta_i\delta_i b_i - k_i + m}^{\hat{\beta}_i\delta_i b_i - k_i + m} m f(c_i) dc_i \\
&= \beta_i\delta_i \int_{\hat{\beta}_i\delta_i b_i - k_i}^{\beta_i\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i \\
&\quad + \beta_i\delta_i \int_{\beta_i\delta_i b_i - k_i + m}^{\hat{\beta}_i\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i + m) f(c_i) dc_i \\
&\geq 0
\end{aligned}$$

for $(\hat{\beta}_i - \beta_i)\delta_i b_i < m \leq (1 - \beta_i)\delta_i b_i$. Therefore, any agent who takes up a matched bet with bet stake m would also take up a matched bet with bet stake $m' : m' < m$ which proves the proposed result. ■

(ii) Denote the maximal m for which an agent takes up the bet by $\overline{m}_i$. Rearranging the participation constraint (PC) yields

$$m \leq (1 - \hat{\beta}_i)\delta_i b_i \frac{F(\hat{\beta}_i\delta_i b_i - k_i + m) - F(\hat{\beta}_i\delta_i b_i - k_i)}{F(\beta_i\delta_i b_i - k_i + m)} + \frac{\int_{\hat{\beta}_i\delta_i b_i - k_i}^{\hat{\beta}_i\delta_i b_i - k_i + m} F(c_i) dc_i}{F(\beta_i\delta_i b_i - k_i + m)} = \overline{m}_i. \tag{2.14}$$

As $F(\beta_i\delta_i b_i - k_i + m)$ increases in β_i, both terms decrease in β_i. Therefore, $\overline{m}_i$ decreases in β_i. As a consequence, for any m, there is a threshold for β_i where $\overline{m}_i$ drops below m. ■

(iii) Taking the derivative of $\overline{m}_i$ w.r.t. $\hat{\beta}_i - \beta_i$ keeping β_i fixed is equivalent to taking the derivative of $\overline{m}_i$ w.r.t. $\hat{\beta}_i$. One obtains

$$\frac{\partial \overline{m}_i}{\partial \hat{\beta}_i} = (1 - \hat{\beta}_i)\delta_i^2 b_i^2 \frac{f(\hat{\beta}_i\delta_i b_i - k_i + m) - f(\hat{\beta}_i\delta_i b_i - k_i)}{F(\beta_i\delta_i b_i - k_i + m)} \leq 0$$

as $f(\cdot)$ is weakly decreasing. Therefore, $\overline{m}_i$ decreases in $\hat{\beta}_i$. ■

Proof of Corollary 2.1 ← Insert $\beta_i = \hat{\beta}_i = 1$ into the participation constraint, which becomes

$$\delta_i \int_{\delta_i b_i - k_i}^{\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i + \delta_i \int_{\delta_i b_i - k_i + m}^{\delta_i b_i - k_i + m} m f(c_i) dc_i.$$

For any bet stake $m > 0$ the first term becomes negative and the second term is zero. The participation constraint is therefore never fulfilled for time-consistent agents. ■

Proof of Proposition 2.4 ←

(i) Denote the maximal m for which an agent is better off by taking up the bet by $\overline{m}_i^{BC}$. Transforming the better-off condition yields

$$m \leq \overline{m}_i^{BC} = (1-\beta_i)\delta_i b_i \frac{F(\beta_i\delta_i b_i - k_i + m) - F(\beta_i\delta_i b_i - k_i)}{F(\beta_i\delta_i b_i - k_i + m)} + \frac{\int_{\beta_i\delta_i b_i - k_i}^{\beta_i\delta_i b_i - k_i + m} F(c_i)dc_i}{F(\beta_i\delta_i b_i - k_i + m)} \tag{2.15}$$

No agent is harmed by offering a matched bet if agents only take up a bet if the bet makes them better off in expectation, thus if $\overline{m}_i \leq \overline{m}_i^{BC}$ (cf. Proof of Proposition 2.3.ii). Note that $\overline{m}_i = \overline{m}_i^{BC}$ for sophisticated agents ($\beta_i = \hat{\beta}_i$). As $\frac{\partial \overline{m}_i}{\partial \hat{\beta}_i} \leq 0$ (cf. Proof of Proposition 2.3.iii) and $\beta_i \leq \hat{\beta}_i$, $\overline{m}_i \leq \overline{m}_i^{BC}$ holds for all agents. Therefore, no agent is harmed by offering a matched bet. ■

(ii) Note that an agent is strictly better off if $m < \overline{m}_i \leq \overline{m}_i^{BC}$. From (i) we know that $\overline{m}_i \leq \overline{m}_i^{BC}$. Substituting $F(\beta_i\delta_i b_i - k_i + m)$ for $F(\hat{\beta}_i\delta_i b_i - k_i + m)$ in (2.14) and using the concavity of $F(\cdot)$ one obtains the following condition

$$\begin{aligned} m \leq (1-\hat{\beta}_i)\delta_i b_i &\frac{F(\beta_i\delta_i b_i - k_i + m) - F(\hat{\beta}_i\delta_i b_i - k_i)}{F(\beta_i\delta_i b_i - k_i + m)} \\ &+ m - \frac{[m + (\beta_i - \hat{\beta}_i)\delta_i b_i][F(\beta_i\delta_i b_i - k_i + m) - F(\hat{\beta}_i\delta_i b_i - k_i)]}{2F(\beta_i\delta_i b_i - k_i + m)} \end{aligned}$$

Transforming above inequality yields

$$0 \leq 2\delta_i b_i - \hat{\beta}_i\delta_i b_i - \beta_i\delta_i b_i - m \tag{2.16}$$

from which condition $m \leq (2 - \hat{\beta}_i - \beta_i)\delta_i b_i$ immediately follows. ■

Proof of Proposition 2.5 ←

(i) Due to fair matching, an agent has an expected bet payoff of zero. Therefore, an agent is better off taking up a matched bet if and only if the agent invests more efficiently with the matched bet. From Proposition 2.4.i we know that agents only take up a matched bet if they are better off with it. Thus, all agents who take up the matched bet increase their investment efficiency. ■

(ii) The share of prevented efficiency loss for an agent is

$$\frac{\mathbb{E}[U^W_{i,\mathcal{P}_i=1}] - \mathbb{E}[U^W_{i,\mathcal{P}_i=0}]}{\mathbb{E}[U^W_{i,eff}] - \mathbb{E}[U^W_{i,\mathcal{P}_i=0}]} = \frac{\delta_i \int_{\beta_i\delta_i b_i - k_i}^{\beta_i\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i}{\delta_i \int_{\beta_i\delta_i b_i - k_i}^{\delta_i b_i - k_i} (\delta_i b_i - k_i - c_i) f(c_i) dc_i}$$

For the case that $m \leq (1-\beta_i)\delta_i b_i$ one can transform above expression to

$$\frac{\delta_i \int_{\beta_i\delta_i b_i - k_i}^{\beta_i\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i}{\delta_i \int_{\beta_i\delta_i b_i - k_i}^{\beta_i\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i + \delta_i \int_{\beta_i\delta_i b_i - k_i + m}^{\delta_i b_i - k_i} (\delta_i b_i - k_i - c_i) f(c_i) dc_i}$$

$$\geq \frac{[(\delta_i b_i - k_i)m - \frac{(\beta_i\delta_i b_i - k_i + m)^2}{2} + \frac{(\beta_i\delta_i b_i - k_i)^2}{2}] f(\beta_i\delta_i b_i - k_i + m)}{[(\delta_i b_i - k_i)(1-\beta_i)\delta_i b_i - \frac{(\delta_i b_i - k_i)^2}{2} + \frac{(\beta_i\delta_i b_i - k_i)^2}{2}] f(\beta_i\delta_i b_i - k_i + m)}$$

$$= 1 - \left(1 - \frac{m}{(1-\beta_i)\delta_i b_i}\right)^2$$

as $f(\cdot)$ is weakly decreasing.

Similarly, for $m > (1-\beta_i)\delta_i b_i$ one can rewrite the initial expression to

$$\frac{\delta_i \int_{\beta_i\delta_i b_i - k_i}^{\delta_i b_i - k_i} (\delta_i b_i - k_i - c_i) f(c_i) dc_i + \delta_i \int_{\delta_i b_i - k_i}^{\beta_i\delta_i b_i - k_i + m} (\delta_i b_i - k_i - c_i) f(c_i) dc_i}{\delta_i \int_{\beta_i\delta_i b_i - k_i}^{\delta_i b_i - k_i} (\delta_i b_i - k_i - c_i) f(c_i) dc_i}$$

$$\geq \frac{[(\delta_i b_i - k_i)m - \frac{(\beta_i\delta_i b_i - k_i + m)^2}{2} + \frac{(\beta_i\delta_i b_i - k_i)^2}{2}] f(\delta_i b_i - k_i)}{[(\delta_i b_i - k_i)(1-\beta_i)\delta_i b_i - \frac{(\delta_i b_i - k_i)^2}{2} + \frac{(\beta_i\delta_i b_i - k_i)^2}{2}] f(\delta_i b_i - k_i)}$$

$$= 1 - \left(1 - \frac{m}{(1-\beta_i)\delta_i b_i}\right)^2$$

as $f(\cdot)$ is weakly decreasing.

As Proposition 2.4.i shows that all agents who take up the bet are weakly better off, one obtains the proposed result. ■

(iii) First, note that all mechanisms with a dominant investment strategy can be rewritten as yielding a transfer of $T_i = \mathcal{I}_i m' + f(\mathcal{I}_{-i}, m')$ and increase a bet participant's incentive to invest in period 1 by m'. All mechanisms with a dominant investment strategy thus solely differ in which agents accept a given contract. Second, for sophisticated agents, the better-off condition coincides with the participation constraint in the matched-bet mechanism. Therefore, for any given m there exists no take-it-or-leave-it mechanism with a dominant investment strategy that yields a higher investment efficiency to sophisticated agents than the matched bet. ■

Proof of Proposition 2.A1 ← Taking the first and second derivative of (2.A1) w.r.t. m_i yield

$$\frac{\partial \mathbb{E}[\hat{U}_i^0]}{\partial m_i} = \beta_i\delta_i[(1-\hat{\beta}_i)\delta_i b_i f(\hat{\beta}_i\delta_i b_i - k_i + m_i) + F(\hat{\beta}_i\delta_i b_i - k_i + m_i)]$$
$$- \beta_i\delta_i[F(\beta_i\delta_i b_i - k_i + m_i) + m_i f(\beta_i\delta_i b_i - k_i + m_i)]$$

$$\frac{\partial^2 \mathbb{E}[\hat{U}_i^0]}{\partial^2 m_i} = \beta_i\delta_i[(1-\hat{\beta}_i)\delta_i b_i f'(\hat{\beta}_i\delta_i b_i - k_i + m_i) + f(\hat{\beta}_i\delta_i b_i - k_i + m_i)]$$
$$- \beta_i\delta_i[2f(\beta_i\delta_i b_i - k_i + m_i) + m_i f'(\beta_i\delta_i b_i - k_i + m_i)]$$

Inserting $\hat{\beta}_i = \beta_i$ into the first derivative, we obtain the first order condition

$$\frac{\partial \mathbb{E}[\hat{U}_i^0]}{\partial m_i} = \beta_i\delta_i[(1-\beta_i)\delta_i b_i - m] f(\beta_i\delta_i b_i - k_i + m_i) \overset{!}{=} 0$$

which is fulfilled only for $m_i = (1-\beta_i)\delta_i b_i$ if $f(\beta_i\delta_i b_i - k_i + m_i) > 0$ which can be assumed without loss of generality. Inserting $\hat{\beta}_i = \beta_i$ and $m_i = (1-\beta_i)\delta_i b_i$ into the second derivative, it simplifies to

$$\frac{\partial^2 \mathbb{E}[\hat{U}_i^0]}{\partial^2 m_i} = -\beta_i\delta_i f(\beta_i\delta_i b_i - k_i + m_i) < 0.$$

Sophisticated agents thus choose the optimal bet stake $m_i^* = (1-\beta_i)\delta_i b_i$. Following Proposition 2.2.iii, sophisticated agents thus invest efficiently. ■

Proof of Proposition 2.A2 ← From Proposition 2.4.ii it follows that all present-biased agents $\beta_i < 1$ take up a matched bet with bet stake $m = (1-\beta_i)\delta_i b_i$. Now, substitute m by $(1-\beta_i)\delta_i b_i$ in $\mathbb{E}[U^W_{i,\mathcal{P}_i=1}]$. One obtains $\mathbb{E}[U^W_{i,eff}]$. All agents thus invest efficiently. ■

2.C Trial Round

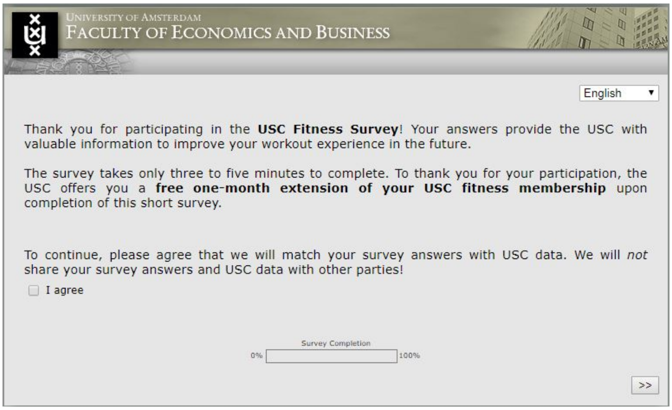
I conducted a trial round of the matched bet experiment with a similar design in May/June 2017. The trial round had a bet take-up rate of only 10%. I used survey answers of subjects of the trial round to make participation in the main experiment more appealing. The trial round differed from the main round as follows. The trial round also included non-student gym members and members who attended the gym on more than four days during the matching period. Bet participants could choose between a bet stake of €3 and €5 and were rewarded with this amount up to a cap of 10 visits during the four-week bet period. The trial round also grouped participants according to their past gym attendance. Unlike in the main experiment, in which bet participants are grouped with all other participants who recorded the same gym visits during the matching period, bet participants in the trial round were grouped with only one partner. In the trial round, participants were required to check out at exit gates to make the gym visit count for the bet. Also, the matched bet was framed as a bet rather than a challenge (as in the main experiment). The differences between the main experiment and the trial round are summarized in Table 2.C1.

Table 2.C1: Differences between Experiment and Trial Round

	Experiment	Trial Round
Sample	Only student members	All members
	Only non-frequent gym visitors	All members
Bet stake	€5 bet stake	Choice of €3 and €5 bet stake
Cap	Cap of 8 visits	Cap of 10 visits
Matching	Several partners	One partner
Exit gates	No exit gates	Exit gates
Framing	Challenge	Bet
Timing	Beginning of Winter	Beginning of Summer

2.D Survey Questions

Figure 2.D1: Baseline Survey Questions



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English

Thank you for participating in the **USC Fitness Survey**! Your answers provide the USC with valuable information to improve your workout experience in the future.

The survey takes only three to five minutes to complete. To thank you for your participation, the USC offers you a **free one-month extension of your USC fitness membership** upon completion of this short survey.

To continue, please agree that we will match your survey answers with USC data. We will *not* share your survey answers and USC data with other parties!

I agree

Survey Completion
0% 100%

>>

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English

How much do you agree with the following statements?

	Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
I am physically fit							
I am motivated to exercise							
I am satisfied with my exercising frequency at the USC							
Over the past four weeks I visited the USC less often than I usually do							
Over the past four weeks I visited the USC more often than I usually do							
I have procrastinated exercising sessions at the USC in the past four weeks							
I expect to procrastinate exercising sessions at the USC in the next four weeks							
I am willing to take risks							
I am competitive							
I have led a healthy lifestyle when it comes to eating, drinking and smoking in the past four weeks							
I am happy with my life in general							

Survey Completion
0% 100%

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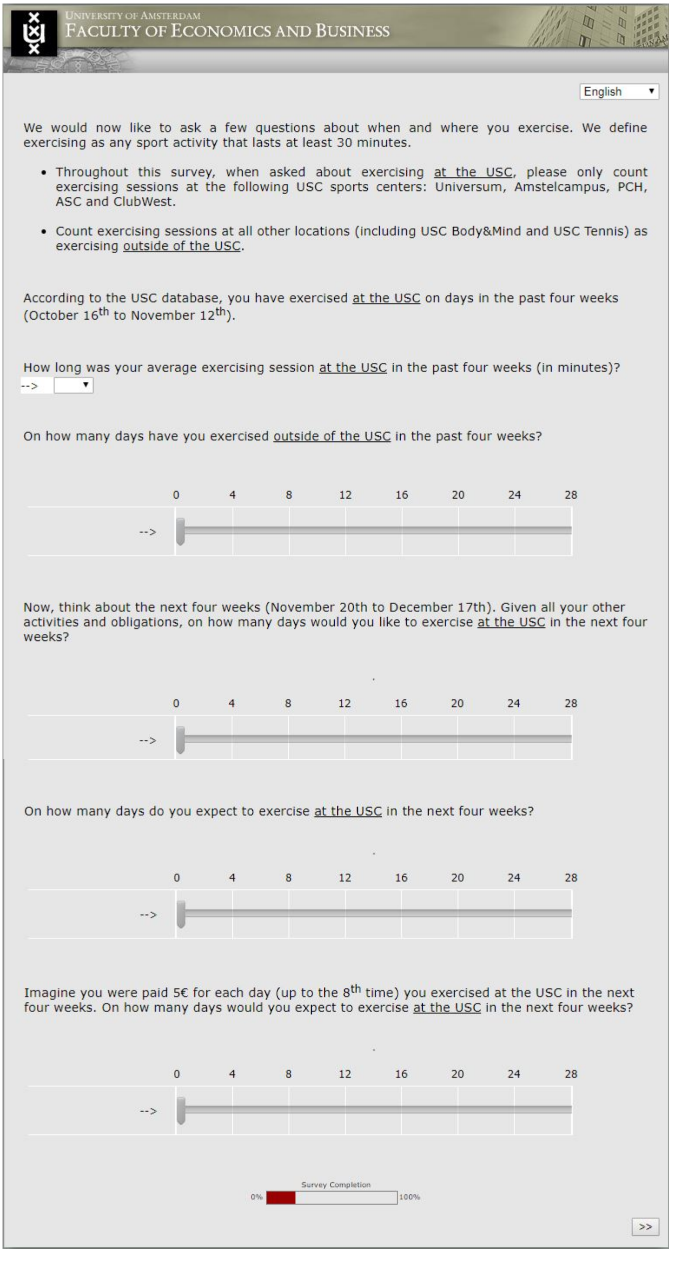

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English

We would now like to ask a few questions about when and where you exercise. We define exercising as any sport activity that lasts at least 30 minutes.

- Throughout this survey, when asked about exercising at the USC, please only count exercising sessions at the following USC sports centers: Universum, Amstelcampus, PCH, ASC and ClubWest.
- Count exercising sessions at all other locations (including USC Body&Mind and USC Tennis) as exercising outside of the USC.

According to the USC database, you have exercised at the USC on days in the past four weeks (October 16th to November 12th).

How long was your average exercising session at the USC in the past four weeks (in minutes)?
-->

On how many days have you exercised outside of the USC in the past four weeks?

0 4 8 12 16 20 24 28
-->

Now, think about the next four weeks (November 20th to December 17th). Given all your other activities and obligations, on how many days would you like to exercise at the USC in the next four weeks?

0 4 8 12 16 20 24 28
-->

On how many days do you expect to exercise at the USC in the next four weeks?

0 4 8 12 16 20 24 28
-->

Imagine you were paid 5€ for each day (up to the 8th time) you exercised at the USC in the next four weeks. On how many days would you expect to exercise at the USC in the next four weeks?

0 4 8 12 16 20 24 28
-->

Survey Completion
0% 100%

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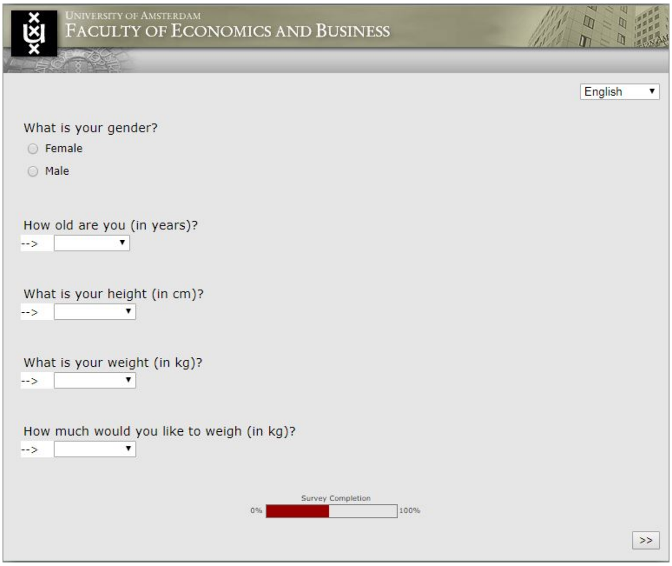
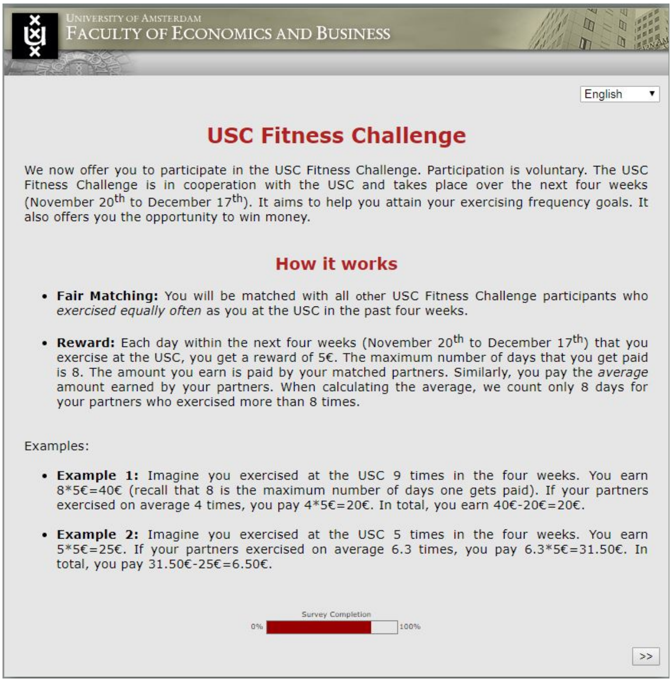


Figure 2.D2: Baseline Survey Control Group

Figure 2.D3: Baseline Survey Bet Treatment



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USC Fitness Challenge

We now offer you to participate in the USC Fitness Challenge. Participation is voluntary. The USC Fitness Challenge is in cooperation with the USC and takes place over the next four weeks (November 20th to December 17th). It aims to help you attain your exercising frequency goals. It also offers you the opportunity to win money.

How it works

- **Fair Matching:** You will be matched with all other USC Fitness Challenge participants who *exercised equally often* as you at the USC in the past four weeks.
- **Reward:** Each day within the next four weeks (November 20th to December 17th) that you exercise at the USC, you get a reward of 5€. The maximum number of days that you get paid is 8. The amount you earn is paid by your matched partners. Similarly, you pay the *average* amount earned by your partners. When calculating the average, we count only 8 days for your partners who exercised more than 8 times.

Examples:

- **Example 1:** Imagine you exercised at the USC 9 times in the four weeks. You earn 8*5€=40€ (recall that 8 is the maximum number of days one gets paid). If your partners exercised on average 4 times, you pay 4*5€=20€. In total, you earn 40€-20€=20€.
- **Example 2:** Imagine you exercised at the USC 5 times in the four weeks. You earn 5*5€=25€. If your partners exercised on average 6.3 times, you pay 6.3*5€=31.50€. In total, you pay 31.50€-25€=6.50€.

Survey Completion
0% 100%

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Why participate?

Motivating
Do you have problems sticking to your exercising goals? *Boost your motivation* with the USC Fitness Challenge! The reward for each workout might give you the extra motivation you need to leave the couch and go to the gym.

Rewarding
Get fit and be paid for it! The USC Fitness Challenge offers you a fair chance to *win money* while getting in shape.

Kickstarting
Well begun is half done! The USC Fitness Challenge offers you a unique opportunity to kickstart your exercising habit. One month of regular training is often enough for a person to *form an exercising habit*. Challenge yourself now and you may benefit from it also in the months to come.

Survey Completion
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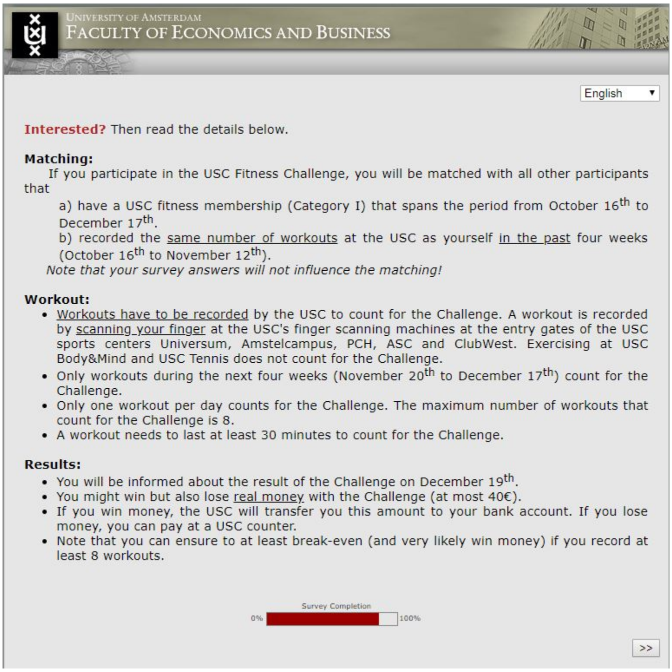

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English

Interested? Then read the details below.

Matching:
If you participate in the USC Fitness Challenge, you will be matched with all other participants that
a) have a USC fitness membership (Category I) that spans the period from October 16^{th} to December 17^{th}.
b) recorded the same number of workouts at the USC as yourself in the past four weeks (October 16^{th} to November 12^{th}).
Note that your survey answers will not influence the matching!

Workout:
- Workouts have to be recorded by the USC to count for the Challenge. A workout is recorded by scanning your finger at the USC's finger scanning machines at the entry gates of the USC sports centers Universum, Amstelcampus, PCH, ASC and ClubWest. Exercising at USC Body&Mind and USC Tennis does not count for the Challenge.
- Only workouts during the next four weeks (November 20^{th} to December 17^{th}) count for the Challenge.
- Only one workout per day counts for the Challenge. The maximum number of workouts that count for the Challenge is 8.
- A workout needs to last at least 30 minutes to count for the Challenge.

Results:
- You will be informed about the result of the Challenge on December 19^{th}.
- You might win but also lose real money with the Challenge (at most 40€).
- If you win money, the USC will transfer you this amount to your bank account. If you lose money, you can pay at a USC counter.
- Note that you can ensure to at least break-even (and very likely win money) if you record at least 8 workouts.

Survey Completion
0% 100%

>>

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English

USC Fitness Challenge

Motivating **Rewarding** **Kickstarting**

Now, you will be asked whether you want to participate in the USC Fitness Challenge. Click here for a Summary of how the USC Fitness Challenge works. Note, that your answer is binding once you complete this survey.

Do you want to participate in the USC Fitness Challenge as explained before?

- **Yes, I want to participate**
- **No, I do not want to participate**

Survey Completion
0% 100%

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Figure 2.D4: Baseline Survey Bet Participants

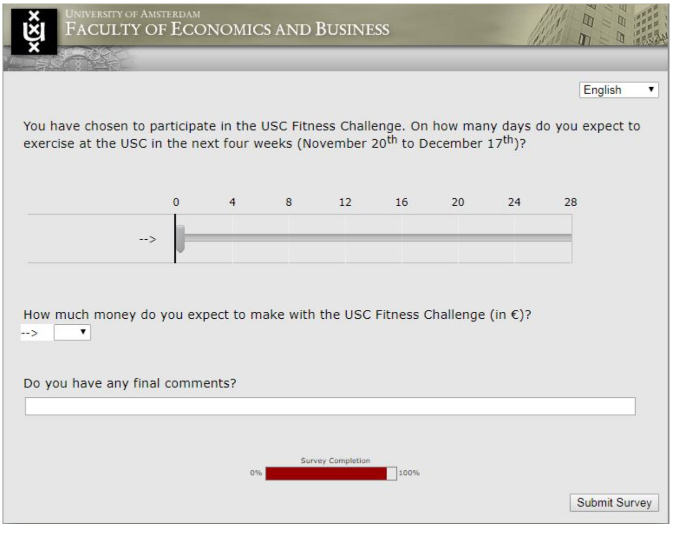
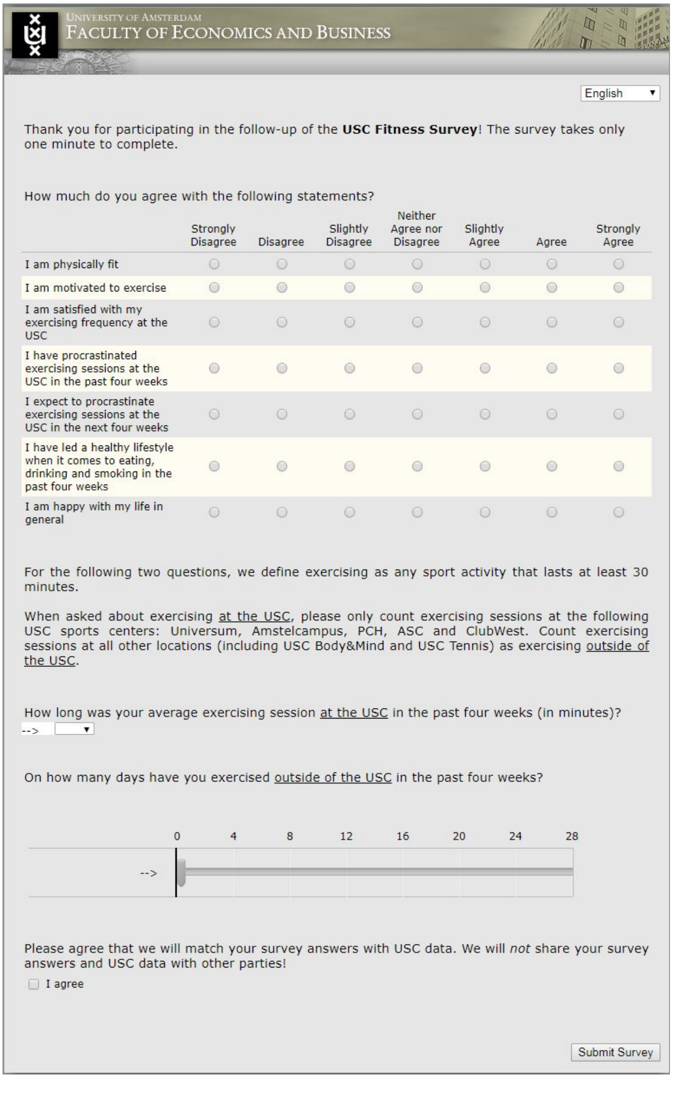


Figure 2.D5: Baseline Survey Bet Rejecters

Figure 2.D6: Follow-up Survey Questions Control Group & Bet Rejecters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English

Thank you for participating in the follow-up of the **USC Fitness Survey**! The survey takes only one minute to complete.

How much do you agree with the following statements?

	Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
I am physically fit							
I am motivated to exercise							
I am satisfied with my exercising frequency at the USC							
I have procrastinated exercising sessions at the USC in the past four weeks							
I expect to procrastinate exercising sessions at the USC in the next four weeks							
I have led a healthy lifestyle when it comes to eating, drinking and smoking in the past four weeks							
I am happy with my life in general							

For the following two questions, we define exercising as any sport activity that lasts at least 30 minutes.

When asked about exercising at the USC, please only count exercising sessions at the following USC sports centers: Universum, Amstelcampus, PCH, ASC and ClubWest. Count exercising sessions at all other locations (including USC Body&Mind and USC Tennis) as exercising outside of the USC.

How long was your average exercising session at the USC in the past four weeks (in minutes)?
-->

On how many days have you exercised outside of the USC in the past four weeks?

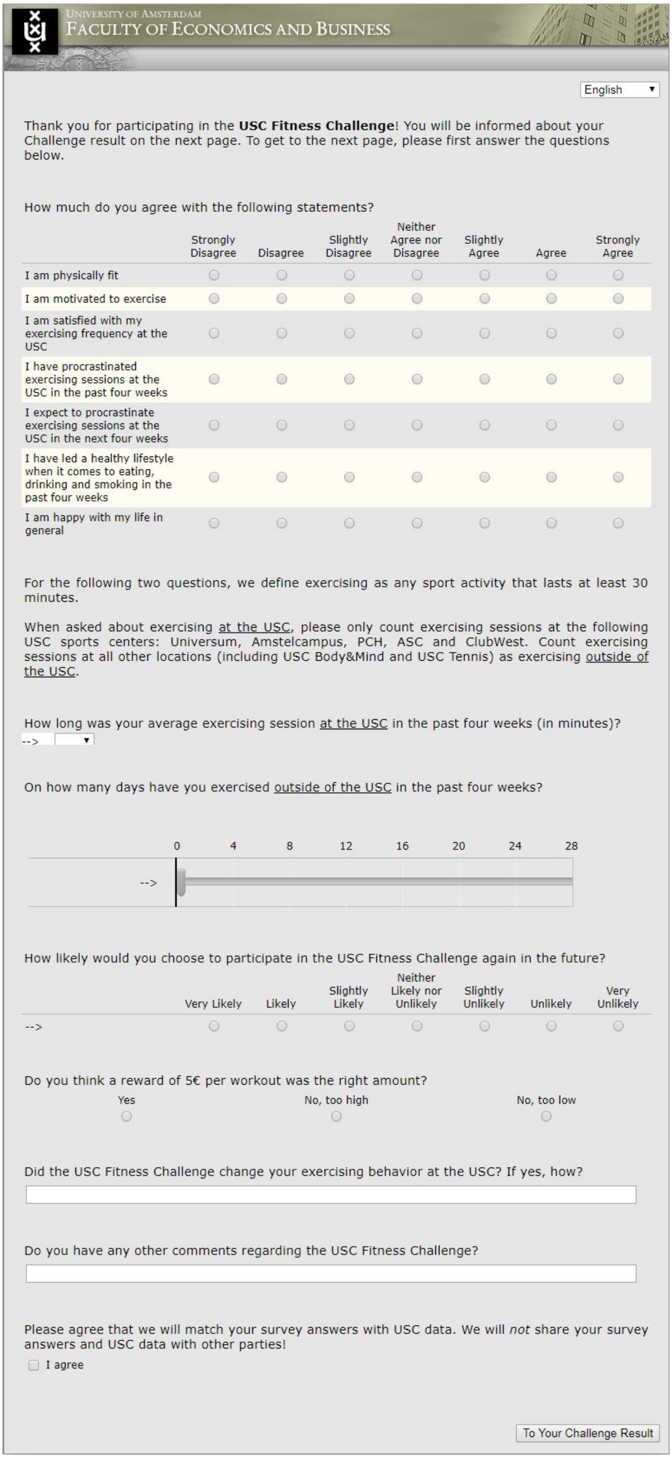
0 4 8 12 16 20 24 28
-->

Please agree that we will match your survey answers with USC data. We will *not* share your survey answers and USC data with other parties!

I agree

Submit Survey

Figure 2.D7: Follow-up Survey Questions Bet Participants


UNIVERSITY OF AMSTERDAM
FACULTY OF ECONOMICS AND BUSINESS

English

Thank you for participating in the **USC Fitness Challenge**! You will be informed about your Challenge result on the next page. To get to the next page, please first answer the questions below.

How much do you agree with the following statements?

	Strongly Disagree	Disagree	Slightly Disagree	Neither Agree nor Disagree	Slightly Agree	Agree	Strongly Agree
I am physically fit	○	○	○	○	○	○	○
I am motivated to exercise	○	○	○	○	○	○	○
I am satisfied with my exercising frequency at the USC	○	○	○	○	○	○	○
I have procrastinated exercising sessions at the USC in the past four weeks	○	○	○	○	○	○	○
I expect to procrastinate exercising sessions at the USC in the next four weeks	○	○	○	○	○	○	○
I have led a healthy lifestyle when it comes to eating, drinking and smoking in the past four weeks	○	○	○	○	○	○	○
I am happy with my life in general	○	○	○	○	○	○	○

For the following two questions, we define exercising as any sport activity that lasts at least 30 minutes.

When asked about exercising at the USC, please only count exercising sessions at the following USC sports centers: Universum, Amstelcampus, PCH, ASC and ClubWest. Count exercising sessions at all other locations (including USC Body&Mind and USC Tennis) as exercising outside of the USC.

How long was your average exercising session at the USC in the past four weeks (in minutes)?

-->

On how many days have you exercised outside of the USC in the past four weeks?

0 4 8 12 16 20 24 28

-->

How likely would you choose to participate in the USC Fitness Challenge again in the future?

	Very Likely	Likely	Slightly Likely	Neither Likely nor Unlikely	Slightly Unlikely	Unlikely	Very Unlikely
-->	○	○	○	○	○	○	○

Do you think a reward of 5€ per workout was the right amount?

Yes	No, too high	No, too low
○	○	○

Did the USC Fitness Challenge change your exercising behavior at the USC? If yes, how?

Do you have any other comments regarding the USC Fitness Challenge?

Please agree that we will match your survey answers with USC data. We will *not* share your survey answers and USC data with other parties!

☐ I agree

To Your Challenge Result

Figure 2.D8: Rules of Matched Bet

USC Fitness Challenge

We now offer you to participate in the USC Fitness Challenge. Participation is voluntary. The USC Fitness Challenge is in cooperation with the USC and takes place over the next four weeks (November 20th to December 17th). It aims to help you attain your exercising frequency goals. It also offers you the opportunity to win money.

How it works

- **Fair Matching:** You will be matched with all other USC Fitness Challenge participants who *exercised equally* often as you at the USC in the past four weeks.
- **Reward:** Each day within the next four weeks (November 20th to December 17th) that you exercise at the USC, you get a reward of 5€. The maximum number of days that you get paid is 8. The amount you earn is paid by your matched partners. Similarly, you pay the *average* amount earned by your partners. When calculating the average, we count only 8 days for partners who exercised more than 8 times.

Examples:

- **Example 1:** Imagine you exercised at the USC 9 times in the four weeks. You earn 8*5€=40€ (recall that 8 is the maximum number of days one gets paid). If your partners exercised on average 4 times, you pay 4*5€=20€. In total, you earn 40€-20€=20€.
- **Example 2:** Imagine you exercised at the USC 5 times in the four weeks. You earn 5*5€=25€. If your partners exercised on average 6.3 times, you pay 6.3*5€=31.50€. In total, you pay 31.50€-25€=6.50€.

Why participate?

Motivating

Do you have problems sticking to your exercising goals? *Boost your motivation* with the USC Fitness Challenge! The reward for each workout might give you the extra motivation you need to leave the couch and go to the gym.

Rewarding

Get fit and be paid for it! The USC Fitness Challenge offers you a fair chance to *win money* while getting in shape.

Kickstarting

Well begun is half done! The USC Fitness Challenge offers you a unique opportunity to kickstart your exercising habit. One month of regular training is often enough for a person to *form an exercising habit*. Challenge yourself now and you may benefit from it also in the months to come.

Interested? Then read the details below.

Matching:

If you participate in the USC Fitness Challenge, you will be matched with all other participants that

a) have a USC fitness membership (Category I) that spans the period from October 16th to December 17th
b) recorded the same number of workouts at the USC as yourself in the past four weeks (October 16th to November 12th)

Note that your survey answers will not influence the matching!

Workout:

- Workouts have to be recorded by the USC to count for the Challenge. A workout is recorded by scanning your finger at the USC's finger scanning machines at the entry gates of the USC sports centers Universum, Amstelcampus, PCH, ASC and ClubWest. Exercising at USC Body&Mind and USC Tennis does not count for the bet.
- Only workouts during the next four weeks (November 20th to December 17th) count for the Challenge.
- Only one workout per day counts for the Challenge. The maximum number of workouts that count for the Challenge is 8.
- A workout needs to last at least 30 minutes to count for the Challenge.

Results:

- You will be informed about the result of the Challenge on December 19th.
- You might win but also lose real money with the bet (at most 40€).
- If you win money with the bet, the USC will transfer you this amount to your bank account. If you lose money, you can pay at a USC counter.
- Note that you can ensure to at least break-even (and very likely win money) if you record at least 8 workouts.

If you have any questions, please send an e-mail to a.r.s.woerner@uva.nl

Chapter 3

Comparing Crowdfunding Mechanisms: Introducing the Generalized Moulin-Shenker Mechanism

3.1 Introduction

Crowdfunding is booming. Over the past decade-and-a-half it has become increasingly common to raise capital by collecting contributions from individual investors, customers, friends, and family. The Cambridge Center for Alternative Finance estimates the global market for crowdfunding to now

This chapter is based on Woerner et al. (2021a). We thank Matthew Ellman, Peter Katuščák, Laura Razzolini, and seminar participants at the CREED lunch seminar, the ESA world meeting, the TIBER workshop, the BEAM-ABEE workshop, the Tinbergen Institute PhD Lunch Seminar, the CBESS-CeDEx-CREED Meeting and the European University Institute for very useful comments and suggestions. Financial support from the Research Priority Area Behavioral Economics of the University of Amsterdam is gratefully acknowledged.

exceed \$300 billion per year.[1] This is more than the GDP of roughly 80% of the countries in the world. Crowdfunded capital is used for a large variety of purposes, ranging from donations for an individual medical treatment or charities to 'pre-sales' to fund the recording of music albums or the development of a new product like a smartwatch. The latter examples involve crowdfunding used to raise finances for startups or existing businesses that have traditionally relied on other sources like venture capitalists or banks. The widespread use of the internet and social media has made it possible to tap into a large pool of potential funders. Various large-scale crowdfunding platforms like Kickstarter, Indiegogo, and GoFundMe have appeared, where demand and supply for funding are matched using a mechanism chosen by the platform.

When contributing to a business, funders may be rewarded with equity shares (the funder obtains a stake in the business) or a reward. Our focus is on the latter. Reward-based crowdfunding denotes the practice to raise monetary contributions for a project from a large number of people who, in exchange, obtain a non-financial reward.[2] Think of a pre-release streaming of an album, a personalized version of a product, or even a public "thank you" by a celebrity. Reward-based fundraising offers producers a low-cost opportunity to advertise and finance their projects (Belleflamme et al., 2010; Gerber and Hui, 2013), and enables them to gain information about market demand prior to production (Da Cruz, 2018; Chemla and Tinn, 2020).

In spite of its growing importance, reward-based crowdfunding has so far received little attention in the economics literature (notable exceptions are discussed below).[3] As a consequence, little is known about the char-

[1] As reported by P2P Market Data, `https://p2pmarketdata.com/crowdfunding-statistics-worldwide/` (site visited October 26, 2020). More than two-thirds of this amount was raised in China. More than 90% involves credit- (a.k.a. loan-) based crowdfunding, which has been around for centuries (Everett, 2019).

[2] Statista (2019) estimates the global reward-based crowdfunding market in 2020 at \$8.5 billion and expects an annual growth rate of 12%. See Grüner and Siemroth (2019) for further estimates.

[3] In contrast, the management literature has paid ample attention to crowdfunding

acteristics of the mechanisms used by crowdfunding platforms, such as the popular All-or-Nothing mechanism (AON). In this study we address this gap in the literature. We investigate the performance of the AON and ask whether other mechanisms exist that score better. For this purpose, we introduce an alternative crowdfunding mechanism, the Generalized Moulin-Shenker mechanism (GMS). As explained below, GMS generalizes Moulin and Shenker's (1992) serial cost sharing mechanism, while retaining its desirable properties (in particular, group strategy proofness, individual rationality, anonymity, and budget balancedness). Because of these favorable properties, we choose this alternative for the comparison to AON. While AON is the prevailing reward-based crowdfunding mechanism in practice, GMS provides a simple and theoretically promising alternative. We distinguish between a sealed-bid and a dynamic version of GMS. The latter generalizes Deb and Razzolini's (1999) 'English Auction-Like Mechanism' for allocating an indivisible and excludable public good. The dynamic GMS is obviously strategy-proof in the sense of Li (2017), while the sealed-bid GMS is not. Together, this makes the dynamic GMS a promising alternative to the AON.

In our theoretical analysis, we compare these crowdfunding mechanisms using a model in which a producer can develop an indivisible and excludable public good at fixed costs. A producer may do so either for direct profit, or aim to develop the good per se, for example to establish a reputation in the market. We therefore consider two distinct producer objectives: maximiza-

(see Moritz and Block (2016) and Shneor and Vik (2020) for reviews of this literature). A large part of this literature has focused on the relationship between funding success and certain characteristics of the producer and product. A producer's track record, the size of her social network and her locational proximity to potential consumers are positively related to the likelihood of funding success (see. e.g. Agrawal et al., 2015; Zvilichovsky et al., 2015; Lin and Viswanathan, 2016; Buttice et al., 2017; Cai et al., 2019). Further, projects that have a non-profit focus, feature a product video and have low fundraising thresholds and time-limited rewards are more likely to get funded (Belleflamme et al., 2013; Mollick, 2014; Pitschner and Pitschner-Finn, 2014; Lin et al., 2016; Kunz et al., 2017).

tion of profit and maximization of the fundraising success probability. As is standard in crowdfunding practice, the producer decides on a threshold as the amount to be raised and a reservation price. Given this choice, consumers decide on how much to offer for the good. Consumer values for the good are drawn independently from a continuous distribution function. For this environment, we show that for a sufficiently large crowd of consumers, both versions of GMS outperform AON in expected producer profits and success probability. Moreover, aggregate surplus is larger under GMS when the producer's goal is to maximize the likelihood of success.[4]

We test our theoretical predictions in a laboratory experiment. While GMS is predicted to outperform AON when consumers follow the intuitive and weakly dominant strategy to bid their own value, GMS is plagued by a multitude of equilibria. AON may outperform GMS if consumers play according to some of these equilibria. Our experiment allows us to identify which equilibrium is empirically most plausible. Further, our choice to use the laboratory as the environment for our empirical analysis is motivated by its superior level of control. Testing the theoretical properties of the mechanisms we are interested in requires that we create an environment where the basic assumptions of the theory are met (Schram, 2005; List, 2020). Laboratory control allows us to meet this requirement. If the theoretical dominance of GMS over AON is not supported in the controlled setting of the laboratory, there is little reason to expect that GMS will do better in the field. If the laboratory does support the theoretical predictions, then this is a good reason to move forward with trials in the field.[5]

[4]Though we do consider the efficiency of the mechanisms, this is not considered as a main goal of crowdfunding activities. We will see in the following section that for the environment we are interested in, no efficient, incentive-compatible and individually rational mechanism exists where the producer's expected revenue in equilibrium is positive.

[5]Note the similarity to the role of laboratory experiments in the FCC spectrum auctions. Paul Milgrom and Robert Wilson, based on their seminal theoretical contributions, advised the FCC to use the simultaneous multiple round auction. The FCC commissioned experiments to further test this auction format before applying it for the first time in the field in 1994 (McMillan, 1994).

In our experiments, we systematically vary the mechanism, producer objective, and cost level. This allows us to draw conclusions for a wide range of possible crowdfunding scenarios. To capture the ‘crowd’ in crowdfunding, we use comparatively large consumer groups of 15 subjects each. Simulation results show that 15 consumers form a sufficiently large crowd for GMS to outperform AON in terms of expected producer profits and success probability. Our laboratory results show that the dynamic GMS performs consistently better than the sealed-bid GMS and outperforms AON when the producer’s objective is to maximize funding frequency. While subjects play close to the theoretical predictions in both the dynamic GMS and AON, there is severe underbidding in the sealed-bid GMS. In the concluding section, we discuss the implications of our results for crowdfunding in practice.

The remainder of the chapter is organized as follows. The next section discusses the literature on which we build and the contributions we aim to make. Section 3.3 theoretically analyzes the mechanisms, while Section 3.4 describes the experimental design and states the hypotheses. Section 3.5 presents the results and Section 3.6 concludes.

3.2 State of the Art

Our study is related to several strands of the literature. To start, reward-based crowdfunding can be seen as a public good in the sense that all consumers could potentially benefit from the project being completed. Think, for example, of crowdfunding aimed at producing a smartwatch. Pebble Time used the platform Kickstarter to raise funds to set up production facilities for its watch, and raised over \$20 million (Brown et al., 2017). Once the production capacity was set, other consumers could benefit from it by buying the watches it produced. The problem they faced is that Pebble Time would not have raised enough money beforehand if all consumers had waited for the production to be set up. Indeed, for public goods both theory and experiments show that free riding causes severe underprovision, resulting in an inefficient outcome (see Batina and Ihori, 2005 for a review).

In recent decades, several ingenious mechanisms have been developed that mitigate free riding and achieve (almost) efficient provision of the public good in settings with private information (e.g. Arrow, 1979; d'Aspremont and Gérard-Varet, 1979; d'Aspremont and Gerard-Varet, 1979; Walker, 1981; Falkinger, 1996). The most famous of these mechanisms is perhaps the Vickrey-Clarke-Groves mechanism (VCG) (Vickrey, 1961; Clarke, 1971; Groves, 1973; Groves and Loeb, 1975). VCG achieves an efficient outcome by charging or compensating the agents for the externalities that they exert on or are caused by others. VCG, however, is unsuitable for application to crowdfunding because it is generally not weakly budget balanced in that setting, i.e., in expectation, the consumers' equilibrium contributions fall short of the project costs.

This negative result for VCG has important consequences for crowdfunding mechanisms. In particular, there exists no efficient, incentive-compatible and individually rational mechanism that balances the budget in an environment where VCG results in an expected deficit (Krishna and Perry, 1998). Therefore, no efficient crowdfunding mechanism exists where the producer obtains a positive expected revenue in equilibrium. Instead of searching for an efficient mechanism, we therefore resort to finding mechanisms with favorable other properties and comparing them in a setting where consumers can be excluded from consuming the good when produced. Our study contributes by introducing GMS, a strategy-proof, individually rational, anonymous, and (weakly) budget-balanced mechanism, that can be easily implemented in practice and by comparing it to the dominant mechanism used in practice, AON.

A different strand of the non-excludable public-goods literature focuses on revenue rather than efficiency. For some organizations (like charities), revenue is an important objective. Such organizations are therefore interested in the extent to which a fundraising mechanism elicits contributions. A public good provider can increase contributions by bundling the public good with a private good (e.g. Morgan, 2000; Goeree et al., 2005; Lange et al., 2007). By selling the private good in a lottery or auction, the free-rider problem inherent in public-good provision is alleviated by the negative externalities consumers exert on each other when buying lottery tickets or bidding in an auction (Morgan, 2000). Laboratory experiments predominantly confirm the theoretical predictions (e.g. Morgan and Sefton, 2000; Lange et al., 2007; Schram and Onderstal, 2009), while the results of field experiments are mixed (Landry et al., 2006; Onderstal et al., 2013). Our study adds to this literature in that we theoretically and experimentally analyze fundraising mechanisms in a setting with excludable public goods.

There is a small but growing literature studying the theoretical properties of crowdfunding. Compared to traditional financing, crowdfunding introduces efficiency gains because it enables producers to execute projects that would otherwise not have been executed when there is a secondary market for the good (Kumar et al., 2020). Crowdfunding also caters to donors who just want the campaign to succeed (Deb et al., 2019). Moreover, crowdfunding allows firms to explore their market at an early stage to inform possible future investments. This real option value of learning helps to overcome moral-hazard issues (Chemla and Tinn, 2020), though the expected producer profit needs to be sufficiently large to prevent entrepreneurial moral hazard and ensure efficient production (Strausz, 2017). In practice, crowdfunding mechanisms tolerate some fraud to increase profits and welfare (Ellman and Hurkens, 2019a).[6] In the field, crowdfunding indeed acts as a mechanism to reveal demand. Producers that were unsuccessful with their crowdfunding campaign tend to nevertheless release

[6] The term ‘fraud’ refers to an entrepreneur pocketing the money raised in crowdfunding without delivering the project or rewards.

the product if contributions suggest sufficient market demand (Da Cruz, 2018). GMS is particularly informative in this respect due to its strategy proofness, which ensures that consumers have an incentive to reveal their true demand. To focus on a between-mechanism performance comparison, however, our study abstracts from moral-hazard and screening issues. We will show that GMS has favorable properties in comparison to AON even without these issues.

Aside from studies on general crowdfunding characteristics, there is also a small literature that introduces or tests the performance of alternative crowdfunding mechanisms. Cumming et al. (2020) observe empirically that AON outperforms the Keep-it-All mechanism in which the producer may keep the money raised regardless of reaching the threshold. In a setting similar to ours, the profit-maximizing crowdfunding mechanism is impractical (Cornelli, 1996); it leads to the producer making a loss in certain states and conditions funding success on individual bids in a complicated manner. Nevertheless, practical mechanisms could exist that outperform AON. Though AON constitutes the optimal crowdfunding mechanism when consumers' values are binary, it falls considerably short for three or more possible values (Ellman and Hurkens, 2019b). Existing mechanisms like AON can also be modified. For example, producers can increase the success rate of their crowdfunding campaigns by offering refund bonuses (Cason and Zubrickas, 2019; Cason et al., 2021). We depart from such modifications to AON and add to the literature by introducing a promising and easily implementable new crowdfunding mechanism, GMS, and test its performance relative to AON.

GMS is a generalization of the serial cost sharing mechanism by Moulin and Shenker (1992).[7] Amongst budget-balanced and group strategy-proof mechanisms, the worst possible welfare loss is minimized by this serial cost

[7]Moulin and Shenker's (1992) serial cost sharing mechanism was developed for indivisible and excludable public goods. Our generalization consists of endogenizing the threshold amount and minimum price.

sharing mechanism (Moulin and Shenker, 2001). It also maximizes welfare among a restricted set of strategy-proof mechanisms (Deb and Razzolini, 1999). These results are particularly relevant for our study; we will show that for a producer aiming to maximize funding success probability, the optimal funding threshold and reservation price imply that GMS coincides with the serial cost sharing mechanism.

There are a few papers that have tested the serial cost sharing mechanism in laboratory experiments. In groups of three consumers, subjects predominantly bid their value in this mechanism (Gailmard and Palfrey, 2005). In groups of four, subjects deviate from playing the dominant strategy at the beginning of the experiment but converge to it over time (Chen et al., 2007; Razzolini et al., 2007). Such convergence diminishes as the number of players grows (Friedman et al., 2004). Our experiment uses comparatively large groups of consumers. In line with these previous studies, we observe that a substantial number of subjects does not converge to playing the dominant strategy in the sealed-bid GMS. To our knowledge, we are the first to study a *dynamic* serial cost sharing mechanism in the laboratory. In contrast to the sealed-bid GMS, we find that behavior in the dynamic GMS rapidly converges to bidding one's value. While our experiment provides an additional test of the serial cost sharing mechanism for larger groups, we are also the first to test a cost-sharing mechanism when the producer aims to maximize her profits.

3.3 Theory

3.3.1 Model

A risk-neutral producer can develop an indivisible, non-rivalrous, and excludable good at fixed costs $C > 0$. Once the good has been developed, the producer produces the good at constant marginal costs that are normalized to zero. $N \geq 2$ risk-neutral consumers, labelled $i = 1, \ldots, N$, are interested in obtaining a unit of the good. Let v_i denote consumer i's value for the good. We assume that the values are drawn independently from the interval $[0, \overline{v}]$ with distribution function F that is differentiable and strictly increasing over $[0, \overline{v}]$. We assume that $0 < \overline{v} < C$ and $N\overline{v} > C$. This ensures that production requires at least two consumers buying the good and that efficient production is sometimes feasible.

Consumers have quasi-linear utilities. Consumer i's utility is given by

$$u_i = \begin{cases} -p_i, & \text{if she does not obtain a unit} \\ v_i - p_i, & \text{if she obtains a unit} \end{cases}$$

where p_i is the amount paid by consumer i.

The public good is allocated either via AON or GMS. Both are characterized by a threshold T and a reservation price r set by the producer. The AON and sealed-bid GMS are simultaneous-move games in which each consumer i reports a bid. In the dynamic GMS, consumers implicitly report bids, as explained below. All three crowdfunding mechanisms then map bids, threshold and reservation price into an outcome specifying whether the good is produced, and if so, which consumers obtain the good and how much each consumer pays to the producer.

More formally the mechanisms are described as follows.

All-or-Nothing (AON). Each consumer i simultaneously and independently reports a bid $b_i \geq 0$. The good is produced if and only if $\sum_{i=1}^{N} b_i \geq T$. If the good is produced, consumer i pays her own bid b_i to the producer. She obtains a unit if and only if $b_i \geq r$. If the good is not produced, all consumers pay zero.

Sealed-bid Generalized Moulin-Shenker (sGMS). Each consumer i simultaneously and independently reports a bid $b_i \geq 0$. sGMS then proceeds according to the following algorithm:

1. List all bids b_i that satisfy $b_i \geq r$.

2. If there are no bids on the list, the good is not produced, all consumers pay zero, and the algorithm ends. Otherwise, calculate the producer's revenue R assuming that all consumers whose bids are on the list pay the lowest bid on the list.

3. If $R \geq T$, proceed to step 4. Otherwise, remove the lowest bid from the list and go back to step 2.

4. The good is produced. All M consumers whose bids are on the current list obtain a unit of the good and pay $\max\left\{r, \frac{T}{M}\right\}$. The remaining consumers do not obtain a unit of the good and pay zero.

Dynamic Generalized Moulin-Shenker (dGMS): In dGMS, the price is raised successively, starting at the reservation price r. At any price, consumers can drop out. This decision is irrevocable. Let $M(p)$ be the number of consumers remaining at price p. The resulting revenue at price p is $M(p)\,p$. The ascending clock stops when it reaches price p, for which either (1) all consumers have dropped out, in which case the good is not produced and all consumers pay zero or (2) $M(p)\,p \geq T$, in which case the good is produced and all remaining consumers obtain a unit and pay p. Note that this procedure is sequential, but is strategically equivalent to an environment where consumers bid by specifying a priori at which price they wish to drop out. In what follows, we refer to such a drop-out price as a 'bid' in dGMS.

3.3.2 Equilibrium Properties

This is a game of incomplete information involving producers and consumers interacting in two stages. In the first stage, producers choose a threshold T and a reservation price r and in the second stage each consumer is informed about her value v_i and chooses her bid b_i. The mechanism in place subsequently determines whether the good is produced, which consumers receive it, and how much they pay. We start by considering the subgames that can occur between consumers after T and r have been set. For these subgames, we derive Bayesian Nash equilibria (BNE). First, however, we make one assumption regarding the choice of T. This is that no producer will choose a threshold that allows for the possibility of making a loss. That is, we assume that $T \geq C$. We will see below that this condition is fulfilled in the equilibria we are interested in.

3.3.2.1 Bayesian-Nash Equilibria for Consumers

To derive BNE, we start by noting that any consumer strategy in any mechanism is a function mapping values to bids. We label an equilibrium '*truthful*' if all consumers having a value weakly greater than r submit a bid equal to value, that is $b_i = v_i \ \forall \ i : v_i \geq r$. We refer to an equilibrium as '*semi-pooling*' if all consumers having a value weakly greater than r submit a bid equal to r and the remaining consumers bid zero, i.e., $b_i = r \ \forall \ i : v_i \geq r$ and $b_i = 0 \ \forall \ i : v_i < r$.

We start the BNE analysis with AON. In Appendix 3.B, we implicitly derive a general form for a symmetric BNE in AON. That analysis suggests pooling at r for values greater than, but close to, r. The second part of the following theorem establishes that for sufficiently large N, AON has a unique semi-pooling equilibrium.

Theorem 3.1

(i) Suppose $T \geq C$ and $r = 0$. Then the strategy where $B(v) = 0 \ \forall \ v$ constitutes a symmetric BNE of AON.

(ii) Suppose $\overline{v} > r > 0$. Then, for sufficiently large N, AON has a unique BNE in undominated strategies, which is given by:

$$B(v) = \begin{cases} 0 \text{ if } v < r \\ r \ \text{ if } v \geq r \end{cases}$$

Proof See Appendix 3.A

The intuition underlying Theorem 3.1.i is a standard free riding argument. If no positive bid is required to be eligible to receive the good, then the best response to nobody else bidding a positive amount is to bid zero as well. The semi-pooling equilibrium in Theorem 3.1.ii also has an intuitive appeal. Recall that if the threshold is reached, all consumers pay their bid in AON, irrespective of whether they receive the good (which they only do if they bid at least r). For consumers whose value lies below the reservation price, it is then best to bid zero. For consumers with a value above r, the intuition is that if N is large enough, it is unlikely for a consumer's bid to be pivotal for reaching the threshold. This induces her to bid the reservation price, i.e. the lowest possible amount that guarantees her a unit of the good if it is produced. The size (N) needed to obtain a semi-pooling equilibrium need not be restrictively high. Section 3.4.2 shows that for some of our experimental parameters, it is an equilibrium for $N = 15$.

We now turn to GMS. dGMS is strategically equivalent to sGMS. In fact, dGMS is an ascending-price implementation of GMS in the same way as the Japanese auction is an ascending-price implementation of the second-price sealed-bid auction (Milgrom and Weber, 1982). Because the equilibrium properties of dGMS carry over to sGMS, we frame all theoretical results in terms of the more general representation of GMS only, unless indicated otherwise. In GMS, the amount a consumer pays when obtaining the good only depends on the bids of the other consumers, not on her own bid. Moreover, a consumer pays at most her own bid. Theorem 3.2 presents the main equilibrium result for GMS.

Theorem 3.2 *In GMS, $\beta(v_i) = v_i$, $i = 1, \ldots, N$, constitutes a BNE in weakly dominant strategies.*

Proof See Appendix 3.A

Theorem 3.2 establishes that GMS has a truthful equilibrium in weakly dominant strategies. Moreover, following Moulin and Shenker (2001), it can be shown that consumer behavior in GMS is 'group strategy-proof', i.e. no group of consumers has an incentive to lie about their values. Given that bidding one's value also is an intuitive strategy, we expect the truthful equilibrium to be a natural focal point for consumers. However, the truthful equilibrium is not unique; in Appendix 3.B, we show that GMS has a multiplicity of equilibria. Some equilibria involve bidders bidding 'in the neighborhood' of their value. Such equilibria are outcome equivalent to the truthful equilibrium. This is a useful property of the GMS in that small mistakes in consumers' bidding strategies have no effect on the outcome. Other equilibria involve underbidding relative to the truthful equilibrium, including a semi-pooling equilibrium, resulting in lower producer profit and success probability than the truthful equilibrium. Our laboratory data will allow us to investigate which equilibrium is empirically most plausible.

Although they yield the same BNE for any subgame following a producer's choice of T and r, we can still theoretically distinguish between sGMS and dGMS. For the extensive-form representation of a mechanism, Li (2017) introduces the notion of 'obvious strategy-proofness'. This is defined as follows. Strategy s is *obviously dominant* if, for any other strategy s', at the earliest information set where s and s' differ, the worst possible outcome from s is at least as good as the best possible outcome from s'. A mechanism that has an equilibrium in obviously dominant strategies is *obviously strategy-proof*. This yields the following difference between sGMS and dGMS.

Theorem 3.3 *sGMS is not obviously strategy-proof. dGMS is obviously strategy-proof.*

Proof See Appendix 3.A

Li (2017) argues that obviously strategy-proofness has an intuitive behavioral interpretation; a cognitively limited agent can recognize a strategy as weakly dominant if and only if it is obviously dominant. In other words, Theorem 3.3 suggests that for cognitively limited consumers it is easier to recognize that bidding value is a weakly dominant strategy in dGMS than in sGMS.

3.3.2.2 Producers' Best Response

To complete the PBE, we derive the optimal choice of T and r by the producers. We consider two possible producer objectives. The first concerns the maximization of the likelihood of the project's success. The project is marked a success if and only if (1) the project is initiated, i.e. $\sum_{i=1}^{N} p_i \geq T$, and (2) the project's revenues exceed its costs, i.e., $\sum_{i=1}^{N} p_i \geq C$. The second producer objective is the maximization of the project's profit. To derive producer behavior in the PBE, we assume that consumers play the semi-pooling equilibrium in AON (Theorem 3.1.ii) and the truthful equilibrium in GMS (Theorem 3.2). We let T_o^m and r_o^m denote the optimal threshold and reservation price respectively for mechanism $m = \{AON, GMS\}$ and objective $o = \{s, \pi\}$, where s (π) stands for the success (profit) objective.

We first consider the AON when the producer's goal is to maximize the project's success probability. We have

Theorem 3.4 *Suppose that in AON consumers play according to the semi-pooling equilibrium. The producer maximizes the project's success probability by setting* $T_s^{AON} = C$ *and* $r_s^{AON} \in \arg\max_r I_{(1-F(r))}\left(\frac{C}{r}, \frac{(N+1)r-C}{r}\right)$ *s.t.* $r = \left\{\frac{C}{N}, \ldots, \frac{C}{2}\right\}$ & $r \leq \overline{v}$, *where* $I_x(\cdot)$ *denotes the regularized incomplete beta function. The solution involves* $\lim_{N\to\infty} r = 0$.

Proof See Appendix 3.A

While the theorem does not provide a closed-form solution for the optimal producer choices in AON under a success objective, it restricts the number of potentially optimal threshold/reservation price combinations to $N-1$. The producer optimally sets $T_s^{AON} = C$ because consumers who play according to a semi-pooling equilibrium do not make bids that depend on the threshold. Setting $T < C$ puts the producer at risk of a loss, while setting $T > C$ puts the producer at risk of unnecessary project failure. Similarly, the producer chooses a reservation price from the discrete set of prices that potentially fund the project without excess aggregate payments.

When producers in AON aim to maximize profits, we show in Lemma 3.A4 in Appendix 3.A that the producer optimally sets $T_\pi^{AON} = C$. For the optimal reservation price, we find no analytical solution but show in Theorem 3.B2 of Appendix 3.B that r_π^{AON} is larger than or equal to the price that a monopolist would charge in this market if the production costs were sunk. Appendix 3.D shows how the optimal r_π^{AON} can be derived numerically.

Turning to GMS, we again start with the success probability objective. Theorem 3.5 displays the optimal parameters.

Theorem 3.5 *Suppose that in GMS, consumers play according to the truthful equilibrium. Then the producer maximizes the project's success probability by setting* $T_s^{GMS} = C$ *and* $r_s^{GMS} = 0$.

Proof See Appendix 3.A

Thus, the PBE for GMS when producers aim to maximize the likelihood of success is intuitive for both producer and consumers. It involves producers choosing a threshold equal to the project costs and reservation price zero, while consumers bid their value. By choosing $T = C$ and $r = 0$, a producer optimally uses the serial cost sharing mechanism by Moulin and Shenker (1992). The intuition is straightforward. The project should not be produced if the costs are not covered. So, $T_s^{GMS} \geq C$. Then, conditional on the costs being covered, the producer maximizes the likelihood that the project is completed by pushing T and r as low as possible so that $T_s^{GMS} = C$ and $r_s^{GMS} = 0$.

Comparing Theorems 3.4 and 3.5 shows that when the producer aims at maximizing the likelihood of success, $T_s^{AON} = T_s^{GMS} = C$. The optimal reservation price is larger in AON but converges to that in GMS ($r_s^{GMS} = 0$) with increasing N.

For the case of profit maximization under GMS, we have found no generally applicable analytical solutions. We show in Appendix 3.D that these can be easily derived numerically for any specific environment. The numerical solutions all involve $T_\pi^{GMS} \geq C$, because they would otherwise involve including outcomes that yield a loss.

Note that the PBE for both mechanisms and both objectives involve setting the threshold weakly above the costs. This justifies the assumption that $T \geq C$ made above.

3.3.3 Comparing Mechanisms

Our main objective in this theoretical analysis is to compare the equilibrium properties of AON and GMS. Although we have not analytically derived the complete PBE for all cases, the comparison turns out to be straightforward if consumers bid according to the equilibria derived in Theorem 3.1.ii and Theorem 3.2. Our first proposition then shows that GMS outperforms AON in terms of expected producer profit and success probability.

Proposition 3.1 *Consider the PBE for AON and GMS where consumers play according to the semi-pooling equilibrium in AON and the truthful equilibrium in GMS.*

(i) If the producers aims to maximize expected profits, GMS yields weakly higher profit than AON. GMS yields strictly higher expected profit than AON if and only if $\lceil \frac{C}{r_\pi^{AON}} \rceil - 1 > \frac{C}{\bar{v}}$.[8]

[8] $\lceil \cdot \rceil$ denotes a ceiling function that rounds up its argument to the nearest integer.

(ii) *If the producers aims to maximize success probability, GMS yields weakly higher success than AON. GMS yields strictly higher success probability than AON if and only if* $C < (N-1)\overline{v}$.

Proof See Appendix 3.A

In the semi-pooling equilibrium of AON, consumers with value below the reservation price bid 0 and all others bid the reservation price r. The underlying intuition for Proposition 3.1 is that a producer in GMS can always set the threshold and reservation price that are optimal under AON – and will sometimes outperform AON for these choices (because consumers with a value above r have a higher equilibrium bid in GMS than in AON) – but may even do better for other parameter choices.

We also compare the two mechanisms in terms of the aggregate surplus that they generate in their PBE. Recall that no efficient, incentive-compatible and individually rational mechanism exists where the producer's expected revenue in equilibrium is positive. Nevertheless, Proposition 3.2 establishes that GMS is weakly more efficient than AON in equilibrium under a success objective.

Proposition 3.2

Assume that producers' objective is to maximize the project's success probability. In the BNE described in Theorems 3.4 and 3.5, aggregate surplus is weakly higher in GMS than in AON. Expected aggregate surplus is strictly higher in GMS than in AON if and only if $C < (N-1)\overline{v}$.

Proof See Appendix 3.A

Together, Propositions 3.1 and 3.2 establish that GMS outperforms AON both from the producer's perspective (irrespective of their objective) and from the perspective of aggregate welfare (under a success objective). Of course, whether this theoretical dominance is realized depends very much on how consumers bid. To study this behavior, we designed the experiment described in the following section.

3.4 Experimental Design and Hypotheses

3.4.1 Experimental Procedures and Design

The experiment consisted of 18 sessions that were conducted at the CREED laboratory of the University of Amsterdam. For each session we recruited 16 subjects from the CREED subject pool. Subjects were on average about 22 years old. Our sample was almost gender-balanced (54% females) and consisted primarily (68%) of Economics or Business students. 71% of the subjects had no prior experience with crowdfunding. Throughout the experiment, payoffs are denoted by 'francs'. Accumulated earnings are paid out at an exchange rate of 1 Euro for 8 francs. Sessions lasted about 80 minutes and subjects earned 14.14 Euros on average, including a show-up fee of 7.00 Euros.

The experiment is structured as follows. First, subjects read the instructions on their monitor. We then ask subjects to answer questions that test whether they have understood the crowdfunding game. Appendix 3.E presents a transcript of the instructions and comprehension questions. Subjects are allowed to move forward only after they have correctly answered all comprehension questions. Thereafter, subjects are asked some crowdfunding intuition questions concerning theoretically optimal producer and consumer behavior. One of the subjects that has correctly answered the most producer intuition questions is assigned the role of (passive) producer.[9] Once all subjects have answered all test and intuition questions, subjects assigned the role of consumers play the crowdfunding game for 45 rounds, while the subject assigned the role of passive producer plays a non-

[9]This procedure is supposed to reflect that producers tend to be more knowledgeable about using crowdfunding as a fundraising practice than consumers.

incentivized allocation game. Subsequently, all subjects are required to fill out a short survey and are then privately paid out their earnings.

The experiment features a 3x2x3-design. It varies the mechanism (AON, sGMS, dGMS) between subjects, and the producer objective (profit, success) and project costs (low, medium, high) within subjects. As we focus on consumer behavior, we computerize producer decisions. This is common knowledge. In each session, 15 subjects are assigned the role of consumers, while the subject who is assigned the role of a passive producer cannot influence the producer decisions, which are set by the computer.[10]

To provide subjects with sufficient opportunity to learn to play the crowdfunding game, they interact in it for 45 rounds. In 27 of these rounds, the producer has a profit objective. The computerized producer chooses the threshold and reservation price to maximize expected profits as predicted by theory (details are presented below). In the other 18 rounds, the producer has a success objective, setting the threshold and reservation price that maximize funding success probability. Note that the consumers are not informed about the objective, but simply face a given threshold and reservation price in each round. For each producer objective, project costs in any given round are low, medium, or high. In rounds with a profit objective, costs are $C = 50$, $C = 70$, and $C = 90$ respectively. In rounds with a success objective, costs are $C = 60$, $C = 80$, and $C = 100$ respectively. The 45 rounds are split in three blocks of 15, nine with a profit objective and six with a success objective. Project costs are randomly drawn in such a way that in each block, $C = 50$, $C = 70$ and $C = 90$ occur three times each, while $C = 60$, $C = 80$ and $C = 100$ occur twice each. The different cost levels allow us to analyze subject behavior in situations when funding success is

[10]We assign a subject to be a passive producer in order to allow for potential pro-social behavior of consumers towards the producer. In the following chapter we study producer behavior in crowdfunding. That study motivates our selection procedure for producers, described above. Even though producers are passive in the experiment reported here, we use the same procedure in order to maintain consistency across studies.

supposed to be very likely, somewhat likely and unlikely according to the theoretical predictions presented in Section 3.4.2.

At the start of each round, the consumers are informed about the fundraising threshold T and reservation price r, which depend on the round's producer objective and project costs (details are presented below). The consumers are privately informed about their values, which are drawn independently from a discrete uniform distribution over the set $\{0, 1, \ldots, 19, 20\}$. Then, the consumers interact in the crowdfunding mechanism. To reduce noise, the order of the cost levels and the draws of the values are kept constant across mechanisms.[11]

At the end of each round, all subjects are informed about their payoffs, whether the good was produced, what decisions the other consumers made and which price was implemented if the good is produced (in GMS). A consumer's payoff when obtaining the good equals her value minus the payment she made to the producer. If she does not obtain the good, her payoff is equal to zero minus her payment. The earnings of the passive producer are determined by the producer's payoff. Under the profit objective, the producer's payoff in francs is 20% of the profits, that is, 20% of the aggregate consumers' payments minus the project costs, if the product was produced and zero otherwise. Under the success objective, the payoff is 3 francs if the producer managed to successfully fund the project and zero otherwise. At the end of the experiment, each subject's payoffs in francs across all 45 rounds are paid out.

3.4.2 Hypotheses

We apply the theoretical predictions to the parameters of our experiment to derive hypotheses that we will test with the laboratory data. We are

[11]To illustrate, the second session in AON has the same cost order and value draws as the second session in sGMS; it has a different cost order and different value draws than the third session in AON.

interested in the mechanisms' performance from the producers' point of view and in terms of welfare. For this reason, we derive hypotheses both about the producers' profit and probability of success and about overall efficiency.

We first derive the optimal choice of parameters r and T for both mechanisms under each of the two producer objectives. We start by discussing the optimal parameters for AON. Recall from the theory section that consumers face a trade-off between increasing the production likelihood and paying as little as possible to obtain the good. If N is large enough, consumers' behavior is characterized by the semi-pooling equilibrium (cf. Theorem 3.2.ii). For a moderately large crowd of 15 consumers (as used in this experiment), it is already quite unlikely that a consumer's individual contribution is pivotal. In that case, even consumers with a high value are unwilling to pay a price that is substantially higher than the reservation price, r. Nevertheless, it is a priori unclear whether $N = 15$ is sufficient to make semi-pooling the BNE for consumers for all r and T. It is clear, however, that an unwillingness to pay substantially more than r implies that the producer must set high reservation prices to mitigate consumers' scope to free ride.

Aside from the reservation price, the producer has a second instrument, the fundraising threshold T. This allows the producer to only produce the good if the consumers are willing to pay enough for it in aggregate. If the producer sets $T \geq C$, she can ensure to never make a loss.

We use numerical analyses to simultaneously determine the BNE for consumers and the optimal r and T for producers for our experimental parameters (Appendix 3.D describes the algorithm used). For the producers, we find equilibrium behavior in AON as depicted in the top panel of Table 3.1. It appears that the equilibrium threshold not only depends on the project costs but also on the producer's objective. Under the success objective, the producer sets the fundraising threshold equal to the costs (cf. Lemma 3.A4 in the appendix). Under the profit objective, it can be worth-while to choose a threshold that is strictly higher than the costs. A threshold that equals a multiple of the reservation price plus one unit, for example, induces consumers with a high value to deviate from semi-pooling and bid one monetary unit above the reservation price. Consumers are predicted to play according to the semi-pooling equilibrium (see Theorem 3.1.ii) for $C = 50$, $C = 60$ and $C = 80$.

Table 3.1: Equilibrium Thresholds and Reservation Prices

		Success Objective			Profit Objective		
	Costs	60	80	100	50	70	90
AON	Threshold	60	80	100	50	78	97
	Reservation Price	10	10	11	11	11	12
GMS	Threshold	60	80	100	56	78	97
	Reservation Price	0	0	0	11	11	11

Notes: The table presents equilibrium thresholds and reservation prices in AON and GMS for all cost levels used in the experiment.

Next, consider GMS. While GMS has many equilibria, we derive the optimal r and T assuming that consumers play according to the truthful equilibrium, which is an equilibrium in weakly dominant strategies (Theorem 3.2). Therefore, unlike in AON, consumers do not adjust their bids with respect to the threshold and reservation price; this somewhat simplifies the analysis. As in AON, the equilibrium producer behavior depends on the producer's objective. Recall that producer behavior if the producer wants to maximize her success probability coincides with the serial cost sharing mechanism by Moulin and Shenker, i.e. $T_s^{GMS} = C$ and $r_s^{GMS} = 0$ (Theorem 3.5). The intuition is that as consumers bid their own value irrespective of the fundraising threshold and reservation price, setting $T > C$ and $r > 0$ only make it more difficult to reach aggregate payments equal or higher than the costs. This is confirmed in the lower panel of Table 3.1.

If the producer's objective is to maximize expected profits, she should set a relatively high reservation price. By doing so, she can ensure that payments, and therefore profits, are large in case she faces many high-valued consumers. The producer sets a threshold above the costs to still ensure a strictly positive payoff if only few consumers contribute. Using numerical analysis (see Appendix 3.D for the algorithm used), we find equilibrium producer behavior in GMS as depicted in Table 3.1.

Table 3.2 shows the expected performance of AON and GMS in terms of average profit, average surplus, and success frequency. Surplus is defined as the sum of the consumer values for the consumers who obtain the good minus the costs conditional on the good being produced. The sealed-bid and dynamic GMS are predicted to perform equally well, outperforming AON in all four outcome measures (cf. Propositions 3.1 and 3.2). However, the difference in expected performance between GMS and AON is considerably larger for the success objective than for the profit objective.

Table 3.2: Theoretical Predictions

	Success Objective		Profit Objective	
	Success	Surplus	Profit	Surplus
AON	0.559	33.84	15.79	35.77
GMS	0.651	46.73	16.29	37.62

Notes: For the experimental parameters, the table presents theoretical predictions for expected success frequency and surplus under a success objective and expected profit and surplus under a profit objective in AON and GMS.

The superior theoretical performance of GMS compared to AON (cf. Propositions 3.1 and 3.2, and Table 3.1) yields the following two hypotheses that we test in the experiment.

Hypothesis 3.1 *Relative to AON, sGMS yields*

(a) higher average profits under a profit objective

(b) higher average surplus under a profit objective

(c) higher success frequency under a success objective

(d) higher average surplus under a success objective.

Hypothesis 3.2 *Relative to AON, dGMS yields*

(a) higher average profits under a profit objective

(b) higher average surplus under a profit objective

(c) higher success frequency under a success objective

(d) higher average surplus under a success objective.

Theory predicts that sGMS and dGMS should perform equally well on all outcome measures as both mechanisms have a truthful equilibrium in weakly dominant strategies (see Theorem 3.2). However, there is reason to believe that more consumers will recognize that bidding one's own value is weakly dominant in dGMS than in sGMS (cf. Li, 2017; Breitmoser and Schweighofer-Kodritsch, 2019). Consumers that deviate from bidding truthfully might bid according to one of the equilibria as described in Appendix 3.B. As said, these equilibria have some consumers bid below their value. Put together, we expect lower bids in sGMS than in dGMS, leading to the following hypothesis.

Hypothesis 3.3 *Relative to sGMS, dGMS yields*

(a) higher average profits under a profit objective

(b) higher average surplus under a profit objective

(c) higher success frequency under a success objective

(d) higher average surplus under a success objective.

3.5 Results

This section presents the experimental results. We use paired Fisher-Pitman permutation tests to compare the mechanisms' performance. To allow for learning, we base our analysis on rounds 16 to 45. Section 3.5.1 presents results for when the producer aims to maximize profits. Section 3.5.2 shows results for when the producer aims to maximize success probability.[12] Section 3.5.3 analyzes consumer behavior in more detail.

3.5.1 Profit Objective

Figure 3.1 shows average producer profit (left panel) and average surplus (right panel) in AON, sGMS and dGMS under the profit objective.

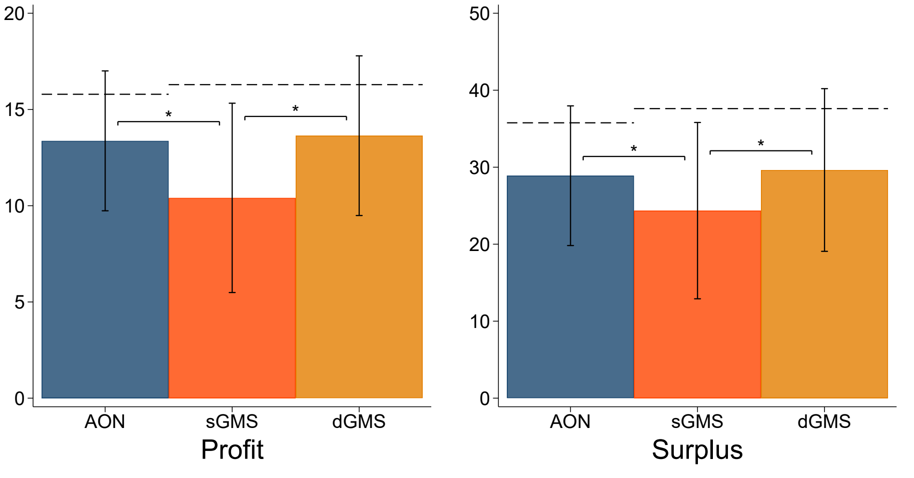
The figure reveals that dGMS yields a slightly and insignificantly higher producer profit than AON (13.64 vs. 13.37; $p = 0.688$).[13] Both yield a marginally significantly higher producer profit than sGMS (10.41; $p = 0.094$ resp. $p = 0.063$). An almost identical pattern is observed for average surplus. dGMS yields an insignificantly higher surplus than AON (29.64 vs. 28.90; $p = 0.688$). Both yield a marginally significantly higher surplus than the sGMS (24.36; $p = 0.094$ resp. $p = 0.063$).

These results are in stark contrast with Hypotheses 3.1a and 3.1b that predict that sGMS outperforms AON on both measures. For Hypotheses 3.2a and 3.2b, we cannot reject the null of no difference in profit and surplus between dGMS and AON. The superior performance of dGMS compared to sGMS is in line with Hypotheses 3.3a and 3.3b. We further observe that all

[12] We provide a separate analysis of the mechanisms' performance under the profit and success objective, even though differences to the theoretical predictions are solely driven by the behavior of consumers, who are unaware of a given round's objective. We nevertheless do so as actual consumer behavior might influence a mechanism's performance differently under the two objectives. In particular, this could be the case in sGMS and dGMS due to the large difference in reservation prices between rounds with a profit and success objective (cf. Table 3.1).

[13] Even though we state directional hypotheses, we show p-values for two-tailed tests in order to err on the conservative side.

Figure 3.1: Producer Profit and Overall Surplus – Profit Objective



Notes: The figure shows average producer profit (left graph) and average overall surplus (right graph) in AON, sGMS and dGMS for a profit objective. Error bars indicate ninety-five percent confidence intervals. The dashed lines denote the theoretical predictions. * $p < 0.1$ in a paired Fisher-Pitman permutation test.

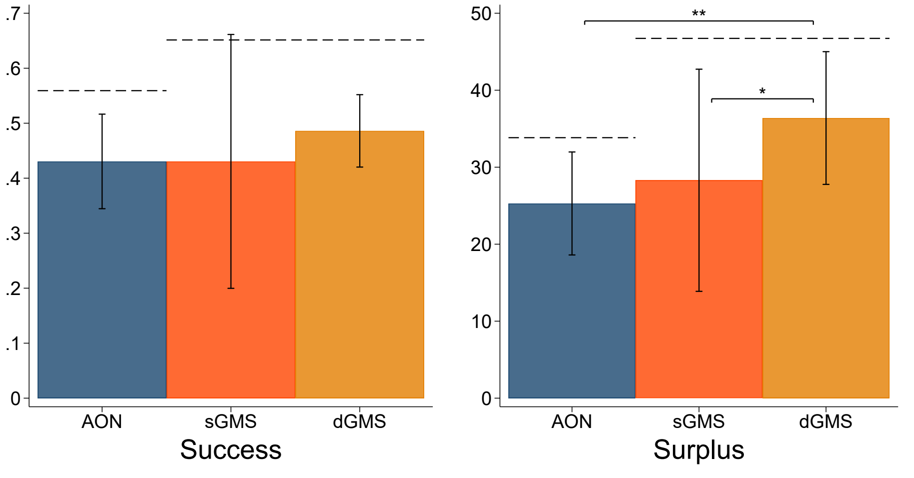
mechanisms yield lower profit and surplus than theoretically predicted. For sGMS this is significantly so; both realized profit and surplus lie outside the 95% confidence interval.

3.5.2 Success Objective

Figure 3.2 shows the success frequency (left panel) and average surplus (right panel) in AON, sGMS and dGMS under the success objective.

We observe that AON and sGMS yield the same success frequency (0.43). dGMS yields a higher success frequency, though this frequency is not statistically significantly different from AON and sGMS (0.49; $p = 0.125$ resp. $p = 0.500$). dGMS does yield a significantly higher surplus than AON (36.39 vs. 25.29; $p = 0.031$) and a marginally significantly higher surplus than sGMS (28.31; $p = 0.063$). The difference in average surplus between AON and sGMS is not significant ($p = 0.500$).

Figure 3.2: Producer Success and Overall Surplus – Success Objective



Notes: The figure shows the average success frequency (left graph) and the average overall surplus (right graph) in AON, sGMS and dGMS for a success objective. Error bars indicate ninety-five percent confidence intervals. The dashed lines denote the theoretical predictions. ** $p < 0.05$, * $p < 0.1$ in a paired Fisher-Pitman permutation test.

The data thus does not confirm the predicted superior performance in success probability and surplus of sGMS compared to AON (Hypotheses 3.1c and 3.1d). Comparing dGMS and AON, the results confirm the predicted higher surplus in dGMS than in AON (Hypothesis 3.2d), but do not allow us to reject the null of no difference in success probability (Hypothesis 3.2c). Similarly, the differences in success probability and surplus between dGMS and sGMS are not sufficiently large to confirm Hypotheses 3.3c and 3.3d. Finally, as also observed for the profit objective, the mechanisms all perform worse than theoretically predicted. In this case, the prediction falls outside of the estimated 95% interval in five out of six cases.

Taking both producer's objectives into account, we find that, as predicted by theory, dGMS weakly outperforms AON. dGMS scores better than AON in all four comparisons and significantly so in one. dGMS also weakly outperforms sGMS. In contrast to theory, the ranking between AON and sGMS is ambiguous.

3.5.3 Consumer Behavior

In order to better understand the differences in the mechanisms' performance, we analyze consumers' bidding behavior. We start with AON.

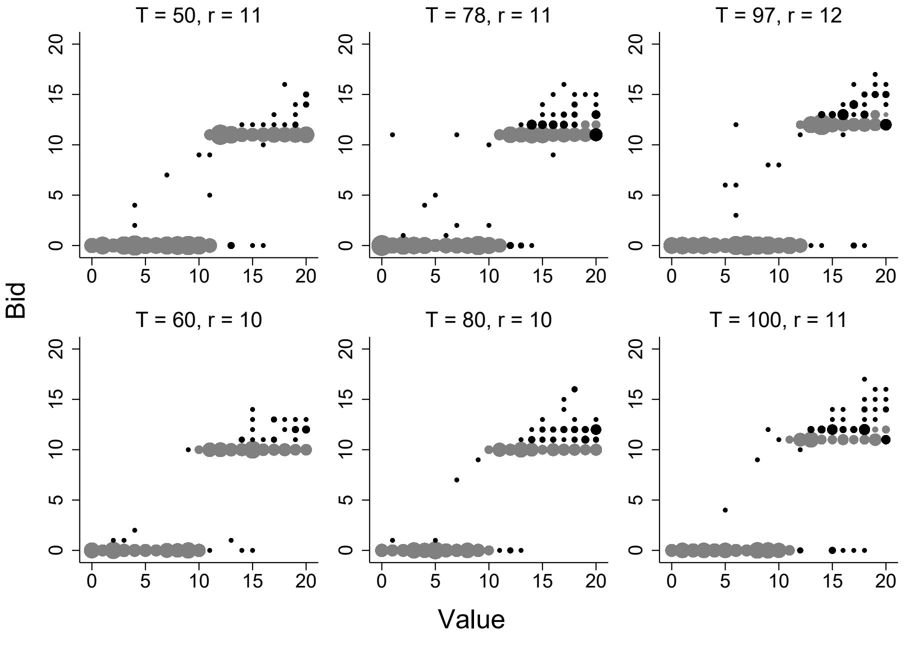
3.5.3.1 AON

Figure 3.3 depicts the frequency of bid-value combinations in AON for each combination of the threshold T and reservation price r. The larger the dot, the more frequent a bid-value combination occurred. Gray dots denote observations corresponding to the symmetric equilibrium bidding functions derived in Section 3.3.2.[14] Black dots denote bids that deviate from these predictions.

We observe that subjects' behavior is close to the theoretical prediction. In total, 89% of the bids correspond to the theoretical equilibrium bidding functions. Subjects with values below the reservation price almost always (98%) bid zero, and subjects with values strictly above the reservation price almost always (97%) bid at least the reservation price. Both observations are consistent with equilibrium behavior (see Lemmas 3.A1 and 3.A2 in Appendix 3.B). Interestingly, about two thirds of the subjects with values equal to the reservation price bid zero rather than the reservation price. While either yields a payoff of zero for oneself, bidding zero harms other subjects as it decreases the likelihood that the good is produced. In line with Lemma 3.B1 in Appendix 3.B, we observe that bids tend to weakly increase in subjects' values. A regression of bids on values v, reservation price r and threshold T for subjects with $v > r$ clustering standard errors at the individual level yields that subjects increase bids by 0.19 units per

[14] Notice that for three parameter sets ($T = 50$, $r = 11$; $T = 60$, $r = 10$; $T = 80$, $r = 10$) AON has a semi-pooling equilibrium, i.e. the best response is r for any value weakly above r. By Propositions 3.1 and 3.2, GMS is then predicted to outperform AON.

Figure 3.3: Bidding Behavior in AON



Notes: The figure depicts the frequency of bid-value combinations in AON for each T, r combination. The larger the dot, the more frequent a bid-value combination occurred. Gray dots denote observations that correspond to the theoretical symmetric equilibrium bidding functions. Black dots denote bids that deviate from the theoretical prediction.

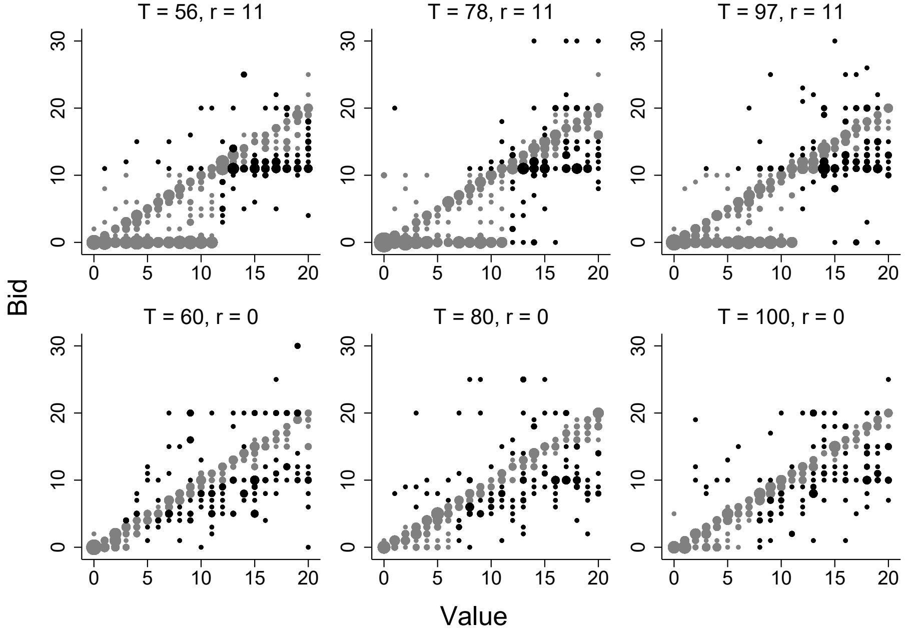
value unit, which is strongly significant ($p < 0.001$). Bids do not significantly increase in the threshold ($p = 0.390$). All in all, 85% of the bids are in line with the theoretical equilibrium bidding functions. There is, however, more overbidding (9%) than underbidding (3%).[15]

[15] Figure 3.C1 in the appendix shows that subjects' behavior approaches the theoretical prediction over time. In particular, we observe that subjects learn to refrain from weakly dominated play. The share of weakly dominated bids drops from 10% (rounds 1-15) to 4% (rounds 16-30) to a mere 2% (rounds 31-45).

3.5.3.2 sGMS

We now turn to GMS. Figure 3.4 depicts the frequency of bid-value combinations in sGMS in the same way that Figure 3.3 does for AON. Note that bidding one's value is not the unique weakly dominant strategy as the set of candidate prices is discrete (cf. Theorem 3.B4 in the appendix). Recall that in GMS the realized price is given by the uniform price $p^* = \max\{\lceil \frac{T}{M} \rceil, r\}$, while anyone bidding less than p^* pays zero and does not obtain the good. Therefore, any bidding strategy that satisfies both $b \geq p^*$ if $v > p^*$ and $b < p^*$ if $v < p^*$ for all $M \in \{1, 2, \ldots, 15\}$ is weakly dominant. The case for higher values follows from the uniform price, while bidding anything positive but below the realized price results in paying zero.

Figure 3.4: Bidding Behavior in sGMS



Notes: The figure depicts the frequency of bid-value combinations in sGMS for each T, r combination. The larger the dot, the more frequent a bid-value combination occurred. Gray dots denote weakly dominant bids. Black dots denote weakly dominated bids.

In total, 73% of the bids are weakly dominant.[16] We observe in Figure 3.4 that the majority of black dots lies below the identity line. Subjects thus tend to underbid (20% of the bids) rather than overbid (7% of the bids). This asymmetry in deviations from weakly dominant play is the reason why sGMS does not outperform AON as predicted by theory. The bidding behavior suggests that a noteworthy share of subjects falsely expects that bidding below value increases one's payoff conditional on the good being produced. Ceteris paribus, an underbidding subject forewent on average 21% of the round's payoff that she would have earned by bidding value. The type of underbidding differs, however, between the two producer's objectives. This is because the two objectives give rise to distinct reservation prices. In rounds with a profit objective (top row), underbidding subjects often (46%) bid the reservation price of 11. In rounds with a success objective (bottom row) the reservation price is zero and most (83%) underbidding subjects bid a few units below their value. A possible explanation for this difference is that the reservation price of 11 acts as a focal point in rounds with a profit objective, but the reservation price of 0 in rounds with a success objective is ill-suited to do so as a bid of zero renders a positive payoff impossible.

Given that the foregone payoff from underbidding is substantial and that subjects play the crowdfunding game for 45 rounds, the question arises why many subjects do not learn over time to play a weakly dominant strategy.[17] One reason might be that useful feedback on one's behavior is rare in this

[16] There is large heterogeneity in the share of weakly dominant bids within consumers. For instance, consumers at the 20th resp. 80th percentile of the distribution of the fraction of weekly dominant bids choose weakly dominant bids in 50% resp. 97% of the rounds.

[17] The overall frequency of underbidding decreases from 30% in the first 15 rounds to 21% in the second 15 rounds. However, we observe little aggregate learning after that as subjects still underbid 18% of the time in the third 15 rounds, as depicted in Table 3.C1 in the appendix. Figure 3.C2 in the appendix shows that the type of underbidding also stays similar over time. At the individual level, Figure 3.C4 in the appendix shows that underbidding is relatively stable over time. Consumers who underbid in the beginning of the crowdfunding game tend to also regularly underbid in the remaining rounds. In contrast, consumers who hardly underbid at the beginning typically do not start underbidding later on (the Pearson correlation coefficient between underbidding in the first 15 and last 30 rounds is 0.69).

environment. In most cases of underbidding (88%), this had no impact on a subject's payoffs compared to if she had placed a bid equal to her value, because either bid would have resulted in the same production outcome and price.

In addition, even when underbidding negatively affected subjects' payoffs, this might be difficult to spot. It is arguably cognitively challenging to recognize that in a case where a product was not produced it would have been produced if one had bid higher. The only 'clear' mistakes occur when a product is produced and underbidding subjects obtain zero payoff but could have obtained a positive payoff by bidding higher. However, this occurs in only 7% of the cases involving underbidding, which might explain why learning by underbidding subjects is rare in sGMS. This issue is particularly pronounced under a profit objective, where a noteworthy minority of subjects bids the reservation price. It then becomes unlikely that a price above the reservation price is implemented. This, in turn, decreases the likelihood that underbidding subjects realize their mistakes.

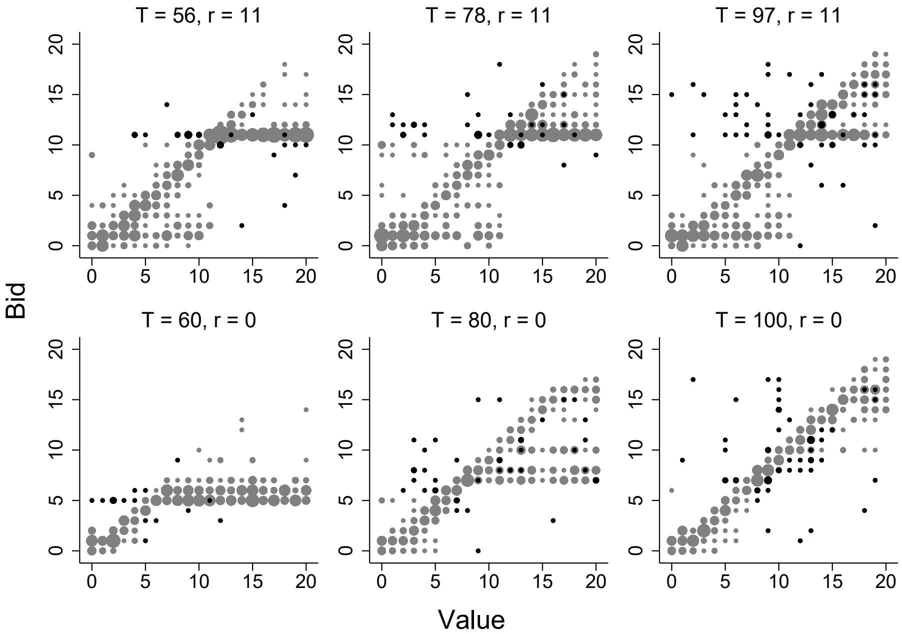
3.5.3.3 dGMS

Analyzing subjects' bidding behavior in dGMS is less straightforward than in AON or sGMS. This is because one cannot observe what subjects would have bid in cases where they had not yet dropped out when the ascending clock stopped. We can, however, denote a bid as the last price that a subject implicitly agreed upon before she either dropped out or the ascending clock stopped. Doing so, we obtain Figure 3.5. Note that we can only identify weakly dominated bids, however, if a subject has dropped out before the ascending clock stops or has not dropped out at a price higher than her value. If a bid is not weakly dominated, we assign it a gray dot.

We observe that the panels are pre-dominantly gray, and, in fact, 92% of the bids are in line with a (possibly) weakly dominant strategy.[18] The

[18]Table 3.C1 and Figure 3.C3 in the appendix show that the frequency of possibly

Figure 3.5: Bidding Behavior in dGMS



Notes: The figure depicts the frequency of bid-value combinations in dGMS for each T, r combination. The larger the dot, the more frequent a bid-value combination occurred. Gray dots denote possibly weakly dominant bids. Black dots denote surely weakly dominated bids. The reason why gray dots are only 'possibly' weakly dominant is explained in the main text.

black dots are distributed evenly above (47% of weakly dominated bids) and below (53% of weakly dominated bids) the identity line.

In order to obtain a fair comparison between subjects' bidding in dGMS and sGMS, we construct counterfactual bids that reflect how subjects in sGMS would have bid in dGMS. To do so, we assume that subjects' bids in sGMS determine the highest price at which a subject would be willing to stay in the market. Doing so shows that 84% of these counterfactual bids in sGMS are in line with a possibly weakly dominant strategy (recall that 73%

weakly dominant bids increases from 81% (rounds 1-15) to 90% (rounds 16-30) to 93% (rounds 31-45), predominantly due to a decrease in underbidding from 14% to 6% to 3%.

of the actual bids are in line with a weakly dominant strategy). This means that at least 16% are part of a weakly dominated strategy. 74% of these (surely) weakly dominated counterfactual bids constitute underbidding, the remaining 26% reflect overbidding. Recall that only 8% of the bids in dGMS are in line with a surely weakly dominated strategy, and that deviations are distributed evenly above and below the identity line. This suggests that subjects deviate from optimal play twice as often in sGMS than in dGMS, and they do so by more excessive underbidding. The differences in optimal play and underbidding are statistically significant (both $p = 0.031$) and are the reasons for why dGMS (weakly) outperforms sGMS along all dimensions.[19]

3.6 Conclusion

This chapter introduces a new reward-based crowdfunding mechanism, the Generalized Moulin-Shenker mechanism (GMS). We theoretically analyze both a sealed-bid and dynamic version of GMS and show that they are promising alternatives to the prevailing All-or-Nothing mechanism (AON). Unlike AON, both versions of GMS are strategy-proof and dGMS, that builds on Deb and Razzolini (1999), is obviously strategy-proof in the sense of Li (2017). For a sufficiently large crowd of consumers we find that both versions of GMS outperform AON, both for the producer and in terms of efficiency.

We test our theoretical predictions in a laboratory experiment. We compare the performance of both versions of GMS with AON, allowing for two producer objectives: profit maximization and success probability maximization. In line with our predictions, we find that dGMS weakly outperforms AON and sGMS. Contrary to the theoretical predictions, however, the per-

[19]Figure 3.C5 in the appendix further shows that the shares of possibly weakly dominant bids by consumer in dGMS first order stochastically dominates the shares in the 'dynamized' sGMS.

formance ranking between sGMS and AON is ambiguous. While subject behavior in dGMS and AON comes close to our predictions, many subjects tend to underbid in sGMS relative to the truthful equilibrium. Their bidding strategies suggest that subjects perceive a (non-existent) trade-off between on the one hand payoffs conditional on obtaining the good and on the other the likelihood of obtaining the good. The obviously strategy-proofness of dGMS removes this perceived trade-off and thereby reduces subjects' inclination to bid suboptimally low.

We believe our results to be informative about reward-based crowdfunding in practice. Our results provide some justification for the prevalent use of AON. Even though deriving equilibrium bidding functions in AON is computationally involved, subjects' bidding is close to the theoretical predictions. Our results suggest that switching to sGMS may not be justified in terms of producer profits, project success probability, or efficiency. The prevalent underbidding in sGMS that underlies this also mitigates its potential as a demand elicitation tool. Our results, however, provide evidence that crowdfunding could become more efficient by using dGMS instead of AON. A challenge, though, is how dGMS can be implemented in practice. It seems unpractical to require all consumers to be available for bidding at the same time or during specified intervals. A good alternative may be to approximate dGMS via proxy agents, where sealed bids act as automatic drop-out prices. This would allow consumers to bid at any time they like but might still prevent underbidding. This practical solution is supported by a recent paper by Breitmoser and Schweighofer-Kodritsch (2019) who compare intermediate auction formats between a second-price sealed-bid auction and an ascending-clock auction. They show that personally responding as the clock increases the price is unnecessary to induce truthful bidding.

For our empirical analysis, we opted for a laboratory experiment. This choice is grounded in the theory-testing nature of our research question. Having introduced a new crowdfunding mechanism and having shown its desirable theoretical properties, the natural first choice is to test these properties under laboratory control (Schram, 2005; List, 2020). This is particularly the case when the theory's predictions involve comparative statics (List, 2020), as is the case with our mechanisms. Laboratory control allows us to optimize internal validity by ensuring that the theory's assumptions are met as closely as possible.

From here, two follow-up steps naturally arise. First, because this study has focused on one side of the crowdfunding market, the consumers, it is natural to study the extent to which the supply side (producer behavior) confirms the theoretical predictions. Once again, the laboratory seems an obvious place to start. This extension is the topic of our companion study in Chapter 4. The second obvious extension involves testing the theory in an environment to which it is ultimately intended to apply (List, 2020). For these crowdfunding mechanisms, this would imply, for example, comparing the results of AON and dGMS on platforms in the field.

3.A Proofs

We first establish three lemmas regarding equilibrium bidding behavior in AON that are needed for the proofs of the theorems and propositions in the main text.

Lemma 3.A1 *In AON, it is a weakly dominant strategy for consumer i to bid $B(v_i) = 0$ if $v_i < r$, $i = 1, ..., N$.*

Proof of Lemma 3.A1 Consider consumer i with $v_i < r$. First, assume that i bids $0 < b_i < r$. Her utility is $u_i = -b_i < 0$, if $\sum_{i=1}^{N} b_i \geq T$, and $u_i = 0$ otherwise. Now, assume that i bids $b_i \geq r$. Her utility is $u_i = v_i - b_i \leq v_i - r < 0$, if $\sum_{i=1}^{N} b_i \geq T$, and $u_i = 0$ otherwise. By bidding $B(v_i) = 0$, i always obtains $u_i = 0$. It is therefore a weakly dominant strategy for consumer i to bid $B(v_i) = 0$ for $v_i < r$. ■

Lemma 3.A2 *In AON, bids $b < r$ are weakly dominated by bidding $B(v_i) = r$ for $v_i > r$.*

Proof of Lemma 3.A2 Consider consumer i with $v_i \geq r$. First, assume $\sum_{j \neq i} b_j + r < T$. The good is not produced, neither for $b_i = r$, nor for $b_i < r$. In both cases, $u_i = 0$. Now, assume $\sum_{j \neq i} b_j + b_i < T \leq \sum_{j \neq i} b_j + r$. By bidding $b_i = r$, consumer i obtains $u_i = v_i - r > 0$. This is higher than $u_i = 0$, which she obtains by bidding $b_i < r$. Lastly, assume $\sum_{j \neq i} b_j + b_i \geq T$. By bidding $b_i = r$, consumer i obtains $u_i = v_i - r > 0$. This is higher than $u_i = -b_i \leq 0$, which she obtains by bidding $b_i < r$. Bidding $b_i < r$ is therefore weakly dominated by bidding $B(v_i) = r$ for $v_i > r$. ■

Lemma 3.A3 *In AON, bids $b \geq v_i$ are weakly dominated by bidding $B(v_i) = r$ for $v_i > r$.*

Proof of Lemma 3.A3 Consider consumer i with $v_i \geq r$. First, assume $\sum_{j \neq i} b_j + b_i < T$. The good is not produced, neither for $b_i = r$, nor for $b_i < r$. In both cases, $u_i = 0$. Now, assume $\sum_{j \neq i} b_j + r < T \leq \sum_{j \neq i} b_j + b_i$. By bidding $b_i = r$, consumer i obtains $u_i = 0$. This is higher than $u_i = v_i - b_i < 0$, which she obtains by bidding $b_i > v_i$. Lastly, assume $\sum_{j \neq i} b_j + r \geq T$. By bidding $b_i = r$, consumer i obtains

$u_i = v_i - r > 0$. This is higher than $u_i = v_i - b_i < 0$, which she obtains by bidding $b_i > v_i$. Bidding $b_i > v_i$ is therefore weakly dominated by bidding $B(v_i) = r$ for $v_i > r$. ■

Proof of Theorem 3.1 ←

(i) Suppose all consumers bid according to $B(v) = 0 \; \forall \; v$. Every consumer then obtains a payoff of 0. Now suppose consumer j deviates by bidding $b_j > 0$. If $T > b_j > 0$, the good is not produced and consumer j still obtains a payoff of 0. If $b_j \geq T$, the good is produced and consumer j obtains $v_j - b_j < 0$ as $T \geq C > \bar{v}$. Therefore, $B(v) = 0 \; \forall \; v$ constitutes a symmetric BNE of AON. ■

(ii) According to Lemmas 3.A1 and 3.A2, any BNE $\beta \equiv (\beta_1, \beta_2, \ldots, \beta_N)$ in undominated strategies of AON satisfies $\beta_i(v_i) = 0$ for $v_i < r$ and $\beta_i(v_i) \geq r$ for $v_i \geq r$. Consider consumer j having value $v_j \geq r$. Suppose all other consumers bid according to β. Then bidding r is a best response for consumer j if and only if

$$P\left\{\sum_{i\neq j} \beta_i(v_i) + r \geq T\right\}\left(v_j - r\right) \geq P\left\{\sum_{i\neq j} \beta_i(v_i) + b_j \geq T\right\}\left(v_j - b_j\right)$$

for all $b_j > r$. The probability on the left-hand [right-hand] side is the probability that the good is produced conditional on consumer j bidding r [b_j] and all other consumers bid according to β. The inequality can be rewritten as follows:

$$P\left\{\sum_{i\neq j} \beta_i(v_i) + b_j \geq T\right\}\left(b_j - r\right) \geq P\left\{b_j \geq T - \sum_{i\neq j} \beta_i(v_i) \geq r\right\}\left(v_j - r\right)$$

Now, for arbitrarily large N, the probability on the left-hand side of the second inequality approaches 1 while the probability on the right-hand side converges to zero for any β satisfying $\beta_i(v_i) = 0$ for $v_i < r$ and $\beta_i(v_i) \geq r$ for $v_i \geq r$. Therefore, bidding r is the best response for consumer j for sufficiently large N. As a result, for sufficiently large N, the semi-pooling equilibrium is the unique BNE in undominated strategies of AON. ■

Proof of Theorem 3.2 ← We show that it is a weakly dominant strategy for consumer i to bid her own value $\beta(v_i) = v_i$ in GMS, following Moulin and Shenker

(1992). First, note that how much a consumer needs to pay to obtain the reward does not depend on her own but only on her fellow consumers' bids. Now assume consumer i deviates from $\beta(v_i) = v_i$ and bids $b_i > v_i$. Denote the candidate price by $p = \max\{\frac{T}{k}, r\}$. If $p > b_i > v_i$, the deviation makes no difference; consumer i does not obtain the reward and thus pays nothing anyways. If $b_i > v_i \geq p$, the deviation again makes no difference; consumer i obtains the reward in both cases and pays p. But if $b_i \geq p > v_i$, the deviation leads to a loss. Consumer i obtains the reward and pays p so that $v_i - p < 0$. Bidding above one's value is thus weakly dominated by bidding exactly one's value. Now assume that consumer i bids $b_i < v_i$. If $p > v_i > b_i$, the deviation makes no difference as consumer i does not obtain the reward and pays nothing with or without deviation. If $v_i > b_i \geq p$, the deviation again does not change anything. Consumer i obtains the reward and pays p. But if $v_i \geq p > b_i$, consumer i gets a payoff of $u_i(b_i < v_i) = 0$, whereas she would have received a positive payoff if she had bid her value, namely $v_i - p \geq 0$. Thus, bidding below one's value is also weakly dominated by bidding one's own value. ■

Proof of Theorem 3.3 ← Li (2017) shows that a strategy is only obviously dominant if it is weakly dominant. For both sGMS and dGMS, any weakly dominant strategy has a consumer bid value if her value exceeds the reservation price. Consider consumer i having value $v_i > \max\{\frac{T}{|N|}, r\}$ who considers the strategies 'bidding v_i' and 'bidding $b_i > v_i$'. For sGMS, the earliest information set where these strategies differ is the point where the consumer submits her bid. Then, the worst possible outcome when bidding v_i is that the good is not developed, resulting in a payoff of zero. The best possible outcome when bidding $b_i > v_i$ is that the good is developed and consumer i obtaining the good for which she pays $\max\{\frac{T}{N}, r\}$. The resulting utility equals $v_i - \max\left\{\frac{T}{N}, r\right\} > 0$. Ergo, sGMS does not have an obviously dominant strategy. Therefore, it is not obviously strategy-proof. In dGMS, the earliest information set where quitting at $b_i > v_i$ diverges from quitting at v_i is when the ascending clock reaches price v_i. When that information set is reached, the best possible outcome from quitting at b_i is not better than the worst possible outcome from quitting at v_i. So, bidding value is an obviously dominant strategy and, consequently, dGMS is obviously strategy proof. ■

Lemma 3.A4 *Setting $T_\pi^{AON} = T_s^{AON} = C$ is weakly dominant when consumers play according to a semi-pooling equilibrium in AON.*

Proof of Lemma 3.A4 Denote the indicator function by $\mathcal{I}\{\cdot\}$. Producer profit equals

$$\pi^{AON}(r,T) = \mathbb{E}\left\{\left[\sum_{i=1}^{N} B(v_i) - C\right] \mathcal{I}\left\{\sum_{i=1}^{N} B(v_i) \geq T\right\}\right\}.$$

Similarly, the success probability equals

$$Pr^{AON}(r,T) = \mathbb{E}\left\{\mathcal{I}\left\{\sum_{i=1}^{N} B(v_i) \geq T \;\middle|\; \sum_{i=1}^{N} B(v_i) \geq C\right\}\right\}.$$

Note that under a semi-pooling equilibrium, $B(v_i)$ only depends on v_i and r but not on T. Now assume that the producer deviates and sets $T > C$. If $\sum_{i=1}^{N} B(v_i) \geq T$, then the project is successful and profit equals $\sum_{i=1}^{N} B(v_i) - C$ either way. If $\sum_{i=1}^{N} B(v_i) < C$, the good is not successful and profit equals 0 either way. If $T > \sum_{i=1}^{N} B(v_i) \geq C$, then the project is not successful and profit equals 0 under the deviation but the project would have been successful and yielded a profit equal to $\sum_{i=1}^{N} B(v_i) - C \geq 0$ for $T = C$. Now assume that the producer deviates and sets $T < C$. If $\sum_{i=1}^{N} B(v_i) \geq C$, then the project is successful and profit equals $\sum_{i=1}^{N} B(v_i) - C$ either way. If $\sum_{i=1}^{N} B(v_i) < T$, the project is not successful and profit is zero either way. If $C > \sum_{i=1}^{N} B(v_i) \geq T$, then the project is not a success either way. Under the deviation, profit equals $\sum_{i=1}^{N} B(v_i) - C < 0$ but would have been 0 for $T = C$. Thus, setting $T_\pi^{AON} = T_s^{AON} = C$ is therefore weakly dominant under a semi-pooling equilibrium in AON. ■

Proof of Theorem 3.4 $\leftarrow$ To maximize the probability of success, it is a dominant strategy to choose $T_s^{AON} = C$ (Lemma 3.A4). For any $r \leq \bar{v}$, the probability that a randomly drawn consumer has $v_i < r$ and will therefore bid 0, is $F(r)$. All other consumers bid r. In a population of N consumers, the number of consumers bidding 0, denoted by n_0, is binomially distributed with $p = F(r)$. The project is successful if $N - n_0 \geq \frac{C}{r}$, or $r \geq \frac{C}{N-n_0}$. Success is therefore only possible if $r \geq \frac{C}{N}$. Also, success is only possible if $r \leq \bar{v} < C$ as $C > \bar{v}$ by assumption. Further, the optimal r_s^{AON} must satisfy $r_s^{AON} \in \left\{\frac{C}{N}, \ldots, \frac{C}{2}\right\}$ as any $\frac{C}{k} < r' < \frac{C}{k-1}, k \in 2, \ldots, N$ is weakly dominated by $r = \frac{C}{k}$ as both r and r' require k consumers to bid r resp. r' but $p = F(r) < F(r')$. The probability of success is then given by $I_{(1-F(r))}\left(N - \frac{rN-C}{r}, \frac{rN-C}{r} + 1\right) = I_{(1-F(r))}\left(\frac{C}{r}, \frac{(N+1)r-C}{r}\right)$, where $I_x(\cdot)$ denotes the regularized incomplete beta function (Askey and Roy, 2010).

The producer's optimization problem is therefore

$$\max_r I_{(1-F(r))}\left(\frac{C}{r}, \frac{(N+1)r - C}{r}\right), \; s.t. \; r \in \left\{\frac{C}{N}, \ldots, \frac{C}{2}\right\} \; \& \; r \leq \overline{v}$$

For given values of $\overline{v}$, N and C, the optimal reservation price can be determined numerically.

As $N \to \infty$, $\frac{C}{N}$ (the lower bound on r) converges to zero. Because $\max_x I_x(a,b) = 1$ and is reached for all (a,b), when $x = 1$, the maximum involves $1 - F(r) \to 1$, therefore $r \to 0$. ■

Proof of Theorem 3.5 ← Recall that in GMS, all consumers who obtain a unit of the good pay the same price. Because consumers bid truthfully in GMS, projects are successful if and only if a price p^* exists for which both $p^* = \min\{p \geq r : p\sum_{i=1}^{N} \mathcal{I}\{v_i \geq p\} \;\geq T\}$ and $p^* \sum_{i=1}^{N} \mathcal{I}\{v_i \geq p^*\} \geq C$. Therefore, the project's success probability is maximized at $T_s^{GMS} = C$ and $r_s^{GMS} = 0$. ■

Proof of Proposition 3.1 ←

(i) Under a profit objective, the producer in AON optimally sets $T_\pi^{AON} = C$ when consumers play according to the semi-pooling equilibrium (Lemma 3.A4). The good is then produced if and only if $Mr_\pi^{AON} \geq C$, where M is the number of consumers having a value of r_π^{AON} or greater. Define by k the minimum number of consumers bidding r_π^{AON} that is required to fund the project, thus $k = \lceil \frac{T_\pi^{AON}}{r_\pi^{AON}} \rceil$. Now, consider GMS with $r^{GMS} = r_\pi^{AON}$ and $T^{GMS} = C + \epsilon < kr^{GMS}$ if $kr_\pi^{AON} > C$ and $T^{GMS} = C + \epsilon < (k+1)r^{GMS}$ if $kr_\pi^{AON} = C$, with consumers playing the truthful equilibrium. If $Mr^{GMS} \geq T^{GMS}$, AON and GMS yield the same profit. GMS yields strictly higher profit if $Mr^{GMS} < T^{GMS}$ and a subset S exists for which $v_i \geq \max\left\{r^{GMS}, \frac{T^{GMS}}{|S|}\right\}$ for all $i \in S$. GMS thus yields weakly higher profit than AON. GMS yields strictly higher expected profit than AON if the subset S exists with strictly positive likelihood. As in GMS every equilibrium price $p < \overline{v}$ is implemented with strictly positive likelihood, there need to be at least two equilibrium prices strictly below $\overline{v}$. This is the case if and only if $C < (k-1)\overline{v}$. As $k = \lceil \frac{C}{r_\pi^{AON}} \rceil$, we obtain that GMS yields strictly higher expected profit than AON if and only if $\lceil \frac{C}{r_\pi^{AON}} \rceil - 1 > \frac{C}{\overline{v}}$. ■

(ii) Under a success objective, the producer in AON also optimally sets $T_s^{AON} = C$ (Lemma 3.A4) and chooses $r_s^{AON} \in \left\{\frac{C}{N}, \ldots, \frac{C}{2}\right\}$ s.t. $r \leq \overline{v}$ (Theorem 3.4).

In GMS, the producer optimally sets $T_s^{GMS} = C$ and $r_s^{GMS} = 0$ (Theorem 3.5). Therefore, equilibrium prices in GMS are in the set $\{\frac{C}{N}, \ldots, C\}$. Thus, producers optimally set the same threshold in AON and GMS, and the set of potentially optimal reservation prices in AON coincides with the set of equilibrium prices in GMS. Therefore, whenever the good is produced in AON, it is also produced in GMS. Now assume that the good is not produced in AON. In this case, the good is produced in GMS if $\exists p : p \sum_{i=1}^{N} \mathcal{I}\{v_i \geq p\} \geq C$. GMS thus yields weakly higher success than AON. GMS yields strictly higher success probability if there are at least two equilibrium prices that are strictly below $\overline{v}$ as every equilibrium price $p < \overline{v}$ is implemented with strictly positive likelihood. Clearly, this is the case if and only if $C < (N-1)\overline{v}$. ■

Proof of Proposition 3.2 ← Producers optimally set the same threshold in AON and GMS, and the set of potentially optimal reservation prices in AON coincides with the set of equilibrium prices in GMS (cf. Proof of Proposition 3.1). Now, fix the value vector v. Consider the case that the good is produced in AON at the optimal threshold/reservation price pair C, r_s^{AON}. Then, it must be the case that $\min\left\{p \geq 0 : p \sum_{i=1}^{N} \mathcal{I}\{v_i \geq p\} \geq C\right\} \leq r_s^{AON}$ because otherwise, the good would not have been produced in AON. AON and GMS yield the same total surplus if $\min\left\{p \geq 0 : p \sum_{i=1}^{N} \mathcal{I}\{v_i \geq p\} \geq C\right\} = r_s^{AON}$, as in this case the same consumers obtain the good paying r_s^{AON} each. If $\exists p < r_s^{AON} : p \sum_{i=1}^{N} \mathcal{I}\{v_i \geq p\} \geq C$, then GMS yields strictly higher surplus. If the good is not produced in AON, then GMS yields strictly higher surplus if $\exists p > r_s^{AON} : p \sum_{i=1}^{N} \mathcal{I}\{v_i \geq p\} \geq C$ & $\exists v_i > p$. Together, this implies that GMS yields weakly higher aggregate surplus than AON. Now, note that all candidate reservation prices in AON are reached with strictly positive likelihood in GMS. Thererefore, GMS yields weakly higher expected aggregate surplus than AON if there are at least two candidate reservation prices that are strictly below $\overline{v}$. Clearly, this is the case if and only if $C < (N-1)\overline{v}$. ■

3.B Additional Theoretical Results

AON. Together, Lemmas 3.A1, 3.A2 and 3.A3 show that, unlike in GMS, consumers have an incentive to bid below their value in AON whenever $v_i \neq r$.

We now turn to the properties of a symmetric Bayesian Nash equilibrium bid function $B : [0, \overline{v}] \rightarrow [0, \overline{v}]$, if one exists. Let $\rho(b) \equiv P\{\sum_{i=1}^{N-1} B(v_i) \geq T - b\}$ for $b \in [r, \overline{v}]$. $\rho(b)$ denotes the probability that – conditional on the other $N-1$ bidders using the equilibrium strategy – a bid b is sufficient to make the threshold. We call $\rho(b)$ the 'threshold probability function'. Note that this can be written as $1 - G(T - b)$, where G is the cumulative distribution function of $[\sum B(v_i)]$, which is fully determined by F and the functional form of B. Also, $\rho(b) \geq 0$ and $\rho'(b) \geq 0$. A consumer's expected payoff in a symmetric Bayesian Nash equilibrium then equals $\rho(b)(v - b)$. Let $\alpha(b, v) \equiv \rho'(b)(v - b) - \rho(b)$ be the derivative of the expected payoff with respect to bid b. The sign of $\alpha(b, v)$ indicates whether a consumer can increase her expected payoff by infinitesimally increasing her bid.

Before we derive an equilibrium strategy, Lemma 3.B1 first establishes a property of all equilibria in AON.

Lemma 3.B1 *Suppose $(N-1)r > T$. If $B(v_i)$ constitutes a Bayesian Nash equilibrium in undominated strategies of AON, then $B(v_i)$ is weakly increasing.*

Proof of Lemma 3.B1 Lemma 3.A1 establishes that, $B(v) = 0$ for $v < r$. For $v \geq r$, the proof is by contradiction. Suppose values $v \geq r$ and $w > v$ exist for which $B(v) > B(w)$. Note that the probability that $N-1$ value draws are all larger than or equal to r is positive; together with Lemma 3.A2 and the assumption that $(N-1)r > T$, this implies that $\rho(b) > 0$ for all $b \in [r, \overline{v}]$. A consumer for whom $\rho(B(v)) \leq \rho(B(w))$, strictly prefers bidding $B(w)$ over $B(v)$, which contradicts the assumption that she bids $B(v)$ when her value is v. Now, assume $\rho(B(v)) > \rho(B(w))$.

In equilibrium, it must be the case that $\rho(B(v))(v-B(v)) \geq \rho(B(w))(v-B(w))$ and

$$\rho(B(w))(w-B(w)) \geq \rho(B(v))(w-B(v)).$$

Because $B(v)$ and $B(w)$ are best responses for v and w, respectively, adding up the two inequalities gives

$$(\rho(B(w)) - \rho(B(v)))(w-v) \geq 0.$$

This implies $\rho(B(w)) \geq \rho(B(v))$, which contradicts $\rho(B(v)) > \rho(B(w))$. ■

The intuition is as follows. Consumers with a value below the reservation price r optimally bid zero (Lemma 3.A1). Consumers with a value above the reservation price face a trade-off: bidding the reservation price maximizes one's payoff if the good is produced while bidding higher increases the likelihood that the good is produced. The latter becomes relatively more important the higher is a consumer's value; this results in a weakly monotonic bidding function.

We can now derive a general form for a symmetric equilibrium bidding strategy under mild assumptions.

Theorem 3.B1 *Suppose $\rho(b)$ is differentiable on the domain $[r, \overline{v}]$ and $\alpha(b,v)$ is decreasing in b for all $b \in [r,v]$ and $v \in [r, \overline{v}]$. Let $\hat{v} \equiv \max\{v : \rho'(r)(v-r) - \rho(r) \leq 0\}$. Consider the bid function B for which $B(v) = 0 \; \forall \; v \in [0,r)$, $B(v) = r \; \forall \; v \in [r, \hat{v})$ and implicitly by $B(v) = v - \frac{\rho(B(v))}{\rho'(B(v))}$ for $v \in [\hat{v}, \overline{v}]$. Then, B constitutes a symmetric BNE of AON.*

Proof of Theorem 3.B1 Consider consumer i. Suppose all other consumers bid according to B. If $v_i < r$, bidding $B(v_i) = 0$ is indeed a best response. By Lemmas 3.A3 and 3.B1, for $v_i \geq r$, the optimal bid B^* is in the interval $[r, v_i]$. So, B^* follows from

$$B^* \in \arg\max_{r \leq b \leq v_i} \rho(b)(v_i - b) \quad .$$

The first order condition is given by

$$\rho'(b)(v_i - b) - \rho(b) = \alpha(b, v_i) \leq 0$$

where equality must hold for any $b > r$ to be a best response. As $\alpha(b)$ is decreasing in b for $b \in [r, v]$ by assumption, the second order condition for a maximum is fulfilled. Therefore, B constitutes a Bayesian Nash equilibrium. ■

Note that B describes a semi-pooling equilibrium when $\hat{v} \geq \overline{v}$. We now present one additional result for optimal producer behavior under a profit objective when consumers play according to such a semi-pooling equilibrium.

Theorem 3.B2 *Suppose that in AON consumers play according to the semi-pooling equilibrium and that F is log-concave. Then for sufficiently large N, the producer maximizes expected profit by setting $r_\pi^{AON} = \frac{1-F(r_\pi^{AON})}{f(r_\pi^{AON})}$.*

Proof of Theorem 3.B2 For any finite C, and $r = \epsilon$, with ϵ small, there is an N, such that $rN > C$. For this reason, as $\epsilon \to 0$, almost every r suffices to cover the costs. To optimize, producers must then choose an r that maximizes the expected revenue. Note that $r = 0$ yields zero revenue and no success. Therefore, consider $r > 0$. Expected revenue is then $N(1-F(r))r$. The first order condition for maximization of the expected revenue is $-f(r)r + 1 - F(r) = 0 \Leftrightarrow r_\pi^{AON} = \frac{1-F(r_\pi^{AON})}{f(r_\pi^{AON})}$ if F is log-concave. ■

Note that Theorem 3.B2 establishes that for large enough N, the reservation price of a profit-maximizing producer will approach the monopoly price. This is intuitive; when N is sufficiently large, the producer does not need to fear falling short of the threshold and can charge any price she feels fit. Also note that this can be achieved for any finite threshold T.

GMS. We now derive additional theoretical results for GMS. We assume that $T \geq C$ and $r < \overline{v}$. Later, we will show that this is fulfilled in any PBE of the two-stage game between producer and consumers.

Let $B_i(v_i)$ denote the bid submitted by consumer i having value $v_i \in [0, \overline{v}]$ and let $p_k \equiv \max\left\{r, \frac{T}{k}\right\}$, $k = 1, \ldots, N$ be the price each successful consumer will pay if k consumers are successful in obtaining the good. Note that p_k is non-increasing in k. The set $\wp = \{p_k, \ k = 1, \ldots, N\}$ then gives all possible prices in GMS. Let $\overline{b} \in [r, T]$ denote a commonly recognized highest equilibrium bid. In other words, all consumers believe that no other consumer will bid higher than $\overline{b}$.

Definition 3.B1 *For $v_i \in [0, \overline{v}]$ and $\overline{b} \in [r, T]$, define the following price levels:*

(i) $p^-(v_i) \equiv \max p_k \in \wp : v_i > p_k$ if such a p_k exists, and 0 otherwise. $p^-(v_i)$ is the highest price in $\wp$ that gives a consumer with value v_i strictly positive earnings if she obtains the good.

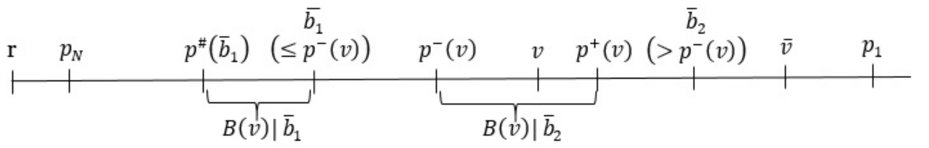
(ii) $p^{\#}\left(\overline{b}\right) \equiv \max p_k \in \wp : \overline{b} \geq p_k$. $p^{\#}\left(\overline{b}\right)$ is the highest price in $\wp$ that is smaller than the maximum bid $\overline{b}$. Note that by its definition, $p_k \geq r, \ \forall k$. Because $\overline{b} \geq r$, we have $p^{\#}\left(\overline{b}\right) \geq r$.

(iii) $p^+(v_i) \equiv \min p_k \in \wp : v_i < p_k$, $p^+(v)$ is the lowest price in $\wp$ that gives a consumer with value v_i negative earnings when obtaining the good for that price.[20] *Note that by assumption $\overline{v} < C \leq T$. Therefore, $p_1 = T > \overline{v} \geq v_i$, so $p^+(v_i)$ always exists for $v_i \in [0, \overline{v}]$. Also note that $p^+(v_i) > p^-(v_i)$.*

Figure 3.B1 denotes the relative positions of the price levels in Definition 3.B1.

[20] To illustrate, for $N = 15$, $T = 5$, and $r = 1$, $\wp = \{5, 2.5, 1.67, 1.25, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1\}$. Assume that $v_i = 1.3$. If $\overline{b} = 2 > v_i$, then $p^-(1.3) = p_4 = 1.25$. If $\overline{b} = r = 1 < v_i$, then $p^{\#}(1) = 1$. Moreover, i has negative earnings for any of the $p_k = 1.67, 2.5, 5$, so $p^+(1.3) = 1.67$.

Figure 3.B1: Illustration of Price Levels



Notes: Variables are defined in the main text and Definition 3.B1. In this example, $p_N > r$, but $p_N = r$ is also possible. $B(v)|\overline{b}$ denotes an equilibrium bid given value v under maximum equilibrium bids $\overline{b} = \overline{b}_1, \overline{b}_2$ (see Theorem 3.B3).

Theorem 3.B3 *Fix $\overline{b} \in [r, T]$. Let, for consumer $i = 1, \ldots, N$, B_i be given by $B_i(v_i) \in [0, r)$ if $v_i < r$, and*

$$B_i(v_i) \in \begin{cases} \left[r, \overline{b}\right] \text{ if } p^{\#}\left(\overline{b}\right) \leq r \\ \left[p^{\#}\left(\overline{b}\right), \overline{b}\right] \text{ if } p^{\#}\left(\overline{b}\right) > r \text{ and } \overline{b} < p^-(v_i) \\ \left[p^-(v_i), \overline{b}\right] \text{ if } p^{\#}\left(\overline{b}\right) > r \text{ and } p^-(v_i) \leq \overline{b} < p^+(v_i) \\ \left[p^-(v_i), p^+(v_i)\right) \text{ if } p^{\#}\left(\overline{b}\right) > r \text{ and } \overline{b} \geq p^+(v_i) \end{cases}$$

otherwise. Then B_i, $i = 1, \ldots, N$, constitutes a Bayesian-Nash equilibrium of GMS.

Proof of Theorem 3.B3 First note that no bids larger than $\overline{b}$ can be sustained in equilibrium, because this would violate the rationality of beliefs. In equilibrium it must therefore hold that $b_i \leq \overline{b}$, $\forall i$. Also note that for consumers with $v < r$, bidding more than r is never profitable, because if the good is produced, they would pay more than its value. Bidding any amount strictly below r results in paying 0 and not obtaining the good and is therefore a weakly best response when $v < r$. In what follows, we consider consumers with $v \geq r$.

Now, first assume that $\overline{b} < p_N = max\left\{r, \frac{T}{N}\right\}$. Because $\overline{b} \geq r$, it holds that $p_N > r$, giving $T > Nr$. That is, at price r, the good is not produced and all consumers earn zero. Because $p_N \leq p_{N-1} \leq \cdots \leq p_1$, $\overline{b} < p^-(v)$, $\forall v \geq p_N$. The theorem then stipulates that $B(v) = \left[r, \overline{b}\right]$ for all consumers with $v \geq r$. This gives a price equal to r, ergo, the good is not produced in equilibrium. Bidding more than r does not change the price, nor the chance of success and is therefore not a profitable deviation. Because no equilibrium exists with bids exceeding $\overline{b}$, this is the only equilibrium when $\overline{b} < p_N$.

For $\overline{b} \geq p_N$, we distinguish between four cases.

1. If $p^{\#}\left(\overline{b}\right) \leq r$, $B(v) = \left[r, \overline{b}\right]$, $\forall v \geq r$. If $T \leq Nr$, there is a positive probability that the good will be produced at price r, giving the consumer with $v > r$ positive expected earnings. Bidding less than r reduces expected earnings to zero irrespective of others' bids. Thus, $B(v) = \left[r, \overline{b}\right]$ is the unique symmetric equilibrium set when $p^{\#}\left(\overline{b}\right) \leq r$.

2. If $p^{\#}\left(\overline{b}\right) > r$, then for $v : \overline{b} < p^{-}(v)$, $B(v) = \left[p^{\#}\left(\overline{b}\right), \overline{b}\right]$. The good is produced with positive probability at a price between r and $p^{\#}\left(\overline{b}\right)$. Bidding $\beta \in \left[r, p^{\#}\left(\overline{b}\right)\right)$ does not affect the consumer's prospects in those realized value distributions where biding $p^{\#}\left(\overline{b}\right)$ yields a price in $[r, \beta]$. If doing so yields a price in $\left(\beta, p^{\#}\left(\overline{b}\right)\right]$, these earnings opportunities are lost by bidding β. This is therefore not a profitable deviation. Similarly, bidding $\beta \in \left[r, p^{\#}\left(\overline{b}\right)\right)$ cannot be part of a symmetric BNE because deviating to the range $\left[p^{\#}\left(\overline{b}\right), \overline{b}\right]$ is profitable.

3. If $p^{\#}\left(\overline{b}\right) > r$, then for $v : p^{-}(v) \leq \overline{b} < p^{+}(v)$, $B(v) = \left[p^{-}(v), \overline{b}\right]$. Bidding $\beta \in [r, p^{-}(v))$ does not affect the consumer's prospects in those realized value distributions where biding $p^{-}\left(\overline{b}\right)$ yields a price in $[r, \beta]$. If doing the latter yields a price in $(\beta, p^{-}(v)]$, these opportunities are lost by bidding β. This is therefore not a profitable deviation. Once again, bidding below $p^{-}(v)$ cannot be part of a symmetric BNE because a deviation to $B(v) = \left[p^{-}(v), \overline{b}\right]$ is profitable.

4. If $p^{\#}\left(\overline{b}\right) > r$, then for $v : \overline{b} \geq p^{+}(v)$, $B(v) = [p^{-}(v), p^{+}(v))$. For the same reason as in (iii), bidding less than $p^{-}(v)$ is not a profitable deviation. Moreover, bidding $p^{+}(v)$ or more only adds realizations of value distributions where the consumer obtains the good, but makes a loss. There is therefore no profitable deviation. On the other hand, bidding more than or equal to $p^{+}(v)$ is not part of a BNE because a profitable deviation to $B(v) = [p^{-}(v), p^{+}(v))$ exists. ■

This equilibrium involves the following bidding. If a consumer believes that the other consumers will bid ‘high’, then the consumer bids in some range around her value. This range is determined by the two prices in $\wp$ that are just below and just above one’s v. This ensures that the consumer will be successful in acquiring the good for all realizations of $p_k \in \wp$ where she has positive earnings and that she will not acquire the good for any $p_k \in \wp$ where her earnings are negative. Notice that the ‘truthful’ equilibrium is included.

Another type of equilibria occurs when bidding close to one’s value would imply bidding higher than the maximum possible bid expected from any other consumer. In this case, the consumer will bid anywhere between the highest price in $\wp$ that is below this maximum and the maximum itself. Note that this makes the maximum a self-fulfilling prophecy. We call this the set of ‘conformism’ equilibria, because it involves consumers conforming to what they expect others to do. If everyone expects all bids to always be below a certain number, then nobody will bid above that number in equilibrium. Observe that conformism equilibria involve common beliefs that may be unlikely to be observed behaviorally. One exception is that consumers might believe that nobody will ever bid more than the reservation price, which can serve as a focal point. In this case, bidding the reservation price whenever $v \geq r$ constitutes a BNE for consumers under GMS, which yields a semi-pooling equilibrium if consumers with $v < r$ bid $b = 0$.[21]

The equilibrium set displayed in Theorem 3.B3 is large. At the same time, many equilibria are ‘implausible’ in that they involve weakly dominated strategies. To obtain a sharper equilibrium prediction, we first present results regarding weakly dominant bidding.

[21] Conformism equilibria arise because our assumptions that $C > \overline{v}$ and $T \geq C$ make it impossible for any consumer to fund the good alone. It is then never profitable to bid more than the maximum expected from others because this could only change the price and production decision to a level where only the lone consumer would remain.

Lemma 3.B2 *In GMS, for consumer i having value $v_i < max\left\{r, \frac{T}{N}\right\}$, bidding $b \geq max\left\{r, \frac{T}{N}\right\}$ is weakly dominated by bidding 0.*

Proof of Lemma 3.B2 Suppose consumer i has value $v_i < max\left\{r, \frac{T}{N}\right\}$. Then, her expected utility when bidding 0 equals zero. When bidding $b \geq max\left\{r, \frac{T}{N}\right\}$, her expected utility equals 0 if she does not obtain the good and is strictly negative if does obtain the good (because the price she pays is at least $max\left\{r, \frac{T}{N}\right\}$, which is greater than v_i). The latter case occurs if all other consumers bid b. ∎

Lemma 3.B3 *In GMS, for consumer i having value $v_i > max\left\{r, \frac{T}{N}\right\}$, bidding $b < p^-(v_i)$ is weakly dominated by bidding $B_i(v_i) = v_i$.*

Proof of Lemma 3.B3 Suppose consumer i has value $v_i > max\left\{r, \frac{T}{N}\right\}$. As $B_i(v_i) = v_i$ is a weakly dominant strategy (Theorem 3.2), consumer i's expected utility from bidding $B_i(v_i) = v_i$ is at least as great as when bidding $b < p^-(v_i)$ for any strategy profile chosen by the other consumers. To construct a strategy profile by the other consumers for which consumer i obtains strictly higher expected utility by bidding $B_i(v_i) = v_i$ than by bidding b, take $k \in \{1, \ldots, N\}$ for which $p_k = p^-(v_i)$. Suppose $k - 1$ consumers other than consumer i always bid p_k regardless of their value and the remaining $N - k$ consumers bid 0 regardless of their value. Notice that $b < p^-(v_i) = p_k = max\left\{r, \frac{T}{k}\right\}$ implies that no price $p \geq r$ exists for which $p \leq b$ and $kp \geq T$. As a result, consumer i obtains zero utility when bidding b because the good will not be produced. In contrast, when bidding $B_i(v_i) = v_i$, consumer i obtains the good for price $p_k = p^-(v_i) < v_i$ and realizes utility $v_i - p_k > 0$. ∎

Lemma 3.B4 *In GMS, for consumer i having value $v_i > max\left\{r, \frac{T}{N}\right\}$, bidding $b \geq p^+(v_i)$ is weakly dominated by bidding $B_i(v_i) = v_i$.*

Proof of Lemma 3.B4 Suppose consumer i has value $v_i > max\left\{r, \frac{T}{N}\right\}$. As $B_i(v_i) = v_i$ is a weakly dominant strategy (Theorem 3.2), consumer i's expected utility from bidding $B_i(v_i) = v_i$ is at least as great as when bidding $b \geq p^+(v_i)$ for any strategy profile chosen by the other consumers. To construct a strategy profile by the other consumers for which consumer i obtains strictly higher expected utility by bidding $B_i(v_i) = v_i$ than by bidding b, take $k \in \{1, \ldots, N\}$

for which $p_k = p^+(v_i)$. Observe that (1) $p^+(v_i) > v_i$ by definition and (2) $v_i > max\left\{r, \frac{T}{N}\right\} \geq r$ by assumption. Therefore, $p_k = p^+(v_i) > v_i > r$ so that, in turn, $p_k \equiv max\left\{r, \frac{T}{k}\right\} = \frac{T}{k}$. Suppose $k-1$ consumers other than consumer i always bid p_k regardless of their value and the remaining $N-k$ consumers bid 0 regardless of their value. Notice that $v_i < p^+(v_i) = p_k = \frac{T}{k}$ implies that no price $p \geq r$ exists for which $p \leq B_i(v_i) = v_i$ and $kp \geq T$. As a result, consumer i obtains zero utility when bidding $B_i(v_i) = v_i$ because the good will not be produced. In contrast, when bidding b, consumer i obtains the good for price $p_k = p^+(v_i) > v_i$ and realizes utility $v_i - p_k < 0$. ■

Lemmas 3.B2, 3.B3 and 3.B4 imply that a large range of equilibria displayed in Theorem 3.B3 is weeded out if the equilibrium set is limited to equilibria in undominated strategies. The following result presents the resulting equilibria in undominated strategies.

Theorem 3.B4 *Bidding strategies B_i, $i = 1, \ldots, N$, constitute a Bayesian-Nash equilibrium in undominated strategies of GMS if and only if $B_i(v_i) \in [p^-(v_i), p^+(v_i))$.*

Proof of Theorem 3.B4 First, note that every bid $p^-(v_i) \leq b_i < p^+(v_i)$ always yields the same payoff as $b_i = v_i$ as in both cases, consumer i obtains the good if the good is produced and a price $p \leq p^-(v_i)$ is implemented. As bidding one's own value is weakly dominant (Theorem 3.2), bidding $p^-(v_i) \leq b_i < p^+(v_i)$ is thus also weakly dominant. For $v_i > \max\left\{r, \frac{T}{N}\right\}$ all other bids are weakly dominated (Lemmas 3.B3 and 3.B4). For $v_i < \max\left\{r, \frac{T}{N}\right\}$, bidding $p^-(v_i) \leq b_i < p^+(v_i)$ translates to bidding $0 \leq b_i < v_i < \max\left\{r, \frac{T}{N}\right\}$. Such a bid always yields the same payoff as bidding zero as in both cases consumer i never obtains the good and thus obtains a payoff of zero. Other bids are weakly dominated (Lemma 3.B2). For $v_i = \max\left\{r, \frac{T}{N}\right\}$ bidding $p^-(v_i) \leq b_i < p^+(v_i)$ translates to bidding $0 \leq b_i < \min p_k \in \wp : v_i < p_k$. For all these bids, consumer i always obtains a payoff of zero. In contrast, bidding $b_i \geq \min p_k \in \wp : v_i < p_k$ yields a loss if the consumer obtains the good and is thus weakly dominated. Put together, bidding strategies B_i, $i = 1, \ldots, N$, constitute a Bayesian-Nash equilibrium in undominated strategies of GMS if and only if $B_i(v_i) \in [p^-(v_i), p^+(v_i))$. ■

To weed out Bayesian-Nash equilibria in undominated strategies, an extension of (trembling-hand) perfect equilibrium to continuous games with incomplete information can be used (see e.g. Bajoori et al., 2016). More in particular, let $\underline{m} \equiv \min\{k = 1, \ldots, N : p_k > r\}$. Then, weakly dominated strategies are not in the set of best responses of any perturbed game that puts a strictly positive probability mass on bids in each of the intervals $\left[r, p_{\underline{m}}\right), \left[p_{\underline{m}}, p_{\underline{m}-1}\right), \ldots, [p_3, p_2), \ [p_2, p_1 = T]$.

While the equilibrium set established in Theorem 3.B4 is still large, the equilibria are essentially equivalent – with the exception of zero-mass events where $v_i = p_k$ for some i, k. They are equivalent in that given a set of values drawn, the equilibria are outcome identical, i.e. they yield the same allocation (whether or not the good is produced and if so, which of the consumers obtains it) and the same price, if the good is produced. We make this claim more precise in the following analysis.

Definition 3.B2 *Let* $v \equiv (v_1, v_2, \ldots, v_N)$ *be the vector of values and* $M(p, v) \equiv \{\#i, 1 \leq i \leq N : v_i \geq p\}$ *the number of consumers whose value is at least* $p \geq r$. *Define the following price level, if it exists:*

$$p^s(v) \equiv \min\{p \in \wp : pM(p, v) \geq T\}$$

Theorem 3.B5

(i) In any non-zero mass trembling-hand perfect equilibrium of GMS, the good is produced if and only if $p^s(v)$ *exists.*

(ii) If $p^s(v)$ *exists, the good is allocated to all consumers* i *for whom* $v_i \geq p^s(v)$. *Those consumers pay* $p^s(v)$.

Proof of Theorem 3.B5 Theorem 3.B4 presents the full set of trembling-hand perfect equilibria of GMS. Take such an equilibrium and let $B(v) \equiv (B_1(v_1), \ldots, B_N(v_N))$ be the vector of bids submitted given value realizations

$v_1, v_2, \ldots, v_N$. Part (i) follows directly from the definitions of the GMS mechanism and $p^s(v)$. To prove part (ii), note that $B_i(v_i) \in [p^-(v_i), p^+(v_i))$ implies that for all $p \in \wp$, $v_i \geq p \Leftrightarrow B_i(v_i) \geq p$. As a result, $M(p, B(v)) = M(p, v)$. Therefore, the equilibrium price $p^*(B(v))$, if it exists, is given by $p^*(B(v)) = \min\{p \in \wp : pM(p, B(v)) \geq T\} = \min\{p \in \wp : pM(p, v) \geq T\} = p^s(v)$. Moreover, consumer i obtains the good if and only if $B_i(v_i) \geq p^*(B(v))$ or, equivalently, if and only if $v_i \geq p^s(v)$. ■

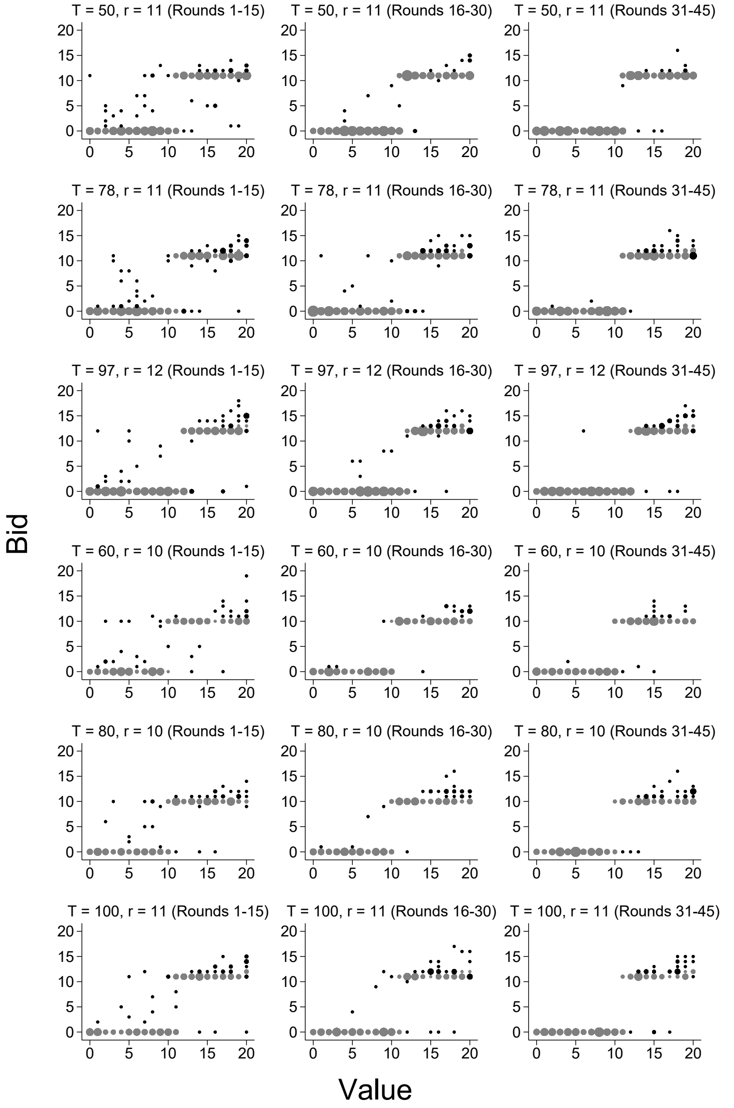
3.C Additional Tables and Figures

Table 3.C1: Bidding Behavior over Time

		Rounds 1 – 15	16 – 30	31 – 45
AON	Overbidding	0.14	0.10	0.08
	Best response	0.82	0.87	0.89
	Underbidding	0.04	0.03	0.02
sGMS	Overbidding	0.07	0.07	0.07
	Weakly Dominant Bids	0.63	0.72	0.75
	Underbidding	0.30	0.21	0.18
dGMS	Overbidding	0.05	0.04	0.03
	Possibly Weakly Dominant Bids	0.81	0.90	0.93
	Underbidding	0.14	0.06	0.03

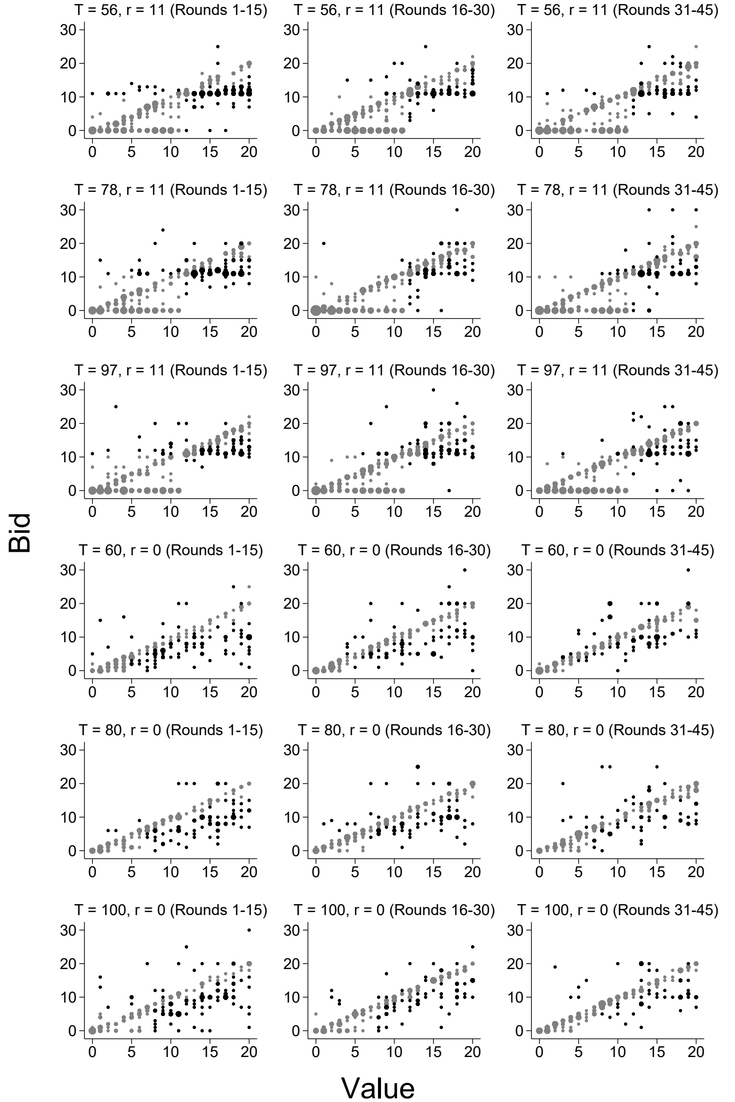
Notes: The table depicts the frequency of overbidding, underbidding and bids in line with the theoretical Bayesian-Nash equilibrium (AON) resp. weakly dominant bids (sGMS and dGMS) over rounds 1 to 15, 16 to 30 and 31 to 45.

Figure 3.C1: Bidding Behavior in AON over Time



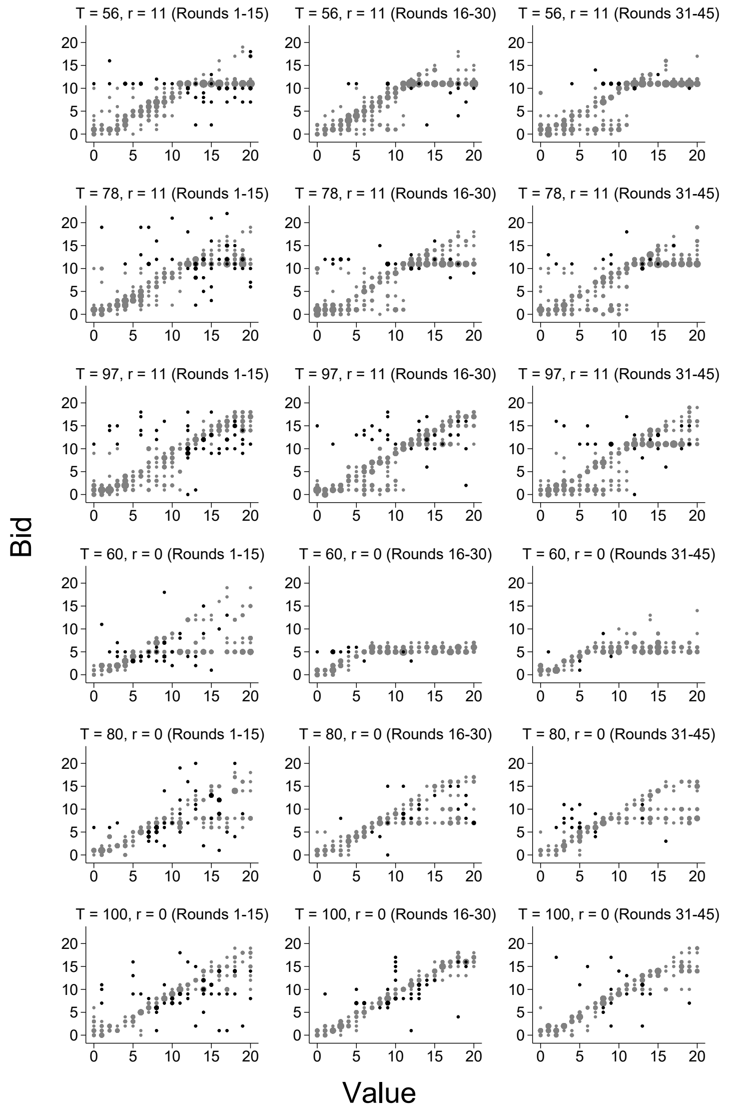
Notes: The figure depicts the frequency of bid-value combinations in AON for each T, r combination, split by rounds. The larger the dot, the more frequent a bid-value combination occurred. Gray dots denote observed best responses to the symmetric theoretical equilibrium bidding functions. Black dots denote bids that deviate from the best responses.

Figure 3.C2: Bidding Behavior in sGMS over Time



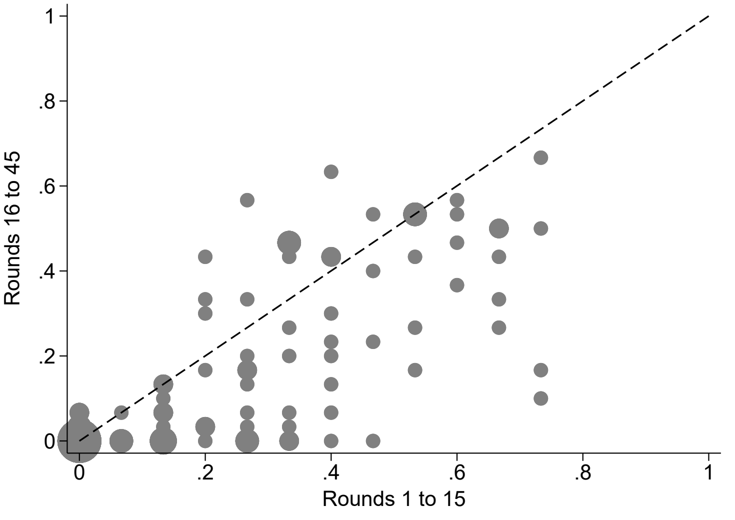
Notes: The figure depicts the frequency of bid-value combinations in sGMS for each T, r combination, split by rounds. The larger the dot, the more frequent a bid-value combination occurred. Gray dots denote weakly dominant bids. Black dots denote weakly dominated bids.

Figure 3.C3: Bidding Behavior in dGMS over Time



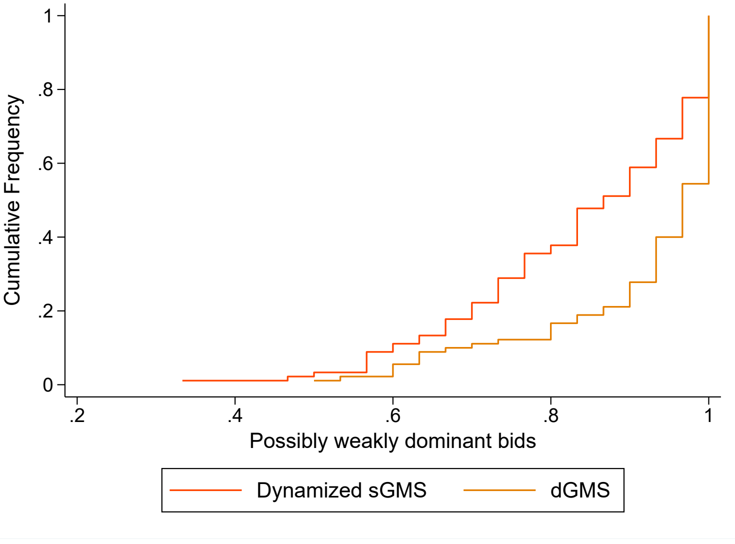
Notes: The figure depicts the frequency of bid-value combinations in dGMS for each T, r combination, split by rounds. The larger the dot, the more frequent a bid-value combination occurred. Gray dots denote possibly weakly dominant bids. Black dots denote surely weakly dominated bids.

Figure 3.C4: Share of Underbidding over Time in sGMS



Notes: The figure depicts the share of underbidding in sGMS in rounds 1 to 15 (horizontal axis) and 16 to 45 (vertical axis) for every consumer. The larger the dot, the more frequent a combination occurred.

Figure 3.C5: Distribution of Possibly Weakly Dominant Bids



Notes: The figure depicts the distribution of consumers' shares of possibly weakly dominant bids in dGMS and in the dynamized sGMS.

3.D Simulations

This section describes the algorithms that we used in our simulations to obtain theoretical predictions for AON and GMS for the experimental parameters.

AON: We use simulations to determine equilibrium producer's behavior in AON using the following simulation algorithm.

1. Specify the number of consumers $N = 15$, project costs $C \in \{50, 60, \ldots, 100\}$, and number of simulations S. Set simulation $s = 1$. Set threshold $T = 0$, and minimum price $r = 0$. Set the candidate price $p = r$. Draw a matrix of $N \times S$ with i.i.d. values from a discrete uniform distribution $\{0, 1, \ldots, 19, 20\}$. Denote this matrix by v. Create a matrix *Payoff* of 21×21 with each element $Payoff_{ij} = i - j$. Create a matrix *Bid* of $S \times 21$ with elements $Bid_{ij} = j - 1$. Set $count = 1$. Set $rounds = 1000$.

2. Create a weighing matrix of 21×21 with elements of one. Denote this matrix by *Weight*.

3. If $s \leq S$, randomly draw (with replacement) $N - 1$ elements of *Weight*, add them together, and update elements $SumB_{sj}\ \forall\ j \in \{1, 2 \ldots, 20, 21\}$. Add *SumB* and *Bid* together and compare each element to T. If the result is weakly positive, set $Suc_{sj} = 1$, otherwise set $Suc_{sj} = 0$, set $s = s + 1$, and repeat step 3. If $s > S$, set $s = 1$, and proceed to step 4.

4. Create a matrix *Meansuc* of 21×21 by taking the mean of *Suc* and replicating the resulting row 20 times. Create a matrix *Utility* of 21×21 by elementwise multiplying *Meansuc* with *Payoff*.

5. Determine the vector J of 21×1 that specifies the column of the element that maximizes *Utility* in a given row. Update $Weight_{ij} = Weight_{ij} + count\ \forall\ Weight_{ij} : j = J_i$. Set $count = count + 1$. If $count \leq rounds$, proceed with step 3. If $count > rounds$, set $count = 1$, and proceed with step 6.

6. Create a matrix *Contributions* of $N \times S$ such that $Contributions_{ij} = k$ where k is chosen randomly between $\{1, 2, \ldots, 20, 21\}$ with likelihood $\frac{Weight_{v_{ij}k}}{\sum_{l \in \{1,2,\ldots,20,21\}} Weight_{v_{ij}l}}$. Then create a vector X of $1 \times S$ that column-wise sums

up *Contributions*. Create a vector Y of $1 \times S$ that column-wise sums up all elements in v that are weakly above r.

7. Under a profit objective, if $s \leq S$ & $X_s \geq T$, set $Profit_s = X_s - C$ and $Surplus_s = Y_s - C$. Set $s = s + 1$, and repeat step 7. If $s \leq S$ & $X_s < T$, set $Profit_s = 0$ and $Surplus_s = 0$, set $s = s + 1$, and repeat step 7. If $s > S$, set $s = 1$, and skip to step 8. Under a success objective, if $s \leq S$ & $X_s \geq T$ & $X_s \geq C$, set $Success_s = 1$ and $Surplus_s = Y_s - C$. Set $s = s + 1$, and repeat step 7. If $s \leq S$ & $(X_s < T \mid X_s < C)$, set $Profit_s = 0$ and $Surplus_s = 0$, set $s = s + 1$, and repeat step 7. If $s > S$, set $s = 1$, and skip to step 8.

8. Update elements $Meanprofit_{rT}$, $Meansuccess_{rT}$ and $Meansurplus_{rT}$ by taking the mean of *Profit*, *Success* and *Surplus* respectively. If $T < 300$ & $r < 20$, set $T = T + 1$ and proceed with step 2. If $T \geq 300$ & $r < 20$, set $T = 0$ and $r = r + 1$, and proceed with step 2. If $r \geq 20$, proceed with step 9.

9. Under a profit objective, determine the maximal element of *Meanprofit* and the corresponding r^* and T^*. Under a success objective, determine the maximal element of *Meansuccess* and the corresponding r^* and T^*. In either case, determine the corresponding $Meansurplus_{r^* T^*}$.

GMS: We use the analytic results from Theorem 3.2 that consumers bid their own value, and from Theorem 3.5 that the producer maximizes the project's success probability by setting $T = C$ and $r = 0$. We use simulations to determine optimal producer's behavior under a profit objective using the following simulation algorithm.

1. Specify the number of consumers $N = 15$, project costs $C \in \{50, 60, \ldots, 100\}$, and number of simulations S. Set threshold $T = 0$, and minimum price $r = 0$. Set the candidate price $p = r$. Set simulation $s = 1$. Draw a matrix of $N \times S$ with i.i.d. values from a discrete uniform distribution $\{0, 1, \ldots, 19, 20\}$. Denote this matrix by v.

2. If $s > S$, set $s = 1$ and skip to step 3. If $s \leq S$, create a scalar X by multiplying p with the sum of elements of column s in v that are weakly above p. Compare X with T. If $X < T$ & $p \leq 20$, set $p = p + 1$ and repeat step 2. If $X < T$ & $p > 20$, set elements $Profit_s = 0$ and $Surplus_s = 0$. Then

set $p = r$ and $s = s + 1$, and repeat step 2. If $X \geq T$, create a scalar Y that sums up all elements of column s in v that are weakly above p. Set elements $Profit_s = X - C$ and $Surplus_s = Y - C$. Then set $p = r$ and $s = s + 1$, and repeat step 2.

3. Update elements $Meanprofit_{rT}$ and $Meansurplus_{rT}$ by taking the mean of *Profit* and *Surplus* respectively. If $T < 300$ & $r < 20$, set $T = T + 1$ and proceed with step 2. If $T \geq 300$ & $r < 20$, set $T = 0$ and $r = r + 1$, and proceed with step 2. If $r \geq 20$, proceed with step 4.

4. Determine the maximal element of *Meanprofit* and the corresponding r^* and T^*. Then determine the corresponding $Meansurplus_{r^* T^*}$.

3.E Instructions

3.E.1 AON

Instructions:
A summary of these instructions on paper will be distributed before the experiment starts. Welcome to this experiment on decision making. The instructions for this experiment are simple, and if you follow them carefully, you can earn a considerable amount of money. What you earn depends on the decisions you make and on the decisions of the others. You will be privately paid at the end of the experiment. We ask that you do not communicate with other people during the experiment. Please refrain from verbally reacting to events that occur during the experiment. This is very important. Raise your hand when you have a question and one of the experimenters will come to your table.

These instructions consist of eight pages like this. You may page back and forth by using your mouse to click on "previous page" or "next page" at the bottom of your screen. On the last instruction page you will see the button "ready" at the bottom of your screen. Click this button if you have completely finished with all pages of the instructions.

<u>Producer and Consumers:</u> In this experiment you will be assigned the role of either the producer of a good or a consumer. The payoffs that you obtain during the experiment determine the money that you will receive at the end. Earnings in the experiment will be denoted by "francs". At the end of the experiment, francs will be exchanged for euros. The exchange rate is 1 euro for every 8 francs. We will give you a number of francs to start with. This starting capital equals 56 francs (or 7 euros).

<u>Rounds:</u> Today's experiment consists of 45 rounds. In each round, a producer decides whether or not to produce a fictitious good and sell it to consumers. In the experiment, you will either be producer or consumer. One participant plays the role of producer. The producer can produce a fictitious good that is valuable for the consumers. The 15 other participants play the role of consumer. The producer can only produce the good if she raises sufficient funds to cover her production costs. The producer's production costs are fixed: They do not depend on the

number of goods sold. Moreover, only the producer is informed about her costs. The consumers do not know the producer's costs. The producer's costs may vary from one round to the next. The consumers interact in a market. In this market, it is determined whether the producer actually produces the good. Moreover, if the good is produced, the market determines which consumers buy the good and for what price.

<u>The Value of the Good:</u> The value of the fictitious good will typically differ from one consumer to the next. To be more precise, in every round, the computer will draw a new value for every consumer. Values are randomly drawn from the set 0,1,2,. . . ,19,20. Note the following about the value for the good:

1. The value for a consumer is determined independently of the values for the other consumers;
2. Any value in the set {0,1,2,. . . ,19,20} is equally likely;
3. Each consumer only learns her own value, not the value of the other consumers;
4. The producer is not informed about the values of any of the consumers.

<u>The Market:</u> At the start of a round, the producer is informed about her or his costs and all consumers are told their value. The producer then decides on a target amount and a minimum price. In each period, all consumers offer a price to the producer. The prices that consumers offer may differ from one consumer to another. Consumers can only obtain the good if they offer a price equal to or higher than the minimum price. After all offers have been received, the computer determines whether the producer will actually produce the good. More in particular, the computer adds up all offers. The producer will produce the good if the sum of these offers is equal to or higher than the target amount. If the good is produced, all consumers pay the price they offered. All consumers who offered at least the minimum price obtain the good. Consumers who offered less, do not obtain the good but still pay the price they offered. If the sum of offers is lower than the target amount, the good is not produced. Consumers do not obtain the good and make no payments.

Example: To illustrate the market, suppose the target amount equals 85 and the minimum price is 7. The consumers' offers are

$$0 - 0 - 0 - 1 - 2 - 7 - 7 - 7 - 8 - 8 - 9 - 9 - 10 - 11 - 12$$

The sum of the offers equals 91. Because the target amount is reached, the good will be produced. All 15 consumers pay the price they offered and the 10 consumers who offered at least 7 also obtain the good. The consumers who offered 1 and 2 do not obtain the good but still pay the price they offered.

Producer Payoffs: The way the producer's payoffs are determined varies from one round to the next. In some rounds, the producer's payoffs are determined by her profits (Objective: Profit). The producer then obtains one fifth, i.e. 20%, of the realized profits. The profits are determined as the difference between the sum of consumers' payments and the production costs of the given round. If the good is produced, the producer's payoffs thus are:

$$(\textit{Producer payoffs}) = 20\% * [(\textit{Sum of the consumer payments}) - (\textit{Production costs})]$$

If the good is not produced, the producer obtains zero payoffs. In the other rounds, the producer's payoffs are determined by whether the producer was successful in raising sufficient funds to cover her production costs (Objective: Success). The producer obtains 3 francs if the good is produced and the sum of the consumer payments is equal to or higher than the costs of producing the good. Otherwise the producer obtains zero payoffs. The producer is informed about her objective in the given round. The consumers are not informed about the producer's objective. If you happen to be assigned the role of producer, make sure to pay attention to how the producer's payoffs are determined for the round you are currently playing!

Consumer Payoffs: In every round, the payoffs for the consumers are as follows. If the good is produced and a consumer obtains the good in a given round, her payoffs in that round are:

$$(\textit{Consumer payoffs}) = (\textit{Own value for the good}) - (\textit{Own offer})$$

If the good is produced but the consumer does not obtain the good in a given round, her earnings for that round are:

$$(Consumer\ payoffs) = -(Own\ offer)$$

If the good is not produced in a given round, a consumer's earnings for that round are zero.

Comprehension Questions:
You will now be asked several example questions. Their purpose is to check for your understanding of the game. Note that the parameters used in the following example questions are not representative!

- If the good is produced, do all consumers who obtain the good pay the same price? (yes; no)
- If the good is produced, is it possible that any of the consumers pay more than their offer? (yes; no)
- [Target Amount: 65, Minimum Price: 8, Own value: 13, Own offer: 9, Sum of offers of other consumers: 60] Assume that you are a consumer. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 75, Minimum Price: 14, Own value: 19, Own offer: 17, Sum of offers of other consumers: 55] Assume that you are a consumer. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 45, Minimum Price: 5, Own value: 7, Own offer: 2, Sum of offers of other consumers: 48] Assume that you are a consumer. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 55, Minimum Price: 10, Own value: 9, Own offer: 8, Sum of offers of other consumers: 42] Assume that you are a consumer. There are 14 other consumers. Given the information in the table above, how many francs would you earn?

- [Costs: 74, Objective: Success, Target Amount: 80, Minimum Price: 9, Sum of all offers: 80] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 72, Objective: Success, Target Amount: 62, Minimum Price: 13, Sum of all offers: 70] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 45, Objective: Profit, Target Amount: 54, Minimum Price: 8, Sum of all offers: 55] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 67, Objective: Profit, Target Amount: 60, Minimum Price: 5, Sum of all offers: 62] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?

Intuition Questions:
You will now be asked some more example questions. Their purpose is to let you develop an intuition for how to play the game before we start with the real rounds. Note that the parameters used in the following example questions are not representative.

- [Target Amount: 45, Minimum Price: 7, Own value: X[22]] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What price would you offer?
- [Target Amount: 65, Minimum Price: 4, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What price would you offer?
- [Target Amount: 85, Minimum Price: 12, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What price would you offer?
- [Target Amount: 105, Minimum Price: 9, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What price would you offer?

[22] X indicates a random value drawn from the discrete uniform distribution {0,1,2,...,19,20}.

- [Costs: 55, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 21, Minimum Price = 5; Target Amount = 50, Minimum Price = 5; Target Amount = 56, Minimum Price = 1; *Target Amount = 60, Minimum Price = 10*)[23]
- [Costs: 75, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 70, Minimum Price = 7; *Target Amount = 78, Minimum Price = 12*; Target Amount = 81, Minimum Price = 3; Target Amount = 98, Minimum Price = 16)
- [Costs: 65, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 0, Minimum Price = 4; *Target Amount = 65, Minimum Price = 8*; Target Amount = 66, Minimum Price = 0; Target Amount = 75, Minimum Price = 2)
- [Costs: 85, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 75, Minimum Price = 6; Target Amount = 90, Minimum Price = 4; *Target Amount = 91, Minimum Price = 11*; Target Amount = 91, Minimum Price = 17)

We will continue when everybody has finished reading the instructions and has answered all example questions.

You will now be assigned the role of the producer or of a consumer.

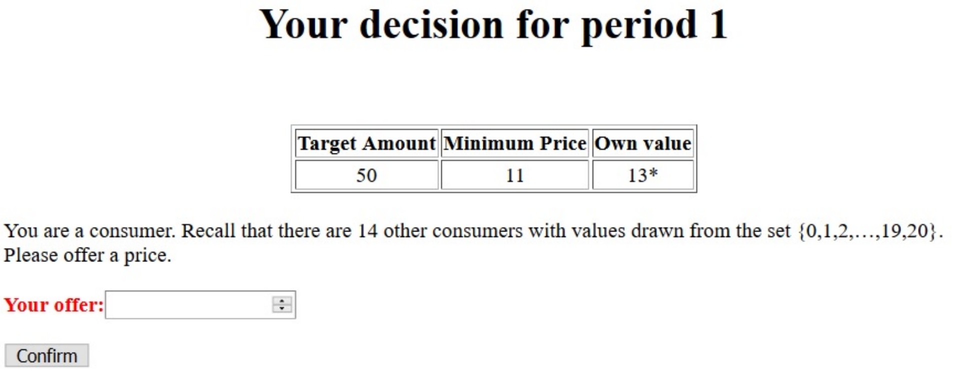
You are assigned the role of [the producer / a consumer].

Important Information: The participant assigned the role of the producer will not set the target amount and minimum price herself. Instead, the computer will set the target amount and minimum price. The way the producer's payoffs is determined does not change. The earnings of the person assigned the role of the producer still

[23] Italic answers indicate 'correct' answers.

exclusively depend on the producer's payoff (which is still computed as is explained in the instruction summary).

Figure 3.E1: Consumers' Decision Screen in AON



Notes: Subjects could state an integer bid between 0 and 30. The asterisk indicates that values were drawn randomly; the asterisk was not shown to subjects.

Questionnaire:

Please fill in this short questionnaire.

- Age: (positive integers)
- Gender: (Male, Female)
- I study at (UvA – Economics and Business; UvA – Social Sciences, Psychology; UvA – Social Sciences, not Psychology; UvA – Science; UvA – IIS, beta gamma bachelor; UvA – Law School; UvA – Humanities; UvA – Medical School; UvA – Dentistry; Another university; A professional school; Otherwise)
- How often have you participated in a crowdfunding campaign? (Never; One time; Two times; Three or more times)
- What strategy did you play?
- What is your feeling towards the other players?
- How fair do you rate the crowdfunding mechanism? (very unfair (1), (2), (3), (4), very fair (5)))
- Do you have any other comments?

3.E.2 sGMS

Instructions:

A summary of these instructions on paper will be distributed before the experiment starts. Welcome to this experiment on decision making. The instructions for this experiment are simple, and if you follow them carefully, you can earn a considerable amount of money. What you earn depends on the decisions you make and on the decisions of the others. You will be privately paid at the end of the experiment. We ask that you do not communicate with other people during the experiment. Please refrain from verbally reacting to events that occur during the experiment. This is very important. Raise your hand when you have a question and one of the experimenters will come to your table.

These instructions consist of eight pages like this. You may page back and forth by using your mouse to click on "previous page" or "next page" at the bottom of your screen. On the last instruction page you will see the button "ready" at the bottom of your screen. Click this button if you have completely finished with all pages of the instructions.

<u>Producer and Consumers:</u> In this experiment you will be assigned the role of either the producer of a good or a consumer. The payoffs that you obtain during the experiment determine the money that you will receive at the end. Earnings in the experiment will be denoted by "francs". At the end of the experiment, francs will be exchanged for euros. The exchange rate is 1 euro for every 8 francs. We will give you a number of francs to start with. This starting capital equals 56 francs (or 7 euros).

<u>Rounds:</u> Today's experiment consists of 45 rounds. In each round, a producer decides whether or not to produce a fictitious good and sell it to consumers. In the experiment, you will either be producer or consumer. One participant plays the role of producer. The producer can produce a fictitious good that is valuable for the consumers. The 15 other participants play the role of consumer. The producer can only produce the good if she raises sufficient funds to cover her production costs. The producer's production costs are fixed: They do not depend on the number of goods sold. Moreover, only the producer is informed about her costs. The consumers do not know the producer's costs. The producer's costs may vary

from one round to the next. The consumers interact in a market. In this market, it is determined whether the producer actually produces the good. Moreover, if the good is produced, the market determines which consumers buy the good and for what price.

The Value of the Good: The value of the fictitious good will typically differ from one consumer to the next. To be more precise, in every round, the computer will draw a new value for every consumer. Values are randomly drawn from the set 0,1,2,...,19,20. Note the following about the value for the good:

1. The value for a consumer is determined independently of the values for the other consumers;
2. Any value in the set {0,1,2,...,19,20} is equally likely;
3. Each consumer only learns her own value, not the value of the other consumers;
4. The producer is not informed about the values of any of the consumers.

The Market: At the start of a round, the producer is informed about her or his costs and all consumers are told their value. The producer then decides on a target amount and a minimum price. In each round, all consumers are asked to state their highest acceptable price. We call this the 'maximum offer' because any consumer may end up receiving the good at a lower price than her or his highest acceptable price. The maximum offers may differ from one consumer to another. Consumers can only obtain the good if their maximum offer is equal to or higher than the minimum price. After all maximum offers have been received, the computer determines whether the producer will actually produce the good and if so, at what price it will be sold. If the good is produced, all consumers who obtain the good pay the same price. More precisely, the computer raises the price step by step, starting from the minimum price, up to the point that the price is sufficiently high to meet the target amount. This is determined as follows.

STEP 0: Start with a 'candidate price' that is equal to this round's minimum price.

STEP 1: Compute the producer's revenue at the candidate price: Determine how many consumers' maximum offers are equal to or higher than the candidate price. Calculate how much revenue this candidate price would raise by multiplying the candidate price with the number of consumers whose maximum offers are equal to or higher than the candidate price.

STEP 2: Compare the producer's revenue calculated in STEP 1 with the target amount.

- If the producer's revenue is equal to or higher than the target amount, proceed to STEP 3.
- If the producer's revenue is lower than the target amount, increase the candidate price by one. If the new candidate price is higher than the highest maximum offer, the good is not produced. Otherwise, go back to STEP 1.

STEP 3: The good is produced. All consumers whose maximum offers are equal to or higher than the current price obtain the good and pay this price to the producer. All other consumers do not obtain the good and pay zero.

Note that no consumer will ever pay more than her or his maximum offer, but will often pay less.

Example: To illustrate the market, suppose the target amount equals 85 and the minimum price is 7. The consumers' offers are:

$$0 – 2 – 2 – 4 – 5 – 6 – 7 – 8 – 14 – 14 – 17 – 18 – 18 – 19 – 20$$

The first candidate price is 7, the minimum price. Multiplying the candidate price (7) by the number of offers that are equal to 7 or higher (9) yields 63. This result is lower than the target amount of 85, so that the candidate price is increased by one. Multiplying the new candidate price (8) by the number of offers that are equal to 8 or higher (8) yields 64. This result is again lower than the target amount of 85 so that again the candidate price is increased by one. Sequentially checking for candidate prices of 9, 10, 11 and 12 also yields results that are lower than the target amount of 85. However, multiplying a candidate price of 13 by the number of offers that are equal to 9 or higher (7) yields 91. As this result is higher than the target amount of 85, the good is produced. The 7 consumers whose offers are equal to 13 or higher obtain the good and all pay a price of 13. The other consumers do not obtain the good and pay zero. The sum of consumer payments is thus 91.

Producer Payoffs: The way the producer's payoffs are determined varies from one round to the next. In some rounds, the producer's payoffs are determined by her profits (Objective: Profit). The producer then obtains one fifth, i.e. 20%, of the realized profits. The profits are determined as the difference between the sum of consumers' payments and the production costs of the given round. If the good is produced, the producer's payoffs thus are:

$$(\textit{Producer payoffs}) = 20\% * [(\textit{Sum of the consumer payments}) - (\textit{Production costs})]$$

If the good is not produced, the producer obtains zero payoffs. In the other rounds, the producer's payoffs are determined by whether the producer was successful in raising sufficient funds to cover her production costs (Objective: Success). The producer obtains 3 francs if the good is produced and the sum of the consumer payments is equal to or higher than the costs of producing the good. Otherwise the producer obtains zero payoffs. The producer is informed about her objective in the given round. The consumers are not informed about the producer's objective. If you happen to be assigned the role of producer, make sure to pay attention to how the producer's payoffs are determined for the round you are currently playing!

Consumer Payoffs: In every round, the payoffs for the consumers are as follows. If a consumer obtains the good in a round, her payoffs in that round are:

$$(\textit{Consumer payoffs}) = (\textit{Own value for the good}) - (\textit{Price paid})$$

If a consumer does not obtain the good in a round, her earnings for that round are zero.

Comprehension Questions:

You will now be asked several example questions. Their purpose is to check for your understanding of the game. Note that the parameters used in the following example questions are not representative!

- If the good is produced, do all consumers who obtain the good pay the same price? (yes; no)
- If the good is produced, is it possible that any of the consumers pay more than their offer? (yes; no)
- [Target Amount: 40, Minimum Price: 2, Own value: 12, Offers of all consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are one of the consumers who made an offer of 4. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 6, Own value: 12, Offers of all consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are one of the consumers who made an offer of 4. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 2, Own value: 12, Offers of all consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are one of the consumers who made an offer of 10. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 6, Own value: 12, Offers of all consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are one of the consumers who made an offer of 10. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 30, Objective: Success, Target Amount: 40, Minimum Price: 2, Offers of consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 45, Objective: Success, Target Amount: 40, Minimum Price: 2, Offers of consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?

- [Costs: 30, Objective: Profit, Target Amount: 40, Minimum Price: 2, Offers of consumers: $0-0-0-0-0-4-4-4-4-4-10-10-10-10-10$] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 45, Objective: Profit, Target Amount: 40, Minimum Price: 2, Offers of consumers: $0-0-0-0-0-4-4-4-4-4-10-10-10-10-10$] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?

Intuition Questions:
You will now be asked some more example questions. Their purpose is to let you develop an intuition for how to play the game before we start with the real rounds. Note that the parameters used in the following example questions are not representative.

- [Target Amount: 45, Minimum Price: 7, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?
- [Target Amount: 65, Minimum Price: 4, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?
- [Target Amount: 85, Minimum Price: 12, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?
- [Target Amount: 105, Minimum Price: 9, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?
- [Costs: 55, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. Which of the following four options would you choose? (Target Amount = 50, Minimum Price = 5; Target Amount = 55, Minimum Price = 3; *Target Amount = 71, Minimum Price = 10*; Target Amount = 90, Minimum Price = 16)

- [Costs: 75, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 38, Minimum Price = 13; Target Amount = 70, Minimum Price = 7; Target Amount = 72, Minimum Price = 2; *Target Amount = 84, Minimum Price = 12*)
- [Costs: 65, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 30, Minimum Price = 5; Target Amount = 60, Minimum Price = 4; *Target Amount = 67, Minimum Price = 8*; Target Amount = 111, Minimum Price = 1)
- [Costs: 85, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 78, Minimum Price = 0; Target Amount = 86, Minimum Price = 17; *Target Amount = 89, Minimum Price = 6*; Target Amount = 103, Minimum Price = 14)

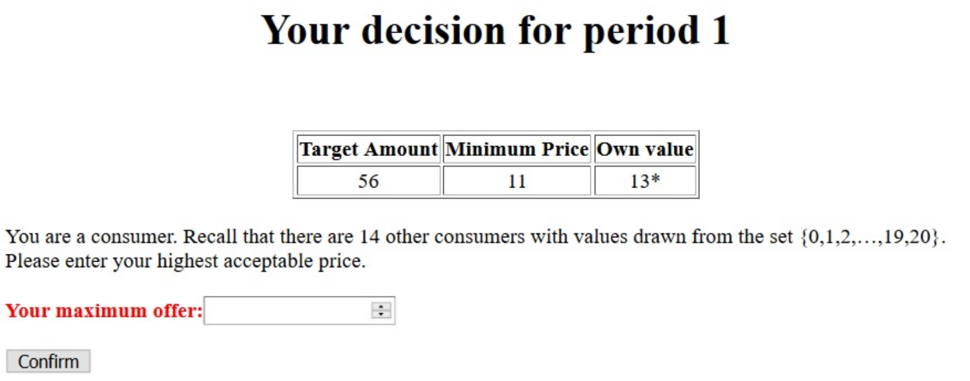
We will continue when everybody has finished reading the instructions and has answered all example questions.

You will now be assigned the role of the producer or of a consumer.

You are assigned the role of [the producer / a consumer].

Important Information: The participant assigned the role of the producer will not set the target amount and minimum price herself. Instead, the computer will set the target amount and minimum price. The way the producer's payoffs is determined does not change. The earnings of the person assigned the role of the producer still exclusively depend on the producer's payoff (which is still computed as is explained in the instruction summary).

Figure 3.E2: Consumers' Decision Screen in sGMS



Your decision for period 1

Target Amount	Minimum Price	Own value
56	11	13*

You are a consumer. Recall that there are 14 other consumers with values drawn from the set {0,1,2,…,19,20}. Please enter your highest acceptable price.

Your maximum offer:

Confirm

Notes: Subjects could state an integer bid between 0 and 30. The asterisk indicates that values were drawn randomly; the asterisk was not shown to subjects.

Questionnaire:

Please fill in this short questionnaire.

- Age: (positive integers)
- Gender: (Male, Female)
- I study at (UvA – Economics and Business; UvA – Social Sciences, Psychology; UvA – Social Sciences, not Psychology; UvA – Science; UvA – IIS, beta gamma bachelor; UvA – Law School; UvA – Humanities; UvA – Medical School; UvA – Dentistry; Another university; A professional school; Otherwise)
- How often have you participated in a crowdfunding campaign? (Never; One time; Two times; Three or more times)
- What strategy did you play?
- What is your feeling towards the other players?
- How fair do you rate the crowdfunding mechanism? (very unfair (1), (2), (3), (4), very fair (5)))
- Do you have any other comments?

3.E.3 dGMS

Instructions:

A summary of these instructions on paper will be distributed before the experiment starts. Welcome to this experiment on decision making. The instructions for this experiment are simple, and if you follow them carefully, you can earn a considerable amount of money. What you earn depends on the decisions you make and on the decisions of the others. You will be privately paid at the end of the experiment. We ask that you do not communicate with other people during the experiment. Please refrain from verbally reacting to events that occur during the experiment. This is very important. Raise your hand when you have a question and one of the experimenters will come to your table.

These instructions consist of eight pages like this. You may page back and forth by using your mouse to click on "previous page" or "next page" at the bottom of your screen. On the last instruction page you will see the button "ready" at the bottom of your screen. Click this button if you have completely finished with all pages of the instructions.

<u>Producer and Consumers:</u> In this experiment you will be assigned the role of either the producer of a good or a consumer. The payoffs that you obtain during the experiment determine the money that you will receive at the end. Earnings in the experiment will be denoted by "francs". At the end of the experiment, francs will be exchanged for euros. The exchange rate is 1 euro for every 8 francs. We will give you a number of francs to start with. This starting capital equals 56 francs (or 7 euros).

<u>Rounds:</u> Today's experiment consists of 45 rounds. In each round, a producer decides whether or not to produce a fictitious good and sell it to consumers. In the experiment, you will either be producer or consumer. One participant plays the role of producer. The producer can produce a fictitious good that is valuable for the consumers. The 15 other participants play the role of consumer. The producer can only produce the good if she raises sufficient funds to cover her production costs. The producer's production costs are fixed: They do not depend on the number of goods sold. Moreover, only the producer is informed about her costs. The consumers do not know the producer's costs. The producer's costs may vary

from one round to the next. The consumers interact in a market. In this market, it is determined whether the producer actually produces the good. Moreover, if the good is produced, the market determines which consumers buy the good and for what price.

The Value of the Good: The value of the fictitious good will typically differ from one consumer to the next. To be more precise, in every round, the computer will draw a new value for every consumer. Values are randomly drawn from the set 0,1,2,...,19,20. Note the following about the value for the good:

1. The value for a consumer is determined independently of the values for the other consumers;
2. Any value in the set {0,1,2,...,19,20} is equally likely;
3. Each consumer only learns her own value, not the value of the other consumers;
4. The producer is not informed about the values of any of the consumers.

The Market: At the start of a round, the producer is informed about her or his costs and all consumers are told their value. He or she will then try to raise money to be able to produce the good. To do so, the producer decides on a target amount and a minimum price. The target amount is the sum of money that the producer wants to at least raise from all consumers together. The minimum price is the lowest price that the producer wants to receive from any single consumer. Note that not every consumer may be willing to pay that price. To determine which consumers are willing to pay a price and how much revenue a price will give to the producer, we use the following procedure in each round. The computer will start by proposing a price equal to 1. Any consumer not willing to pay this price can click the button "Drop Out". Then, every few seconds the computer raises the price by 1. As the price increases, any consumer may drop out of this round's market at any price by clicking the "Drop Out" button. Consumers who drop out will not buy the good. Once you drop out, you cannot re-enter in the current round. As the price increases and consumers drop out, three things might happen. First, the price might be below the minimum price. In this case, it is increased further. Second, too many consumers might drop out, so that it becomes impossible for the producer to raise her or his target amount. In this case, the good is not produced and the round ends. Third, it can happen that at a price of at least the minimum price, enough consumers are still willing to buy the good so that together they pay at least the target amount. The good is then produced because the target amount and the minimum price are reached. Then, all remaining consumers obtain the good and pay the last displayed price. For these consumers, the payoff they get from buying the good is equal to their value for this round minus the price at which the computer stopped. In summary, the computer determines whether the good is produced and who obtains the good in the following way.

STEP 0: Start with a 'candidate price' of 1.

STEP 1: Check whether the candidate price is below the minimum price. If so, increase the candidate price by 1 and repeat STEP 1. If not, continue with STEP 2.

STEP 2: Determine how many consumers remain in the market, i.e. have not yet clicked on "Drop Out". Check how much money this candidate price would raise by multiplying the candidate price with the number of remaining consumers. This would be the producer's revenue at the candidate price.

STEP 3: Compare the producer's revenue calculated in STEP 2 with the target amount.

- If the producer's revenue is equal to or higher than the target amount, proceed to STEP 4.
- If the producer's revenue is lower than the target amount, increase the candidate price by 1. If the number of remaining consumers multiplied by the highest possible price (30) is less than the target amount, the good is not produced and the next round starts. Otherwise, go back to STEP 2.

STEP 4: The good is produced. All remaining consumers obtain the good and pay the current price to the producer. All consumers who dropped out do not obtain the good and pay zero.

Example: To illustrate the market, suppose the target amount equals 85 and the minimum price is 7. The first candidate price is 1. As this candidate price is lower than 7, the minimum price, the price increases by 1 every few seconds until a price of 7. Suppose that at the price of 7, 6 consumers have dropped out already. This leaves 9 remaining consumers at the minimum price of 7. Multiplying this price by the number of remaining consumers yields 63. This is lower than the target amount of 85, so that the candidate price is increased to 8. At this price of 8, one consumer drops out. Multiplying the new candidate price by the number of remaining consumers (8) yields 64, which is again lower than the target amount of 85. The candidate price is increased to 9. Again, one consumer drops out. Multiplying the new candidate price (9) by the number of remaining consumers (7) yields 63, which is again lower than the target amount of 85. The candidate price is increased to 10. Now, suppose that all 7 consumers remain at a candidate price of 10. Still, multiplying 10 by 7 yields 70 which is lower than the target amount of 85. The same occurs for candidate prices of 11 ($7*11<85$) and 12 ($7*12<85$) respectively. However, if all 7 remaining consumers also remain at a candidate price of 13, the good is produced because 7*13=91 is higher than the target amount of 85. The process stops and the 7 remaining consumers obtain the good and pay a price of 13. The 8 consumers who dropped out do not obtain the good and pay zero. The sum of consumer payments is thus 91.

Producer Payoffs: The way the producer's payoffs are determined varies from one round to the next. In some rounds, the producer's payoffs are determined by her profits (Objective: Profit). The producer then obtains one fifth, i.e. 20%, of the realized profits. The profits are determined as the difference between the sum of consumers' payments and the production costs of the given round. If the good is produced, the producer's payoffs thus are:

$$(\textit{Producer payoffs}) = 20\% * [(\textit{Sum of the consumer payments}) - (\textit{Production costs})]$$

If the good is not produced, the producer obtains zero payoffs. In the other rounds, the producer's payoffs are determined by whether the producer was successful in raising sufficient funds to cover her production costs (Objective: Success). The producer obtains 3 francs if the good is produced and the sum of the consumer payments is equal to or higher than the costs of producing the good. Otherwise the producer obtains zero payoffs. The producer is informed about her objective in the given round. The consumers are not informed about the producer's objective.

If you happen to be assigned the role of producer, make sure to pay attention to how the producer's payoffs are determined for the round you are currently playing!

Consumer Payoffs: In every round, the payoffs for the consumers are as follows. If a consumer obtains the good in a round, her payoffs in that round are:

$$(\textit{Consumer payoffs}) = (\textit{Own value for the good}) - (\textit{Price paid})$$

If a consumer does not obtain the good in a round, her earnings for that round are zero.

Comprehension Questions:

You will now be asked several example questions. Their purpose is to check for your understanding of the game. Note that the parameters used in the following example questions are not representative!

- If the good is produced, do all consumers who obtain the good pay the same price? (yes; no)
- If the good is produced, is it possible that any of the consumers pay more than their offer? (yes; no)
- [Target Amount: 40, Minimum Price: 2, Own value: 12, Offers of all consumers: $0-0-0-0-0-4-4-4-4-4-4-4-4-4-4$] Assume that you are one of the consumers who made an offer of 4. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 6, Own value: 12, Offers of all consumers: $0-0-0-0-0-4-4-4-4-4-4-4-4-4-4$] Assume that you are one of the consumers who made an offer of 4. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 6, Own value: 12, Offers of all consumers: $0-0-0-0-0-4-4-4-4-4-8-8-8-8-8$] Assume that you are one of the consumers who made an offer of 4. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 6, Own value: 12, Offers of all consumers: $0-0-0-0-0-4-4-4-4-4-8-8-8-8-8$] Assume that you are

one of the consumers who made an offer of 8. There are 14 other consumers. Given the information in the table above, how many francs would you earn?

- [Costs: 30, Objective: Success, Target Amount: 40, Minimum Price: 2, Offers of consumers: $1-1-1-1-1-4-4-4-4-4-4-4-4-4-4$] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 45, Objective: Success, Target Amount: 40, Minimum Price: 2, Offers of consumers: $1-1-1-1-1-4-4-4-4-4-4-4-4-4-4$] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 30, Objective: Profit, Target Amount: 40, Minimum Price: 2, Offers of consumers: $1-1-1-1-1-4-4-4-4-4-4-4-4-4-4$] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 45, Objective: Profit, Target Amount: 40, Minimum Price: 2, Offers of consumers: $1-1-1-1-1-4-4-4-4-4-4-4-4-4-4$] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?

Intuition Questions:
You will now be asked some more example questions. Their purpose is to let you develop an intuition for how to play the game before we start with the real rounds. Note that the parameters used in the following example questions are not representative.

- [Target Amount: 45, Minimum Price: 7, Own value: X, Current Price: Y[24]] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What offer would you make?
- [Target Amount: 65, Minimum Price: 4, Own value: X, Current Price: Y] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What offer would you make?

[24] Price increases every four seconds by one.

- [Target Amount: 85, Minimum Price: 12, Own value: X, Current Price: Y] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What offer would you make?
- [Target Amount: 105, Minimum Price: 9, Own value: X, Current Price: Y] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What offer would you make?
- [Costs: 55, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 50, Minimum Price = 5; Target Amount = 55, Minimum Price = 3; *Target Amount = 71, Minimum Price = 10*; Target Amount = 90, Minimum Price = 16)
- [Costs: 75, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 38, Minimum Price = 13; Target Amount = 70, Minimum Price = 7; Target Amount = 72, Minimum Price = 2; *Target Amount = 84, Minimum Price = 12*)
- [Costs: 65, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 30, Minimum Price = 5; Target Amount = 60, Minimum Price = 4; *Target Amount = 67, Minimum Price = 8*; Target Amount = 111, Minimum Price = 1)
- [Costs: 85, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 78, Minimum Price = 0; Target Amount = 86, Minimum Price = 17; *Target Amount = 89, Minimum Price = 6*; Target Amount = 103, Minimum Price = 14)

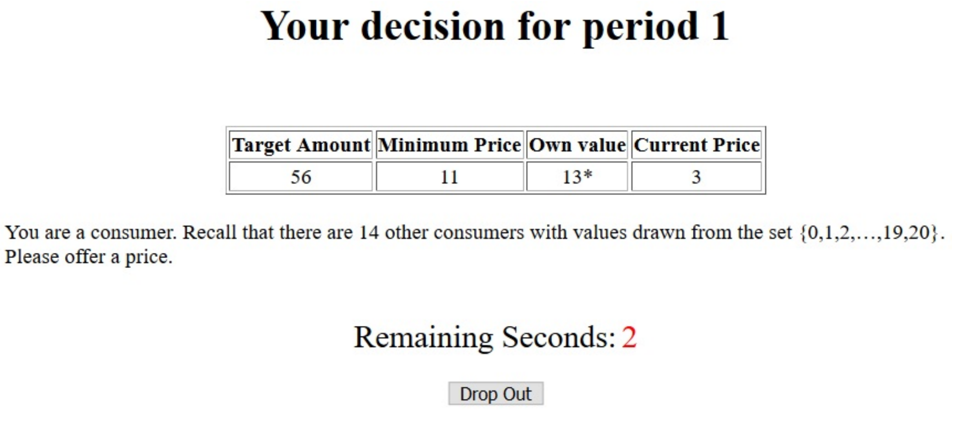
We will continue when everybody has finished reading the instructions and has answered all example questions.

You will now be assigned the role of the producer or of a consumer.

You are assigned the role of [the producer / a consumer].

Important Information: The participant assigned the role of the producer will not set the target amount and minimum price herself. Instead, the computer will set the target amount and minimum price. The way the producer's payoffs is determined does not change. The earnings of the person assigned the role of the producer still exclusively depend on the producer's payoff (which is still computed as is explained in the instruction summary).

Figure 3.E3: Consumers' Decision Screen in dGMS



Notes: The price increases every four seconds by one (up to a maximum of 30). The asterisk indicates that values were drawn randomly; the asterisk was not shown to subjects.

Questionnaire:

Please fill in this short questionnaire.

- Age: (positive integers)
- Gender: (Male, Female)
- I study at (UvA – Economics and Business; UvA – Social Sciences, Psychology; UvA – Social Sciences, not Psychology; UvA – Science; UvA – IIS, beta gamma bachelor; UvA – Law School; UvA – Humanities; UvA – Medical School; UvA – Dentistry; Another university; A professional school; Otherwise)
- How often have you participated in a crowdfunding campaign? (Never; One time; Two times; Three or more times)

- What strategy did you play?
- What is your feeling towards the other players?
- How fair do you rate the crowdfunding mechanism? (very unfair (1), (2), (3), (4), very fair (5)))
- Do you have any other comments?

Chapter 4

Reservation Prices and Thresholds: Producer Behavior in Crowdfunding

4.1 Introduction

Crowdfunding has become an important source of funds for individual causes, charities, and startups. Reward-based crowdfunding – where funders receive a tangible reward like an autographed album or first use of a product – has become a market estimated to be worth about \$8.5 billion per year with an annual growth rate of 12% (Grüner and Siemroth, 2019; Statista, 2020). Yet, despite the overall success of crowdfunding, many reward-based projects fail to be funded. For example, on Kickstarter (the leading reward-based crowdfunding platform) two thirds of the projects

This chapter is based on Woerner et al. (2021b). We thank Matthew Ellman, Peter Katuščák, Laura Razzolini, and seminar participants at the CREED lunch seminar, the ESA world meeting, the TIBER workshop, the BEAM-ABEE workshop, the Tinbergen Institute PhD Lunch Seminar, the CBESS-CeDEx-CREED Meeting and the European University Institute for very useful comments and suggestions. Financial support from the Research Priority Area Behavioral Economics of the University of Amsterdam is gratefully acknowledged.

fail to reach the threshold (Cason and Zubrickas, 2019) and are therefore never started.

The management literature has identified several features that are associated with project failure, most of which are related to producer (founder) characteristics. Crowdfunding campaigns are likely to fail if the producer is inexperienced, possesses only a small social network or lives geographically remote from potential consumers/funders (e.g. Agrawal et al., 2015; Zvilichovsky et al., 2015; Lin and Viswanathan, 2016; Buttice et al., 2017; Kunz et al., 2017). This literature cannot, however, distinguish between project failure due to these characteristics per se and poor decisions made in the crowdfunding process (that may be correlated with such characteristics). To address this gap, our study abstracts from producer characteristics and focuses directly on producer decisions and whether these can explain crowdfunding failures. The decisions we are interested in are concerned with the two main parameters set by producers in reward-based crowdfunding: the fundraising threshold and the reservation price.[1]

To study this, we conduct a laboratory experiment in which we analyze how producers set fundraising thresholds and minimum prices in distinct crowdfunding mechanisms. Our experiment allows us to draw *causal* inference of producer behavior on crowdfunding performance, something that has thus far been missing in the literature. Studies based on observational data have found a negative relationship between project success and fundraising thresholds and a positive relationship between project success and the number of rewards as well as the ratio of (reservation) prices to fundraising thresholds (Mollick, 2014; Lin et al., 2016; Kunz et al., 2017). Such correlational studies, however, do not allow for an analysis of the extent to which producers optimally set the thresholds and reservation prices. This is because such an analysis requires a knowledge of both the supply side

[1] The parameters that producers are required to set may vary with the mechanism concerned. For many mechanisms, including those we study, these parameters include an aggregate funding threshold and a reservation price.

(production costs) and the demand side (consumer preferences) that is unavailable with observational data. The laboratory allows us to induce both costs and preferences and thus provides an optimal environment to study producers' choices.

Of course, producers' actual and optimal choices may both vary with the allocation mechanism applied by a crowdfunding platform. We compare producer behavior in two such mechanisms. The first is the so-called All-or-Nothing mechanism (AON), which is the prevalent reward-based crowdfunding mechanism in the field. As an alternative, we apply the novel Generalized Moulin-Shenker mechanism (GMS), which we introduced in Chapter 3. For the latter, we again distinguish between a sealed-bid (sGMS) and a dynamic version (dGMS). sGMS generalizes Moulin and Shenker's (1992) serial cost sharing mechanism, while dGMS generalizes Deb and Razzolini's (1999) 'English Auction-Like Mechanism'. In the previous chapter, we show that both versions are group strategy-proof, individually rational, anonymous, and budget-balanced. Both theoretically outperform AON in terms of producer performance (profit and funding frequency) and efficiency. Experimental data in the previous chapter provides support for these predictions for dGMS but not for sGMS. Note that the previous chapter focuses on the response of consumers to the mechanisms. The choices of the producers are made by a robot that is programmed to choose the theoretically optimal parameters.

In this chapter, we introduce producer decisions. This allows us to determine how producers deviate from optimal play and to what extent these deviations explain crowdfunding failures. Inexperienced producers in particular may fail to set the optimal parameters for their crowdfunding campaign. This is empirically relevant because about 87% of projects in 2014 on Kickstarter are launched by producers who had not launched a project on this platform before (Buttice et al., 2017). Further, our experiment allows us to test whether dGMS is as promising as Chapter 3 suggests in a setting that more closely resembles crowdfunding in practice (where human producers choose important parameters). For this purpose, we compare the performance of AON, sGMS and dGMS in a between-subject design. We vary the objective that the producer pursues (either profit or success probability) and production costs within subjects.[2] To capture that crowdfunding typically attracts a large group of consumers, our experiment uses relatively large experimental groups, consisting of one producer and 15 consumers each.[3] Surprisingly, we find that, contrary to theoretical predictions, AON outperforms both sGMS and dGMS. Comparing this to the results in Chapter 3 allows us to conclude that the poor performance of the two GMS mechanisms is mostly driven by suboptimal producer behavior rather than consumer choices. In this way, our experimental results highlight the importance of considering both sides of the market when comparing mechanisms.[4]

This study mainly relates to two strands of the literature (see Chapter 3 for further references). First, there is a small literature in economics that theoretically analyzes or experimentally tests crowdfunding mechanisms. Cornelli (1996) derives the profit-maximizing crowdfunding mechanism in a setting similar to ours. Unfortunately, this ‘optimal’ mechanism is highly impractical. First, it requires that the producer is willing to make a loss in some states. Second, the mechanism is difficult to explain to consumers as funding success depends on individual bids in an intricate and non-intuitive way. AON and the GMS mechanisms are arguably more practical. AON is analyzed by Ellman and Hurkens (2019b). In a setting with binary consumer values, they show that AON constitutes the optimal crowdfunding

[2]As argued in the previous chapter, some producers may care more about getting a project started than about the profits of this endeavor. One reason may be related to expected future profits once the project is underway.

[3]Simulation results suggest that consumer groups of 15 are sufficiently large to capture behavior in large crowds. More information is available upon request.

[4]Of course, one might argue that producers in the field have particular knowledge or talents that might mitigate the errors they make. As will be explained below, we took this into account by using a selection process to choose the producer in a session. Whether an even stronger selection takes place in field is a question left for future research.

mechanism. AON is, however, far from optimal for three or more possible values. It yields inefficiencies due to underprovision of goods as it induces consumers to free-ride (Strausz, 2017; Ellman and Hurkens, 2019b). The experiments by Cason and Zubrickas (2017) and our study in the previous chapter support this prediction. This suggests that there is scope for other practical mechanisms to outperform AON.[5] sGMS and dGMS are such practical alternatives.

sGMS and dGMS generalize Moulin and Shenker's (1992) serial cost sharing mechanism and Deb and Razzolini's (1999) 'English Auction-Like Mechanism' respectively by endogenizing the threshold and minimum price. The serial cost sharing mechanism minimizes the worst possible welfare loss in the set of budget-balanced and group strategy-proof cost-sharing mechanisms (Moulin and Shenker, 2001), and it maximizes welfare among a restricted set of strategy-proof mechanisms (Deb and Razzolini, 1999). In the laboratory, the serial cost sharing mechanism yields significantly more efficient allocations than the average cost sharing mechanism (Chen et al., 2007) and cost-sharing mechanisms with proportional rebates and without rebates (Gailmard and Palfrey, 2005). We are the first to test a dynamic variant of the serial cost sharing mechanism in the lab.

Second, our study relates to auction studies that experimentally test seller behavior. This literature finds that sellers systematically deviate from optimal play. For example, sellers tend to set reservation prices below the theoretical optimum and exhibit behavioral biases at least as much as buyers do (Davis et al., 2011; Shachat and Tan, 2019). Experience, however, helps sellers to approach theoretically optimal behavior (Banerjee et al., 2018). Our study adds to this literature by showing that producers in crowdfunding also set reservation prices below what is theoretically optimal when trying to maximize their profits. Interestingly, experience has no effect on producer

[5]For example, introducing refund bonuses to AON (paid to contributors if the project is not funded) increases the success rate of crowdfunding campaigns (Cason and Zubrickas, 2019; Cason et al., 2021).

decisions in our experiment; we do not observe that producers make better choices over time.

The remainder of this chapter is organized as follows. Section 4.2 describes the experimental design. Section 4.3 explains AON, sGMS and dGMS, and provides theoretical predictions and hypotheses. Section 4.4 presents the results. Section 4.5 concludes.

4.2 Experimental Procedures and Design

We conducted the experimental sessions in the spring of 2016 and fall of 2017 at the CREED laboratory of the University of Amsterdam. The experiment consisted of 18 sessions with 16 participants each. We had six sessions for each of the mechanisms distinguished below. Participants were members of the CREED participant pool and were invited via email to sign up for one session each. They were on average 22 years old. We had a balanced share of female and male participants. 66% of the participants studied Economics or Business. 64% of the participants had never participated in a crowdfunding campaign. Sessions lasted about 90 minutes. Throughout the experiment, we denote payoffs in 'francs'. At the end of the experiment, each participant's payoffs in francs are exchanged for euros at a rate of one euro per eight francs. Average earnings were 15.13 Euros for the participants playing producers and 17.93 Euros for the participants playing consumers, both including a seven euro show-up fee.

The experimental design closely resembles that used in Chapter 3. It features a 3x2x3-design in which we vary the mechanism (AON, sGMS, dGMS) between subjects, and the producer objective (profit, success) and the project costs (low, medium, high) within subjects. In every session, a single participant is assigned the role of the producer. The remaining 15 participants are assigned the role of consumers. We describe the mechanisms in detail in the next section.

The structure of the experiment is as follows. Participants first read the instructions. They are then required to answer questions that test their correct understanding of the rules.[6] Participants can only move to the next section after they have answered all the questions correctly. Next, participants are asked questions that test their crowdfunding intuition. These intuition questions determine which participant is assigned the role of producer.[7] The participant with the highest number of correct answers is chosen as producer; in case of a tie one of the tied participants is chosen at random. This procedure is common knowledge. As explained in footnote 4, it aims at selecting a comparatively skilled producer, as one might expect to occur via 'natural' selection on crowdfunding platforms in the field.

After a producer has been selected, participants play the crowdfunding game for 45 consecutive rounds. We use this large number of repetitions in order to provide participants with opportunities to learn. After the final round, participants are required to fill out a short questionnaire. Finally, they are paid out their earnings in private.

Each round follows the following steps. First, the producer is informed about this round's objective and project costs. She then sets a funding threshold $T \in \{0, 1, \ldots, 300\}$ and a reservation price $r \in \{0, 1 \ldots, 30\}$. For consumers, we use a private value setting where, in every round, consumers' values for a unit of the good are drawn independently from a discrete uniform distribution over the set $\{0, 1, \ldots, 19, 20\}$. Consumers learn their own value, the threshold and reservation price, and subsequently privately report their integer bids between 0 and 30. The crowdfunding mechanism in place (described in Section 4.3.1) then determines whether the good is produced, and if so, which consumers obtain a unit of the good. At the end of every round, both the producer and consumers are informed about their payoffs, the production outcome, consumers' individual bids and, in the

[6] Appendix 4.D provides the experimental instructions.

[7] Intuition questions were multiple choice questions with four possible answers, one of them being theoretically superior to the other three (cf. Appendix 4.D).

GMS treatments, also the implemented price conditional on production.[8]

Of the 45 rounds, the producer is assigned a profit objective in 27 and a success objective in 18 rounds. Project costs are $C = 50$, $C = 70$ and $C = 90$ (9 times each) in rounds with the profit objective, and $C = 60$, $C = 80$ or $C = 100$ (6 times each) in rounds with the success objective. These cost levels allow us to analyze consumer and producer behavior in situations where funding success is predicted to be either very likely, somewhat likely or unlikely (cf. Section 3). The 45 rounds consist of three blocks of 15. In each block, nine rounds are run with a profit objective (three for each cost level) and six with a success objective (two for each cost level). Under these restrictions, costs and objective are randomly determined. In order to reduce noise, we keep the order of project costs and consumer values constant across mechanisms.

A consumer's payoff in francs conditional on obtaining the good equals her value minus her payment to the producer. If a consumer does not obtain the good, her payoff equals zero minus her payment. The producer's payoffs are determined as follows. In rounds with a profit objective, the payoff in francs equals 20% of the profits, i.e. 20% of the aggregate consumers' payments minus the project costs if the product was produced and zero otherwise. In rounds with a success objective, the payoff is 3 francs if the producer managed to successfully fund her project – that is, if the aggregate payments are larger than both the threshold and costs – and zero otherwise. For both consumers and producers, earnings in francs are aggregated across the 45 rounds.

[8] As explained below, GMS applies a uniform price. In AON, the price for any consumer is equal to her bid.

4.3 Mechanisms and Predictions

4.3.1 Mechanisms

All three mechanisms consist of a producer and consumer stage. In the producer stage, the producer sets a threshold $T \in \{0, 1, \ldots, 300\}$ and reservation price $r \in \{0, 1, \ldots, 30\}$. In the consumer stage, consumers place their bids. The mechanisms differ in how the bids are made and how they lead to an allocation of the good and a price to be paid.

All-or-Nothing (AON):
In AON, each consumer i simultaneously and independently reports a bid $b_i \in \{0, 1, \ldots, 30\}$. The good is produced if and only if $\sum_i b_i \geq T$. If the good is produced, every consumer pays her own bid to the producer. Consumer i obtains a unit of the good if and only if $b_i \geq r$. If the good is not produced, no consumer obtains the good and all pay zero.

Sealed-bid Generalized Moulin-Shenker (sGMS):
In sGMS, each consumer i simultaneously and independently reports a bid $b_i \in \{0, 1, \ldots, 30\}$. Let $M(p)$ be the number of consumers who bid at least p. The resulting revenue at price p is $M(p)\,p$. The good is produced if and only if a price $p \in \{r, r+1, \ldots, 30\}$ exists for which $M(p)\,p \geq T$. If such a price does not exist the good is not produced, no consumer obtains the good and all pay zero. Otherwise, the good is produced at price $p^* = \min\{p \in \{r, r+1, \ldots, 30\} : M(p)\,p \geq T\}$. If the good is produced, consumer i obtains the good and pays p^* if and only if $b_i \geq p^*$. If $b_i < p^*$, consumer i does not obtain the good and pays zero.

Dynamic Generalized Moulin-Shenker (dGMS):
In dGMS, the price starts at r and is raised successively, one unit at a time. Consumers can drop out at any price. This decision is irrevocable. Let $M(p)$ be the number of consumers remaining at price p. The resulting revenue

at price p is $M(p)\,p$. The ascending clock stops when it reaches price p, for which either (1) $30 * M(p) < T$, in which case the good is not produced and all consumers pay zero, or (2) $M(p)\,p \geq T$, in which case the good is produced and all remaining consumers obtain the good and pay p.

4.3.2 Predictions

To derive theoretical predictions for the parameterization used in the experiment, we use the Perfect Bayesian equilibrium (PBE) concept. We provide simulation results whenever analytical solutions are not tractable.[9] The producer has two instruments at her disposal to steer consumer behavior: the fundraising threshold and reservation price. The fundraising threshold can ensure that consumers are willing to pay sufficiently *in aggregate*. The reservation price can ensure that each consumer only obtains the good if she is willing to pay sufficiently for it.

The top panel of Table 4.1 shows the equilibrium producer choices for AON. Note that, because consumers pay their own bid in AON, the only reason to bid above the reservation price is to affect the likelihood that the funding threshold is reached. Even for an only moderately large crowd of 15 consumers (as in the experiment), it is unlikely for a consumer's individual contribution to be pivotal. For this reason, even high-valued consumers are unwilling to bid substantially above the reservation price. High reservation prices then mitigate excessive free riding by consumers. Table 4.1 also shows that the equilibrium threshold in AON is weakly above the costs when the producer's goal is to maximize profits. For costs of 70 or 90, the incentives that this gives to high-valued backers to bid strictly above the reservation price outweighs the lower probability of reaching the threshold. Under a success objective, the producer sets the threshold exactly equal to costs to make funding as likely as possible while ensuring to never incur a loss

[9] We refer to Sections 3.3 and 3.D in the previous chapter for a detailed description of the underlying theory and the algorithms underlying the simulations.

ex-post.

Table 4.1: Equilibrium Thresholds and Reservation Prices

		Success Objective			Profit Objective		
	Costs	60	80	100	50	70	90
AON	Threshold	60	80	100	50	78	97
	Reservation Price	10	10	11	11	11	12
GMS	Threshold	60	80	100	56	78	97
	Reservation Price	0	0	0	11	11	11

Notes: The table presents equilibrium thresholds and reservation prices in AON and GMS for all cost levels used in the experiment.

We now turn to GMS. First, we note that equilibrium producer behavior is identical for sGMS and dGMS because both versions are strategically equivalent. sGMS and dGMS have an intuitive 'truthful' equilibrium in weakly dominant strategies in which consumers bid their value (see Theorem 3.2 in the previous chapter). Both sGMS and dGMS are thus strategy proof. The reason is that, similar to a second-price auction, a consumer's bid only determines the maximal price the consumer will pay, and not the actual price she has to pay in order to obtain the good. The strategy-proofness of the GMS simplifies its analysis in comparison to AON. Moreover, as shown in Theorem 3.3 in the previous chapter, dGMS is not only strategy-proof but also obviously strategy-proof in the sense of Li (2017), while sGMS is not. Li (2017) argues that obvious strategy-proofness makes it easy for cognitively limited consumers to recognize that bidding their value is a weakly dominant strategy.

The lower panel of Table 4.1 shows equilibrium producer choices in GMS when consumers play according to the truthful equilibrium. We observe that equilibrium producer behavior differs between producer objectives more in GMS than in AON. Under a success objective, the equilibrium reservation price is zero and the equilibrium threshold equals costs (see Theorem 3.5

in the previous chapter). The intuition is that the producer should set the reservation price and threshold as low as possible conditional on covering the costs. Under a profit objective, the producer sets an equilibrium reservation price equal to the monopoly price of 11 and an equilibrium threshold strictly above the costs. The former ensures to maximize profits when consumer demand is relatively high, while the latter retains the possibility to obtain a positive profit also when consumers' demand is relatively low, as in this case the equilibrium reservation price becomes non-consequential. Note that under both producer objectives, the producer sets (weakly) higher reservation prices in AON than in GMS.

Assuming equilibrium behavior by producers and consumers, we can predict the performance of AON and GMS. Table 4.2 shows the expected success frequency and surplus under a success objective, and the expected profit and surplus under a profit objective. Surplus is defined as the sum of the consumer values for the consumers who obtain the good minus the costs conditional on the good being produced. If the good is not produced, surplus equals zero.

Table 4.2: Theoretical Predictions

	Success Objective		Profit Objective	
	Success	Surplus	Profit	Surplus
AON	0.559	33.84	15.79	35.77
GMS	0.651	46.73	16.29	37.62

Notes: For the experimental parameters, the table presents theoretical predictions for expected success frequency and surplus under a success objective and expected profit and surplus under a profit objective in AON and GMS.

Both versions of GMS outperform AON in equilibrium, on all four outcome measures. However, the difference in expected performance is considerably larger under the success objective than under the profit objective both in absolute and relative terms.

As this chapter focuses on producer behavior in crowdfunding, our main hypotheses are about how producers choose thresholds and reservation prices. The theoretical predictions regarding equilibrium behavior (cf. Table 4.1) suggest the following hypotheses to be tested in the laboratory experiment.

Hypothesis 4.1

(a) In AON, producers set the same reservation prices under a profit objective and success objective.[10]

(b) In AON, producers set thresholds such that there is a higher difference between thresholds and costs under a profit objective than under a success objective.

Hypothesis 4.2

(a) In sGMS, producers set higher reservation prices under a profit objective than under a success objective.

(b) In sGMS, producers set thresholds such that there is a higher difference between thresholds and costs under a profit objective than under a success objective.

Hypothesis 4.3

(a) In dGMS, producers set higher reservation prices under a profit objective than under a success objective.

(b) In dGMS, producers set thresholds such that there is a higher difference between thresholds and costs under a profit objective than under a success objective.

[10] We consider a one-unit difference (cf. Table 4.1) to be 'too small to measure' in the experiment.

4.4 Results

This section presents the experimental results. For pairwise comparisons, we use the paired Fisher-Pitman permutation test. To give both producers and consumers time to learn, we focus on rounds 16 to 45. We start in Section 4.4.1 by comparing aggregate mechanism performance. This can be seen as a robustness check of the results reported in Sections 3.5.1 and 3.5.2 in the previous chapter, now for the case of producer decisions made by human subjects. Section 4.4.2 then identifies what part of the performance differences can be attributed to producer behavior. Section 4.4.3 analyzes producer behavior in more detail and tests our hypotheses.

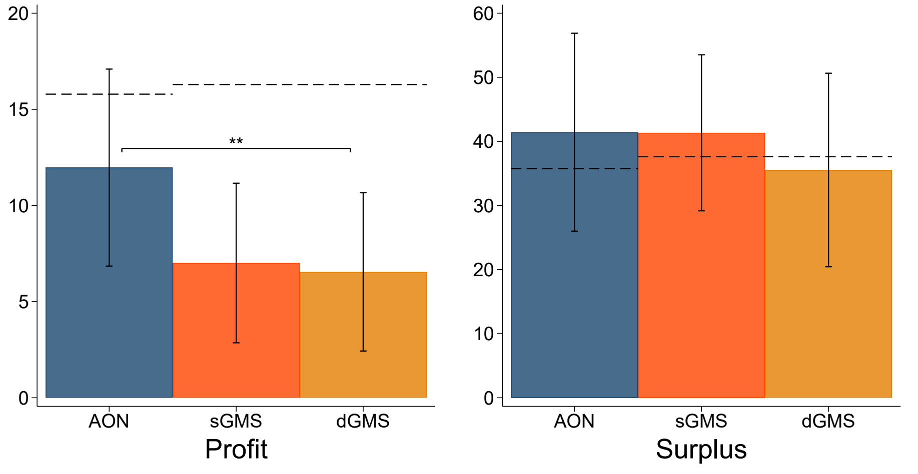
4.4.1 Mechanisms' Performance

In analyzing mechanism performance, we distinguish between the two producer objectives. This is because producers may deviate from the equilibrium predictions differently, depending on the objective. We first consider aggregate mechanism performance (which, of course, also depends on consumer behavior).

Figure 4.1 depicts the average observed producer profit (left panel) and average surplus (right panel) in AON, sGMS and dGMS under a profit objective. We observe that AON yields a significantly higher producer profit than dGMS (11.97 vs. 6.54, $p = 0.031$) and an insignificantly higher producer profit than sGMS (7.01, $p = 0.125$). The two GMS mechanisms yield a similar profit ($p = 1.000$). Comparing average surplus, we observe that AON and sGMS yield almost the exact same surplus (41.44 vs. 41.34, $p = 0.969$). They both yield a higher surplus than dGMS, but the differences are insignificant (35.54, $p = 0.563$ resp. $p = 0.406$). AON thus tends to perform better than both versions of the GMS under a profit objective.

Comparing the experimental results to the theoretical predictions, we observe that average surplus in the experiment is close to what is pre-

Figure 4.1: Producer Profit and Overall Surplus – Profit Objective



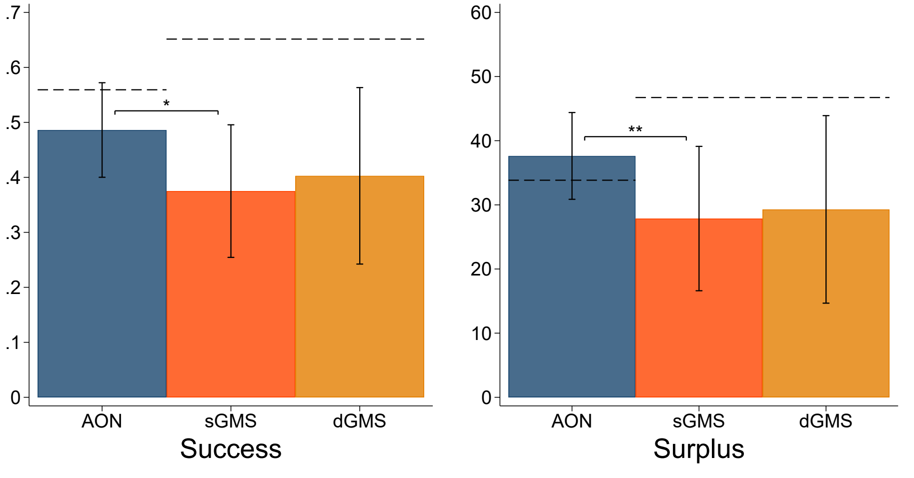
Notes: The figure shows average producer profit (left graph) and average surplus (right graph) in AON, sGMS dGMS under a profit objective. Error bars indicate ninety-five percent confidence intervals. The dashed lines denote the theoretical predictions. ** $p < 0.05$ in a paired Fisher-Pitman permutation test.

dicted. For all three mechanisms, the predicted surplus lies in the 95% confidence interval of the observed surplus. As observed from the profits, however, there is a substantial difference in all three mechanisms in how the surplus is split between the producer and consumers. Producers earn a significantly smaller share of the surplus in the experiment (AON: 28.89%; sGMS: 16.95%; dGMS: 18.42%) than predicted by theory (AON: 44.14%; sGMS and dGMS: 43.31%; all three $p = 0.031$).

Figure 4.2 shows the success frequency (left panel) and average surplus (right panel) in AON, sGMS and dGMS under a success objective. It appears that AON yields a marginally significantly higher success frequency than sGMS (0.486 vs. 0.375, $p = 0.063$) and an insignificantly higher success frequency than dGMS (0.403; $p = 0.313$). The difference between sGMS and dGMS is insignificant ($p = 0.750$). We observe a similar pattern for average surplus. Here, AON yields a significantly higher surplus than sGMS (37.63

vs. 27.86, $p = 0.031$). AON also yields a higher surplus than dGMS (29.29), but this difference is insignificant ($p = 0.281$). The difference in surplus between sGMS and dGMS is small and insignificant ($p = 0.844$). Again, AON thus tends to perform better than both versions of the GMS.

Figure 4.2: Producer Success and Overall Surplus – Success Objective



Notes: The figure shows average success frequency (left graph) and average surplus (right graph) in AON, sGMS, and dGMS under a success objective. Error bars indicate ninety-five percent confidence intervals. The dashed lines denote the theoretical predictions. ** $p < 0.05$, * $p < 0.1$ in a paired Fisher-Pitman permutation test.

Comparing these results to the theoretical predictions, we observe that the experimental performance of AON is close to theory. Both sGMS and dGMS perform considerably worse in the experiment than theoretically predicted, as predicted success frequency and surplus lie outside of the 95% confidence interval of the observed success frequency and surplus.

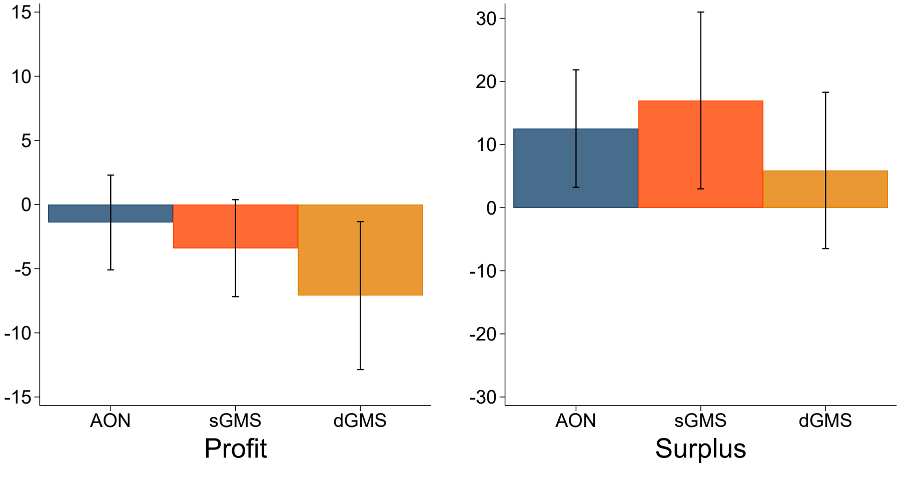
In summary, when considering the two producer objectives, we find that AON weakly outperforms both versions of the GMS, while the performance ranking between sGMS and dGMS is ambiguous.

4.4.2 Producer Performance

The previous section establishes that AON weakly outperforms sGMS and dGMS in the experiment, which is in contrast to the theoretical predictions. This result could be driven by deviations in behavior of producers or consumers. To differentiate between the two, we compare the experimental results reported here to our companion study in Chapter 3. In the previous chapter, we isolate the effects of consumer behavior by applying an automated producer that always chooses equilibrium levels of the threshold and reservation price. This allows us to identify here the effects of active producer decisions on the mechanisms' performance.

For this purpose, Figure 4.3 shows the difference in average producer profit (left panel) and difference in average surplus (right panel) between sessions with an active (this chapter) and those with an automated (previous chapter) producer under a profit objective.

Figure 4.3: Effects of Active Producers – Profit Objective



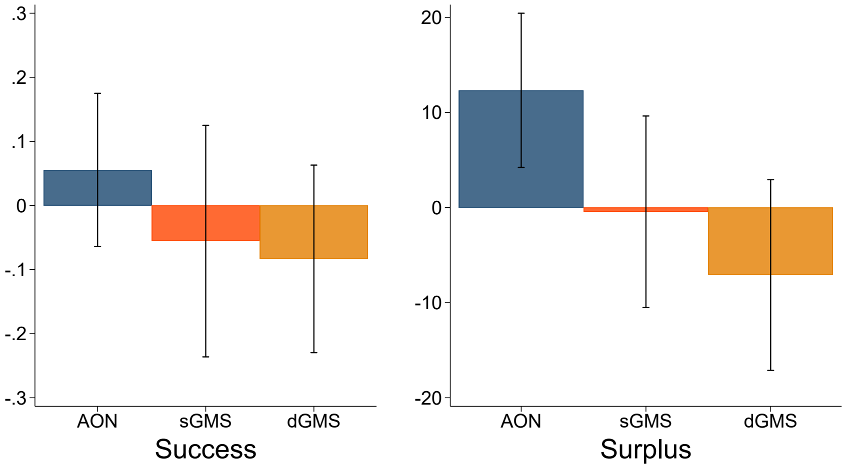
Notes: The figure shows the difference in average producer profit (left graph) and the difference in average overall surplus (right graph) between sessions with an active and an automated producer in AON, sGMS, dGMS under a profit objective. Error bars indicate ninety-five percent confidence intervals.

The figure shows that active producers earn a lower profit than automated producers in all three mechanisms. The difference is insignificant for AON (–1.40, $p = 0.500$) and sGMS (–3.40, $p = 0.125$), but significant for dGMS (–7.09, $p = 0.031$). Interestingly, the active producer decisions tend to increase welfare. Overall surplus is marginally significantly higher in AON and sGMS (12.54, $p = 0.063$ resp. 16.98, $p = 0.063$) in sessions with an active producer than in sessions with an automated producer. The difference is smaller and insignificant in dGMS (5.90, $p = 0.281$). Higher average surplus combined with lower average profit in sessions with active producers compared to automated producers implies that consumers benefit from the suboptimal producer decisions under a profit objective (see the left panel of Figure 4.B1 in the appendix). In all three mechanisms, consumers earn significantly more (albeit only marginally so in dGMS) in sessions with an active compared to an automated producer (AON: 15.37, $p = 0.031$; sGMS: 22.24, $p = 0.031$; dGMS: 12.99, $p = 0.063$).

We now turn to the success objective. Figure 4.4 depicts the difference in success frequency (left panel) and difference in average surplus (right panel) between sessions with an active (this chapter) and an automated (previous chapter) producer in the three mechanisms under a success objective.

While active producers manage to obtain a slightly higher success frequency than automated producers in AON, the difference is small and insignificant (0.056, $p = 0.281$). In both sGMS and dGMS, active producers have an insignificantly lower success frequency than automated producers (–0.056, $p = 0.750$ resp. –0.083, $p = 0.188$). The right panel of Figure 4.4 shows that allowing for active producer decisions yields distinct effects in the three mechanisms in terms of overall welfare. In AON, overall surplus is significantly higher in sessions with an active producer (12.33, $p = 0.031$). There is little difference regarding surplus in sGMS (–0.44, $p > 0.999$), while surplus in dGMS is marginally significantly lower (–7.10, $p = 0.063$). We observe a similar pattern for consumer welfare (see the right panel of Figure 4.B1 in

Figure 4.4: Effects of Active Producers – Success Objective



Notes: The figure shows the difference in average success frequency (left graph) and the difference in average overall surplus (right graph) between sessions with an active and an automated producer in AON, sGMS and dGMS under a success objective. Error bars indicate ninety-five percent confidence intervals.

the appendix). In AON, consumers earn significantly more in sessions with an active producer compared to an automatized producer (12.79, $p = 0.031$). In contrast, active producer decisions significantly decrease consumers' payoffs in dGMS (–8.47, $p = 0.031$). There is no significant difference in terms of consumer welfare in sGMS (–1.96, $p = 0.689$).

In summary, we find that, in AON, active producers manage to earn a similar amount as automated producers under both producer objectives. In contrast, in sGMS and dGMS, active producers tend to earn less than automated producers.[11] Further, active producer decisions increase overall and consumer welfare in AON, but have ambiguous effects in sGMS and dGMS. These results suggest that it might be easier for producers to make

[11] The gap in producer performance between AON and both versions of the GMS tends to widen over time (see Figure 4.B2 in the appendix), which suggests that the differing effects of active producer decisions on the mechanisms' performance are persistent and do not disappear over time.

good decisions in AON or that crowdfunding outcomes are more robust to deviations from optimal play in AON than in sGMS and dGMS. The following section investigates which of these two potential explanations is supported by the data.

4.4.3 Producer Behavior

To better explain the mechanisms' relative performance, we analyze producer behavior in more detail.[12] We compare observed producer behavior to theoretical benchmarks. These benchmarks depend on how consumers bid – in line with the (truthful) Bayesian Nash equilibrium or their actual bidding behavior. To derive the producer's best response to consumers' actual bidding behavior, we estimate an empirical bid function that describes consumer bidding in AON and sGMS.[13] We fit the data by regressing a bid on a consumer's value, and the threshold and reservation price she faces. More specifically, we estimate the bid functions using the following ordinary least-squares linear regression model:

$$b_{sti}^{mw} = \beta_0^{mw} + \beta_1^{mw} v_{sti} + \beta_2^{mw} T_{st}^{mw} + \beta_3^{mw} \left(T_{st}^{mw}\right)^2 + \beta_4^{mw} r_{st}^{mw} + \beta_5^{mw} \left(r_{st}^{mw}\right)^2 + \epsilon_{sti}^{mw} \quad (4.1)$$

where bids are given by b, values by v, thresholds by T and reservation prices by r; $m = \{AON, sGMS\}$ denotes the mechanism; $w = \{v < r, v = r, v > r\}$ distinguishes between cases where the bidder's value is smaller than, equal to, or larger than the reservation price; $s = \{1, 2, \dots, 6\}$ distinguishes between sessions; $t = \{16, 17, \dots, 45\}$ is the period, and $i = \{1, 2, \dots, 15\}$ represents the individual.[14] ϵ_{sti}^{mw} is normally distributed. Standard errors are robust and clustered at the individual level.

[12] We refer to Appendix 4.A for an analysis of consumer behavior.

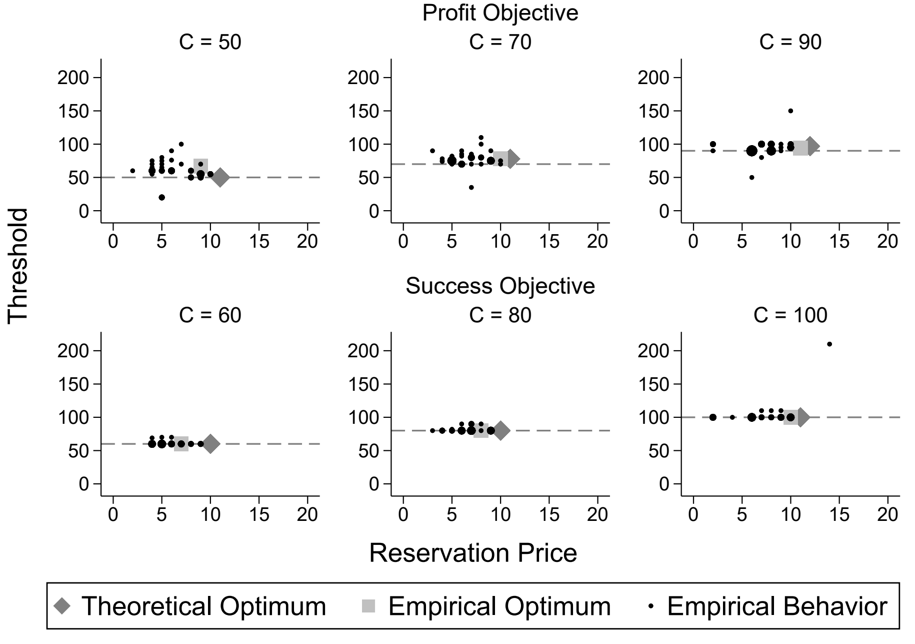
[13] As we will discuss below in more detail, for dGMS, we cannot estimate the bidding function (4.1) because we do not observe what participants would have bid when they had not yet dropped out at the price at which the ascending clock stopped.

[14] v_{sti} is excluded from the equation when $v = r$ due to perfect collinearity between v and r.

We use the empirical bidding functions obtained by estimating (4.1) in simulations that we run to derive empirically optimal producer behavior. Details on the regression results and the simulations are given in Appendix 4.C.

Figure 4.5 depicts the threshold/reservation price combinations observed in AON for the various cost levels used.[15]

Figure 4.5: Producer Behavior in AON



Notes: The figure depicts the frequency of threshold (vertical axis) and reservation price (horizontal axis) combinations set by the producers in AON for each project cost C. The larger a black dot, the more frequent a combination occurred in the experiment. Dark gray diamonds denote equilibrium producer behavior. Light gray squares denote empirically optimal producer behavior in response to bids predicted by eq. (4.1). The dashed horizontal line depicts $T = C$. Producers' rewards are based on profits in the top row of graphs and on success in the bottom row.

[15] Figure 4.B3 in the appendix splits producer behavior in AON by rounds 1 to 15, 16 to 30 and 31 to 45. The figure suggests that producer behavior in AON does not systematically change over time.

We observe that there is a considerable variance in reservation prices within all cost levels, and less so between cost levels. Nevertheless, despite this large spread, the producers set reservation prices strictly below the equilibrium prediction in all rounds except one (out of 180). In addition, a vast majority (84%) of observed reservation prices is also strictly below what is empirically optimal. The average observed reservation prices, as depicted in Table 4.3, are significantly lower than the theoretical optima (paired Fisher-Pitman permutation test, $p = 0.031$); they are marginally significantly lower than the empirical optima ($p = 0.063$). The latter implies that while some of the differences between observed reservation prices and the equilibrium values might be explained by producers anticipating out-of-equilibrium bidding, reservation prices remain too low, even after correcting for this. Note, however, that the low reservation prices are the reason why overall surplus is higher in sessions with an active than with an automated producer. Due to these lower prices, more consumers can obtain the good. Finally, given consumer behavior, Table 4.3 shows that the optimal reservation price is weakly increasing in C. Though observed prices are indeed increasing, this effect is statistically insignificant; a regression of the reservation price on cost levels clustering standard errors at the session level gives a statistically insignificant coefficient under both objectives ($p = 0.242$ resp. $p = 0.145$).

We now test our formal hypothesis that producers set the same reservation prices under a profit objective and success objective. Unlike the other hypotheses, Hypothesis 4.1a proposes a null effect. To test it, we thus need to use Bayesian inference. We compare the null hypothesis with a prior of $N \sim (0, 0.07834)$ for the difference in average reservation prices under a profit and success objective on the producer level to an alternative hypothesis with a prior of $N \sim (1, 0.07834)$. For the alternative hypothesis we propose a mean of 1 as this is in line with our theoretical predictions (cf Table 4.1). The standard deviations that we use for both priors are the average squared standard errors of the differences in reservation prices under a profit and success objective in sGMS and dGMS. Running paired t-tests, we find that producers set similar reservation prices under both objectives, though the result of Bayesian hypothesis testing shows only moderate support for Hypothesis 4.1a (Bayes factor of 0.141). This implies that it is about 7 times as likely for the data to occur under the null hypothesis than under the alternative hypothesis.

Table 4.3: Comparing Producer Behavior in AON

	Profit Objective			Success Objective		
Costs	50	70	90	60	80	100
			Reservation Price			
Equilibrium	11	11	12	10	10	11
Empirically optimal	9	10	11	7	8	10
Observed	6.36	6.61	7.19	5.79	6.54	7.29
			Threshold			
Equilibrium	50	78	97	60	80	100
Empirically optimal	67	78	94	60	80	100
Observed	60.86	77.53	93.92	61.33	81.75	105.83

Notes: The table presents equilibrium, empirically optimal and average observed reservation prices and thresholds in AON for all cost levels.

Turning to the fundraising threshold, we observe similar increasing patterns under the two producer objectives. In contrast to the reservation price, however, producers deviate from the theoretical and empirical optima both up-and downwards. 52% and 37% of the thresholds under a profit objective are strictly above the, respectively, theoretical and empirical optima, while 44% and 62% are strictly below.[16] Under a success objective, producers predominantly (81%) play theoretically and empirically optimally by setting thresholds equal to the project costs.

[16] Only 5% of the thresholds under a profit objective are strictly below the project costs. This suggests that participants understand the basic incentives involved but have a hard time anticipating how consumers will respond.

As predicted, producers significantly increase thresholds in project costs under both producer objectives (regression of the threshold on cost levels clustering standard errors at the session level; both $p < 0.001$). Controlling for costs, producers set higher thresholds under a profit than under a success objective. However, the difference is only marginally significant ($p = 0.063$), so that the data does not confirm Hypothesis 4.1b. On average, producers come close to the empirically optimal thresholds.[17] This suggests that, contrary to the reservation price, producers do correct the chosen threshold for bidders' out-of-equilibrium behavior.

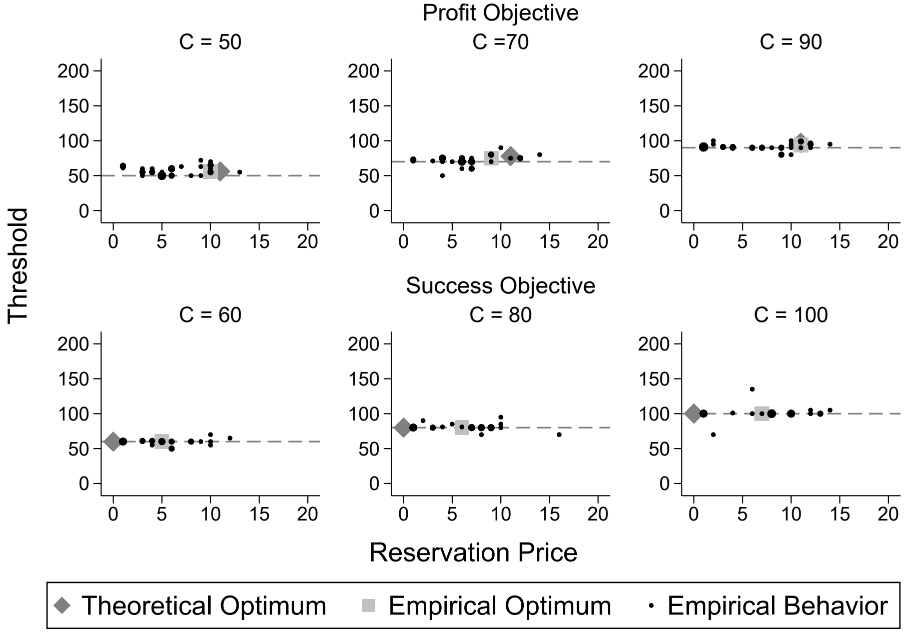
In summary, producers in AON tend to set reasonable thresholds but reservation prices that are too low. The latter raises the question why active producers nevertheless manage to earn a payoff that is similar to that of automated producers (Figures 4.3 and 4.4). Recall that automated producers set the thresholds and reservation prices according to Bayesian Nash equilibria that assume selfish, rational and risk-neutral consumers. Our analysis of consumer behavior in Appendix 4.A suggests that these assumptions are not all met; there is substantial overbidding by consumers in active producer sessions, significantly more so than in sessions with an automated producer (33% vs. 9%, $p = 0.031$ in a paired Fisher-Pitman permutation test). Consumers may be risk-averse or may overestimate their likelihood of being pivotal. Active producers deviate from theoretically optimal play in the right direction as lower reservation prices allow more consumers to overbid compared to the higher theoretically optimal reservation prices.

sGMS. We turn next to sGMS. Figure 4.6 shows the frequency of threshold/reservation price combinations in the sealed-bid GMS depending for the various project costs C.[18]

[17] The larger difference between the average and equilibrium thresholds for costs of 100 is driven by a single outlier with $T = 210$.

[18] As for AON, producer behavior remains relatively constant over time (see Figure 4.B4 in the appendix).

Figure 4.6: Producer Behavior in sGMS



Notes: The figure depicts the frequency of threshold (vertical axis) and reservation price (horizontal axis) combinations set by the producers in sGMS for each C. The larger a black dot, the more frequent a combination occurred in the experiment. Dark gray diamonds denote equilibrium producer behavior. Light gray squares denote empirically optimal producer behavior in response to bids predicted by eq. (4.1). The dashed horizontal line depicts $T = C$. Producers' rewards are based on profits in the top row of graphs and on success in the bottom row.

Similar to AON, we observe a considerable variance in reservation prices for each cost level, but less so between cost levels. Under the profit objective, 88% and 79% of the reservation prices are strictly below the, respectively, theoretical and empirical optima. Under the success objective, 60% and 56% of the reservation prices are strictly *above* the theoretical and empirical optima.[19] As a consequence, there is no significant difference in the

[19]Note that in theory all reservation prices between 0 and 4 ($C = 60$), 0 and 6 ($C = 80$) resp. 0 and 7 ($C = 100$) are optimal as consumers always need to pay at least $\frac{T}{15}$ in order to fund the project and producers set $T = C$.

reservation prices between producer objectives (p = 0.375), which contradicts Hypothesis 4.2a.

Table 4.4 shows that *average* observed reservation prices under a success objective come close to the empirically optimal reservation prices. There is, however, an asymmetry between setting a reservation price strictly below and strictly above the empirical optimum. Unlike too high reservation prices, too low reservation prices do not decrease the set of potential prices. Because of this, downward deviations do not decrease funding success probability and overall surplus as much as upward deviations. Under both producer objectives, producers increase reservation prices in project costs, though this is significant only under a success objective (regression of the reservation price on cost levels clustering standard errors at the session level; profit objective: p = 0.199, success objective: p = 0.049). Interestingly, even though producers heavily deviate from the theoretically predicted behavior both in AON and sGMS, the observed reservation prices in AON and sGMS are not significantly different from each other (profit objective: p = 0.844; success objective: p = 0.969).

Table 4.4: Comparing Producer Behavior in sGMS

	Profit Objective			Success Objective		
Costs	50	70	90	60	80	100
			Reservation Price			
Equilibrium	11	11	11	0	0	0
Empirically optimal	10	9	11	5	6	7
Observed	5.69	6.03	6.86	5.46	6.38	7.54
			Threshold			
Equilibrium	56	78	97	60	80	100
Empirically optimal	56	75	94	60	80	100
Observed	57.72	72.06	91.42	59.54	80.71	100.71

Notes: The table presents equilibrium, empirically optimal and average observed reservation prices and thresholds in sGMS for all cost levels.

We now turn to the threshold. Figure 4.6 shows that, under a profit objective, producers have the tendency to set the fundraising threshold too low (74% and 61% of the, respectively, theoretical and empirical optima). Under a success objective, producers predominantly (67%) set the threshold equal to the project costs. The difference between thresholds under the profit and success objective, when controlling for costs, is only marginally significant ($p = 0.063$) so that we cannot reject the null of no difference in markups (Hypothesis 4.2b). As in AON, producers significantly increase the threshold in project costs with increasing C, under both producer objectives (regression of the threshold on cost levels clustering standard errors at the session level; both $p < 0.001$). Again, thresholds come close to the empirically optimal thresholds.

In summary, producers in sGMS predominantly set thresholds quite well, but fail to adjust reservation prices to the producer objective.[20] This yields reservation prices that are too low under a profit and too high under a success objective. The suboptimal reservation prices explain why allowing for active producer decisions tends to decrease producer payoffs in sGMS, and is one of the reasons why AON weakly outperforms sGMS in our setting. The other reason is prevalent and persistent underbidding by consumers in sGMS (see the analysis of consumer behavior in Appendix 4.A), as we observed to a very similar extent in sessions with automated producers (see Section 3.5.3.2 in the previous chapter). Recall that in AON, in contrast, the detrimental effect of suboptimally low reservation prices on producer payoff is attenuated by an increase in overbidding.

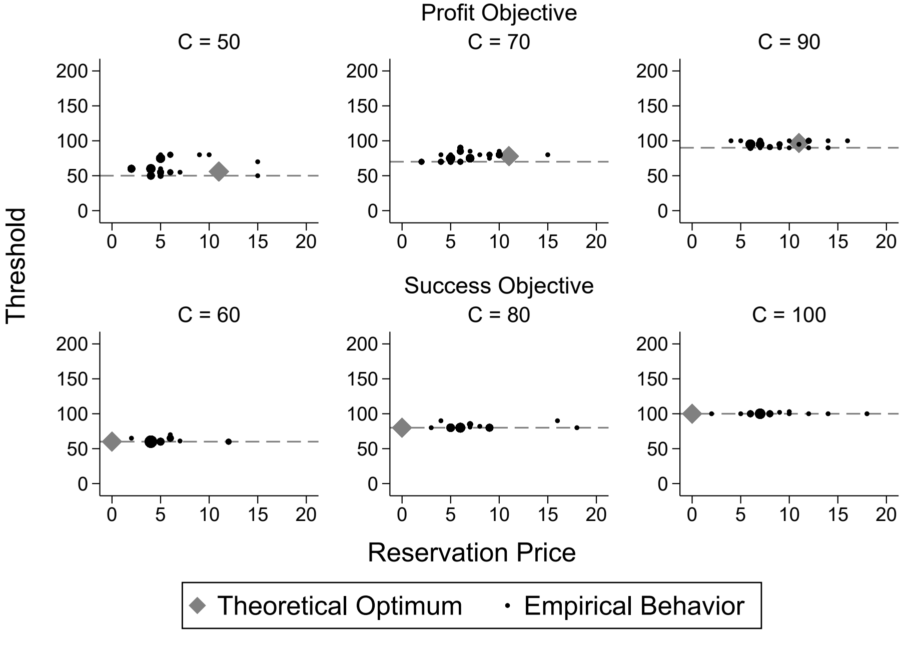
dGMS. Finally, Figure 4.7 depicts the frequency of threshold/reservation price combinations in dGMS depending on the project costs C.[21] For dGMS,

[20]The Pearson correlation coefficient between the average reservation prices that the six producers set under a profit and success objective equals 0.98.

[21]Again, as for AON and sGMS, producer behavior does not systematically change between earlier and later rounds (see Figure 4.B5 in the appendix).

we cannot observe what participants would have bid if they have not yet dropped out when the ascending clock stops. As a consequence, we cannot estimate the bidding function (4.1) in dGMS. We therefore have no predictions based on the empirical best response.

Figure 4.7: Producer Behavior in dGMS



Notes: The figure depicts the frequency of threshold (vertical axis) and reservation price (horizontal axis combinations set by the producers in dGMS for each C. The larger a black dot, the more frequent a combination occurred in the experiment. Dark gray diamonds denote equilibrium producer behavior. The dashed horizontal line depicts $T = C$. Producers' rewards are based on profits in the top row of graphs and on success in the bottom row.

We again observe a considerable variance in reservation prices for all cost levels. Similar to sGMS, and in contrast to Hypothesis 4.3a, we find no difference in the reservation prices between rounds with profit and success objective (p = 0.813). 91% of the reservation prices are strictly below the theoretical optimum under a profit objective, while, under a success objective, 43% of reservation prices are strictly above the theoretical optimum. Table 4.5 depicts average observed reservation prices in dGMS. In contrast to theory, producers significantly increase reservation prices in project costs under both producer objectives (profit objective: $p = 0.001$, success objective: $p = 0.014$; regression of reservation price on costs clustering standard errors at the session level).

Table 4.5: Comparing Producer Behavior in dGMS

	Profit Objective			Success Objective		
Costs	50	70	90	60	80	100
	Reservation Price					
Equilibrium	11	11	11	0	0	0
Observed	5.36	6.53	8.22	5.21	7.21	8.04
	Threshold					
Equilibrium	56	78	97	60	80	100
Observed	62.78	77.36	95.14	61.29	81.38	100.33

Notes: The table presents equilibrium and average observed reservation prices and thresholds in dGMS for all cost levels.

For the fundraising threshold, we observe that producers, unlike in sGMS, do not systematically set thresholds that are too low compared to the theoretical optimum under a profit objective. While 54% of thresholds are strictly below, 46% are strictly above the theoretical prediction. Under a success objective, producers predominantly (78%) set the threshold equal to the project costs and thus play according to the theoretical prediction in the majority of cases. Deviations from equilibrium play are only minor and all producers set thresholds between C and $C + 10$. Controlling for costs, producers set significantly higher thresholds under a profit than under a success objective ($p = 0.031$), which confirms Hypothesis 4.3b. As in AON and sGMS, producers significantly increase the threshold in project costs under both producer objectives (both $p < 0.001$; regression of threshold on costs clustering standard errors at the session level).

To sum up, producers in dGMS predominantly set thresholds optimally under a success objective and within a relatively small range around the optimum under a profit objective, at least when $C = 70$ and $C = 90$. Similar to sGMS, producers in dGMS set reservation prices too low in rounds with a profit and too high in rounds with a success objective, suggesting that producers do not discriminate between producer objectives.[22] Similar to sGMS, the suboptimal reservation prices help to explain why AON outperforms dGMS. Recall that sGMS and dGMS perform equally well on all outcome measures. The reason is that both producers and consumers behave very similarly in the two versions of the GMS. Even though producers set on average slightly higher thresholds and reservation prices in dGMS than in sGMS under both producer objectives, these differences are not significant (profit objective: $p = 0.188$ and $p = 0.781$, respectively; success objective: $p = 0.625$ and $p = 0.844$). As in sGMS, many consumers persistently underbid in dGMS and do so to the same extent (see Appendix 4.A).[23] The added 'obvious strategy-proofness' of dGMS thus does not improve consumer behavior in sessions with an active producer. This is in contrast to the findings in the previous chapter in which consumers underbid significantly less in dGMS than sGMS in sessions with an automated producer, causing dGMS to weakly outperform sGMS in that setting. Taken together, the results explain why active producer decisions tend to decrease producer payoffs even more in dGMS than sGMS.

All in all, we find similar producer behavior in all three mechanisms. Producers predominantly set reasonable thresholds but systematically sub-

[22] This is further supported by a high Pearson correlation coefficient of 0.82 between the average reservation prices the six producers set under a profit and success objective.

[23] In order to compare consumer behavior in sGMS and dGMS, we need to dynamize the bidding process in sGMS. We can do so by assuming that consumers' bids in sGMS indicate the maximum price at which consumers would still be willing to remain in the market before dropping out, and then letting the market play out as in dGMS.

optimal reservation prices.[24]

4.5 Conclusion

In this chapter, we have experimentally studied producer behavior in three reward-based crowdfunding mechanisms: The All-or-Nothing mechanism (AON) and a sealed-bid and a dynamic version of the Generalized-Moulin-Shenker mechanism (GMS). The AON is commonly used in practice while the GMS is a theoretically promising alternative that builds on Moulin and Shenker's (1992) serial cost sharing mechanism and was introduced in our companion study in Chapter 3.

We have examined producer decisions regarding the threshold and reservation price under two producer objectives: profit maximization and fundraising success maximization. Contrary to theoretical predictions, we find that AON weakly outperforms both the sealed-bid and dynamic GMS in terms of average profit, fundraising success and overall surplus. By comparing our results to the results in the previous chapter (which uses the same experimental design but automatically sets producer decisions to the equilibrium levels), we conclude that the superior performance of AON here is driven by introducing active producer decisions. Even though producer decisions deviate substantially from the theoretical predictions in all three mechanisms, producer payoffs are comparatively robust to these deviations only in AON.

Remarkably, producers behave similarly in all three mechanisms. They set reasonable thresholds but choose reservation prices poorly. In AON, reservation prices are too low under both producer objectives, even when accounting for the substantial overbidding by consumers. Producers in both

[24]Experience does not help producers to make better decisions over time. Figure 4.B6 in the appendix shows that the average Euclidian distance between producers' choices and the theoretical and empirical optima does not systematically decrease from rounds 1-15 to 16-30 to 31-45 in any of the mechanisms. This implies that producers do not converge to optimal play and suggests limited learning.

sGMS and dGMS do not condition reservation prices on the producer objective, yielding suboptimally low (high) reservation prices under a profit (success) objective. We thus observe considerably smaller differences in producer decisions between mechanisms and between producer objectives than theoretically predicted.

Our experimental results may contribute to explaining why AON is prevalent in reward-based crowdfunding in practice. First, producer payoffs in AON are relatively robust to deviations from optimal play. Second, the deviations observed in AON are beneficial to consumers. In contrast, the suboptimal producer decisions in both versions of GMS decrease producer payoffs and have ambiguous effects on consumer welfare. Interestingly, we find no difference in performance between the sealed-bid and dynamic GMS. This is surprising as dynamizing the GMS leads to better consumer behavior and thereby better overall performance in the study in Chapter 3. However, incorporating producer behavior mitigates this effect.

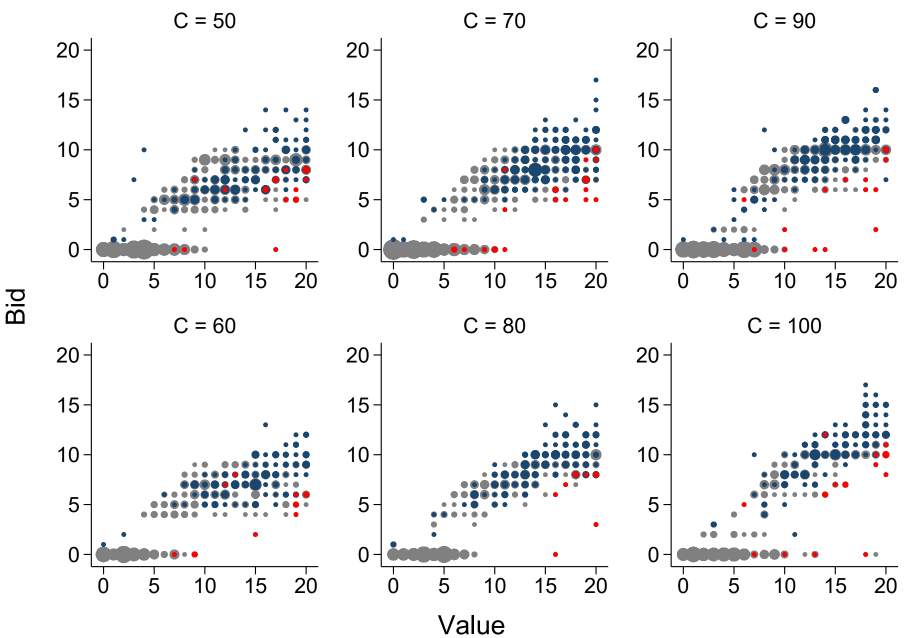
Our results highlight why it is important for properly comparing mechanisms to look at both sides of the market. This is especially called for when producer decisions greatly impact outcomes and when producers are relatively inexperienced, as is the case in reward-based crowdfunding (Buttice et al., 2017). In the experiment, consumers regularly benefit from suboptimal producer decisions in AON. This suggests that policy makers and crowdfunding platforms that use AON need to carefully consider how to aid producers to make 'better' decisions. It is clearly in their overall interest to help producers set thresholds equal to or slightly higher than the production costs as thresholds below the costs put projects at risk of delay, failure or fraud (Mollick, 2014; Belavina et al., 2020). In contrast, it is debatable whether it is in the interest of policy makers and platforms to educate producers about 'optimal' reservation prices as suboptimally low reservation prices might potentially increase overall surplus as our experimental data indicate.

Our results further show that producers struggle to properly condition their behavior on a given producer objective. This is a particular concern for both versions of the GMS in which equilibrium reservation prices under a profit objective and success objective are very different. To help producers in GMS, policy makers and platforms should make the relationship between funding objective and optimal reservation prices salient to producers. Alternatively, one could think about implementing a GMS-like mechanism on a platform that solely features non-profit projects. On such a platform, one could restrict producers to only decide on the fundraising threshold while reservation prices are automatically set to zero. This modification considerably simplifies a producer's optimization problem and is likely to increase overall surplus.

4.A Consumer Behavior

AON. This section analyzes consumer behavior. Figure 4.A1 depicts consumer behavior in AON. The size of the dots denotes the frequency of bid-value combinations. The colors signify whether a bid is lower (red), equal (gray) or higher (blue) than the best response to the symmetric equilibrium bidding function.[25]

Figure 4.A1: Consumer Behavior in AON



Notes: The figure depicts the frequency of bid-value combinations in AON split by cost levels C. The larger the dot, the more frequent a bid-value combination occurred. Gray dots denote observed best responses to the symmetric theoretical equilibrium bidding functions. Blue resp. red dots denote bids that deviate upward resp. downward from the best responses.

The majority (63%) of bids is in line with a best response to the theoret-

[25]Note that this figure differs from its counterpart Figure 3.3 in the previous chapter in that there is now variation in the threshold and reservation price within cost levels.

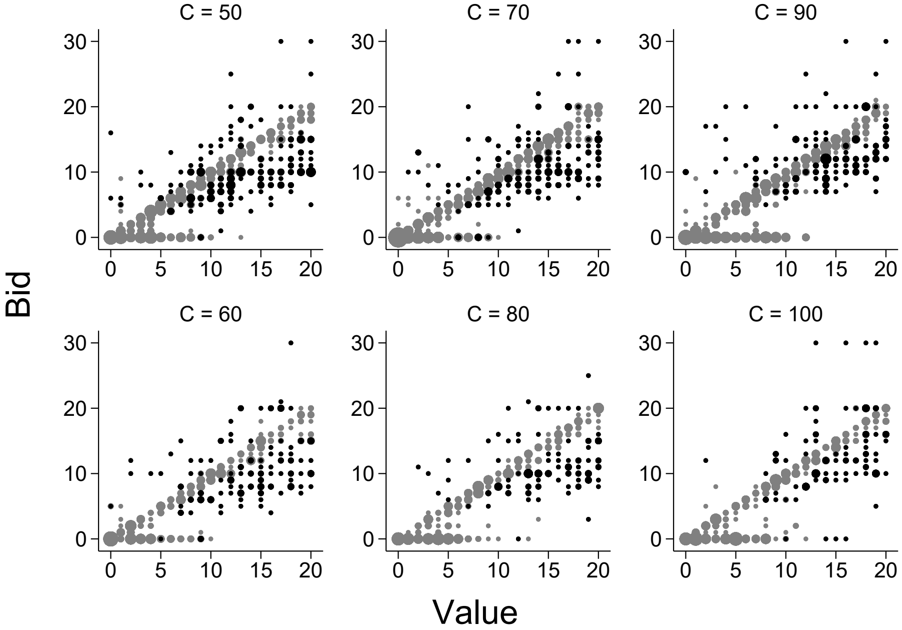
ical equilibrium bidding functions. Deviations are asymmetric. We observe much more overbidding (33%) than underbidding (4%).[26] In almost all cases (96%), overbidding consumers have values strictly above the reservation price. Consumers with values strictly below the reservation price almost exclusively (96%) bid zero. This suggests that the observed overbidding is caused by consumers overestimating the likelihood of their bid being pivotal rather than by altruistic motives. The prevalent overbidding can explain why the empirically optimal reservation prices are lower than their theoretical counterparts. Compared to sessions with an automated producer (cf. Section 3.5.3.1 in the previous chapter), we observe significantly more overbidding in sessions with an active producer (33% vs. 9%, $p = 0.031$ in a paired Fisher-Pitman permutation test). Note that this overbidding does not seem to be caused by a difference in understanding of the AON mechanism as consumers choose weakly dominated bids (see Lemmas 3.A1, 3.A2 and 3.A3 in the previous chapter) only very rarely in both treatments (2% vs. 2%, $p > 0.999$).

sGMS. Figure 4.A2 depicts consumer behavior in sGMS. The size of the dots denotes the frequency of bid-value combinations. Gray resp. black dots represent weakly dominant resp. weakly dominated bids. We observe a similar pattern for all cost levels. In total, 69% of the bids are weakly dominant. Black dots are predominantly below the identity line; while 22% of the bids are too low, only 8% of the bids are too high. In the great majority of cases (92%) underbidding participants bid a few units below their value but at least $\max\{\lceil \frac{T}{15} \rceil, r\}$. Even though we observe prevalent underbidding, 92% of the bids that are too low yielded the same payoff to the consumer as bidding one's value would have, making it difficult for

[26] The shares of best responses and overbidding are relatively constant, while the share of underbidding decreases over time. The respective shares are 64%, 30% and 7% (in rounds 1-15), 61%, 36% and 4% (in rounds 16-30) and 66%, 31% and 3% (in rounds 31-45).

underbidding consumers to realize their mistakes.[27]

Figure 4.A2: Consumer Behavior in sGMS



Notes: The figure depicts the frequency of bid-value combinations in sGMS split by cost levels C. The larger the dot, the more frequent a bid-value combination occurred. Gray dots denote weakly dominant bids. Black dots denote weakly dominated bids.

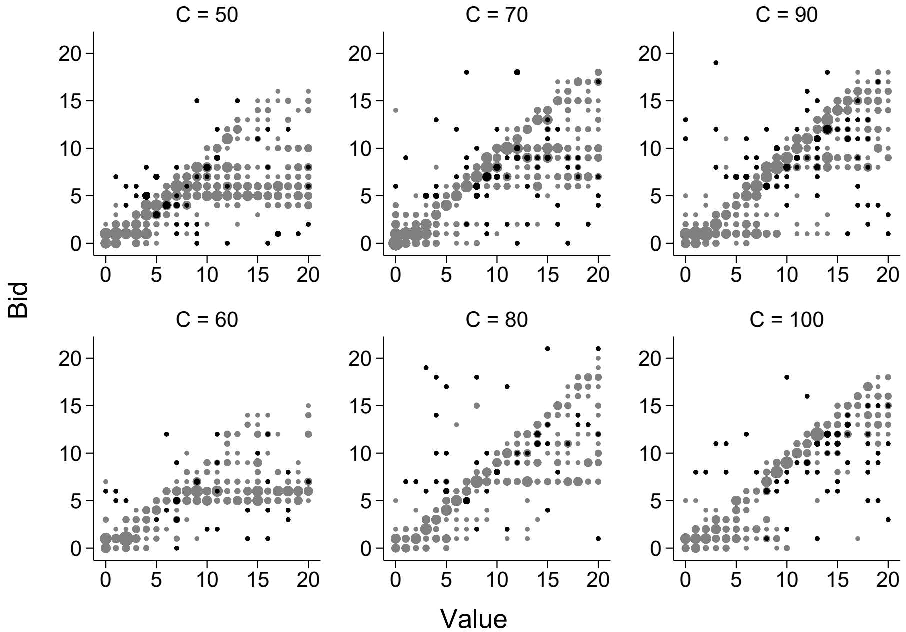
As theory predicts that consumers should bid their value irrespective of the threshold and reservation price, we can easily compare consumer behavior in active producer sessions with behavior in automated producer sessions. In automated producer sessions, consumers bid very similarly; 73% of the bids are weakly dominant, 20% are too low and 7% are too high (cf. Section 3.5.3.2 in the previous chapter). The difference in weakly dominant bids is not significant ($p = 0.375$). As consumer behavior in sGMS is very

[27]There is some learning by consumers at the beginning of the experiment. The frequency of underbidding drops from 34% to 23% to 22% from rounds 1 to 15, 16 to 30 and 31 to 45. In contrast, the frequency of overbidding stays almost constant at 7%, 8% and 9%.

similar in sessions with an active and automated producer, differences in the performance outcome are due to distinct producer behavior.

dGMS. Figure 4.A3 depicts consumer behavior in dGMS. The size of the dots denotes the frequency of bid-value combinations. Gray dots represent possibly weakly dominant bids. Black dots represent surely weakly dominated bids. The reason why gray dots indicate only possibly weakly dominant bids is because one cannot determine exactly what a remaining consumer would have bid when the ascending clock has stopped at a price below or equal to the consumer's value.

Figure 4.A3: Consumer Behavior in dGMS



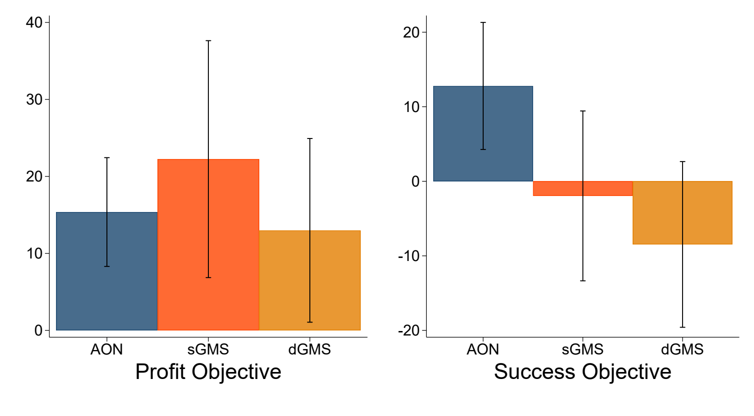
Notes: The figure depicts the frequency of bid-value combinations in dGMS split by cost levels C. The larger the dot, the more frequent a bid-value combination occurred. Gray dots denote possibly weakly dominant bids. Black dots denote surely weakly dominated bids. The reason why gray dots are only 'possibly' weakly dominant is explained in the main text.

We observe that the dots are predominantly gray. In total, 88% of the bids are in line with a weakly dominant strategy. There is significantly more underbidding than overbidding (9% vs. 3%, $p = 0.031$ in a paired Fisher-Pitman permutation test).[28] The dynamic aspect of dGMS prevents a straightforward comparison of consumer behavior in dGMS and sGMS. In order to compare the two versions of the GMS, we need to dynamize the bidding process in sGMS. We can construct counterfactual bids in sGMS by assuming that consumers' bids indicate the maximum price at which consumers would still be willing to remain in the market before dropping out. Doing so, we obtain that 85% of the counterfactual bids are possibly weakly dominant, while 10% of these bids are too low and 5% too high. As the share in possibly weakly dominant bids is not significantly different in dGMS and the dynamized sGMS ($p = 0.531$), the obvious strategy-proofness of dGMS does not noticeably help consumers to bid better in sessions with active producers. This is in contrast to sessions with automated producers, in which consumers choose possibly weakly dominant bids significantly more often in dGMS than in the dynamized sGMS (cf. Section 3.5.3.3 in the previous chapter; $p = 0.031$). Recall that there was no significant difference in consumer behavior in sGMS between sessions with an active and automated producer. This result does not carry over to dGMS. In sessions with automated producers, 92% of the bids are in line with a weakly dominant strategy, only 4% are too low and 4% are too high. The difference in underbidding between sessions with an active and automated producer in dGMS is significant ($p = 0.031$).

[28] Similar to sGMS, the share of underbidding in dGMS decreases over time from 15% (rounds 1-15) to 10% (rounds 16-30) to 8% (rounds 31-45), while the share of overbidding hardly changes at 5%, 3% and 4%.

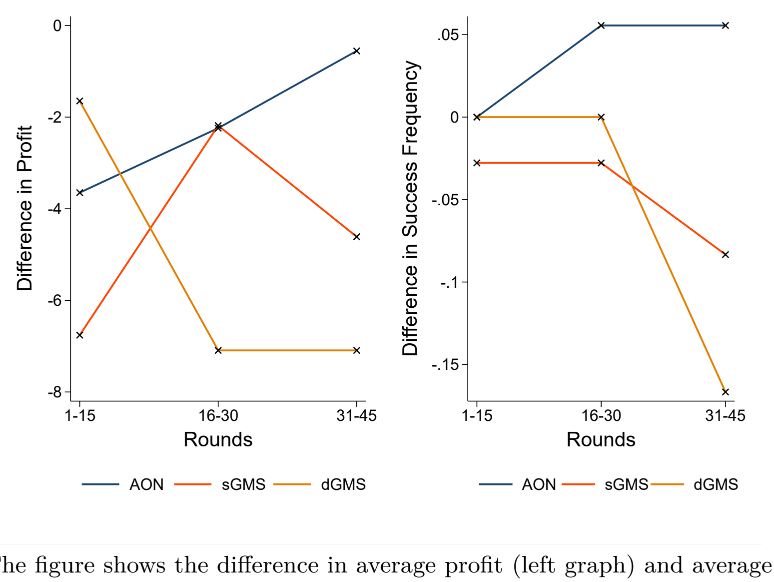
4.B Additional Tables and Figures

Figure 4.B1: Difference in Consumer Welfare



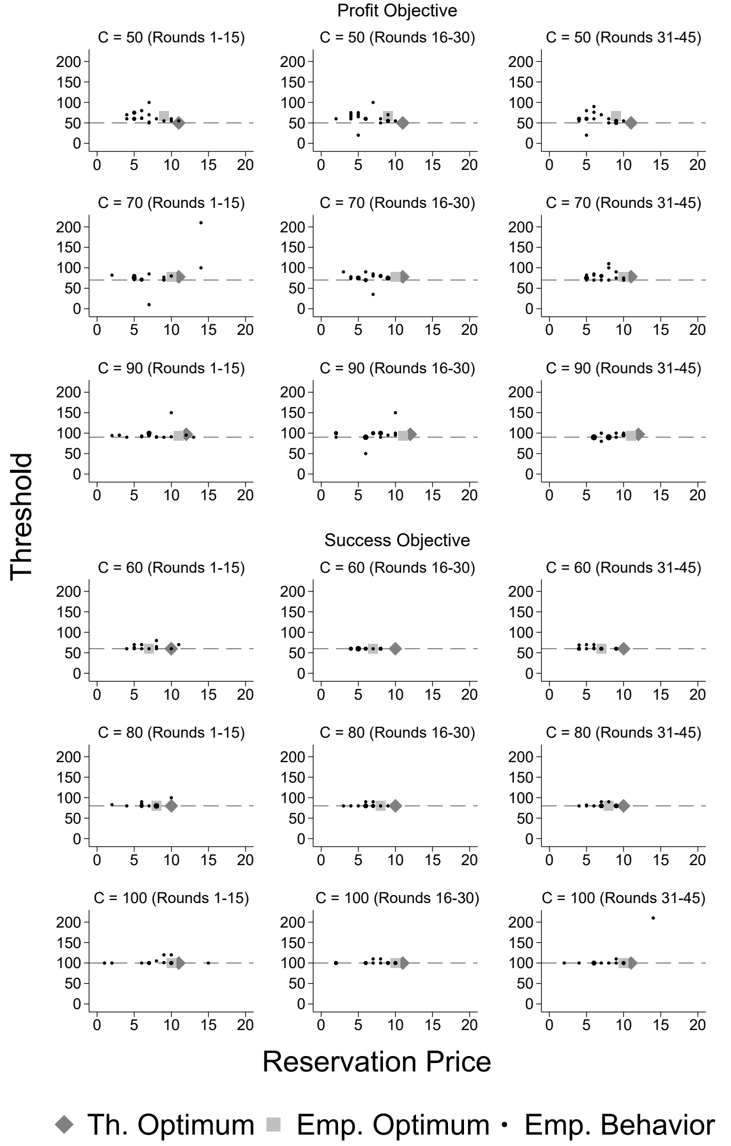
Notes: The figure shows the difference in consumer welfare between sessions with an active and an automated producer in AON, sGMS and dGMS under a profit (left graph) and success objective (right graph). Error bars indicate ninety-five percent confidence intervals.

Figure 4.B2: Difference in Profit and Success Frequency over Time



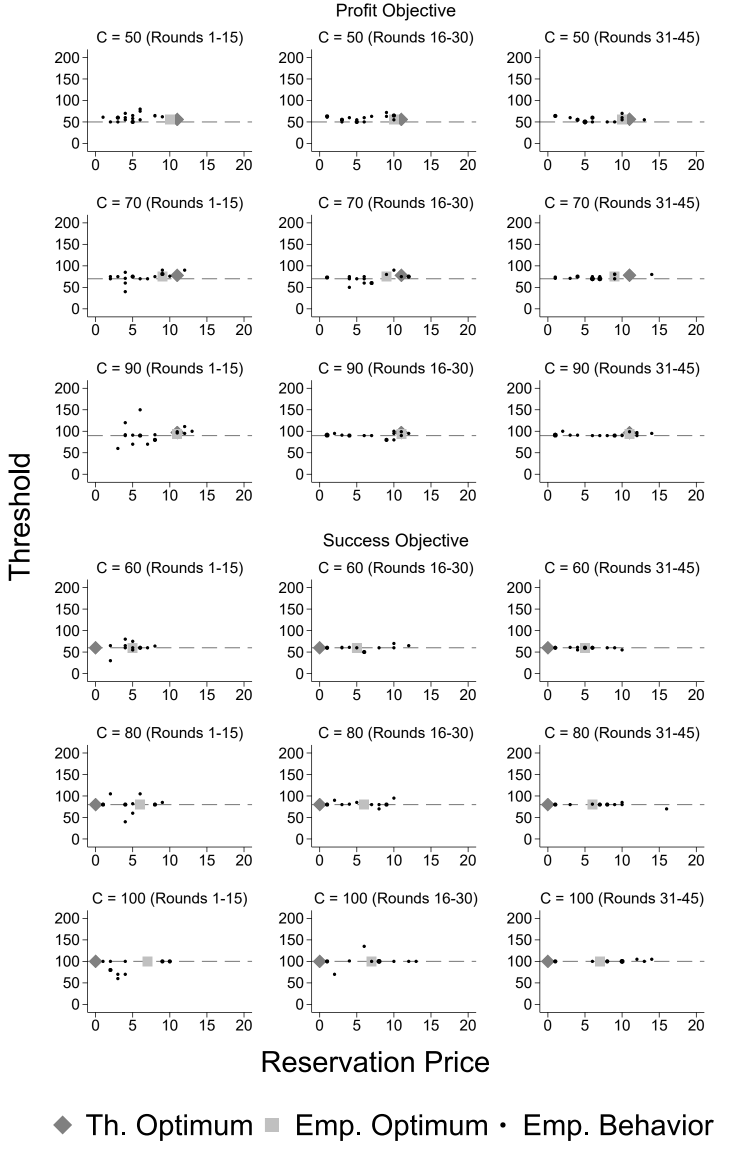
Notes: The figure shows the difference in average profit (left graph) and average success frequency (right graph) of sessions with an active and an automated producer in AON, sGMS and dGMS, split by rounds.

Figure 4.B3: Producer Behavior in AON over Time



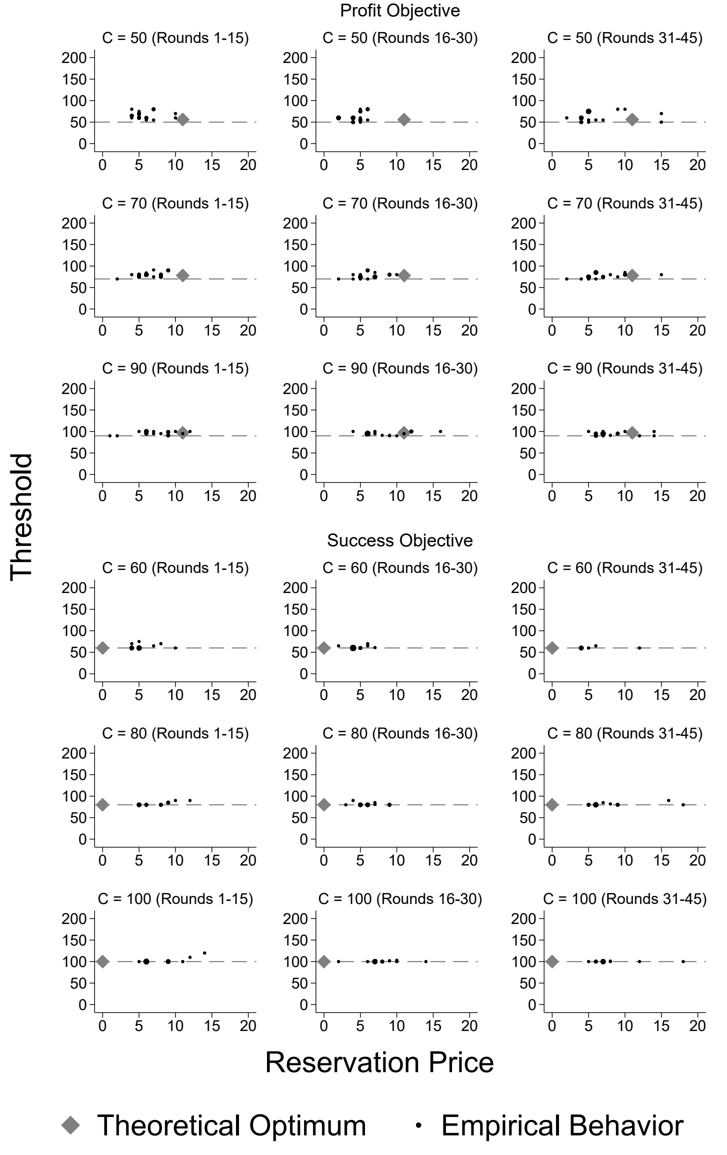
Notes: The figure depicts the frequency of threshold (vertical axis) and reservation price (horizontal axis) combinations set by the producers in AON depending on the project costs C, split by rounds. The larger a black dot, the more frequent a combination occurred in the experiment. Dark gray diamonds denote equilibrium producer behavior. Light gray squares denote empirically optimal producer behavior in response to bids predicted by eq. (4.1).

Figure 4.B4: Producer Behavior in sGMS over Time



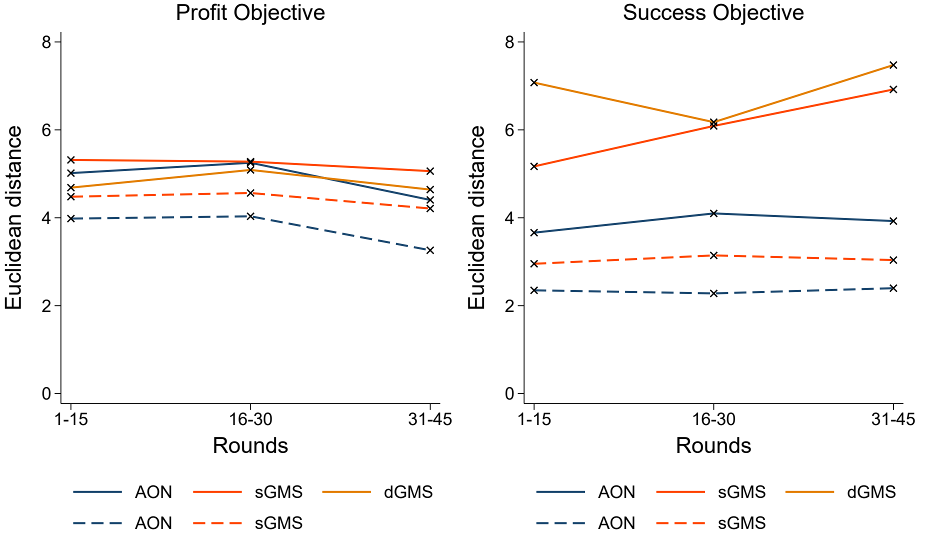
Notes: The figure depicts the frequency of threshold (vertical axis) and reservation price (horizontal axis) combinations set by the producers in sGMS depending on the project costs C, split by rounds. The larger a black dot, the more frequent a combination occurred in the experiment. Dark gray diamonds denote equilibrium producer behavior. Light gray squares denote empirically optimal producer behavior in response to bids predicted by eq. (4.1).

Figure 4.B5: Producer Behavior in dGMS over Time



Notes: The figure depicts the frequency of threshold (vertical axis) and reservation price (horizontal axis) combinations set by the producers in dGMS depending on the project costs C, split by rounds. The larger a black dot, the more frequent a combination occurred in the experiment. Dark gray diamonds denote equilibrium producer behavior.

Figure 4.B6: Quality of Producer Decisions over Time



Notes: The figure depicts the average Euclidean distance from threshold and reservation price combinations to the theoretical optimum (solid line) and empirical optimum (dashed line) in the AON, sGMS and dGMS under a profit (left panel) and success objective (right panel), split by rounds. The Euclidean distance is computed as $D_i = \sqrt{(r_i - r^*)^2 + \left(\frac{T_i - T^*}{10}\right)^2}$ where r_i and T_i denote a producer's decision and r^* and T^* denote the theoretical resp. empirical optimum as depicted in Tables 4.3, 4.4 and 4.5.

4.C Simulations

Table 4.C1: Estimated Empirical Bidding Function in AON

	$v < r$	$v = r$	$v > r$
v	0.0406**		0.3171***
	(0.0187)		(0.0182)
T	0.0015	0.0200	0.0716***
	(0.0040)	(0.0475)	(0.0235)
T^2	-0.0000	0.0000	-0.0003*
	(0.0000)	(0.0003)	(0.0002)
r	0.0126	0.6265	0.1728
	(0.1312)	(0.8371)	(0.1963)
r^2	-0.0003	-0.0017	0.0254*
	(0.0115)	(0.0758)	(0.0137)
Constant	-0.1472	-2.1517	-2.3421**
	(0.3115)	(2.4708)	(1.0024)
Observations	848	131	1721
R^2	0.015	0.162	0.578

Notes: The table shows OLS estimates for the empirical bidding function in AON. The dependent variable is the stated bid. The independent variables are value v, threshold T, the square of the threshold T^2, reservation price r and the square of the reservation price r^2. Robust standard errors clustered on the individual level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.C2: Estimated Empirical Bidding Function in sGMS

	$v < r$	$v = r$	$v > r$
v	0.5153***		0.7777***
	(0.0770)		(0.0468)
T	0.0197	0.0100	0.0770*
	(0.0519)	(0.2152)	(0.0430)
T^2	-0.0001	-0.0001	-0.0004
	(0.0003)	(0.0014)	(0.0003)
r	-0.1775	0.0262	0.1746
	(0.1743)	(0.4101)	(0.2428)
r^2	0.0078	0.0379	-0.0088
	(0.0113)	(0.0339)	(0.0172)
Constant	0.1829	1.7988	-3.1694*
	(2.0645)	(8.0617)	(1.7601)
Observations	813	119	1768
R^2	0.182	0.209	0.539

Notes: The table shows OLS estimates for the empirical bidding function in sGMS. The dependent variable is the stated bid. The independent variables are value v, threshold T, the square of the threshold T^2, reservation price r and the square of the reservation price r^2. Robust standard errors clustered on the individual level are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The following algorithms were used to obtain the empirical optima in AON and sGMS.

AON:

1. Specify the number of consumers $N = 15$, project costs $C \in \{50, 60, \ldots, 100\}$, and number of simulations S. Set threshold $T = 0$, and reservation price $r = 0$. Set the candidate price $p = r$. Set simulation $s = 1$. Draw a matrix of $N \times S$ with i.i.d. values from a discrete uniform distribution $\{0, 1, \ldots, 19, 20\}$. Denote this matrix by v.

2. Create a bidding matrix called b of $N \times S$ according to the estimated bidding function in Table 4.C1 using r, T and v.

3. If $s > S$, set $s = 1$ and skip to step 4. If $s \leq S$, create a scalar X by summing up the elements of column s in b. Compare X with T. If $X < T$, set elements

$Profit_s = 0$ and $Success_s = 0$. Set $s = s + 1$, and repeat step 3. If $X \geq T$, set element $Profit_s = X - C$. Set $Success_s = 0$ if $X < C$ and $Success_s = 1$ if $X \geq C$. Then set $s = s + 1$, and repeat step 3.

4. Update elements $Meanprofit_{rT}$ and $Meansuccess_{rT}$ by taking the mean of *Profit* and *Success* respectively. If $T < 300$ & $r < 20$, set $T = T + 1$ and proceed with step 2. If $T \geq 300$ & $r < 20$, set $T = 0$ and $r = r + 1$, and proceed with step 2. If $r \geq 20$, proceed with step 5.

5. Determine the maximal elements of *Meanprofit* and *Meansuccess* and their corresponding r^* and T^*.

GMS:

1. Specify the number of consumers $N = 15$, project costs $C \in \{50, 60, \ldots, 100\}$, and number of simulations S. Set threshold $T = 0$, and reservation price $r = 0$. Set the candidate price $p = r$. Set simulation $s = 1$. Draw a matrix of $N \times S$ with i.i.d. values from a discrete uniform distribution $\{0, 1, \ldots, 19, 20\}$. Denote this matrix by v.

2. Create a bidding matrix called b of $N \times S$ according to the estimated bidding function in Table 4.C2 using r, T and v.

3. If $s > S$, set $s = 1$ and skip to step 4. If $s \leq S$, create a scalar X by multiplying p with the sum of elements of column s in b that are weakly above p. Compare X with T. If $X < T$ & $p \leq 20$, set $p = p + 1$ and repeat step 3. If $X < T$ & $p > 20$, set elements $Profit_s = 0$ and $Success_s = 0$. Then set $p = r$ and $s = s + 1$, and repeat step 3. If $X \geq T$, set element $Profit_s = X - C$. Set $Success_s = 0$ if $X < C$ and $Success_s = 1$ if $X \geq C$. Then set $p = r$ and $s = s + 1$, and repeat step 3.

4. Update elements $Meanprofit_{rT}$ and $Meansuccess_{rT}$ by taking the mean of *Profit* and *Success* respectively. If $T < 300$ & $r < 20$, set $T = T + 1$ and proceed with step 2. If $T \geq 300$ & $r < 20$, set $T = 0$ and $r = r + 1$, and proceed with step 2. If $r \geq 20$, proceed with step 5.

5. Determine the maximal elements of *Meanprofit* and *Meansuccess* and their corresponding r^* and T^*.

4.D Instructions

4.D.1 AON

Instructions:

A summary of these instructions on paper will be distributed before the experiment starts. Welcome to this experiment on decision making. The instructions for this experiment are simple, and if you follow them carefully, you can earn a considerable amount of money. What you earn depends on the decisions you make and on the decisions of the others. You will be privately paid at the end of the experiment. We ask that you do not communicate with other people during the experiment. Please refrain from verbally reacting to events that occur during the experiment. This is very important. Raise your hand when you have a question and one of the experimenters will come to your table.

These instructions consist of eight pages like this. You may page back and forth by using your mouse to click on "previous page" or "next page" at the bottom of your screen. On the last instruction page you will see the button "ready" at the bottom of your screen. Click this button if you have completely finished with all pages of the instructions.

<u>Producer and Consumers:</u> In this experiment you will be assigned the role of either the producer of a good or a consumer. The payoffs that you obtain during the experiment determine the money that you will receive at the end. Earnings in the experiment will be denoted by "francs". At the end of the experiment, francs will be exchanged for euros. The exchange rate is 1 euro for every 8 francs. We will give you a number of francs to start with. This starting capital equals 56 francs (or 7 euros).

<u>Rounds:</u> Today's experiment consists of 45 rounds. In each round, a producer decides whether or not to produce a fictitious good and sell it to consumers. In the experiment, you will either be producer or consumer. One participant plays the role of producer. The producer can produce a fictitious good that is valuable for the consumers. The 15 other participants play the role of consumer. The producer can only produce the good if she raises sufficient funds to cover her production costs. The producer's production costs are fixed: They do not depend on the

number of goods sold. Moreover, only the producer is informed about her costs. The consumers do not know the producer's costs. The producer's costs may vary from one round to the next. The consumers interact in a market. In this market, it is determined whether the producer actually produces the good. Moreover, if the good is produced, the market determines which consumers buy the good and for what price.

The Value of the Good: The value of the fictitious good will typically differ from one consumer to the next. To be more precise, in every round, the computer will draw a new value for every consumer. Values are randomly drawn from the set 0,1,2,. . . ,19,20. Note the following about the value for the good:

1. The value for a consumer is determined independently of the values for the other consumers;
2. Any value in the set {0,1,2,. . . ,19,20} is equally likely;
3. Each consumer only learns her own value, not the value of the other consumers;
4. The producer is not informed about the values of any of the consumers.

The Market: At the start of a round, the producer is informed about her or his costs and all consumers are told their value. The producer then decides on a target amount and a minimum price. In each period, all consumers offer a price to the producer. The prices that consumers offer may differ from one consumer to another. Consumers can only obtain the good if they offer a price equal to or higher than the minimum price. After all offers have been received, the computer determines whether the producer will actually produce the good. More in particular, the computer adds up all offers. The producer will produce the good if the sum of these offers is equal to or higher than the target amount. If the good is produced, all consumers pay the price they offered. All consumers who offered at least the minimum price obtain the good. Consumers who offered less, do not obtain the good but still pay the price they offered. If the sum of offers is lower than the target amount, the good is not produced. Consumers do not obtain the good and make no payments.

Example: To illustrate the market, suppose the target amount equals 85 and the minimum price is 7. The consumers' offers are

$$0 - 0 - 0 - 1 - 2 - 7 - 7 - 7 - 8 - 8 - 9 - 9 - 10 - 11 - 12$$

The sum of the offers equals 91. Because the target amount is reached, the good will be produced. All 15 consumers pay the price they offered and the 10 consumers who offered at least 7 also obtain the good. The consumers who offered 1 and 2 do not obtain the good but still pay the price they offered.

Producer Payoffs: The way the producer's payoffs are determined varies from one round to the next. In some rounds, the producer's payoffs are determined by her profits (Objective: Profit). The producer then obtains one fifth, i.e. 20%, of the realized profits. The profits are determined as the difference between the sum of consumers' payments and the production costs of the given round. If the good is produced, the producer's payoffs thus are:

$$(\textit{Producer payoffs}) = 20\% * [(\textit{Sum of the consumer payments}) - (\textit{Production costs})]$$

If the good is not produced, the producer obtains zero payoffs. In the other rounds, the producer's payoffs are determined by whether the producer was successful in raising sufficient funds to cover her production costs (Objective: Success). The producer obtains 3 francs if the good is produced and the sum of the consumer payments is equal to or higher than the costs of producing the good. Otherwise the producer obtains zero payoffs. The producer is informed about her objective in the given round. The consumers are not informed about the producer's objective. If you happen to be assigned the role of producer, make sure to pay attention to how the producer's payoffs are determined for the round you are currently playing!

Consumer Payoffs: In every round, the payoffs for the consumers are as follows. If the good is produced and a consumer obtains the good in a given round, her payoffs in that round are:

$$(\textit{Consumer payoffs}) = (\textit{Own value for the good}) - (\textit{Own offer})$$

If the good is produced but the consumer does not obtain the good in a given round, her earnings for that round are:

$$(Consumer\ payoffs) = -(Own\ offer)$$

If the good is not produced in a given round, a consumer's earnings for that round are zero.

Comprehension Questions:
You will now be asked several example questions. Their purpose is to check for your understanding of the game. Note that the parameters used in the following example questions are not representative!

- If the good is produced, do all consumers who obtain the good pay the same price? (yes; no)
- If the good is produced, is it possible that any of the consumers pay more than their offer? (yes; no)
- [Target Amount: 65, Minimum Price: 8, Own value: 13, Own offer: 9, Sum of offers of other consumers: 60] Assume that you are a consumer. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 75, Minimum Price: 14, Own value: 19, Own offer: 17, Sum of offers of other consumers: 55] Assume that you are a consumer. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 45, Minimum Price: 5, Own value: 7, Own offer: 2, Sum of offers of other consumers: 48] Assume that you are a consumer. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 55, Minimum Price: 10, Own value: 9, Own offer: 8, Sum of offers of other consumers: 42] Assume that you are a consumer. There are 14 other consumers. Given the information in the table above, how many francs would you earn?

- [Costs: 74, Objective: Success, Target Amount: 80, Minimum Price: 9, Sum of all offers: 80] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 72, Objective: Success, Target Amount: 62, Minimum Price: 13, Sum of all offers: 70] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 45, Objective: Profit, Target Amount: 54, Minimum Price: 8, Sum of all offers: 55] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 67, Objective: Profit, Target Amount: 60, Minimum Price: 5, Sum of all offers: 62] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?

Intuition Questions:
You will now be asked some more example questions. Their purpose is to let you develop an intuition for how to play the game before we start with the real rounds. Note that the parameters used in the following example questions are not representative.

- [Target Amount: 45, Minimum Price: 7, Own value: X[29]] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?
- [Target Amount: 65, Minimum Price: 4, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?
- [Target Amount: 85, Minimum Price: 12, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?
- [Target Amount: 105, Minimum Price: 9, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?

[29] X indicates a random value drawn from the discrete uniform distribution $\{0,1,2,\ldots,19,20\}$.

- [Costs: 55, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 21, Minimum Price = 5; Target Amount = 50, Minimum Price = 5; Target Amount = 56, Minimum Price = 1; *Target Amount = 60, Minimum Price = 10*)[30]
- [Costs: 75, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 70, Minimum Price = 7; *Target Amount = 78, Minimum Price = 12*; Target Amount = 81, Minimum Price = 3; Target Amount = 98, Minimum Price = 16)
- [Costs: 65, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 0, Minimum Price = 4; *Target Amount = 65, Minimum Price = 8*; Target Amount = 66, Minimum Price = 0; Target Amount = 75, Minimum Price = 2)
- [Costs: 85, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 75, Minimum Price = 6; Target Amount = 90, Minimum Price = 4; *Target Amount = 91, Minimum Price = 11*; Target Amount = 91, Minimum Price = 17)

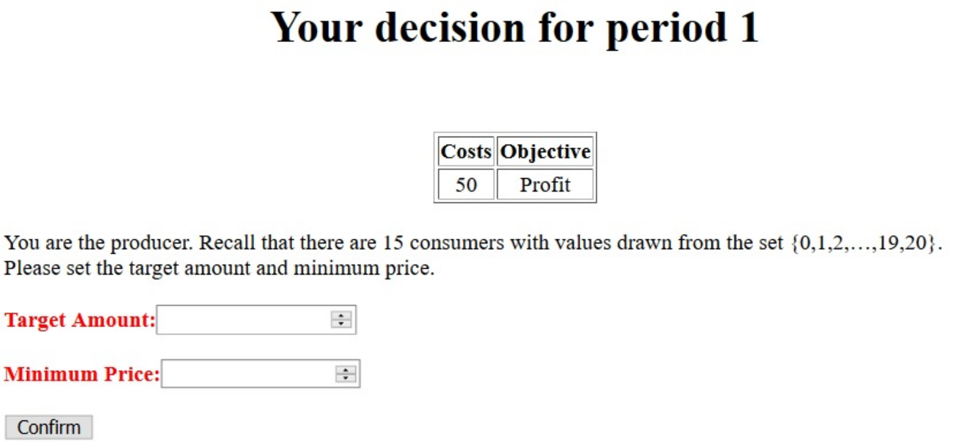
We will continue when everybody has finished reading the instructions and has answered all example questions.

You will now be assigned the role of the producer or of a consumer.

You are assigned the role of [the producer / a consumer].

[30] Italic answers indicate ‘correct’ answers.

Figure 4.D1: Producer's Decision Screen in AON



Your decision for period 1

Costs	Objective
50	Profit

You are the producer. Recall that there are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Please set the target amount and minimum price.

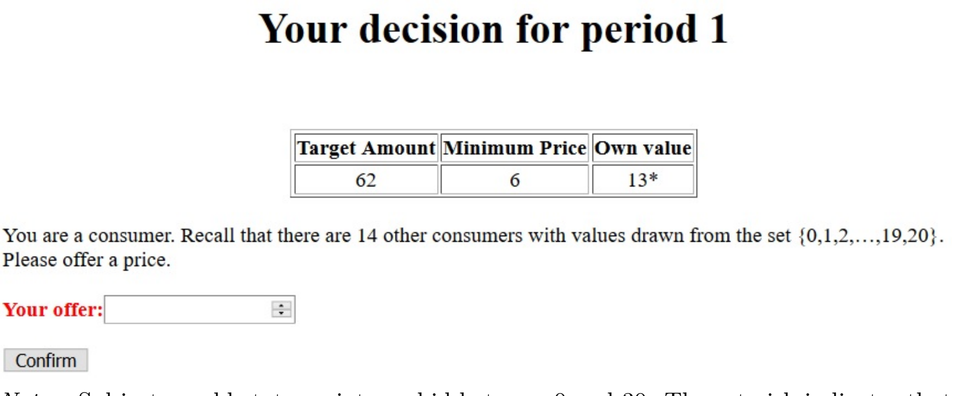
Target Amount:

Minimum Price:

Confirm

Notes: Subjects could state an integer target amount between 0 and 300 and an integer minimum price between 0 and 30.

Figure 4.D2: Consumers' Decision Screen in AON



Your decision for period 1

Target Amount	Minimum Price	Own value
62	6	13*

You are a consumer. Recall that there are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. Please offer a price.

Your offer:

Confirm

Notes: Subjects could state an integer bid between 0 and 30. The asterisk indicates that values were drawn randomly; the asterisk was not shown to subjects.

Questionnaire:

Please fill in this short questionnaire.

- Age: (positive integers)
- Gender: (Male, Female)

- I study at (UvA – Economics and Business; UvA – Social Sciences, Psychology; UvA – Social Sciences, not Psychology; UvA – Science; UvA – IIS, beta gamma bachelor; UvA – Law School; UvA – Humanities; UvA – Medical School; UvA – Dentistry; Another university; A professional school; Otherwise)
- How often have you participated in a crowdfunding campaign? (Never; One time; Two times; Three or more times)
- What strategy did you play?
- What is your feeling towards the other players?
- How fair do you rate the crowdfunding mechanism? (very unfair (1), (2), (3), (4), very fair (5)))
- Do you have any other comments?

4.D.2 sGMS

Instructions:
A summary of these instructions on paper will be distributed before the experiment starts. Welcome to this experiment on decision making. The instructions for this experiment are simple, and if you follow them carefully, you can earn a considerable amount of money. What you earn depends on the decisions you make and on the decisions of the others. You will be privately paid at the end of the experiment. We ask that you do not communicate with other people during the experiment. Please refrain from verbally reacting to events that occur during the experiment. This is very important. Raise your hand when you have a question and one of the experimenters will come to your table.

These instructions consist of eight pages like this. You may page back and forth by using your mouse to click on "previous page" or "next page" at the bottom of your screen. On the last instruction page you will see the button "ready" at the bottom of your screen. Click this button if you have completely finished with all pages of the instructions.

<u>Producer and Consumers:</u> In this experiment you will be assigned the role of either the producer of a good or a consumer. The payoffs that you obtain during the

experiment determine the money that you will receive at the end. Earnings in the experiment will be denoted by "francs". At the end of the experiment, francs will be exchanged for euros. The exchange rate is 1 euro for every 8 francs. We will give you a number of francs to start with. This starting capital equals 56 francs (or 7 euros).

Rounds: Today's experiment consists of 45 rounds. In each round, a producer decides whether or not to produce a fictitious good and sell it to consumers. In the experiment, you will either be producer or consumer. One participant plays the role of producer. The producer can produce a fictitious good that is valuable for the consumers. The 15 other participants play the role of consumer. The producer can only produce the good if she raises sufficient funds to cover her production costs. The producer's production costs are fixed: They do not depend on the number of goods sold. Moreover, only the producer is informed about her costs. The consumers do not know the producer's costs. The producer's costs may vary from one round to the next. The consumers interact in a market. In this market, it is determined whether the producer actually produces the good. Moreover, if the good is produced, the market determines which consumers buy the good and for what price.

The Value of the Good: The value of the fictitious good will typically differ from one consumer to the next. To be more precise, in every round, the computer will draw a new value for every consumer. Values are randomly drawn from the set 0,1,2,...,19,20. Note the following about the value for the good:

1. The value for a consumer is determined independently of the values for the other consumers;
2. Any value in the set $\{0,1,2,\ldots,19,20\}$ is equally likely;
3. Each consumer only learns her own value, not the value of the other consumers;
4. The producer is not informed about the values of any of the consumers.

The Market: At the start of a round, the producer is informed about her or his costs and all consumers are told their value. The producer then decides on a target amount and a minimum price. In each round, all consumers are asked to state their highest acceptable price. We call this the ‘maximum offer’ because any consumer may end up receiving the good at a lower price than her or his highest acceptable price. The maximum offers may differ from one consumer to another. Consumers can only obtain the good if their maximum offer is equal to or higher than the minimum price. After all maximum offers have been received, the computer determines whether the producer will actually produce the good and if so, at what price it will be sold. If the good is produced, all consumers who obtain the good pay the same price. More precisely, the computer raises the price step by step, starting from the minimum price, up to the point that the price is sufficiently high to meet the target amount. This is determined as follows.

> STEP 0: Start with a ‘candidate price’ that is equal to this round’s minimum price.
>
> STEP 1: Compute the producer’s revenue at the candidate price: Determine how many consumers’ maximum offers are equal to or higher than the candidate price. Calculate how much revenue this candidate price would raise by multiplying the candidate price with the number of consumers whose maximum offers are equal to or higher than the candidate price.
>
> STEP 2: Compare the producer’s revenue calculated in STEP 1 with the target amount.
>
> - If the producer’s revenue is equal to or higher than the target amount, proceed to STEP 3.
> - If the producer’s revenue is lower than the target amount, increase the candidate price by one. If the new candidate price is higher than the highest maximum offer, the good is not produced. Otherwise, go back to STEP 1.
>
> STEP 3: The good is produced. All consumers whose maximum offers are equal to or higher than the current price obtain the good and pay this price to the producer. All other consumers do not obtain the good and pay zero.

Note that no consumer will ever pay more than her or his maximum offer, but will often pay less.

Example: To illustrate the market, suppose the target amount equals 85 and the minimum price is 7. The consumers' offers are:

0 – 2 – 2 – 4 – 5 – 6 – 7 – 8 – 14 – 14 – 17 – 18 – 18 – 19 – 20

The first candidate price is 7, the minimum price. Multiplying the candidate price (7) by the number of offers that are equal to 7 or higher (9) yields 63. This result is lower than the target amount of 85, so that the candidate price is increased by one. Multiplying the new candidate price (8) by the number of offers that are equal to 8 or higher (8) yields 64. This result is again lower than the target amount of 85 so that again the candidate price is increased by one. Sequentially checking for candidate prices of 9, 10, 11 and 12 also yields results that are lower than the target amount of 85. However, multiplying a candidate price of 13 by the number of offers that are equal to 9 or higher (7) yields 91. As this result is higher than the target amount of 85, the good is produced. The 7 consumers whose offers are equal to 13 or higher obtain the good and all pay a price of 13. The other consumers do not obtain the good and pay zero. The sum of consumer payments is thus 91.

Producer Payoffs: The way the producer's payoffs are determined varies from one round to the next. In some rounds, the producer's payoffs are determined by her profits (Objective: Profit). The producer then obtains one fifth, i.e. 20%, of the realized profits. The profits are determined as the difference between the sum of consumers' payments and the production costs of the given round. If the good is produced, the producer's payoffs thus are:

$$(\textit{Producer payoffs}) = 20\% * [(\textit{Sum of the consumer payments}) - (\textit{Production costs})]$$

If the good is not produced, the producer obtains zero payoffs. In the other rounds, the producer's payoffs are determined by whether the producer was successful in raising sufficient funds to cover her production costs (Objective: Success). The producer obtains 3 francs if the good is produced and the sum of the consumer payments is equal to or higher than the costs of producing the good. Otherwise the producer obtains zero payoffs. The producer is informed about her objective in the given round. The consumers are not informed about the producer's objective. If you happen to be assigned the role of producer, make sure to pay attention to how the producer's payoffs are determined for the round you are currently playing!

Consumer Payoffs: In every round, the payoffs for the consumers are as follows. If a consumer obtains the good in a round, her payoffs in that round are:

$$(\textit{Consumer payoffs}) = (\textit{Own value for the good}) - (\textit{Price paid})$$

If a consumer does not obtain the good in a round, her earnings for that round are zero.

Comprehension Questions:

You will now be asked several example questions. Their purpose is to check for your understanding of the game. Note that the parameters used in the following example questions are not representative!

- If the good is produced, do all consumers who obtain the good pay the same price? (yes; no)
- If the good is produced, is it possible that any of the consumers pay more than their offer? (yes; no)
- [Target Amount: 40, Minimum Price: 2, Own value: 12, Offers of all consumers: 0–0–0–0–0–4–4–4–4–4–10–10–10–10–10] Assume that you are one of the consumers who made an offer of 4. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 6, Own value: 12, Offers of all consumers: 0–0–0–0–0–4–4–4–4–4–10–10–10–10–10] Assume that you are one of the consumers who made an offer of 4. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 2, Own value: 12, Offers of all consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are one of the consumers who made an offer of 10. There are 14 other consumers. Given the information in the table above, how many francs would you earn?

- [Target Amount: 40, Minimum Price: 6, Own value: 12, Offers of all consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are one of the consumers who made an offer of 10. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 30, Objective: Success, Target Amount: 40, Minimum Price: 2, Offers of consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 45, Objective: Success, Target Amount: 40, Minimum Price: 2, Offers of consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 30, Objective: Profit, Target Amount: 40, Minimum Price: 2, Offers of consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 45, Objective: Profit, Target Amount: 40, Minimum Price: 2, Offers of consumers: 0 – 0 – 0 – 0 – 0 – 4 – 4 – 4 – 4 – 4 – 10 – 10 – 10 – 10 – 10] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?

Intuition Questions:
You will now be asked some more example questions. Their purpose is to let you develop an intuition for how to play the game before we start with the real rounds. Note that the parameters used in the following example questions are not representative.

- [Target Amount: 45, Minimum Price: 7, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?
- [Target Amount: 65, Minimum Price: 4, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?

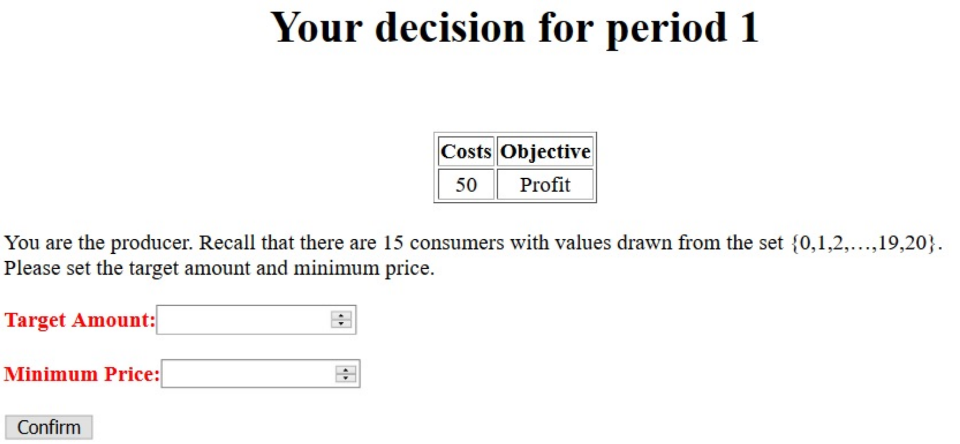
- [Target Amount: 85, Minimum Price: 12, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?
- [Target Amount: 105, Minimum Price: 9, Own value: X] Assume that you are a consumer. There are 14 other consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. What price would you offer?
- [Costs: 55, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. Which of the following four options would you choose? (Target Amount = 50, Minimum Price = 5; Target Amount = 55, Minimum Price = 3; *Target Amount = 71, Minimum Price = 10*; Target Amount = 90, Minimum Price = 16)
- [Costs: 75, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. Which of the following four options would you choose? (Target Amount = 38, Minimum Price = 13; Target Amount = 70, Minimum Price = 7; Target Amount = 72, Minimum Price = 2; *Target Amount = 84, Minimum Price = 12*)
- [Costs: 65, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. Which of the following four options would you choose? (Target Amount = 30, Minimum Price = 5; Target Amount = 60, Minimum Price = 4; *Target Amount = 67, Minimum Price = 8*; Target Amount = 111, Minimum Price = 1)
- [Costs: 85, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set $\{0,1,2,\ldots,19,20\}$. Which of the following four options would you choose? (Target Amount = 78, Minimum Price = 0; Target Amount = 86, Minimum Price = 17; *Target Amount = 89, Minimum Price = 6*; Target Amount = 103, Minimum Price = 14)

We will continue when everybody has finished reading the instructions and has answered all example questions.

You will now be assigned the role of the producer or of a consumer.

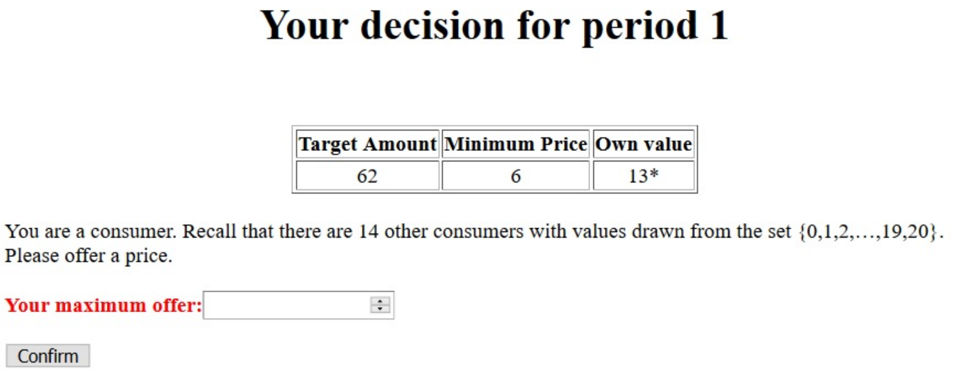
You are assigned the role of [the producer / a consumer].

Figure 4.D3: Producer's Decision Screen in sGMS



Notes: Subjects could state an integer target amount between 0 and 300 and an integer minimum price between 0 and 30.

Figure 4.D4: Consumers' Decision Screen in sGMS



Notes: Subjects could state an integer bid between 0 and 30. The asterisk indicates that values were drawn randomly; the asterisk was not shown to subjects.

Questionnaire:

Please fill in this short questionnaire.

- Age: (positive integers)
- Gender: (Male, Female)

- I study at (UvA – Economics and Business; UvA – Social Sciences, Psychology; UvA – Social Sciences, not Psychology; UvA – Science; UvA – IIS, beta gamma bachelor; UvA – Law School; UvA – Humanities; UvA – Medical School; UvA – Dentistry; Another university; A professional school; Otherwise)
- How often have you participated in a crowdfunding campaign? (Never; One time; Two times; Three or more times)
- What strategy did you play?
- What is your feeling towards the other players?
- How fair do you rate the crowdfunding mechanism? (very unfair (1), (2), (3), (4), very fair (5)))
- Do you have any other comments?

4.D.3 dGMS

Instructions:
A summary of these instructions on paper will be distributed before the experiment starts. Welcome to this experiment on decision making. The instructions for this experiment are simple, and if you follow them carefully, you can earn a considerable amount of money. What you earn depends on the decisions you make and on the decisions of the others. You will be privately paid at the end of the experiment. We ask that you do not communicate with other people during the experiment. Please refrain from verbally reacting to events that occur during the experiment. This is very important. Raise your hand when you have a question and one of the experimenters will come to your table.

These instructions consist of eight pages like this. You may page back and forth by using your mouse to click on "previous page" or "next page" at the bottom of your screen. On the last instruction page you will see the button "ready" at the bottom of your screen. Click this button if you have completely finished with all pages of the instructions.

<u>Producer and Consumers:</u> In this experiment you will be assigned the role of either the producer of a good or a consumer. The payoffs that you obtain during the

experiment determine the money that you will receive at the end. Earnings in the experiment will be denoted by "francs". At the end of the experiment, francs will be exchanged for euros. The exchange rate is 1 euro for every 8 francs. We will give you a number of francs to start with. This starting capital equals 56 francs (or 7 euros).

Rounds: Today's experiment consists of 45 rounds. In each round, a producer decides whether or not to produce a fictitious good and sell it to consumers. In the experiment, you will either be producer or consumer. One participant plays the role of producer. The producer can produce a fictitious good that is valuable for the consumers. The 15 other participants play the role of consumer. The producer can only produce the good if she raises sufficient funds to cover her production costs. The producer's production costs are fixed: They do not depend on the number of goods sold. Moreover, only the producer is informed about her costs. The consumers do not know the producer's costs. The producer's costs may vary from one round to the next. The consumers interact in a market. In this market, it is determined whether the producer actually produces the good. Moreover, if the good is produced, the market determines which consumers buy the good and for what price.

The Value of the Good: The value of the fictitious good will typically differ from one consumer to the next. To be more precise, in every round, the computer will draw a new value for every consumer. Values are randomly drawn from the set 0,1,2,...,19,20. Note the following about the value for the good:

1. The value for a consumer is determined independently of the values for the other consumers;
2. Any value in the set $\{0,1,2,\ldots,19,20\}$ is equally likely;
3. Each consumer only learns her own value, not the value of the other consumers;
4. The producer is not informed about the values of any of the consumers.

The Market: At the start of a round, the producer is informed about her or his costs and all consumers are told their value. He or she will then try to raise money to be able to produce the good. To do so, the producer decides on a target amount and a minimum price. The target amount is the sum of money that the producer wants to at least raise from all consumers together. The minimum price is the lowest price that the producer wants to receive from any single consumer. Note that not every consumer may be willing to pay that price. To determine which consumers are willing to pay a price and how much revenue a price will give to the producer, we use the following procedure in each round. The computer will start by proposing a price equal to 1. Any consumer not willing to pay this price can click the button “Drop Out”. Then, every few seconds the computer raises the price by 1. As the price increases, any consumer may drop out of this round’s market at any price by clicking the “Drop Out” button. Consumers who drop out will not buy the good. Once you drop out, you cannot re-enter in the current round. As the price increases and consumers drop out, three things might happen. First, the price might be below the minimum price. In this case, it is increased further. Second, too many consumers might drop out, so that it becomes impossible for the producer to raise her or his target amount. In this case, the good is not produced and the round ends. Third, it can happen that at a price of at least the minimum price, enough consumers are still willing to buy the good so that together they pay at least the target amount. The good is then produced because the target amount and the minimum price are reached. Then, all remaining consumers obtain the good and pay the last displayed price. For these consumers, the payoff they get from buying the good is equal to their value for this round minus the price at which the computer stopped. In summary, the computer determines whether the good is produced and who obtains the good in the following way.

STEP 0: Start with a ‘candidate price’ of 1.

STEP 1: Check whether the candidate price is below the minimum price. If so, increase the candidate price by 1 and repeat STEP 1. If not, continue with STEP 2.

STEP 2: Determine how many consumers remain in the market, i.e. have not yet clicked on “Drop Out”. Check how much money this candidate price would raise by multiplying the candidate price with the number of remaining consumers. This would be the producer’s revenue at the candidate price.

STEP 3: Compare the producer’s revenue calculated in STEP 2 with the target amount.

- If the producer's revenue is equal to or higher than the target amount, proceed to STEP 4.
- If the producer's revenue is lower than the target amount, increase the candidate price by 1. If the number of remaining consumers multiplied by the highest possible price (30) is less than the target amount, the good is not produced and the next round starts. Otherwise, go back to STEP 2.

STEP 4: The good is produced. All remaining consumers obtain the good and pay the current price to the producer. All consumers who dropped out do not obtain the good and pay zero.

Example: To illustrate the market, suppose the target amount equals 85 and the minimum price is 7. The first candidate price is 1. As this candidate price is lower than 7, the minimum price, the price increases by 1 every few seconds until a price of 7. Suppose that at the price of 7, 6 consumers have dropped out already. This leaves 9 remaining consumers at the minimum price of 7. Multiplying this price by the number of remaining consumers yields 63. This is lower than the target amount of 85, so that the candidate price is increased to 8. At this price of 8, one consumer drops out. Multiplying the new candidate price by the number of remaining consumers (8) yields 64, which is again lower than the target amount of 85. The candidate price is increased to 9. Again, one consumer drops out. Multiplying the new candidate price (9) by the number of remaining consumers (7) yields 63, which is again lower than the target amount of 85. The candidate price is increased to 10. Now, suppose that all 7 consumers remain at a candidate price of 10. Still, multiplying 10 by 7 yields 70 which is lower than the target amount of 85. The same occurs for candidate prices of 11 ($7*11<85$) and 12 ($7*12<85$) respectively. However, if all 7 remaining consumers also remain at a candidate price of 13, the good is produced because $7*13=91$ is higher than the target amount of 85. The process stops and the 7 remaining consumers obtain the good and pay a price of 13. The 8 consumers who dropped out do not obtain the good and pay zero. The sum of consumer payments is thus 91.

Producer Payoffs: The way the producer's payoffs are determined varies from one round to the next. In some rounds, the producer's payoffs are determined by her profits (Objective: Profit). The producer then obtains one fifth, i.e. 20%, of the realized profits. The profits are determined as the difference between the sum of consumers' payments and the production costs of the given round. If the good is produced, the producer's payoffs thus are:

$$(\textit{Producer payoffs}) = 20\% * [(\textit{Sum of the consumer payments}) - (\textit{Production costs})]$$

If the good is not produced, the producer obtains zero payoffs. In the other rounds, the producer's payoffs are determined by whether the producer was successful in raising sufficient funds to cover her production costs (Objective: Success). The producer obtains 3 francs if the good is produced and the sum of the consumer payments is equal to or higher than the costs of producing the good. Otherwise the producer obtains zero payoffs. The producer is informed about her objective in the given round. The consumers are not informed about the producer's objective. If you happen to be assigned the role of producer, make sure to pay attention to how the producer's payoffs are determined for the round you are currently playing!

Consumer Payoffs: In every round, the payoffs for the consumers are as follows. If a consumer obtains the good in a round, her payoffs in that round are:

$$(\textit{Consumer payoffs}) = (\textit{Own value for the good}) - (\textit{Price paid})$$

If a consumer does not obtain the good in a round, her earnings for that round are zero.

Comprehension Questions:

You will now be asked several example questions. Their purpose is to check for your understanding of the game. Note that the parameters used in the following example questions are not representative!

- If the good is produced, do all consumers who obtain the good pay the same price? (yes; no)
- If the good is produced, is it possible that any of the consumers pay more than their offer? (yes; no)

- [Target Amount: 40, Minimum Price: 2, Own value: 12, Offers of all consumers: $0-0-0-0-0-4-4-4-4-4-4-4-4-4-4$] Assume that you are one of the consumers who made an offer of 4. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 6, Own value: 12, Offers of all consumers: $0-0-0-0-0-4-4-4-4-4-4-4-4-4-4$] Assume that you are one of the consumers who made an offer of 4. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 6, Own value: 12, Offers of all consumers: $0-0-0-0-0-4-4-4-4-4-8-8-8-8-8$] Assume that you are one of the consumers who made an offer of 4. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Target Amount: 40, Minimum Price: 6, Own value: 12, Offers of all consumers: $0-0-0-0-0-4-4-4-4-4-8-8-8-8-8$] Assume that you are one of the consumers who made an offer of 8. There are 14 other consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 30, Objective: Success, Target Amount: 40, Minimum Price: 2, Offers of consumers: $1-1-1-1-1-4-4-4-4-4-4-4-4-4-4$] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 45, Objective: Success, Target Amount: 40, Minimum Price: 2, Offers of consumers: $1-1-1-1-1-4-4-4-4-4-4-4-4-4-4$] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 30, Objective: Profit, Target Amount: 40, Minimum Price: 2, Offers of consumers: $1-1-1-1-1-4-4-4-4-4-4-4-4-4-4$] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?
- [Costs: 45, Objective: Profit, Target Amount: 40, Minimum Price: 2, Offers of consumers: $1-1-1-1-1-4-4-4-4-4-4-4-4-4-4$] Assume that you are the producer. There are 15 consumers. Given the information in the table above, how many francs would you earn?

Intuition Questions:

You will now be asked some more example questions. Their purpose is to let you develop an intuition for how to play the game before we start with the real rounds. Note that the parameters used in the following example questions are not representative.

- [Target Amount: 45, Minimum Price: 7, Own value: X, Current Price: Y[31]] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What offer would you make?
- [Target Amount: 65, Minimum Price: 4, Own value: X, Current Price: Y] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What offer would you make?
- [Target Amount: 85, Minimum Price: 12, Own value: X, Current Price: Y] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What offer would you make?
- [Target Amount: 105, Minimum Price: 9, Own value: X, Current Price: Y] Assume that you are a consumer. There are 14 other consumers with values drawn from the set {0,1,2,...,19,20}. What offer would you make?
- [Costs: 55, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 50, Minimum Price = 5; Target Amount = 55, Minimum Price = 3; *Target Amount = 71, Minimum Price = 10*; Target Amount = 90, Minimum Price = 16)
- [Costs: 75, Objective: Profit] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 38, Minimum Price = 13; Target Amount = 70, Minimum Price = 7; Target Amount = 72, Minimum Price = 2; *Target Amount = 84, Minimum Price = 12*)
- [Costs: 65, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,...,19,20}. Which of the following four options would you choose? (Target Amount = 30, Minimum

[31] Price increases every four seconds by one.

Price = 5; Target Amount = 60, Minimum Price = 4; *Target Amount = 67, Minimum Price = 8*; Target Amount = 111, Minimum Price = 1)

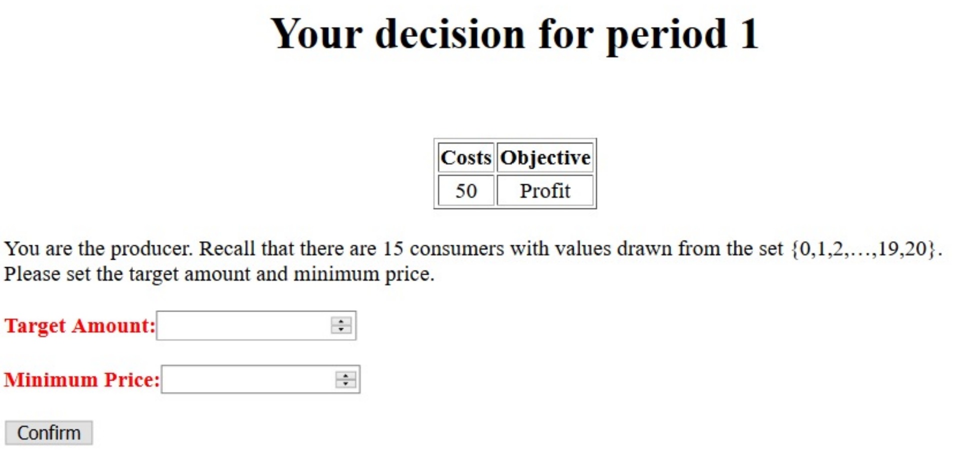
- [Costs: 85, Objective: Success] Assume that you the producer. There are 15 consumers with values drawn from the set {0,1,2,. . . ,19,20}. Which of the following four options would you choose? (Target Amount = 78, Minimum Price = 0; Target Amount = 86, Minimum Price = 17; *Target Amount = 89, Minimum Price = 6*; Target Amount = 103, Minimum Price = 14)

We will continue when everybody has finished reading the instructions and has answered all example questions.

You will now be assigned the role of the producer or of a consumer.

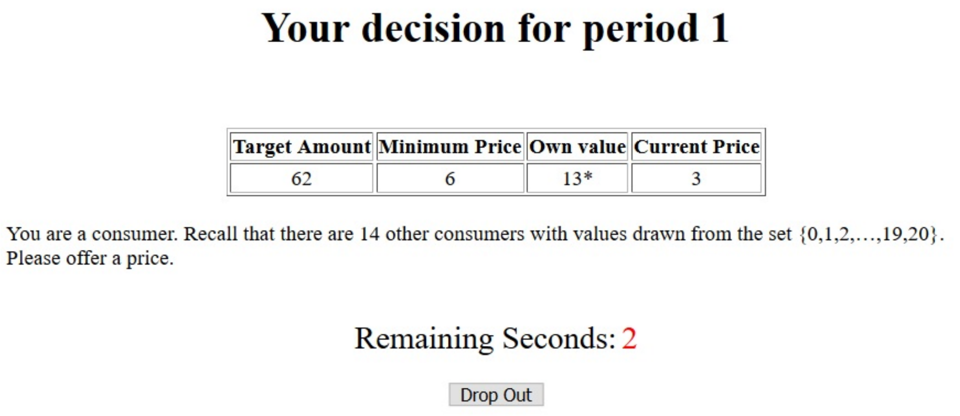
You are assigned the role of [the producer / a consumer].

Figure 4.D5: Producer's Decision Screen in dGMS



Notes: Subjects could state an integer target amount between 0 and 300 and an integer minimum price between 0 and 30.

Figure 4.D6: Consumers' Decision Screen in dGMS



Notes: The price increases every four seconds by one (up to a maximum of 30). The asterisk indicates that values were drawn randomly; the asterisk was not shown to subjects.

Questionnaire:

Please fill in this short questionnaire.

- Age: (positive integers)
- Gender: (Male, Female)
- I study at (UvA – Economics and Business; UvA – Social Sciences, Psychology; UvA – Social Sciences, not Psychology; UvA – Science; UvA – IIS, beta gamma bachelor; UvA – Law School; UvA – Humanities; UvA – Medical School; UvA – Dentistry; Another university; A professional school; Otherwise)
- How often have you participated in a crowdfunding campaign? (Never; One time; Two times; Three or more times)
- What strategy did you play?
- What is your feeling towards the other players?
- How fair do you rate the crowdfunding mechanism? (very unfair (1), (2), (3), (4), very fair (5)))
- Do you have any other comments?

Bibliography

Acland, D. and M. R. Levy (2015): "Naiveté, projection bias, and habit formation in gym attendance," *Management Science*, 61, 146–160.

Aggarwal, S., R. Dizon-Ross, and A. D. Zucker (2020): "Incentivizing Behavioral Change: The Role of Time Preferences," Tech. rep., National Bureau of Economic Research.

Agrawal, A., C. Catalini, and A. Goldfarb (2015): "Crowdfunding: Geography, social networks, and the timing of investment decisions," *Journal of Economics & Management Strategy*, 24, 253–274.

Arada, A., U. Gneezyb, and E. Mograbia (2020): "Intermittent Incentives to Encourage Exercising in the Long Run," Working paper, Tel Aviv University.

Arrow, K. J. (1979): "The Property Rights Doctrine and Demand Revelation under Incomplete Information," in *Economics and Human Welfare*, ed. by M. Boskin, New York, NY: Academic Press, 23–39.

Ashraf, N., D. Karlan, and W. Yin (2006): "Tying Odysseus to the mast: Evidence from a commitment savings product in the Philippines," *The Quarterly Journal of Economics*, 121, 635–672.

Askey, R. A. and R. Roy (2010): "Beta function," *NIST digital library of mathematical functions.*

Augenblick, N., M. Niederle, and C. Sprenger (2015): "Working over time: Dynamic inconsistency in real effort tasks," *The Quarterly Journal of Economics*, 130, 1067–1115.

Augenblick, N. and M. Rabin (2019): "An experiment on time preference and misprediction in unpleasant tasks," *Review of Economic Studies*, 86, 941–975.

Augurzky, B., T. K. Bauer, A. R. Reichert, C. M. Schmidt, and H. Tauchmann (2018): *Habit formation, obesity, and cash rewards*, 750, Ruhr Economic Papers.

Bachireddy, C., A. Joung, L. K. John, F. Gino, B. Tuckfield, L. Foschini, and K. L. Milkman (2019): "Effect of Different Financial Incentive Structures on Promoting Physical Activity Among Adults: A Randomized Clinical Trial," *JAMA network open*, 2, e199863–e199863.

Bajoori, E., J. Flesch, and D. Vermeulen (2016): "Behavioral perfect equilibrium in Bayesian games," *Games and Economic Behavior*, 98, 78–109.

Banerjee, P., S. Khare, and P. Srikant (2018): "Learning to set the reserve price optimally in laboratory first price auctions," *Games*, 9, 79.

Batina, R. G. and T. Ihori (2005): *Public goods: theories and evidence*, Springer Science & Business Media.

Beatty, T. K. and B. Katare (2018): "Low-cost approaches to increasing gym attendance," *Journal of health economics*, 61, 63–76.

Belavina, E., S. Marinesi, and G. Tsoukalas (2020): "Rethinking crowdfunding platform design: mechanisms to deter misconduct and improve efficiency," *Management Science*, 66, 4980–4997.

Belleflamme, P., T. Lambert, and A. Schwienbacher (2010): "Crowdfunding: An industrial organization perspective," in *Prepared for the workshop Digital Business Models: Understanding Strategies', held in Paris on June*, 25–26.

——— (2013): "Individual crowdfunding practices," *Venture Capital*, 15, 313–333.

Beshears, J., J. J. Choi, C. Harris, D. Laibson, B. C. Madrian, and J. Sakong (2020): "Which early withdrawal penalty attracts the most deposits to a commitment savings account?" *Journal of public economics*, 183, 104144.

BREITMOSER, Y. AND S. SCHWEIGHOFER-KODRITSCH (2019): "Obviousness around the clock," Tech. rep., Discussion Paper.

BROWN, T. E., E. BOON, AND L. F. PITT (2017): "Seeking funding in order to sell: Crowdfunding as a marketing tool," *Business Horizons*, 60, 189–195.

BRYAN, G., D. KARLAN, AND S. NELSON (2010): "Commitment devices," *Annu. Rev. Econ.*, 2, 671–698.

BURGER, N. AND J. LYNHAM (2010): "Betting on weight loss... and losing: personal gambles as commitment mechanisms," *Applied Economics Letters*, 17, 1161–1166.

BUTTICE, V., M. G. COLOMBO, AND M. WRIGHT (2017): "Serial crowdfunding, social capital, and project success," *Entrepreneurship Theory and Practice*, 41, 183–207.

CAI, W., F. POLZIN, AND E. STAM (2019): "Crowdfunding and Social Capital: A Systematic Literature Review," *Available at SSRN 3361748*.

CALZOLARI, G. AND M. NARDOTTO (2016): "Effective reminders," *Management Science*, 63, 2915–2932.

CAMPOS-MERCADE, P. AND E. WENGSTRÖM (2020): "Threshold Incentives and Academic Performance," Working paper, University of Copenhagen.

CAPPELEN, A. W., G. CHARNESS, M. EKSTRÖM, U. GNEEZY, AND B. TUNGODDEN (2017): "Exercise improves academic performance," *NHH Dept. of Economics Discussion Paper*.

CARRERA, M., H. ROYER, M. STEHR, AND J. SYDNOR (2018a): "Can financial incentives help people trying to establish new habits? Experimental evidence with new gym members," *Journal of health economics*, 58, 202–214.

——— (2020): "The structure of health incentives: Evidence from a field experiment," *Management Science*, 66, 1890–1908.

CARRERA, M., H. ROYER, M. STEHR, J. SYDNOR, AND D. TAUBINSKY (2018b): "The limits of simple implementation intentions: Evidence from a field experiment on making plans to exercise," *Journal of health economics*, 62, 95–104.

Cason, T. N., A. Tabarrok, and R. Zubrickas (2021): "Early Refund Bonuses Increase Successful Crowdfunding," Working paper, Purdue University.

Cason, T. N. and R. Zubrickas (2017): "Enhancing fundraising with refund bonuses," *Games and Economic Behavior*, 101, 218–233.

——— (2019): "Donation-based crowdfunding with refund bonuses," *European Economic Review*, 119, 452–471.

Charness, G. and U. Gneezy (2009): "Incentives to exercise," *Econometrica*, 77, 909–931.

Chemla, G. and K. Tinn (2020): "Learning through crowdfunding," *Management Science*, 66, 1783–1801.

Chen, Y., L. Razzolini, and T. L. Turocy (2007): "Congestion allocation for distributed networks: an experimental study," *Economic Theory*, 33, 121–143.

Clarke, E. H. (1971): "Multipart pricing of public goods," *Public choice*, 11, 17–33.

Cornelli, F. (1996): "Optimal selling procedures with fixed costs," *Journal of Economic Theory*, 71, 1–30.

Cumming, D. J., G. Leboeuf, and A. Schwienbacher (2020): "Crowdfunding models: Keep-it-all vs. all-or-nothing," *Financial Management*, 49, 331–360.

Da Cruz, J. V. (2018): "Beyond financing: crowdfunding as an informational mechanism," *Journal of Business Venturing*, 33, 371–393.

d'Aspremont, C. and L.-A. Gérard-Varet (1979): "Incentives and incomplete information," *Journal of Public economics*, 11, 25–45.

d'Aspremont, C. and L.-A. Gerard-Varet (1979): "On Bayesian incentive compatible mechanisms," in *Aggregation and Revelation of Preferences*, ed. by J.-J. Laffont, Amsterdam: North-Holland, 269–288.

Davis, A. M., E. Katok, and A. M. Kwasnica (2011): "Do auctioneers pick optimal reserve prices?" *Management Science*, 57, 177–192.

DEB, J., A. OERY, AND K. R. WILLIAMS (2019): "Aiming for the goal: Contribution dynamics of crowdfunding," Tech. rep., National Bureau of Economic Research.

DEB, R. AND L. RAZZOLINI (1999): "Auction-like mechanisms for pricing excludable public goods," *Journal of Economic Theory*, 88, 340–368.

DELLAVIGNA, S. AND U. MALMENDIER (2004): "Contract design and self-control: Theory and evidence," *The Quarterly Journal of Economics*, 119, 353–402.

ELLMAN, M. AND S. HURKENS (2019a): "Fraud tolerance in optimal crowdfunding," *Economics Letters*, 181, 11–16.

——— (2019b): "Optimal crowdfunding design," *Journal of Economic Theory*, 184, 104939.

EVERETT, C. R. (2019): "Origins and Development of Credit-Based Crowdfunding." *Banking & Finance Review*, 11.

EXLEY, C. L. AND J. K. NAECKER (2016): "Observability increases the demand for commitment devices," *Management Science*, 63, 3262–3267.

FALKINGER, J. (1996): "Efficient private provision of public goods by rewarding deviations from average," *Journal of Public Economics*, 62, 413–422.

FEDYK, A. (2018): "Asymmetric naivete: Beliefs about self-control," *Available at SSRN 2727499.*

FRICKE, H., M. LECHNER, AND A. STEINMAYR (2018): "The effects of incentives to exercise on student performance in college," *Economics of Education Review*, 66, 14–39.

FRIEDMAN, E., M. SHOR, S. SHENKER, AND B. SOPHER (2004): "An experiment on learning with limited information: nonconvergence, experimentation cascades, and the advantage of being slow," *Games and Economic Behavior*, 47, 325–352.

FRYER JR, R. G. (2011): "Financial incentives and student achievement: Evidence from randomized trials," *The Quarterly Journal of Economics*, 126, 1755–1798.

Gailmard, S. and T. R. Palfrey (2005): "An experimental comparison of collective choice procedures for excludable public goods," *Journal of Public Economics*, 89, 1361–1398.

Galperti, S. (2015): "Commitment, flexibility, and optimal screening of time inconsistency," *Econometrica*, 83, 1425–1465.

Garon, J.-D., A. Masse, and P.-C. Michaud (2015): "Health club attendance, expectations and self-control," *Journal of Economic Behavior & Organization*, 119, 364–374.

Gerber, E. M. and J. Hui (2013): "Crowdfunding: Motivations and deterrents for participation," *ACM Transactions on Computer-Human Interaction (TOCHI)*, 20, 1–32.

Giné, X., D. Karlan, and J. Zinman (2010): "Put your money where your butt is: a commitment contract for smoking cessation," *American Economic Journal: Applied Economics*, 2, 213–35.

Gneezy, U., S. Meier, and P. Rey-Biel (2011): "When and why incentives (don't) work to modify behavior," *Journal of Economic Perspectives*, 25, 191–210.

Goeree, J. K., E. Maasland, S. Onderstal, and J. L. Turner (2005): "How (not) to raise money," *Journal of Political Economy*, 113, 897–918.

Groves, T. (1973): "Incentives in teams," *Econometrica*, 41, 617–631.

Groves, T. and M. Loeb (1975): "Incentives and public inputs," *Journal of Public economics*, 4, 211–226.

Grüner, H. P. and C. Siemroth (2019): "Crowdfunding, efficiency, and inequality," *Journal of the European Economic Association*, 17, 1393–1427.

Halpern, S. D., B. French, D. S. Small, K. Saulsgiver, M. O. Harhay, J. Audrain-McGovern, G. Loewenstein, T. A. Brennan, D. A. Asch, and K. G. Volpp (2015): "Randomized trial of four financial-incentive programs for smoking cessation," *New England Journal of Medicine*, 372, 2108–2117.

John, L. K., G. Loewenstein, and K. G. Volpp (2012): "Empirical observations on longer-term use of incentives for weight loss," *Preventive Medicine*, 55, S68–S74.

Kaur, S., M. Kremer, and S. Mullainathan (2015): "Self-control at work," *Journal of Political Economy*, 123, 1227–1277.

Kominers, S. D., A. Teytelboym, and V. P. Crawford (2017): "An invitation to market design," *Oxford Review of Economic Policy*, 33, 541–571.

Krishna, V. and M. Perry (1998): "Efficient mechanism design," *Available at SSRN 64934*.

Kumar, P., N. Langberg, and D. Zvilichovsky (2020): "Crowdfunding, financing constraints, and real effects," *Management Science*, 66, 3561–3580.

Kunz, M. M., U. Bretschneider, M. Erler, and J. M. Leimeister (2017): "An empirical investigation of signaling in reward-based crowdfunding," *Electronic Commerce Research*, 17, 425–461.

Laibson, D. (1997): "Golden eggs and hyperbolic discounting," *The Quarterly Journal of Economics*, 112, 443–478.

——— (2015): "Why don't present-biased agents make commitments?" *American Economic Review*, 105, 267–72.

Landry, C. E., A. Lange, J. A. List, M. K. Price, and N. G. Rupp (2006): "Toward an understanding of the economics of charity: Evidence from a field experiment," *The Quarterly journal of economics*, 121, 747–782.

Lange, A., J. A. List, and M. K. Price (2007): "Using lotteries to finance public goods: Theory and experimental evidence," *International Economic Review*, 48, 901–927.

Li, S. (2017): "Obviously strategy-proof mechanisms," *American Economic Review*, 107, 3257–87.

Lin, M. and S. Viswanathan (2016): "Home bias in online investments: An empirical study of an online crowdfunding market," *Management Science*, 62, 1393–1414.

Lin, Y., W.-C. Lee, and C.-C. H. Chang (2016): "Analysis of rewards on reward-based crowdfunding platforms," in *2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, IEEE, 501–504.

List, J. A. (2020): "Non est disputandum de generalizability? a glimpse into the external validity trial," Tech. rep., National Bureau of Economic Research.

Lusher, L. (2017): "College Better: Parimutuel Betting Markets as a Commitment Device and Monetary Incentive," Tech. rep., The Field Experiments Website.

März, O. (2019): "Comment on "Naiveté, Projection Bias, and Habit Formation in Gym Attendance"," *Management Science*, 65, 2442–2443.

McMillan, J. (1994): "Selling spectrum rights," *Journal of Economic Perspectives*, 8, 145–162.

Milgrom, P. R. and R. J. Weber (1982): "A theory of auctions and competitive bidding," *Econometrica*, 50, 1089–1122.

Milkman, K. L., J. A. Minson, and K. G. Volpp (2014): "Holding the Hunger Games hostage at the gym: An evaluation of temptation bundling," *Management science*, 60, 283–299.

Mollick, E. (2014): "The dynamics of crowdfunding: An exploratory study," *Journal of business venturing*, 29, 1–16.

Morgan, J. (2000): "Financing public goods by means of lotteries," *The Review of Economic Studies*, 67, 761–784.

Morgan, J. and M. Sefton (2000): "Funding public goods with lotteries: experimental evidence," *The Review of Economic Studies*, 67, 785–810.

Moritz, A. and J. H. Block (2016): "Crowdfunding: A literature review and research directions," in *Crowdfunding in Europe*, Springer, 25–53.

Moulin, H. and S. Shenker (1992): "Serial cost sharing," *Econometrica*, 60, 1009–1037.

——— (2001): "Strategyproof sharing of submodular costs: budget balance versus efficiency," *Economic Theory*, 18, 511–533.

O'Donoghue, T. and M. Rabin (1999): "Doing it now or later," *American Economic Review*, 89, 103–124.

——— (2001): "Choice and procrastination," *The Quarterly Journal of Economics*, 116, 121–160.

Onderstal, S., A. J. Schram, and A. R. Soetevent (2013): "Bidding to give in the field," *Journal of Public Economics*, 105, 72–85.

Phelps, E. S. and R. A. Pollak (1968): "On second-best national saving and game-equilibrium growth," *The Review of Economic Studies*, 35, 185–199.

Pitschner, S. and S. Pitschner-Finn (2014): "Non-profit differentials in crowd-based financing: Evidence from 50,000 campaigns," *Economics Letters*, 123, 391–394.

Pope, L. and J. Harvey-Berino (2013): "Burn and earn: a randomized controlled trial incentivizing exercise during fall semester for college first-year students," *Preventive medicine*, 56, 197–201.

Razzolini, L., M. Reksulak, and R. Dorsey (2007): "An experimental evaluation of the serial cost sharing rule," *Theory and decision*, 63, 283–314.

Rohde, K. I. and W. Verbeke (2017): "We like to see you in the gym - A field experiment on financial incentives for short and long term gym attendance," *Journal of Economic Behavior & Organization*, 134, 388–407.

Royer, H., M. Stehr, and J. Sydnor (2015): "Incentives, commitments, and habit formation in exercise: evidence from a field experiment with workers at a Fortune-500 company," *American Economic Journal: Applied Economics*, 7, 51–84.

Sadoff, S. and A. Samek (2019): "Can interventions affect commitment demand? A field experiment on food choice," *Journal of Economic Behavior & Organization*, 158, 90–109.

Schilbach, F. (2019): "Alcohol and self-control: A field experiment in India," *American economic review*, 109, 1290–1322.

Schram, A. (2005): "Artificiality: The tension between internal and external validity in economic experiments," *Journal of Economic Methodology*, 12, 225–237.

Schram, A. J. and S. Onderstal (2009): "Bidding to give: An experimental comparison of auctions for charity," *International Economic Review*, 50, 431–457.

Shachat, J. and L. Tan (2019): "How Auctioneers Set Ex-Ante and Ex-Post Reserve Prices in English Auctions," MPRA Paper No. 96225.

Shneor, R. and A. A. Vik (2020): "Crowdfunding success: a systematic literature review 2010–2017," *Baltic Journal of Management*, 15, 149–182.

Statista (2020): "Digital Market Outlook," `https://www.statista.com/outlook/335/100/crowdfunding/worldwide`, accessed: September 3, 2020.

Strausz, R. (2017): "A theory of crowdfunding: A mechanism design approach with demand uncertainty and moral hazard," *American Economic Review*, 107, 1430–76.

Strotz, R. H. (1955): "Myopia and inconsistency in dynamic utility maximization," *The Review of Economic Studies*, 23, 165–180.

Thaler, R. H. and S. Benartzi (2004): "Save more tomorrow™: Using behavioral economics to increase employee saving," *Journal of political Economy*, 112, S164–S187.

Vickrey, W. (1961): "Counterspeculation, auctions, and competitive sealed tenders," *The Journal of finance*, 16, 8–37.

Walker, M. (1981): "A simple incentive compatible scheme for attaining Lindahl allocations," *Econometrica*, 49, 65–71.

Woerner, A. (2021): "Overcoming Time Inconsistency with a Matched Bet: Theory and Evidence from Exercising," Working paper, Ludwig Maximilian University of Munich.

Woerner, A., S. Onderstal, and A. J. Schram (2021a): “Comparing Crowdfunding Mechanisms: Introducing the Generalized Moulin-Shenker Mechanism,” Working paper, Ludwig Maximilian University of Munich.

——— (2021b): “Reservation Prices and Targets: Producer Behavior in Crowdfunding,” Working paper, Ludwig Maximilian University of Munich.

Zvilichovsky, D., Y. Inbar, and O. Barzilay (2015): “Playing both sides of the market: Success and reciprocity on crowdfunding platforms,” *Available at SSRN 2304101*.

Summary: Behavioral and Financial Change – Essays in Market Design

This thesis consists of three essays in market design covering two topics: incentives for behavioral change (Chapter 2) and allocation mechanisms in reward-based crowdfunding (Chapters 3 and 4).

Chapter 2 introduces the matched-bet mechanism. The matched bet is an easily applicable and strictly budget-balanced mechanism that aims to help people overcome time-inconsistent behavior. I show theoretically that offering a matched bet helps both sophisticated and naive procrastinators to reduce time-inconsistent behavior. I conduct a field experiment to test the matched-bet mechanism in a natural area of application: exercising. My experimental results confirm the theoretical predictions: offering a matched bet has a significant positive effect on gym attendance. Moreover, self-reported procrastinators are significantly more likely to take up the matched bet than others. Overall, the matched bet proves a promising device to help people exercise more. I discuss how a matched bet could also be implemented in other areas such as academic performance, weight loss and smoking cessation.

Chapters 3 and 4 are about reward-based crowdfunding. Even though

crowdfunding has become an important fundraising practice, it has received remarkably little attention in the economics literature. In particular, the allocation mechanisms used by crowdfunding platforms remain under-studied. Chapter 3 tries to fill this gap. We study the performance of the prevailing All-or-Nothing mechanism (AON). We also introduce a new, strategy-proof, crowdfunding mechanism, the Generalized Moulin-Shenker mechanism (GMS). We show that, in theory, GMS outperforms AON in terms of equilibrium profit and funding success. We test these theoretical predictions in a laboratory, distinguishing between a sealed-bid and a dynamic version of GMS. Our results show that the dynamic GMS performs better than the sealed-bid GMS and that it outperforms AON when the producer's objective is to maximize funding success.

Chapter 4 builds on Chapter 3 and focuses on producer behavior. Introducing decisions by human producers, we find that AON now weakly outperforms both the sealed-bid and dynamic GMS. Even though producer decisions deviate substantially from the theoretical predictions in all three mechanisms, producer payoffs are comparatively robust to these deviations only in AON. In all three mechanisms, producers typically set reasonable thresholds but poor reservation prices. Our experimental results of Chapters 3 and 4 contribute to explaining why AON is the prevalent reward-based crowdfunding mechanism in practice. Further, our results suggest that the current standard of financing projects when producers aim to maximize funding success probability could be improved upon by implementing a crowdfunding mechanism that is similar to the dynamic GMS.

Samenvatting: Gedrags- en Financiële Verandering – Essays over Marktontwerp

Dit proefschrift bestaat uit drie essays over marktontwerp die twee onderwerpen behandelen: stimulansen voor gedragsverandering (Hoofdstuk 2) en allocatiemechanismen in op beloning gebaseerde crowdfunding (Hoofdstukken 3 en 4).

Hoofdstuk 2 introduceert het matched-bet mechanisme. De matched bet is een makkelijk toepasbaar en strikt gebalanceerd mechanisme dat als doel heeft mensen te helpen tijd-inconsistent gedrag te overwinnen. Ik laat theoretisch zien dat het aanbieden van een matched bet zowel geavanceerde als naïeve uitstellers helpt om tijd-inconsistent gedrag te verminderen. Ik voer een veldexperiment uit om het matched-bet mechanisme te testen in een voor de hand liggend toepassingsgebied: sporten. Mijn experimentele resultaten bevestigen de theoretische voorspellingen: het aanbieden van een matched bet heeft een significant positief effect op het bezoek aan de sportschool. Bovendien zijn zelfgerapporteerde uitstellers aanzienlijk meer geneigd om de matched bet aan te gaan dan anderen. De matched bet is een veelbelovend apparaat om mensen te helpen meer te bewegen. Ik bespreek hoe een matched bet ook kan worden geïmplementeerd op andere gebieden, zoals academische prestaties, gewichtsverlies en stoppen met roken.

Hoofdstukken 3 en 4 gaan over op beloning gebaseerde crowdfunding. Hoewel crowdfunding een belangrijke manier van fondsenwerving is geworden, heeft het opvallend weinig aandacht gekregen in de economische literatuur. Met name de allocatiemechanismen die door crowdfundingplatforms worden gebruikt, blijven onderbelicht. Hoofdstuk 3 probeert deze leegte op te vullen. We bestuderen de prestaties van het veelgebruikte All-or-Nothing mechanisme (AON). We introduceren ook een nieuw, strategisch bestendige crowdfunding-mechanisme, het Generalized Moulin-Shenker mechanisme (GMS). We laten zien dat GMS in theorie beter presteert dan AON in termen van evenwichtswinst en financieringssucces. We testen deze theoretische voorspellingen in een laboratorium, waarbij we onderscheid maken tussen een gesloten bieding en een dynamische versie van GMS. Onze resultaten laten zien dat de dynamische GMS beter presteert dan de gesloten GMS, en dat deze beter presteert dan AON wanneer het doel van de producent is om het financieringssucces te maximaliseren.

Hoofdstuk 4 bouwt voort op Hoofdstuk 3 en richt zich op het gedrag van producenten. Bij de introductie van beslissingen van menselijke producenten, zien we dat AON nu iets beter presteert dan zowel het gesloten bod GMS als de dynamische GMS. Hoewel producentenbeslissingen substantieel afwijken van de theoretische voorspellingen in alle drie de mechanismen, zijn alleen in AON de uitbetalingen van producenten relatief robuust voor deze afwijkingen. In alle drie de mechanismen stellen producenten doorgaans redelijke drempels vast, maar slechte reserveringsprijzen. Onze experimentele resultaten van Hoofdstukken 3 en 4 dragen bij aan het verklaren waarom AON in de praktijk het meest voorkomende op beloning gebaseerde crowdfundingmechanisme is. Verder suggereren onze resultaten dat de huidige standaard van het financieren van projecten wanneer producenten streven naar een zo groot mogelijke kans op succes van de financiering, kan worden verbeterd door een crowdfundingmechanisme te implementeren dat vergelijkbaar is met het dynamische GMS.

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Two chapters are the result of a collaboration with my thesis supervisors Sander Onderstal (University of Amsterdam) and Arthur Schram (University of Amsterdam and European University Institute):

- Chapter 3, titled **Comparing Crowdfunding Mechanisms: Introducing the Generalized Moulin-Shenker Mechanism**, is based on joint work with Sander Onderstal (University of Amsterdam) and Arthur Schram (University of Amsterdam and European University Institute). I proposed the novel crowdfunding mechanism, conducted the experimental analysis, wrote the first study draft, and, together with Sander Onderstal, conducted the experimental sessions. All authors jointly developed the experimental design, derived theoretical results and improved the first draft in content and style.
- Chapter 4, titled **Reservation Prices and Thresholds: Producer Behavior in Crowdfunding**, is also based on joint work with Sander Onderstal (University of Amsterdam) and Arthur Schram (University of Amsterdam and European University Institute). I conducted the experimental analysis, wrote the first study draft, and, together with Sander Onderstal, conducted the experimental sessions. All authors jointly developed the experimental design and improved the first draft in content and style.

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