Strategic Behavior in Tight, Loose and Polarized Norms

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Abstract

Social norms guide our behaviors in many decision contexts and influence our decisions such as whether to trust or cooperate with others. To do so, individuals observe and interpret the social signals that their peers provide through their behavior. In this paper, we investigate how individuals navigate strategic environments that are characterized by different distributions of behavior and we contribute to a burgeoning literature probing how different social environments inform one's own decisions. We focus on the difference between tight (i.e., characterized by low behavioral variance), loose (i.e., characterized by high behavioral variance), and polarized (i.e., characterized by U-shaped behavior) environments. Our results show that individuals strongly adapt their actions to the variance and distribution (polarized/single-peaked) of one's peers. In particular, higher variance environments generate greater variance of replies, and polarized environments generate polarized responses. This implies that tight, loose, and polarized (empirical) norms are self-sustaining. Moreover, we find that personal values have a stronger importance for actual behavior in polarized and loose than in tight environments.

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1 Introduction

Empirical norms – widespread behavioral regularities among members of one's reference group – have been found to play a key role in shaping individual incentives in both strategic and non-strategic settings (Cialdini and Trost, 1998; Bicchieri, 2005, 2016; Bicchieri and Dimant, 2019; Dimant, 2019). Much of the existing literature in the social sciences focuses on the *average* or modal behavior when characterizing the behavior of others (see e.g. Chaudhuri et al., 2006; Bicchieri and Xiao, 2009; Krupka and Weber, 2013; Feldhaus et al., 2019). We argue that this approach misses out on an essential feature of norms—namely the *variance*. Gelfand et al. (2011) speak in this context of *tight* versus *loose* norms and show that this distinction can help to understand systematic differences across cultures. Tight cultures are characterized by strong social norms and well-defined behavior, while loose cultures show a pattern of weak social norms and greater behavioral variance.[1]

In this paper, we focus on empirical norms, i.e. how information about the behavior of others affects individual decisions. While this puts the focus on a particular aspect of norms, we believe it is a very useful starting point to study strategic behavior in environments with different degrees of variance. The type of behavior we examine in this study is cooperation. Previous research has shown that there is substantial heterogeneity in the variance of cooperation across cultures (Henrich et al., 2001a,b; Gächter et al., 2010), making it a particularly interesting case study for examining the effects of different variances. Understanding when and how variance matters can thus help to develop a better understanding of human cooperation.

While there have been many studies of tight-loose in psychology, most are correlational (see e.g. Gelfand, 2021), and few studies have manipulated tight and loose behavior and examined its impact on human cooperation in economic games (see Roos et al., 2015; De et al., 2017, for computational models of TL and the evolution of cooperation). In addition to the variance, in this study we investigate another important feature of the distribution of behavior: its shape. More precisely, we are interested in polarized norms, which we define as situations where behavior is not single-peaked but follows a u-shaped distribution. Previous research suggests that group affiliation affects an individual's willingness to contribute to a public good (Henrich et al., 2001a; Fehr and Fischbacher, 2003; Bowles and Gintis, 2013; Robbett and Matthews, 2021), with polarization having the potential to increase differences between in- and out-groups. Understanding how people react to polarized environments is thus an important issue, even more so in the face of increasing political polarization and the detrimental societal outcomes that are related to it (Fiorina and Abrams, 2008; Iyengar and Westwood, 2015; Dimant, 2021; Gelfand et al., 2021).

To conceptualize how the distribution (*shape* and *variance*) of others' behavior affects one's the own willingness to cooperate, we start with the premise that people are conditional cooperators (see e.g. Gächter et al., 2010, 2017) and thus would choose different levels of cooperation depending on how willing others are to cooperate. In other words, if they cooperate more or less

[1] Consider for instance a collective action problem, and suppose that individuals in a given society contribute an average of 5 (on a scale from 0 to 10). This may reflect a situation where *everyone* contributes 5, a situation where each contribution level (0, 1, 2 .. 10) is selected by *one tenth* of the population, or a situation where *half* of the population contribute nothing and half contribute everything. Although all these scenarios generate an average contribution of 5, they clearly depict very different societies in terms of the underlying environment.

than others, they suffer a disutility. We assume that individuals do not know how the people they interact with will behave, but are aware of the overall distribution within society. Different distributions of cooperation behavior then generate different degrees of strategic risk. In very tight environments, where there is low variance in behavior, strategic risk is minimal, while in loose environments where there is high variance, the behavior of other individuals is less predictable, and strategic risk is substantial. We then investigate both theoretically and empirically how people respond to different levels of strategic risk. In a theoretical framework, we show that the answer depends on the exact specification of the utility function. People may react only to the mean of the distribution they face, ignoring strategic risk entirely (in the case of quadratic utility) or they may react to both the mean and the shape of the distribution (in the case of a linear-kinked utility). Which of these cases applies has important implications in terms of cultural sustainability. If best replies depend only on the mean of the distribution, a society will inevitably converge to the same distribution of behavior independently of whether the initial environment is tight or loose. Instead, in the case of linear-kinked utility, we show that optimal reactions will reproduce the initial distribution. When facing a tight environment, people will react in a tight way, while when facing a loose environment their reactions will be more spread out. Finally, when facing a polarized distribution, people will tend to show very heterogeneous responses, replicating the initial polarization in behavior. This suggests that different environments (tight/loose/polarized) may be self-sustaining. Moreover, when faced with high levels of strategic uncertainty, we expect people to rely on their personal to guide their decisions. Hence, when an individual faces a loose environment with a lot of variance in behavior or faces a polarized environment, responses will be very different between people depending on their individual values (see Elster and Gelfand, 2021). Noteworthy, we expect behavioral polarization to occur in spite of the fact that individual values are not polarized. In contrast, when faced with a tight environment, most individuals will select similar cooperation levels and personal values become a weaker predictor of behavior.

In a well-powered and pre-registered study, we utilize a representative sample of the U.S. population to test these different hypotheses empirically (N=1203). We do so in the context of a variant of the established public goods game (PGG) with two players. Players receive a number of tokens at the beginning of the game and can decide to either keep them for themselves or to invest them in a public good that is then multiplied by a positive factor and shared equally among both players. This creates the classical dilemma between the socially optimal decision of allocating everything to the public good and the individually rational one of contributing zero (Ledyard, 1995; Fischbacher et al., 2001). The experiment consists of two parts. While in the first part, participants play the PGG with a random partner and without any additional information, at the beginning of Part II we provide information about the distribution from which their co-player will be drawn before participants select their contribution. This allows us to investigate the reaction of individuals to different environments (tight/loose/polarized), while controlling for their baseline cooperative behavior and beliefs. Having both a measure before and after individuals learn about the distribution of contributions has the big advantage that we can both determine individual types of contributors and explore how individuals change their initial behavior in the face of new information. In a between-subject design we implement six different treatments that vary both the mean, dispersion and shape of the co-player's distribution. Our empirical results confirm the predictions under a linear-kinked utility function: the dispersion and shape of the co-player's distribution matter substantially for individual behavior. More precisely, we find that loose and tight behavior is self-sustaining, meaning that if participants are faced with a higher dispersion, their contributions show a higher variance as well. Similarly, when participants are faced with polarized distributions, their reactions are highly divergent: they either choose to contribute a lot or very little. Our data also confirms that, in line with previous studies, observing higher average contributions increases cooperation. This is an intuitive consequence of conditionality and shows that individuals aim to match the contributions of others. Our data shows that the main mechanism through which distributions affect behavior is via successfully shifting beliefs about the co-player's behavior. This means that when confronted with the distribution of behavior within the population, participants update their expectations about how their co-player will behave. As most people are conditional cooperators this in turn affects their own contribution decisions. Finally, in accordance with the theory, we find that personal values have a higher impact on individual contributions in loose/polarized environments relative to tight norm environments.[2] This underlines the importance to consider both personal values and social norms (see e.g. Capraro et al., 2019; Bašić and Verrina, 2020) and provides additional insights on their interaction and their relative importance in different environments.

Our study contributes to the existing literature in various ways. Firstly, we provide causal evidence on how tightness and looseness affect behavioral responses in a strategic context. Previous studies have either been correlational (see e.g. Gelfand, 2021) or focused on non-strategic settings (d'Adda et al., 2020). Secondly, we incorporate polarized norms in our framework by also looking at the *shape* of the distribution, which allows for a richer investigation of behavioral responses. Finally, we put a norm elicitation approach as discussed by Dimant (2022) to a test, which allows us to measure not only beliefs about *modal* behavior (as is the case in established elicitation methods such as Bicchieri and Chavez, 2010; Krupka and Weber, 2013) but also about the whole distribution in an incentivized way. We thus put forward a more fine-grained measurement that helps to develop a better understanding of empirical norms and their impact on behavior. Our results also have practical implications for policy makers. For instance, the finding that personal values have a higher impact in loose and polarized environments suggests that behavioral change interventions should target them more in these circumstances. By contrast, if norms are tight, it may be more fruitful to focus on the behaviors of others. From a policy perspective, insight also has direct implications on how norm information can be used to nudge good behavior (Bicchieri and Dimant, 2019; Dimant and Shalvi, 2022)

The remainder of this paper is structured as follows. Section 2 provides an overview of related literature. In Section 3, we outline our theoretical framework before Section 4 describes the experimental design and states our hypotheses. Section 5 presents the empirical results, before Sections 6 and 7 provide a discussion and conclude.

[2]The same pattern holds for risk aversion, the aversion of being a free-rider, or the aversion of being taken advantage of by the other player. All these individual preferences play a smaller role for contribution decisions in tight as compared to loose or polarized environments.

2 Related Literature

Our study contributes to a growing body of research that explores the effect of empirical norms on individual behavior. Many studies have shown in different contexts that providing information on what other people did in a given situation influences individual decisions. This has been found both in non-strategic settings such as dictator games (Bicchieri and Xiao, 2009), voluntary payments (Shang and Croson, 2009; Feldhaus et al., 2019) and donations to charities (Dimant, 2019; Bicchieri et al., 2022), but also for strategic interactions such as PGGs (Chaudhuri et al., 2006; Kerr et al., 2009). The way almost all studies communicate the information about others is by focusing on the mean or modal behavior. Our study confirms that differences in means have a significant effect on subsequent decisions. However, we extend these findings by exploring differences between whole distributions. Furthermore, by investigating the normative dimension of the public goods game, we are building on seminal work by Bicchieri (2005) and Bicchieri and Chavez (2010), proposing a theory of norms based on empirical and normative expectations that together with personal values affect preferences and behavior. We find that the different distributions shift normative expectations in addition to beliefs about the co-players behavior. Moreover, we find that the importance of personal values depends on the relative tightness and looseness of the environment.

More recently, several studies have investigated norms in ambiguous settings. Fosgaard et al. (2020) for instance integrate random transfers in a standard dictator game and find that uncertainty about the source of transfers decreases aggregate norm compliance. Similarly, Ciranka and van den Bos (2020) develop and test a model in which social influence depends on individual uncertainty. Bicchieri et al. (2020) finally investigate both theoretically and experimentally environments in which signals about the applicable norms remain vague. The results suggest that individuals distort their interpretation of applicable norms to justify self-serving behavior. In our setup, however, we find no evidence of self-serving belief manipulation. Our work also has parallels to d'Adda et al. (2020). In their study, before selecting their action, dictators are shown different distributions of normative views taken from a previous study (baseline, low mean and high variance). Their results show that when the variance of the shown distribution is lower, the variance of dictator contributions decreases as well. While building on their findings, our study differs from their set-up in several important ways. Firstly, the environment we analyze is one where individuals interact strategically and where each participant is confronted with strategic uncertainty. The psychological mechanism behind our results is therefore fundamentally different. Moreover, we consider a wider range of distributions and vary not only their variance but also their shape. We believe that the case of polarized norms is a particularly interesting one to study in the face of an increasing discussion about societal polarization (Dimant, 2021). Lastly, by measuring behavior both before and after participants are shown the distributions, we are able to identify within-individual shifts and control for baseline behavior in our analysis.

As we explore how different information about the behavior of others affects contributions in a PGG, we add to a literature that stresses the importance of conditional cooperation when trying to understand contributions to a public good (see e.g. Fischbacher and Gächter, 2010; Bowles and Gintis, 2013; Gächter et al., 2017). Our work has thereby parallels to previous cooperation research that examines how group composition (Chaudhuri et al., 2006; Kerr et al.,

2009) and heterogeneity in contributions affect (conditional) cooperation (Croson, 2007; Cheung, 2014; Hartig et al., 2015; Wolff, 2017). Using the strategy method Cheung (2014) and Hartig et al. (2015) show that people do not only react to averages but also to the variation in individual contributions in a setup where all individual contributions are known. Our results extend these findings, showing that behavioral heterogeneity also matters under strategic uncertainty.

Finally, by investigating how polarized norms affect individuals' decisions and beliefs this work is moreover linked to the literature on polarization and its effects on behavior and preferences (see e.g. Fiorina and Abrams, 2008; Iyengar and Westwood, 2015; McConnell et al., 2018; Iyengar et al., 2019; Bursztyn et al., 2020; Dimant, 2021; Robbett and Matthews, 2021). Bénabou and Tirole (2016) argue that polarization is maintained as people interpret and process the same information in very different ways along with a growing divergence in beliefs. We show experimentally, that observing polarized behavior in fact leads to very heterogeneous reactions with different people focusing on different parts of the distribution. This translates into both polarized beliefs and actions and thus a re-enforcement of the initial distribution.

3 Theoretical framework

Let x_i denote own contribution, x_j is co-player's contribution and X is the endowment. It is well known that, in strategic environments, reciprocity plays an important role in determining an individual's choice of action. The presence of reciprocity motives has also been extensively documented by the literature on public good games (see e.g. Fischbacher and Gächter, 2010; Bowles and Gintis, 2013; Gächter et al., 2017). The underlying idea is that individuals incur a psychological cost whenever their contribution differs from that of their co-player. Consequently, they adapt their behavior to the behavior of their co-player. We are interested in a setup where individuals do not observe their co-player's behavior before selecting their action, but know that the action of their co-player is drawn from a distribution $f(x_j)$ on $[0, \overline{x}]$ with mean μ_x and variance σ_x^2. Intuitively, this depicts the idea that, when engaging in everyday interactions, people may not know what their counterPartwill do, but may be aware of the typical distribution of behavior within society. Since their co-player's contribution is unobserved at the time when they choose their action, agents are exposed to *strategic risk*. Their choice needs to trade off the risk of contributing too little (relative to their co-player) and the risk of contributing too much. These competing motives will determine the optimal contribution for an individual when confronted with a distribution of co-player's actions.

How do people react to environments with loose vs tight norms? How do they react to polarized norms? These are important questions that help shed light on what we may expect to observe within society. Suppose for instance that, when confronted with polarized norms – i.e., the distribution from which their co-player action is drawn is U-shaped – individuals tend to react by selecting an action that is middle of the road, in order to hedge the amount of strategic risk they are exposed to. This would suggests that societies characterized by polarized norms will tend to unravel, since the optimal reaction by individuals when confronted with polarized norms is to choose actions that are tightly distributed rather than polarized. If by contrast individuals show very heterogeneous reactions to polarized norms, the existing equilibrium is self-sustaining.

The optimal reaction to a given distribution of co-player's actions depends on the nature of the utility function. There are two natural ways in which the agents' concern for matching their co-player's action can be captured formally: (i) through a quadratic loss function – where the psychological cost incurred is proportional to the square of the difference between the two contributions, or (ii) through a linear-kinked loss function, where the cost is proportional to the absolute value of the difference between the two contributions. Quadratic loss functions are commonly used for instance in models of conformity or coordination (see e.g. Kandel and Lazear, 1992). The linear-kinked loss function was introduced by Fehr and Schmidt (1999) and has been widely used ever since.

3.1 Quadratic loss function

Consider the following stylized model of reciprocal preferences:

$$u_i = X - x_i + \gamma(x_i + x_j) - \frac{\eta_i}{2}(x_i - x_j)^2 \tag{1}$$

where $X - x_i + \gamma(x_i + x_j)$ is material payoff, $\frac{1}{2} < \gamma < 1$ and η_i parametrizes i's reciprocity concerns.[3] The last term in (1) captures the desire to minimize the psychological costs incurred whenever the player's contribution differs from that of the co-player. Each individual i selects x_i to maximize their expected utility, where the expectation is taken with respect to x_j. We denote i's optimal contribution as x_i^*.

Lemma 1: *When utility is given by (1), we have (i) $x_i^* = 0$ if $\eta_i < (1-\gamma)/\mu_x$, (ii) $x_i^* = \mu_x - (1-\gamma)\frac{1}{\eta_i}$ otherwise.*

In other words: i's contribution (when positive) is equal to j's expected contribution minus a constant which is decreasing in i's concern for reciprocity. The implication is that,

Proposition 1: *When utility is given by (1), the optimal contribution depends on the distribution of co-player's contribution only through the distribution's mean μ_x.*

Intuitively, the quadratic loss function implies that individuals are *averse to strategic risk.* They therefore choose their contribution to minimize the strategic risk they are exposed to. The optimal solution to this problem indexes i's contribution to μ_x, the co-player's mean contribution. This ensures that the difference between x_i and x_j is never too large. Crucially, it implies that i's choice *only* depends on $f(x_j)$ through μ_x, and is independent of the other features of the distribution of co-player's behavior.

3.2 Linear-kinked loss function

Suppose now that utility is

$$u_i = X - x_i + \gamma(x_i + x_j) - \alpha_i (x_i - x_j)|_{x_j < x_i} - \beta_i (x_i - x_j)|_{x_j > x_i} \tag{2}$$

[3] Note that, although η_i will typically depend on the degree of intentionality in the co-player's action, for the purpose of our design, where action intentionality is the same across all treatments, it can be treated as constant.

This utility function differs from (1) in that the psychological loss incurred by individuals is proportional to the *absolute value* of the difference between their contribution and that of their co-player. The parameter α_i (resp., β_i) measures the marginal disutility obtained from selecting a contribution that exceeds (resp., is lower than) the co-player's contribution.

Lemma 2: *Let* $\varphi_i \equiv \frac{\beta_i-(1-\gamma)}{\alpha_i+\beta_i}$. *When utility is given by (2), we have (i)* $x_i^* = 0$ *if* $\varphi_i \leq 0$, *(ii)* $x_i^* = \overline{x}$ *if* $\varphi_i \geq 1_i$, *(iii)* x_i^* *satisfies* $F(x_i^*) = \varphi_i$ *otherwise.*

Figure 1 represents the function $F(x)$ for the case of (i) single-peaked distributions and a (ii) polarized (U-shaped) distribution. In panel (i), the solid line represents a distribution with a smaller variance compared to the dashed line. The horizontal straight lines represent φ_i.

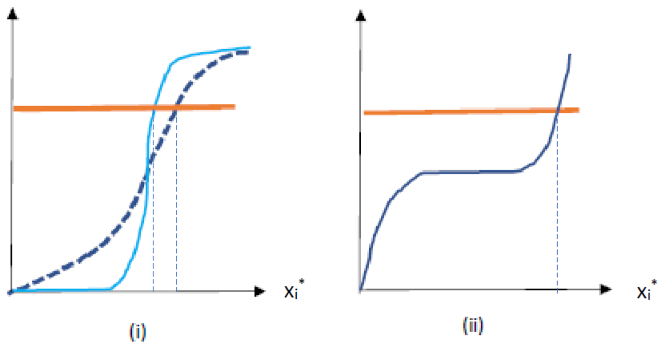


Figure 1: F(x) for single peaked (i) and polarized (ii) distributions

As can be seen from Figure 1, the point where $F(x)$ and φ_i cross depends on the nature of the distribution of co-player contributions. For instance, when $f(.)$ is polarized, $F(x)$ is steep at the extremes and flat in the middle. This implies that, typically, $F(x)$ and φ_i will cross when x takes extreme values – either very low or very high (panel (ii) of the figure illustrates the latter possibility). When facing a polarized distribution, individuals thus exhibit strategic-risk taking behavior: they prefer to take a gamble and risk ending up in a completely mismatched position vis-à-vis their co-player rather than opting for a "middle of the road" contribution level which would minimize risk.

In contrast, when the distribution of co-player contributions is single-peaked, $F(x)$ is flat at the extremes and steep in the middle. Consequently, $F(x)$ and φ_i will tend to cross when x takes intermediate values. As the variance of $f(.)$ increases, though, x_i^* will tend to become progressively more extreme, as can be seen by comparing the solid and the dashed lines in panel (i) of Figure 1. These observations lead to,

Proposition 2: *When utility is given by (2), the optimal contribution will typically depend on the variance and shape of the distribution of co-player's contribution in addition to the distribution's mean* μ_x.

The following result formalizes the notion that, as the variance of co-player contribution increases, individuals tend to select more extreme contributions. Consider two distributions f_0 and f_1 with the same mean μ_x and suppose that f_0 is single-crossing stochastic dominant over f_1 (Machina and Pratt, 1997). Note that this implies that f_1 is a mean-preserving spread of f_0. Denoting the optimal contribution under f_k as x_{ik}^*, the following holds.

Proposition 2a: *There exists* $z \in (0, \overline{x})$*such that the following holds; (i) if* $x^*_{i0} \in (0, z)$: $x^*_{i1} < x^*_{i0}$; *(ii) if* $x^*_{i0} \in (z, \overline{x}) : x^*_{i1} > x^*_{i0}$.

Finally, from Lemma 2 is is straightforward to see that,

Proposition 2b: *Consider* f_2 *and* f_3 *such that* $F_2(x) < F_3(x)\, \forall x$. *Then,* $x^*_{i2} \leq x^*_{i3}$ *with strict inequality whenever at least one of* x^*_{i2} *and* x^*_{i3} *is interior.*

This corresponds to the case where the distributions of co-player contributions have different means (but the same variance).

3.3 The role of personal values

We now allow agents to also be concerned with abiding to their own personal values when selecting their contribution, in addition to their desire to match their co-player's action. Let x^a_i represents i's perception of what constitutes "the right thing to do" (the "appropriate action"), and suppose that individuals suffer a psychological loss when their contribution differs from x^a_i. Concern for own personal values introduces two additional channels through which the distribution of co-player's actions may influence the agent's contribution. First, they may affect the agent's perception of what is appropriate. For instance, the distribution of co-player contributions might reveal information about what others consider to be the right thing to do, and this may affect what i sees as appropriate. Second, in the case of a linear-kinked loss function, the shape of the distribution of co-player's behavior may mediate the extent to which the appropriate action x^a_i affects the individual's optimal contribution. To see this, let us augment the linear-kinked utility described in (2) with appropriateness concerns as follows.

$$u_i = X - x_i + \gamma(x_i + x_j) - \alpha_i \left(x_i - x_j\right)|_{x_j<x_i} - \beta_i \left(x_i - x_j\right)|_{x_j>x_i} - \frac{\delta_i}{2}\left(x_i - x^a_i\right)^2 \qquad (3)$$

where δ_i parametrizes the importance that i ascribes to doing the right thing.[4]

Lemma 3: Let $\phi_i \equiv \beta_i + \delta_i x^a_i - (1-\gamma)$. *When utility is given by (3), we have (i)* $x^*_i = 0$ *if* $\phi_i \leq 0$, *(ii)* $x^*_i = \overline{x}$ *if* $\phi_i \geq \delta_i \overline{x} + \alpha_i + \beta_i$, *(iii)* x^*_i *given by* $\delta_i x^*_i + F\left(x^*_i\right)\left(\alpha_i + \beta_i\right) = \phi_i$ *otherwise.*

Proposition 3: *Suppose that utility is given by (3). Whenever* x^*_i*is interior, we have*

$$\frac{\partial x^*_i}{\partial x^a_i} = \frac{\delta_i}{\delta_i + f(x^*_i)\left(\alpha_i + \beta_i\right)}$$

In other words, the optimal contribution is more responsive to differences in an agent's personal values when the $F(.)$ function is flatter – reflecting higher variance in the distribution of co-player's actions.

[4]The results described in the previous subsections are robust to the inclusion of concern for personal values. Details available upon request.

4 Experimental Design

To empirically test the propositions derived in our theoretical framework, we design an experiment that exogeneously varies the *mean* and *variance/shape* of the co-player's behavior in a PGG. More concretely, the experiment consists of two parts. Participants learn the details of the second Partonly upon completion of the first. Part Ielicits baseline measures for the PGG, consisting of two blocks that are presented in a random order. We use the 'ABC of cooperation' (Gächter et al., 2017) to measure contributions, beliefs about the co-player's contribution, and a conditional contribution schedule. In addition, we elicit personal values (PVs) of what an individual thinks one should do in the PGG, normative expectations (NEs) about what other people think one should do and empirical expectations (EEs) about what most other people will actually do.

At the beginning of PartII, each participant observes one of six possible distributions of behavior from a previous session and are informed that their co-player for Part II will be randomly drawn from this distribution.[5] We then again employ the ABC method and elicit PVs, NEs and EEs.[6] The distributions vary along two dimensions: *mean* (high, low) and *variance/shape* (high variance, low variance, u-shaped). Figure 2 illustrates the design. Tying this design decision back to our motivation, the low variance conditions are an example of a tight environment, while high variance conditions are an example of loose environments. The u-shaped conditions, finally, depict the case of a polarized environment.

4.1 Hypotheses

Before describing the experimental design in more detail, we lay out how our theoretical framework informs the behavior we expect to see in the experiment.[7] As shown in the theoretical framework, the effect of tight, loose, and polarized behavior depends on the assumptions about the underlying loss function. As *proposition 1* states, under a quadratic loss function we expect participants to only react to changes in the mean of the observed distribution. If we assume a linear-kinked loss function, by contrast, we expect in line with *proposition 2* that the variance/shape of the distribution matters as well. Given previous findings on the importance of heterogeneity in contributions (Croson, 2007; Cheung, 2014; Hartig et al., 2015), we expect that participants in the experiment will in fact react to the changes in the distribution, favouring the linear-kinked loss function. In this case, our theoretical framework does not only predict that individuals react to different distributions, but also the direction of the effect. In particular, we expect higher dispersion to lead to more extreme contributions and thus a larger behavioral variance. If the observed behavior is polarized, we expect to see a polarization in contributions.

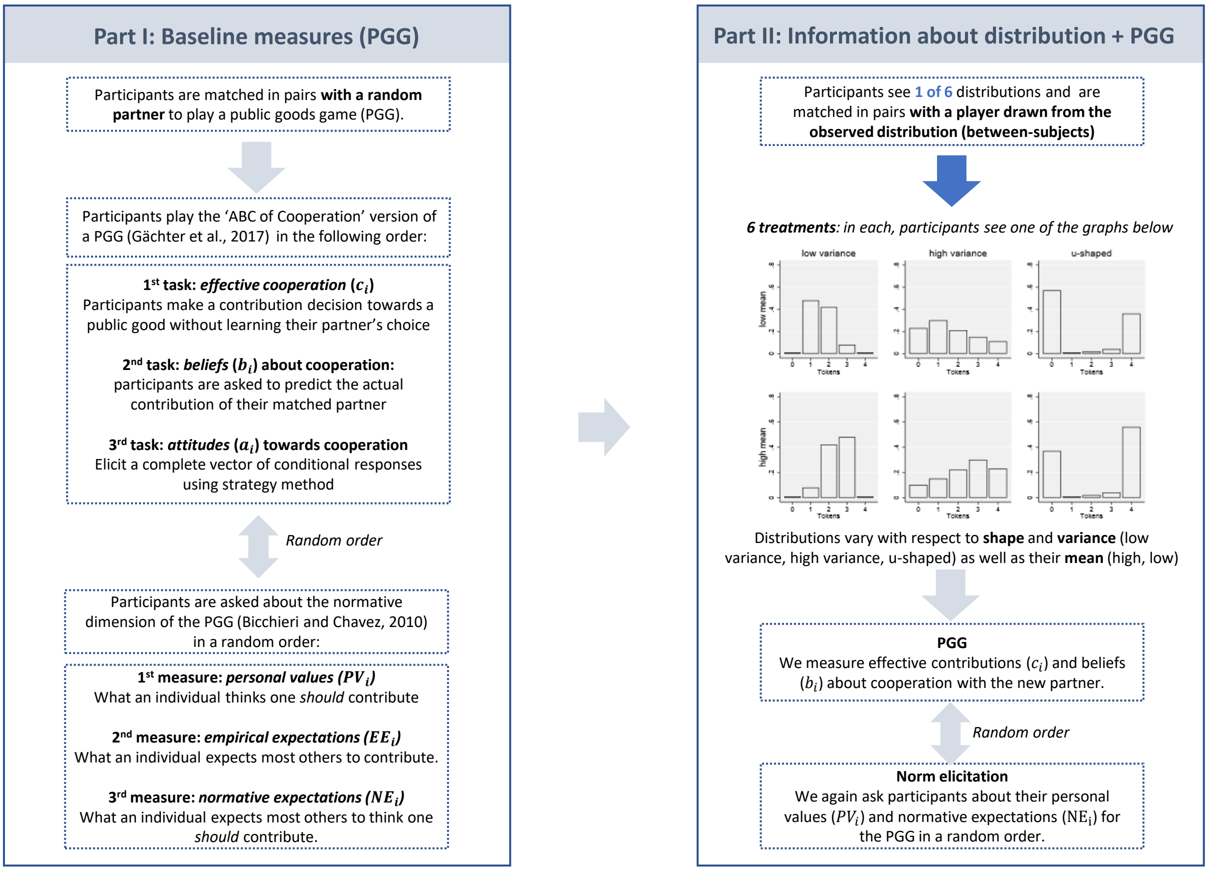
Hypothesis 1. *Assuming a linear-kinked loss function, loose environments lead to a larger variance in contribution behavior. Moreover, when loose environments are polarized (U-shaped)*

[5]The distributions are generated through non-random sampling. We are completely transparent with participants regarding the origin of these distributions. See Section 4.2 for more details.

[6]As in Part I the order between ABC method and norm elicitation as well as the order of PVs, EEs and NEs is randomised.

[7]The experiment and our hypotheses were pre-registered in November 2021. The pre-registration is available under: https://aspredicted.org/pm7fu.

Figure 2: Overview of the experimental design



they generate polarized behavior.

Secondly, independent of the variance and the shape of the distribution we expect contributions to be higher in the high mean conditions. This is in line with the prevalence of conditional cooperation in PGGs and shows a desire to match the contributions of the other player.

Hypothesis 2. *Individual contributions depend on the distribution's mean, implying that contributions in high mean conditions are higher than in low mean conditions.*

Finally, *proposition 3* shows that if we take personal values or what individuals see as the appropriate action into account, the variance/shape of the distribution mediates the extent to which personal values affect behavior. Under the assumption of a linear-kinked loss function, we expect a higher influence of personal values on behavior in loose/polarized than in tight environments.

Hypothesis 3. *Assuming a linear-kinked loss function, personal values have a higher impact on contribution decisions in loose and polarized compared to tight environments.*

	Single-peaked				*Double-peaked*	
	Low variance		**High variance**		**U-shaped**	
	mean	var	mean	var	mean	var
High mean	1.6	0.5	1.6	1.6	1.6	3.6
Low mean	2.4	0.5	2.4	1.6	2.4	3.6

Table 1: Experimental conditions

4.2 Treatment conditions

Our experiment is based on a between-subject design, where participants are randomly assigned to one of six treatment conditions. More precisely, we use a 2x3 design, resulting in six experimental conditions that combine high and low means with three different variances/shapes (low variance, high variance, u-shaped). Table 1 gives an overview of the different treatment conditions, including their mean (μ) and variance (σ^2).

While Part I is identical across treatments, participants observe different distributions at the beginning of Part II.[8] The latter are constructed through non-random sampling of a previous session.[9] Participants are told in the experiment that we invited several hundred people, who took part before them, to play the same game and that we used their answers to construct six different sub-groups. Moreover, they know that in the second part of the experiment, we will randomly show them the behavior of one of these sub-groups. We are thus completely transparent with participants and acknowledge that the distributions do not represent overall behavior in a PGG, but only represent the behavior of our constructed sub-groups. Most importantly, participants know that their co-player's contribution choice will be drawn randomly from the observed distribution and thus affect their payoffs. Likewise, their decisions affect the payoffs of the randomly drawn player. We illustrate the distributions of all six conditions that participants saw at random in Figure 3.[10]

4.3 Measuring contributions and beliefs

In Part I, we elicit individual behavior as well as perceived norms in a standard PGG without any additional information about distributions (Ledyard, 1995; Fischbacher et al., 2001). This allows us to later control for baseline behavior in our analysis. We use a two-player variant of the PGG in which each participant can contribute up to four tokens to the public good. Any token invested in the public good is then multiplied by 1.4 and shared between both participants. As mentioned above, the game embodies the classic tension between private and collective interest: while fully contributing to the public good maximizes joint payoffs, each player's self-interest is maximized by contributing nothing. To disentangle the underlying motives to contribute, we follow the 'ABC of cooperation' (**A**ttitudes-**B**eliefs-**C**ontribution) method developed by Gächter

[8] See Appendix B for experimental instructions.

[9] A similar approach is used for example by Frey and Meier (2004), Bicchieri and Xiao (2009), Krupka and Weber (2009), and Bursztyn et al. (2020).

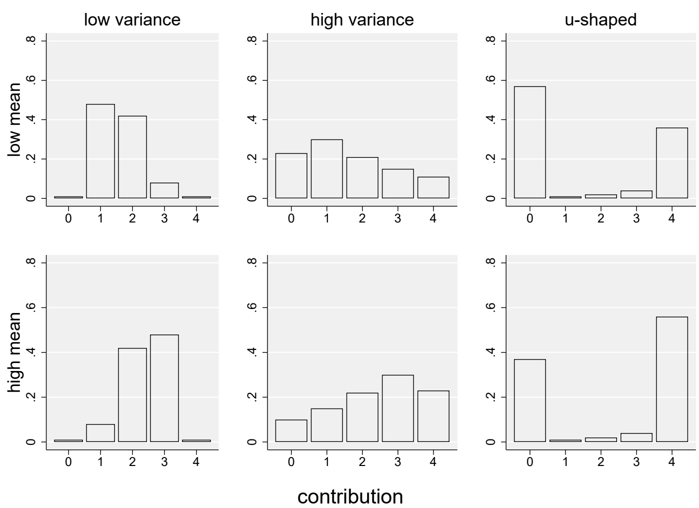
[10] For an exact representation of how participants receive the information about distributions see Appendix B, Instructions Part 2.

et al. (2017). The ABC method embodies three distinct elicitations: a one-shot sequential PGG played with the strategy method to measure attitudes of cooperation (A), a belief-elicitation task to measure expectations of others' contribution (B), and a one-shot simultaneous PGG played with the direct response method to measure effective contributions (C). We always first measure contributions, followed by beliefs and attitudes. The elicited attitudes give us a conditional contribution vector that can then be used to classify participants into different *cooperation types*. Following the seminal paper by Fischbacher et al. (2001) and the refinement by Thöni and Volk (2018) we distinguish the following five types:

1. *Free riders*: contribute zero, independent of the other's contribution.
2. *Conditional cooperators*: show either a monotonically increasing pattern or a strong positive correlation between own and other's contribution (Pearson $\rho \geq 0.5$).
3. *Unconditional cooperators*: contribute the same positive amount, independent of the other's contribution.
4. *Triangle cooperators*: reach a maximum contribution at a middle value x. Contributions either show a strong positive correlation to the left and a strong negative correlation to the right or are monotonically increasing until x, then decreasing.
5. *Others*: cannot be classified using the criteria specified above.

In addition to contributions, we are also interested in the perceived normative dimension of the PGG. Following Bicchieri and Chavez (2010), we measure both personal values (PV), i.e. what an individual thinks one *should* do[11], as well as empirical and normative expectations (EE and NE) about what an individual expects most others to do and most others to think one *should* do.[12] All three measures (PV, EE, NE) are elicited in a randomized order. In Part II of the

Figure 3: Experimental conditions: distribution of co-player's contribution



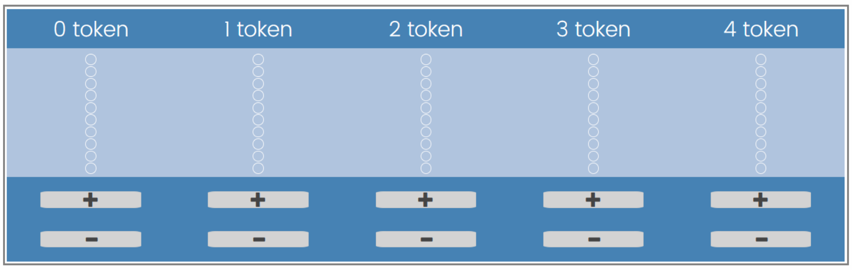
[11]The literature also refers to this as personal normative beliefs.

[12]When eliciting PV and EE, we ask what an individual considers to be the most *appropriate* action or the action that most people would agree upon as being "correct" or "moral" (see Bašić and Verrina, 2020).

experiment, we again ask for individual contributions and beliefs, as well as participants' PVs and NEs. The only difference to Part I is that we are not using the strategy method and that the co-player is not chosen randomly but drawn from the shown distribution. The rational for using the strategy method in Part I was to classify individuals into generic types of contributors. We therefore did not repeat this procedure in Part II. In both parts we randomize whether participants first make their contribution decisions or indicate their normative views.[13]

Participants are paid for both the contribution decision in Part I and II but receive no information about their payoffs between parts. In addition, to avoid hedging opportunities we randomly select one of all belief, NE and EE questions to be payoff relevant.

Figure 4: Belief elicitation screen



Note. Participants have to allocate a total of 10 points across all available options. The more likely they think an option is the more points they should allocate to it.

As we are interested in the effect of the variance, we do not only capture beliefs about modal behavior, but about the whole distribution of the participants' beliefs. To do so, we follow the approach discussed in Dimant (2022) and ask participants to allocate points across all possible outcomes (see Figure 4).[14] The more likely participants think an option is, the more points they should allocate to it. To incentivize decisions, payoffs are calculated using a quadratic scoring rule (QSR): $Q_j(p) = \alpha + 2\beta * p_j - \beta * \sum_{i=1}^{n}(p_i)^2$, where p_j is the probability a participant assigns to the true option.[15] We use this approach for three sets of beliefs: one's beliefs about the co-player's contribution, NEs, and EEs.[16] To avoid hedging between the different questions, we randomly select one of them to be payoff relevant at the end of the experiment. In addition, we elicit a participant's confidence in the stated belief distribution and evaluate this alongside the stated beliefs.

[13] We control for order effects in all our analysis but do not find significant results.

[14] This method is inspired by existing work on eliciting distributions of subjective beliefs (e.g., Lau et al., 1998; Goldstein and Rothschild, 2014; Harrison et al., 2017) as well as an oral presentation given by Don Ross at the 2019 "Norms and Behavior Change" (NoBeC) workshop. For the purposes of our investigation, we apply those insights to our context of tight, loose, and polarized environments.

[15] In the experiment we set $\alpha = \beta = 0.5$, which implies that participants earn between \$0 and \$1 depending on their stated beliefs and the truth.

[16] In order to make the rule as easy to understand as possible, we adapt the instructions developed by Artinger et al. (2010) that allow a transparent representation of the QSR even for non-binary decisions and use an intuitive interface to make decisions (see Quentin, 2016). For details see instructions in Appendix B.

4.4 Sample and data collection

We programmed the experiment using Qualtrics (2005) and recruited participants online via Prolific in December 2021.[17] In total, we recruited a sample of about 1200 US participants that is representative in terms of age, gender and ethnicity (see Table 2 for observations per treatment). The chosen sample size was determined using data from a pilot and allows us to detect an effect size of $\eta^2 = 0.01$ at a 5% significance level with 90% power. On average participants needed 17 minutes to complete the study and earned $3.20.

	Single-peaked		**U-shaped**
	low variance	high variance	u-shaped
high mean	201	201	201
low mean	199	200	201

Table 2: Sample size and experimental conditions

To construct the six distributions, we collected data from 685 MTurkers in September 2021. They initially received a show-up fee and then earned an additional bonus depending on the decisions of the participants in the main experiment.

After completing the experiment, participants filled out an ex-post survey that provides further controls for our analysis. In terms of demographics and general characteristics we collected information on participant's gender, age, highest education level, trust, attitudes towards risk (Dohmen et al., 2011), as well as negative and positive reciprocity (Falk et al., 2016). In addition, we asked questions about the observed distributions and the experiment. In particular, participants stated how they perceived average contributions as well as their variance in the observed distribution (low, medium, high) and how difficult they found interpreting the graph (on a scale from 1 to 7). As we told participants that they see observations from one of the six sub-groups we constructed from previous sessions, we also asked how representative they think this behavior is on a scale from 1 to 7. Finally, to proxy their aversion of contributing too much/ too little, we asked them on a scale from 1-7 "How upset would you be if you invested everything in the group account and discovered that the participant you have been matched with invested nothing?" (*sucker aversion*) and "How ashamed would you be if you invested nothing in the group account and discovered that the participant you have been matched with invested everything?" (*free-rider aversion*).

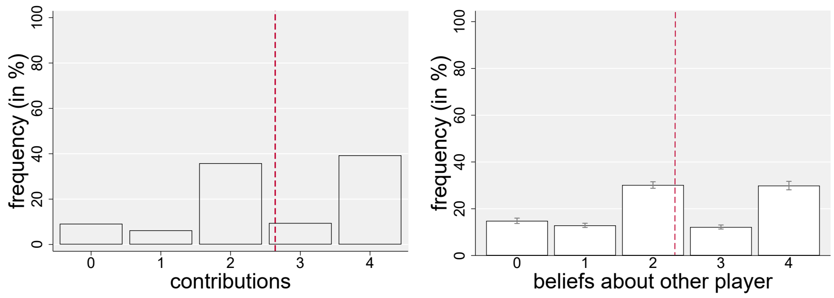
5 Results

5.1 Baseline measures: behavior in Part I

We first provide an overview of our baseline measures before participants receive any information about other players. We do so both with respect to the ABC method as well as PVs and expectations about others (EEs and NEs).

[17]The project obtained IRB approval in November 2021.

Figure 5: Contributions and beliefs in Part I



Note. The dashed lines represent averages. Whiskers show 95% confidence intervals.

The contribution schedule reveals a strong pattern of conditional cooperation among participants, which is in line with existing literature. Following the type definitions developed by Fischbacher et al. (2001) and Thöni and Volk (2018), we classify 84% of all participants as conditional contributors.[18] On average, participants contributed 2.6 out of their 4 tokens to the public good. The most common contribution levels were thereby 2 and 4 tokens (see Figure 5). Beliefs about the co-player's contribution were on average slightly more pessimistic (2.3 token).[19] Moreover, we observe substantial variation in responses, stressing the strategic uncertainty of the PGG. As the right graph in Figure 5 shows, the most common beliefs are that the other contributes 2 or 4 tokens and are thus aligned with actual contributions.[20]

We see a very similar pattern for EEs and NEs (see Figure 6). Not surprisingly, when asked about what most other people actually contribute participants answer in the same way as when asked about their co-player's likely contribution. NEs, are shifted slightly to the right, indicating that people think other's contribute less than they say one should. Interestingly, participants also appear to be more certain about what others say one should contribute than actual contributions. Although the difference is small, our confidence measure is significantly higher for NEs than EEs about the other player (Wilcoxon signed-rank test, $p = 0.01$). The difference between ideal and actual behavior also holds true for the participants themselves. On average participants state that one should contribute 2.9 token to the public good. This means personal values are significantly higher than the actual contributions we observe in Part I (Wilcoxon signed-rank test, $p < 0.001$).

The data from Part I already allows us to conduct a first test of our **Hypotheses 1** and **2**. Even though we do not have exogenous variation in the behavior of the other player, we can test whether the average belief as well as the variance of the belief about the other player have an effect in line with our theoretical predictions. To do so, we split our sample in two groups, one with average beliefs above the median (> 2) and one below the median (≤ 2). These two

[18] The rest consists of 5% unconditional contributors, 3% free-riders, 5% triangle contributors and 4% others.

[19] Note that while we measure contributions and PVs directly, we elicit the whole distribution of beliefs, NEs and EEs by asking participants to allocate points across the different tokens depending on how likely they perceive each option. For this reason, we can construct confidence intervals for beliefs about the co-player's contribution, NEs and EEs, but not for contributions and PVs.

[20] Note that Figure 5 depicts the aggregate distribution of beliefs across players. There is substantial heterogeneity in the distribution of beliefs between individuals (see Appendix A, Figure A.1).

Table 3: OLS models. Effect of beliefs (mean and sd) on contributions in Part I

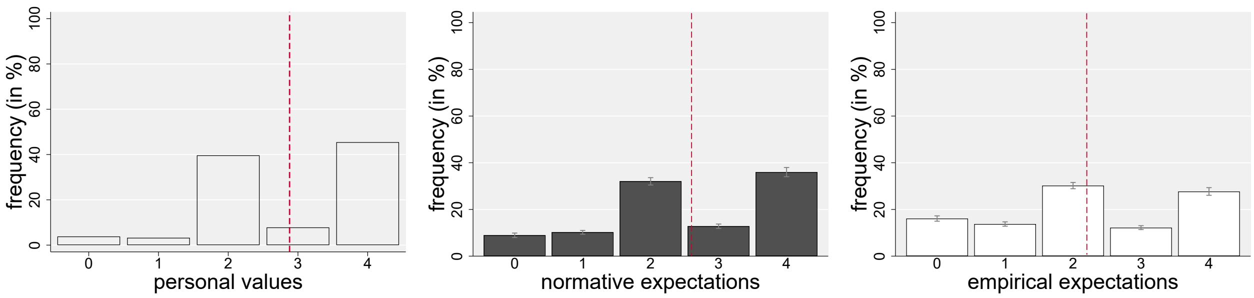
	No Interaction		Interaction	
	(1)	(2)	(3)	(4)
High mean of beliefs	0.82***	0.78***	0.06	0.10
	(0.08)	(0.08)	(0.12)	(0.12)
SD of beliefs	0.02	0.02	-0.17***	-0.16***
	(0.02)	(0.02)	(0.04)	(0.04)
High mean x SD of beliefs			0.35***	0.32***
			(0.05)	(0.05)
Personal values	0.56***	0.55***	0.51***	0.50***
	(0.04)	(0.04)	(0.04)	(0.04)
Constant	0.60***	0.02	1.11***	0.51
	(0.09)	(0.35)	(0.13)	(0.36)
Demographic controls	No	Yes	No	Yes
N observations	1203	1188	1203	1188
R^2	0.50	0.52	0.52	0.54

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.
Note. *High mean of beliefs* is a binary variable with 0 if the average belief is below the median (≤ 2) and 1 if the average belief is above (> 2). Similarly, *SD of beliefs* is a continuous measure for the SD of beliefs. *Personal values* measures the contribution an individual sees as appropriate and ranges between 0 and 4. Demographic controls include age, gender, education, acceptance of risk, trust, sucker aversion, free-rider aversion and measures for negative and positive reciprocity. All regressions control for order effects.

sub-groups serve as a placebo treatment for the high and low mean condition, while we control for the standard deviation (SD) as a measure of the distribution of beliefs.

Table 3 shows the results from a regression of contributions in Part I on average beliefs (high/low), SD of beliefs, and PVs. It confirms that already in the first part of the experiment there is evidence that the mean and variance matter.[21] In particular, we can see that having a higher average belief about the other's contribution significantly increases own contributions. Secondly, we can see that the variance has a separate effect depending on the mean. In particular, we see that for participants with low average beliefs, a higher SD decreases contributions. For participants with high average beliefs by contrast, a higher SD increases contributions. This shows that variance can have heterogeneous effects on contributions and provides first evidence for our conjuncture that looser environments with a higher behavioral variation increase the

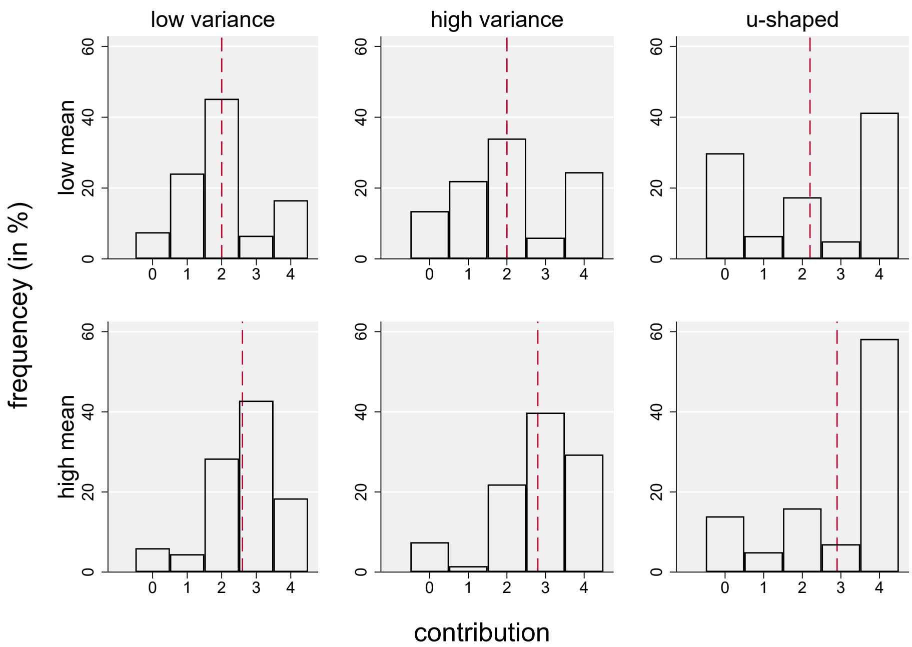
Figure 6: PVs, NEs, and EEs, in Part I



Note. The dashed lines represent averages. Whiskers show 95% confidence intervals.

[21]Table A.1 in Appendix A shows the results of a tobit regression as a robustness check.

Figure 7: Distribution of contributions in Part II by treatment



Note. The dashed lines represent the average contribution in each treatment.

variance in contributions. This is furthermore confirmed when splitting the sample into a high and low variance group[22] and compares the variance in contributions in both groups. Our results show that if beliefs vary more, contributions are also more dispersed (F-test, $p = 0.001$). While this analysis cannot provide causal evidence for the importance of mean and variance, it already provides anecdotal support for our theoretical framework. In the subsequent sections, we turn to a more rigorous test of our hypotheses that accounts for exogenous variation in the presented information about one's peers.

5.2 Effect of variance and shape of a distribution

We now address our main research question, namely how the variance and shape of an empirical norm affects individual responses.[23] Recall that under a linear-kinked loss function, we expect participants to react to the variance such that loose environments lead to a larger variance in behavior. Similarly, a polarized environment is expected to generate polarized behavior.

Figure 7 shows the distribution of contributions in Part II for each experimental condition. We can see that there is a stark difference between treatments. In particular, we see that in tight environments (low variance) participants choose contribution levels that are tightly centered around the mean of the shown distribution ($\sigma^2 = 1.26$). In loose (high variance) environments, by contrast, we see a much larger variation in behavior ($\sigma^2 = 1.65$). In other words, loose

[22]With standard deviations above and below the median.

[23]Figure A.2 in Appendix A shows that participants have a correct interpretation of the observed distributions and state that it was relatively easy to understand them. Moreover, the perception of how difficult to interpret and how common the observed behavior is in a wider population is similar across conditions.

behavior generates loose responses while tight behavior generates tight responses. We also find that a polarized environment, in turn, causes polarized behavior ($\sigma^2 = 2.68$). This means that participants show very heterogeneous reactions to polarized environments and do focus on different parts of the distribution. In Section 5.4 we provide a discussion on possible individual factors that drive this heterogeneity.

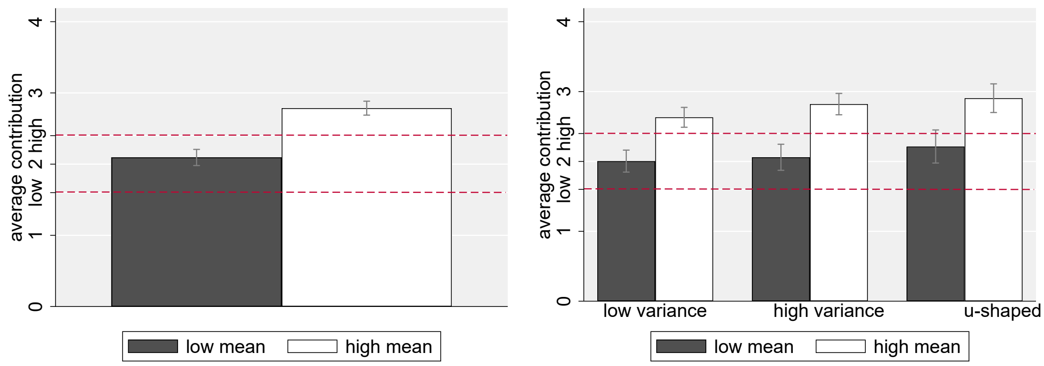
To test the first visual impression, we perform pairwise F-tests for the equality of standard deviations between distributions.[24] Overall, we find that the variance in contributions is significantly higher in the u-shaped than in the high or low variance conditions (for both $F < 0.001$). The high variance conditions in turn have a significantly higher variance than the low variance conditions ($F = 0.007$).[25] Our results thus confirm the importance of both variance and shape of observed behavior for individual decisions. Different environments generate very distinct responses. What is more, we find that they are self-sustaining. Loose, tight, and polarized behavior thus reproduces itself.

Result 1. *Looser environments lead to a larger variance in behavior. When behavior is polarized (U-shaped), it in turn generates polarized responses.*

5.3 Effect of high and low means

When looking at the difference between high and low mean conditions, we find that in line with previous literature contributions are significantly higher in high mean conditions (Wilcoxon-Mann-Whitney test, $p < 0.001$). This is both true when pooling the data and when separately testing the effect for each shape and variance (see Figure 8). As the diff-in-diff between variance

Figure 8: Effect of high or low mean on contributions (left: overall, right: by variance/shape)



Note. The dashed lines represent the mean of the observed distributions (high = 2.4, low = 1.6). Whiskers show 95% confidence intervals.

[24] In Appendix A we moreover provide an alternative test for Hypothesis 2 by splitting the sample into a high and a low contribution sub-sample and investigating the effect of variance in separate regressions (see table A.2). In line with our results from Part I we find that in the high contribution sub-sample a larger variance increases contributions, while the opposite holds true for the low contribution sub-sample.

[25] A χ^2 test confirms that contributions in the u-shaped condition are distributed significantly different than in the two other conditions (for both $p < 0.001$). Likewise, contributions in the low and high variance conditions follow a significantly different distribution ($p = 0.002$). Finally, the distribution of contributions in Part II is significantly different from the distribution in Part I ($p < 0.001$).

Table 4: OLS models. Effect of high and low mean conditions on contributions in Part II

	No interaction			Interaction		
	(1)	(2)	(3)	(4)	(5)	(6)
High mean	0.69***	0.70***	0.66***	0.62***	0.59***	0.55***
	(0.08)	(0.06)	(0.06)	(0.11)	(0.09)	(0.09)
Variance (baseline = low)						
High variance	0.13	0.14**	0.16**	0.05	0.06	0.08
	(0.08)	(0.07)	(0.07)	(0.12)	(0.10)	(0.10)
U-shaped	0.24**	0.29***	0.27***	0.21	0.20	0.19
	(0.10)	(0.08)	(0.08)	(0.15)	(0.13)	(0.12)
Interactions						
High mean x high variance				0.14	0.16	0.17
				(0.17)	(0.13)	(0.13)
High mean x u-shaped				0.07	0.17	0.17
				(0.19)	(0.16)	(0.15)
Constant	2.00***	0.15	-0.07	2.04***	0.21*	-0.01
	(0.09)	(0.10)	(0.39)	(0.10)	(0.11)	(0.40)
Baseline controls	No	Yes	Yes	No	Yes	Yes
Demographic controls	No	No	Yes	No	No	Yes
N observations	1203	1203	1188	1203	1203	1188
R^2	0.07	0.40	0.45	0.07	0.40	0.45

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.
Note. High mean is a binary variable with 0 = low and 1 = high mean. *Variance* is a categorical variable with 0 = low variance, 1 = high variance and 2 = u-shaped. Baseline controls include contributions, average beliefs, and PVs in Part I and can take values between 0 and 4. Demographic controls include age, gender, education, acceptance of risk, trust, sucker aversion, free-rider aversion and measures for negative and positive reciprocity. All regressions control for order effects.

and mean is insignificant, we conclude that the mean has a similar effect across environments.

To test **Hypothesis 2** formally and control for individual characteristics we regress the contribution of individual i in Part II on the observed mean (high/low), variance/ shape of the distribution (high var/low var/u-shaped), as well as their interaction. As Table 4 shows, we find that contributions are significantly higher in the high mean conditions. This finding also holds when controlling for baseline behavior and including demographic controls (see models 2 and 3).[26] Moreover, table 4 confirms that the effect of the mean is independent of the variance/shape of the distribution. All interactions are insignificant. Finally, we see that overall contributions are higher in the high variance and u-shaped conditions than in the low variance conditions. This might be a bit surprising, as a larger variance could give individuals more wiggle room to self-servingly focus on the lower tail of the distribution. It is important to note, however, that participants in our sample state relatively high personal values of what one should contribute to the PGG. As we find that personal values matter more in loose and polarized environments (see Section 5.4), this could explain higher contributions in these conditions.[27]

Result 2. *Participants react to the mean of the distribution. When confronted with higher average contribution levels, they contribute significantly more. This is true independent of the*

[26] As contributions can only take values between 0 and 4, we run tobit regressions as a robustness check and find qualitatively similar results (see Appendix A, Table A.3).

[27] Previous literature has found mixed results when relating variance to contributions. d'Adda et al. (2020) find no effect, while Hartig et al. (2015) find that contributions are lower under higher variance.

Table 5: OLS models. Effect of personal values on contributions in Part II across different environments

	(1)	(2)
Personal values in part I	0.39***	0.31***
	(0.05)	(0.05)
Variance (baseline = low)		
High variance	-0.22	-0.21
	(0.20)	(0.19)
U-shaped	-0.13	-0.20
	(0.25)	(0.24)
Interactions		
High variance × PVs in part I	0.13*	0.13*
	(0.07)	(0.07)
U-shaped × PVs in part I	0.13	0.15*
	(0.08)	(0.08)
High mean	0.73***	0.67***
	(0.07)	(0.07)
Constant	0.87***	0.17
	(0.14)	(0.44)
Demographic controls	No	Yes
N observations	1203	1188
R^2	0.23	0.32

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.
Note. *High mean* is a binary variable with 0 = low and 1 = high mean. *Variance* is a categorical variable with 0 = low variance, 1 = high variance and 2 = u-shaped. *Personal values* in Part I can take values between 0 and 4. Demographic controls include age, gender, education, acceptance of risk, trust, sucker aversion, free-rider aversion and measures for negative and positive reciprocity. All regressions control for order effects.

variance or shape of the distribution.

5.4 Mechanisms: Personal values, beliefs, and individual preferences

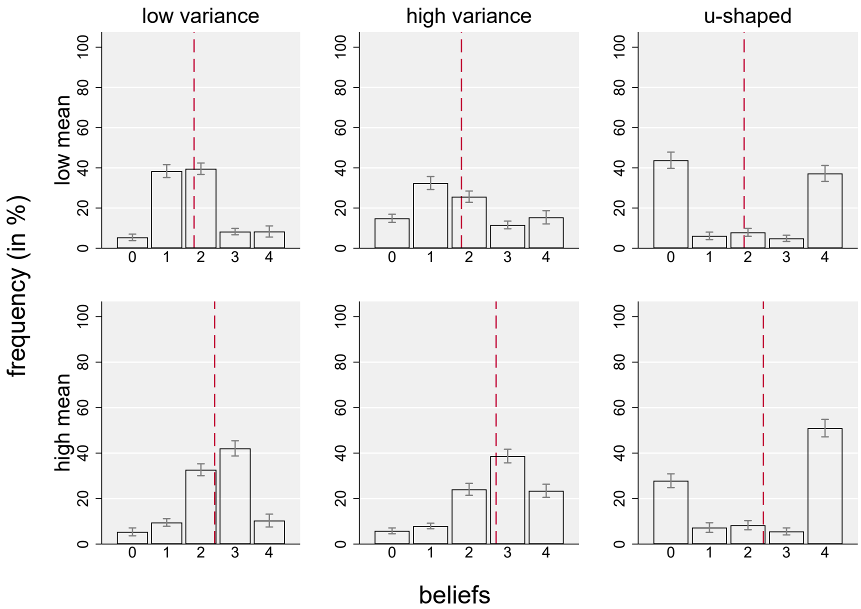
Finally, **Hypothesis 3** states that under a linear-kinked loss function we expect personal values to have a larger effect in loose and polarized than in tight environments. Intuitively, if empirical norms are loose or polarized and people observe a larger behavioral variance, personal values could play a larger role in guiding decisions due to the higher strategic uncertainty. To test this hypothesis formally, we regress contributions in Part II on the mean and variance/shape of the observed distribution, as well as on the interaction between personal values in Part I[28] and variance/shape. As can be seen from Table 5, this interaction is positive and significant for the loose environment. Similarly, for the polarized conditions the interaction is always positive and becomes significant after including controls.[29] Thus, we confirm that the effect of personal values on contribution behavior is stronger in loose and polarized than in tight norm environments.

The finding that personal values have a separate effect depending on the environment also allows us to explain the observed heterogeneity in responses to the high variance, in particular the u-shaped distribution. Personal values moderate contributions in Part II, with higher personal values predicting significantly higher contributions. Applied to the u-shaped scenarios, this

[28] Note that we do not use PVs in Part II as there is a high multicollinearity between our treatment indicators and beliefs, expectations or PVs in Part II.

[29] In model (1) the insignificant p-value for the coefficient on u-shaped x PVs in Part I is $p = 0.11$.

Figure 9: Distribution of beliefs in Part II by treatment



Note. The dashed lines represent the average beliefs in each treatment. Whiskers show 95% confidence intervals.

means that whether an individual focuses on the lower or higher end of the distribution seems to be at least partly driven by their personal values.

Result 3. *Personal values matter more for individual behavior in loose or polarized compared to tight environments.*

To get a better understanding of what drives within-individual changes in contributions between Part I and II, we next turn to the importance of beliefs about the co-player's contribution. Figure 9 shows that these largely mirror the observed distribution, in the sense that a larger variance in the distribution also leads to a larger variance in beliefs.[30] This is both true for beliefs on aggregate, as well as the distribution of beliefs for each individual (see Appendix A, Table A.4). Beliefs are thus highly sensitive to the provided information, suggesting that a main channel through which the provided information affects contribution behavior is through successfully shifting beliefs.[31]

We also confirm the importance of beliefs about the co-player for the change of contributions between Part I and II through a regression analysis (see Appendix A, table A.6). In particular, we find that the larger the change in average beliefs between parts as well as the difference between the variance of the observed distribution and the initial variance of beliefs, the larger the change

[30]Changes in both beliefs and contributions are on average stronger in the low mean conditions (Wilcoxon-Mann-Whitney tests, $p < 0.001$), suggesting that people are more likely to be convinced of lower contributions, consistent with a self-serving contagion (Dimant, 2019). However, initial contributions and beliefs in Part I are relatively high, leaving more room for downward adjustments.

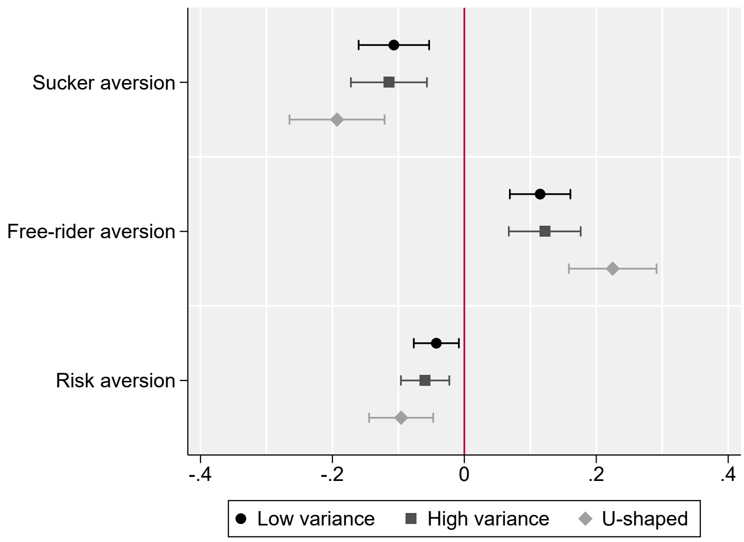
[31]Figure A.4 in Appendix A visualises that participants change their beliefs between parts so that they are closer aligned with the shown distribution. NE show a similar pattern (see Figures A.5 and A.6).

in contributions.[32] Moreover, it is not only the *change* in beliefs that matters. When looking at the initial variation of beliefs, we find that people who have a larger SD in Part I are more likely to change their contribution between parts. We interpret this as people who are relatively unsure about what to expect from other players being more easily convinced by new information, which is in line with the findings by Bicchieri et al. (2022). If, by contrast, an individual has very narrowly distributed beliefs (low variance), they have a clear idea of how they expect others to behave. Intuitively, in this case an individual is harder to convince to change behavior. On the other hand, being confronted with a loose or polarized environment makes individuals less likely to adjust their contributions than in tight environments (see Appendix A, table A.7). Thinking of the relative tightness or looseness as a degree of informativeness in the face of strategic risk, it is reasonable for individuals to react stronger to a tighter distribution. Looser or polarized environments, by contrast, exhibit more uncertainty, making it harder for individuals to predict the behavior of the other player and leaving in turn more room for them to be guided by their own baseline values and beliefs.

Result 4. *Changes in beliefs are the key driver behind changing contributions between Part I and II. The larger the change in average beliefs as well as the individual distribution of beliefs, the larger the change in contribution decisions.*

Finally, in addition to our treatment conditions, we find that certain individual factors correlate with contribution decisions (see Appendix A, Figure A.7). Holding everything else equal

Figure 10: Correlates of contributions in Part II by environment



Note. The figure shows coefficients with 95% confidence intervals of an OLS regression of contributions in Part II on individual characteristics and their interaction with the observed distribution. The difference between low variance and u-shaped conditions is significant at the 10% level for risk and sucker aversion and at the 1% level for free-rider aversion.

[32]The effect of changes in beliefs is also significantly larger than the effect of changes in personal values (Wald-test, $p < 0.001$) or the effect of changing NEs (Wald-test, $p < 0.001$). The change in NEs is not even statistically significant.

participants with a higher degree of risk and sucker aversion contribute significantly less to the public good, while participants with a higher degree of free rider aversion contribute more. Figure 10 shows that this pattern holds across all environments. Analogously to the importance of personal values these characteristics correlate significantly stronger with contributions in the polarized than in the tight conditions.[33] This underlines again that if the observed behavior is less tightly distributed, participants let themselves be guided by their own personal values, risk considerations and preferences to come to a contribution decision.

Result 5. *Individual preferences such as risk, free-rider, and sucker aversion correlate with contribution decisions. Like personal values, these preferences matter more in polarized than in loose environments.*

6 Discussion

Understanding of a polarized norm -> is it one polarized norm or is it two tightly distributed norms (e.g. in separate social groups), importance for norms literature, policy implications...

7 Conclusion

In this study, we investigate how individuals respond to differences in the observed distribution of others' behavior. In particular, we test how different distributions of cooperative behavior affect an individual's own willingness to cooperate. We first develop a theoretical framework that is based on the assumption that individuals are conditional cooperators and interpret differences in observed distribution as a shift in strategic uncertainty. We then test our framework empirically in the context of a PGG. To do so, we measure behavior in the PGG both before and after participants receive information about the distribution from which a co-players contribution is drawn. We thereby vary both the *mean* (high/low) and the *variance/shape* (high variance/ low variance/ u-shaped) of the observed distribution.

Our results confirm previous research showing that information about average behavior has an important effect on subsequent decisions. Individuals contribute significantly more in high mean conditions than in low mean conditions. However, the mean is not the only important feature of the distribution. In line with our theoretical framework, we find that looser environments generate a larger variance in individual responses compared to tighter environments. In other words, "tight breeds tight" and "loose breeds loose". Moreover, we find that, when confronted with a polarized (U-shaped) distribution, participants' responses are polarized as well. A possible interpretation of these results is that people have heterogeneous reactions to situations characterized by high strategic uncertainty, while they react rather similarly when strategic uncertainty is low. Finally, we find that personal values have a higher predictive power for contribution decisions in loose and polarized compared to tight environments. This suggests that an individual's reaction to strategic uncertainty may be mediated by their personal values. This in turn has practical implications for behavioral change interventions. For example, when

[33]See Appendix A Table A.9 for the full regression.

intervening in contexts with loose or polarized empirical norms, it may be more fruitful to focus on personal values, whereas when intervening in contexts with tight empirical norms, it may be more fruitful to focus on the behaviors of others.

Overall, we show that when studying empirical norms it is crucial to not only consider the average behavior, but the whole distribution. Doing so provides substantial analytical richness that can form the basis for a better understanding of the different behavioral patterns observed across societies.

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A Additional figures and analysis

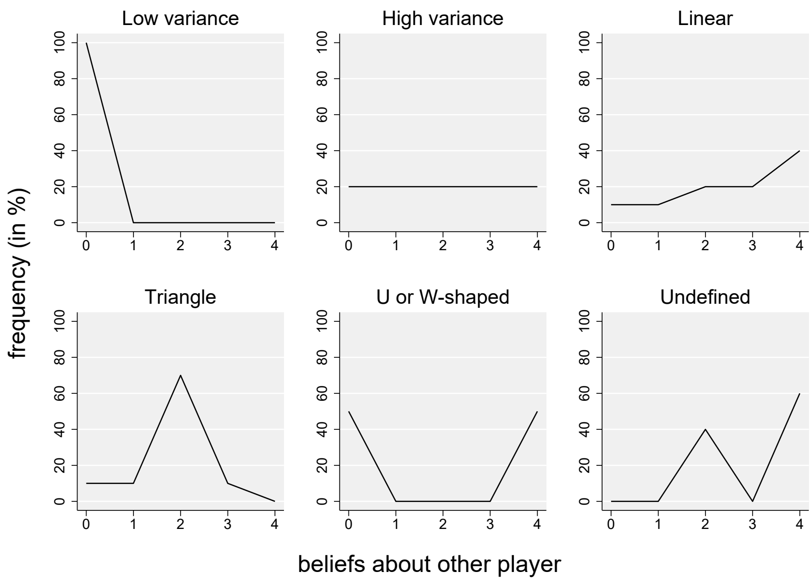
A.1 Baseline measures and manipulation checks

Figure 5 in the main text shows the aggregate distribution of beliefs in Part I, with most people believing that the other will either contribute 2 or 4 tokens. This aggregate distribution hides a substantial heterogeneity between participants in the distribution of beliefs. The individual distributions of beliefs can roughly be categorised into 6 types:

1. Low variance: participants who put more than 80% on one single option
2. High variance: participants who believe outcomes are equally likely (10 - 30% per option)
3. Linear: participants who have either non-decreasing or non-increasing beliefs
4. Triangle: participants with a single modal belief below 80% that is 1,2, or 3 token
5. U- or W-shaped: participants with either two modes (at 0,4) or three modes (at 0,2,4)
6. Others: not defined by the previous categories

Figure A.1 gives examples for each of the types. Using these rules we can classify 92% of participants. The most common distribution of beliefs are triangles (41%), followed by low variance (21%), u-/w-shaped (15%), linear (10%), and high variance types (5%).

Figure A.1: Examples of individual distributions of beliefs in Part I



As contributions can only take values between 0 and 4, we perform the same analysis as in Table 3, using a tobit model instead of an OLS. As Table A.1 shows results are qualitatively the same. While participants with higher beliefs contribute significantly more, there is an interaction between average beliefs and their variance. If beliefs are above the median, a higher SD leads to significantly higher contributions, while if beliefs are below median a higher SD leads to lower contributions.

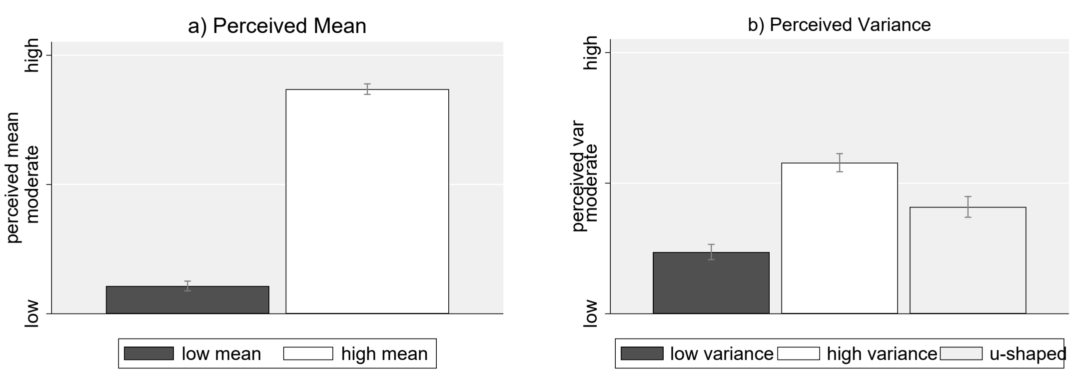
Table A.1: Tobit models. Effect of beliefs (mean and sd) on contributions in Part I

	No interaction		Interaction	
	(1)	(2)	(3)	(4)
High mean of beliefs	1.35***	1.27***	-0.56**	-0.53**
	(0.11)	(0.11)	(0.24)	(0.23)
SD of beliefs	0.14***	0.13***	-0.25***	-0.23***
	(0.05)	(0.05)	(0.06)	(0.06)
High mean x SD of beliefs			0.90***	0.85***
			(0.10)	(0.10)
Personal values	0.99***	0.96***	0.87***	0.85***
	(0.05)	(0.05)	(0.05)	(0.05)
Constant	-0.63***	-1.70***	0.42**	-0.68
	(0.19)	(0.54)	(0.21)	(0.54)
Demographic controls	No	Yes	No	Yes
N observations	1203	1188	1203	1188
Pseudo R^2	0.21	0.22	0.23	0.24

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.
Note. *High mean of beliefs* is a binary variable with 0 if the mean belief is below the median (≤ 2) and 1 if the mean belief is above (> 2). Similarly, *SD of beliefs* is a continuous measure for the SD of beliefs. *Personal values* measure the contribution an individual sees as appropriate and ranges between 0 and 4. Demographic controls include age, gender, education, acceptance of risk, trust, sucker aversion, free-rider aversion and measures for negative and positive reciprocity. All regressions control for order effects.

In the ex-post survey we ask participants about their perceptions of the shown distribution. As Figure A.2a shows, participants in high mean conditions also have a significantly higher perception of the mean (Wilcoxon-Mann-Whitney test, $p < 0.001$). In terms of the variance (Figure A.2b), participants perceive the low variance condition as significantly less varying than the high variance and the u-shaped conditions, and the u-shaped as less varying than the high variance condition (Wilcoxon-Mann-Whitney tests, for all $p < 0.001$). In addition, we ask participants about their perceived difficulty to interpret the distribution and how common they think this distribution is in the general population. On a scale from 1 (very easy) to 7 (very difficult) the average difficulty rating is 2.1, indicating that participants do not seem to have trouble interpreting the information. Moreover, there is no difference in the difficulty rating between high and low mean conditions or u-shaped and low variance conditions. Only the high

Figure A.2: Manipulation checks



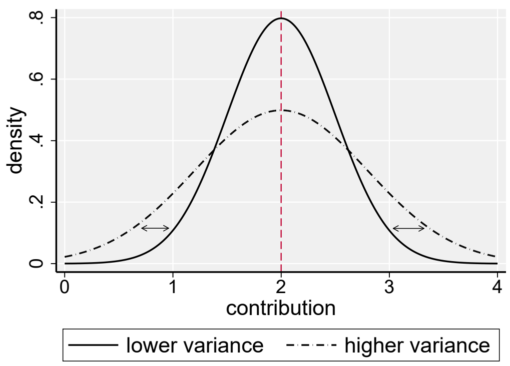
Note. Whiskers show 95% confidence intervals.

variance condition is described as significantly harder to understand than both the u-shaped (Wilcoxon-Mann-Whitney tests, $p = 0.03$) or the low mean condition (Wilcoxon-Mann-Whitney tests, $p = 0.08$). The average frequency rating on a scale from 1 (very rare) to 7 (very common) is 5.0. Again, there are no differences between high and low mean conditions or u-shaped and high/low variance conditions. Only the high variance condition is perceived as slightly less common than the low variance condition (Wilcoxon-Mann-Whitney tests, $p = 0.009$).

A.2 Effect of variance and shape of a distribution

A more indirect test of whether the variation in contribution increases with the observed variance is by splitting our sample in Part II in a high and a low contribution group (contributions above/ below the median) and compare their reactions to different environments. If a higher observed variation increases the overall variance in contributions, we would expect this to translate into lower contributions for the *low contribution sub-sample* and higher contributions for the *high contribution sub-sample*, resulting in an overall wider spread of contributions (see Figure A.3).

Figure A.3: Different variances and their effect on the high/low end of the distribution



Note. As the figure shows a higher variance implies more extreme contributions in both tails of the distribution

Table A.2 shows the results of regressing contributions on treatment conditions for each sub-sample. We can see that in fact in the high contribution sub-sample, both the high variance and the u-shaped conditions lead to a significant increase in contributions relative to the low variance condition. For the low contribution sub-sample, by contrast, we see the exact opposite pattern. In this case, a higher variance is associated with lower contributions. We thus confirm that both the u-shaped and the high variance condition increase the overall variation of contributions.

Table A.2: OLS models. Effect of variance on contributions in Part II for different sub-samples

	(1) High contributions (>2)	(2) Low contributions (<=2)
Variance (baseline = low)		
High variance	0.22***	-0.11
	(0.05)	(0.07)
U-shaped	0.66***	-0.54***
	(0.06)	(0.08)
Constant	1.53***	0.74**
	(0.26)	(0.34)
Baseline controls	Yes	Yes
Demographic controls	Yes	Yes
N observations	906	602
R^2	0.39	0.28

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.
Note. *Variance* is a categorical variable with 0 = low variance, 1 = high variance and 2 = u-shaped. Baseline controls include contributions, average beliefs, and PVs in Part I and can take values between 0 and 4. Demographic controls include baseline behavior, age, gender and education, risk, trust sucker aversion, free-rider aversion and measures for negative and positive reciprocity. High and low contribution sub-samples are generated by dividing participants in a group with contributions in Part II above and below the median.

A.3 Effect of high and low means

Table A.3 shows that when running a tobit regression, results are qualitatively the same as for the OLS regressions in Section 5.3. Participants in the high mean conditions contribute significantly more to the public good in all specifications. Moreover, there is no interaction between high variance and high mean condition. The only difference is that the effect of the high mean conditions seems to be stronger in the u-shaped than in the low mean conditions.

Table A.3: Tobit models. Effect of high and low mean conditions on contributions in Part II

	No interaction			Interaction		
	(1)	(2)	(3)	(4)	(5)	(6)
High mean	1.00***	0.99***	0.93***	0.70***	0.64***	0.58***
	(0.14)	(0.11)	(0.10)	(0.23)	(0.18)	(0.17)
Variance (baseline = low)						
High variance	0.23	0.26**	0.26**	0.08	0.09	0.09
	(0.16)	(0.13)	(0.12)	(0.23)	(0.18)	(0.17)
U-shaped	0.61***	0.66***	0.61***	0.29	0.28	0.24
	(0.17)	(0.13)	(0.13)	(0.23)	(0.18)	(0.18)
Interactions						
High mean x high variance				0.29	0.33	0.35
				(0.33)	(0.26)	(0.25)
High mean x u-shaped				0.65*	0.80***	0.78***
				(0.34)	(0.27)	(0.26)
Constant	2.05***	-1.10***	-1.77***	2.21***	-0.93***	-1.56***
	(0.16)	(0.21)	(0.58)	(0.19)	(0.22)	(0.58)
Baseline controls	No	Yes	Yes	No	Yes	Yes
Demographic controls	No	No	Yes	No	No	Yes
N observations	1203	1203	1188	1203	1203	1188
Pseudo R^2	0.02	0.14	0.17	0.02	0.14	0.17

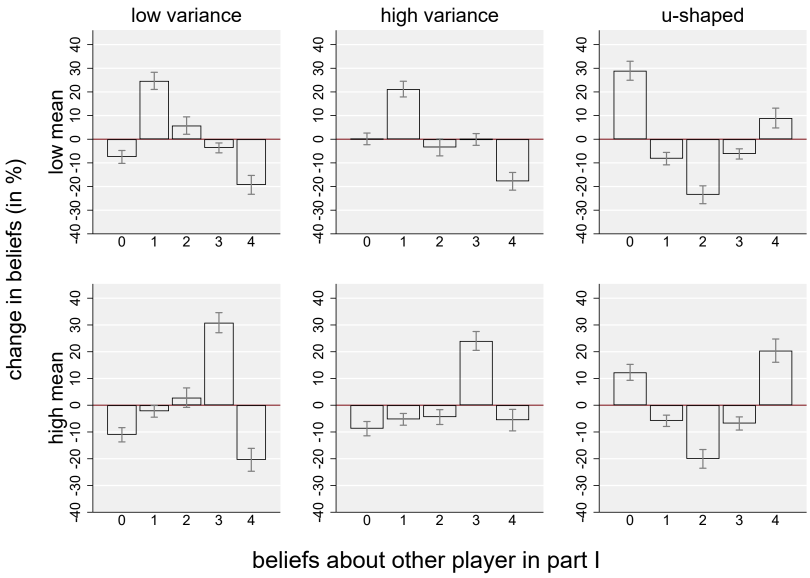
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.

Note. High mean is a binary variable with 0 = low and 1 = high mean. *Variance* is a categorical variable with 0 = low variance, 1 = high variance and 2 = u-shaped. Baseline controls include contributions, average beliefs, and PVs in Part I and can take values between 0 and 4. Demographic controls include age, gender, education, acceptance of risk, trust, sucker aversion, free-rider aversion and measures for negative and positive reciprocity. All regressions control for order effects.

A.4 Mechanisms: Personal values, beliefs, and individual preferences

Figure A.4 shows that participants change their beliefs in line with the shown distributions. For instance, for the u-shaped conditions, beliefs that the other player contributed 0 or 4 tokens increase substantially between Part I and II of the experiment, while intermediate values (1-3) decrease. The opposite is true for the low and high variance conditions, where in line with the observed distribution beliefs that the other contributes 0 or 4 tokens decrease in favor of intermediate values..

Figure A.4: Changes in beliefs between parts



Note. Whiskers show 95% confidence intervals.

That the distribution of beliefs changes between parts is not only true on aggregate, but also confirmed when looking at the individual distributions of beliefs. In particular, we see that the composition of types changes between Part I and II (see Table A.4. For all three environments, the distribution of types differs significantly between Part I and II (χ^2-test, $p < 0.001$). While for both loose and tight environments, the triangle type continues to be the most prevalent one and even increases in share, in the polarized environment we, in line with intuition, see a strong increase in the share of u- or w-shaped type. While there are significant changes in the individual distributions, there is also an element of persistence. Correlation between Part I and II for belief

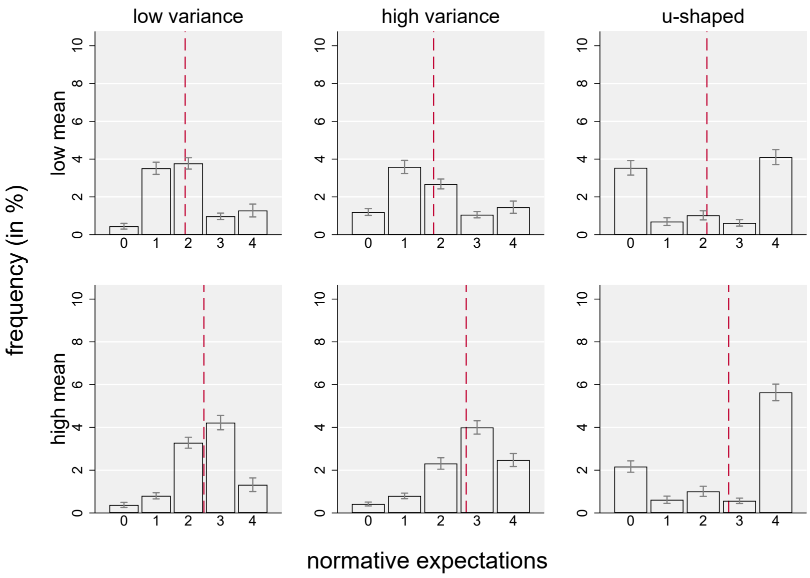
	Part I	**Part II**		
		Tight	Loose	Polarized
Low variance	0.21	0.15	0.12	0.24
High variance	0.05	0.02	0.05	0.03
Linear	0.10	0.02	0.07	0.04
Triangle	**0.41**	**0.76**	**0.66**	0.07
U- or W-shaped	0.15	0.02	0.04	**0.47**
Undefined	0.08	0.03	0.06	0.15

Table A.4: Belief types across parts

types is 0.3 ($p < 0.001$), indicating that people are also guided by their initial distribution of beliefs on top of the observed distribution.

Figure A.5 shows the distribution of NEs in Part II. Like beliefs, they are highly influenced by the observed distributions.

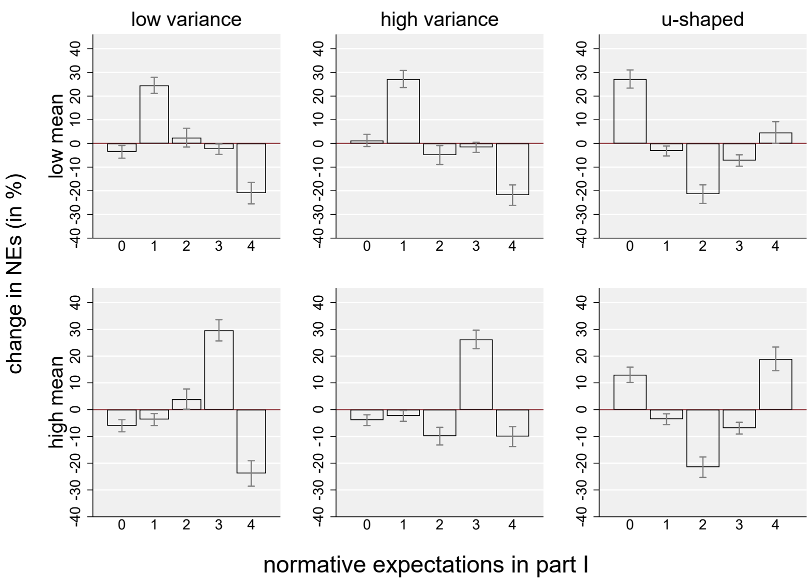
Figure A.5: Distribution of normative expectations in Part II by treatment



Note. The dashed lines represent the average NEs in each treatment. Whiskers show 95% confidence intervals.

When looking at the change in NEs between Part I and II, we see a similar pattern as for the change in beliefs. NEs are sensitive to the shape of the provided behavioral information. As Figure A.6 shows the adjustments between parts are in line with the shown distribution.

Figure A.6: Changes in NE between parts



Note. Whiskers show 95% confidence intervals.

Table A.6 shows the results of regressing the change in contributions between Part II and I on several individual characteristics. The change in contributions (and other variables) is simply calculated by subtracting the value in Part I from the corresponding value in Part II. As discussed in the main text, the results show that the strongest predictor for a change in contributions is the change in average beliefs. In addition, we find that participants with a larger SD of beliefs (in Part I) change their contributions more than those with an initially tighter distribution.

Table A.5: Determinants for the change in contributions between Part I and II

	Low variance	High variance	U-shaped
Change in mean beliefs	0.58***	0.61***	0.63***
	(0.10)	(0.09)	(0.09)
Change in personal values	0.28***	0.34***	0.38***
	(0.07)	(0.07)	(0.07)
Change in mean NE	0.06	-0.03	-0.13
	(0.09)	(0.08)	(0.08)
SD of initial beliefs	0.04	0.03	0.08
	(0.04)	(0.04)	(0.05)
Constant	0.01	-0.37**	-0.34*
	(0.16)	(0.15)	(0.19)
Observations	400	401	402
Baseline controls	Yes	Yes	Yes
Demographic controls	No	No	No
R^2	0.53	0.49	0.38

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.
Note. Baseline controls include contributions, average beliefs, and PVs in Part I and can take values between 0 and 4. All regressions control for order effects.

Table A.6: Determinants for the change in contributions between Part I and II

	OLS		Tobit	
	(1)	(2)	(3)	(4)
Change in mean beliefs	0.64***	0.61***	1.23***	1.16***
	(0.06)	(0.05)	(0.14)	(0.14)
Change in personal values	0.34***	0.31***	0.65***	0.58***
	(0.04)	(0.04)	(0.10)	(0.10)
Change in mean NE	-0.06	-0.04	-0.21	-0.18
	(0.05)	(0.05)	(0.13)	(0.13)
Observed SD - SD of initial beliefs	0.13**	0.12**	0.46***	0.46***
	(0.06)	(0.06)	(0.18)	(0.17)
SD of initial beliefs	0.18***	0.16**	0.38**	0.37**
	(0.07)	(0.06)	(0.19)	(0.19)
Constant	-0.42***	-0.61*	-1.76***	-2.89***
	(0.11)	(0.34)	(0.43)	(0.94)
Observations	1203	1188	1203	1188
Baseline controls	Yes	Yes	Yes	Yes
Demographic controls	No	Yes	No	Yes
(Pseudo) R^2	0.45	0.48	0.22	0.23

* p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors in parentheses.
Note. Baseline controls include contributions, average beliefs, and PVs in Part I and can take values between 0 and 4. Demographic controls include age, gender, education, acceptance of risk, trust, sucker aversion, free-rider aversion and measures for negative and positive reciprocity. All regressions control for order effects.

When observing that different distributions shift people's contribution behavior, a natural question is whether there are some people that are more likely to change their behavior. Table A.7 regresses changes in contributions on treatment indicators and individual characteristics. We find that compared to the tight condition (low variance), participants are less likely to change in loose and polarized environments. This is in line with the higher importance of personal values in these conditions. Apart from the treatment indicators, the only significant individual characteristic is sucker aversion. Intuitively, if individuals are highly averse to being taken advantage of, they might react stronger to information about the co-player's behavior.

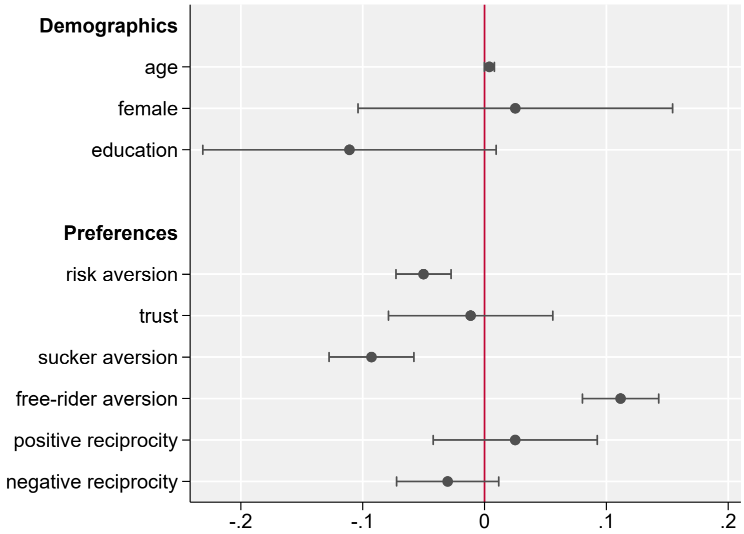
Table A.7: Linear probability model. Likelihood of changing contributions between Part I and II

	(1)	(2)	(3)
High mean	-0.02	-0.02	-0.01
	(0.03)	(0.03)	(0.03)
Variance (baseline = low)			
High variance	-0.07**	-0.07*	-0.07*
	(0.04)	(0.04)	(0.04)
U-shaped	-0.07**	-0.07**	-0.07*
	(0.04)	(0.04)	(0.03)
Individual characteristics			
Risk aversion			0.00
			(0.01)
Trust			-0.02
			(0.02)
Sucker aversion			0.03***
			(0.01)
Free-rider aversion			-0.00
			(0.01)
Positive reciprocity			0.02
			(0.01)
Negative reciprocity			-0.01
			(0.01)
Constant	0.48***	0.57***	0.35**
	(0.04)	(0.05)	(0.15)
N observations	1203	1203	1188
Baseline controls	No	Yes	Yes
Demographic controls	No	No	Yes
R^2	0.01	0.02	0.05

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.
Note. The dependent variable is binary, taking the value 0 if participants did not change their contributions between Part I and II and 1 if they did. *High mean* is a binary variable with 0 = low and 1 = high mean. *Variance* is a categorical variable with 0 = low variance, 1 = high variance and 2 = u-shaped. Baseline controls include contributions, average beliefs, and PVs in Part I and can take values between 0 and 4. Demographic controls include age, gender and education. None of them has an effect on the likelihood of change. All regressions control for order effects.

Figure A.7 visualizes the results from regressing contributions in Part II on demographics and individual preferences. While demographics do not seem to play a role, we see that several individual preferences correlate with contribution decisions. Holding everything else equal participants with a higher degree of risk and sucker aversion contribute significantly less to the public good, while participants with a higher degree of free rider aversion contribute more. Intuitively, the more people shy away from risk and the more they would be upset when finding out that they contributed everything and their co-player nothing (*sucker aversion*), the lower

Figure A.7: Correlates of contributions in Part II



Note. The figure shows coefficients with 95% confidence intervals of an OLS regression of contributions in Part II on individual characteristics. Regression controls for baseline behavior and order effects and uses robust standard errors.

their contributions. By contrast, the more people would feel ashamed when contributing nothing and finding out that their co-player contributed everything (*free-rider aversion*), the higher their contributions. In addition, we find that certain demographic variables correlate with these types of aversion (see Table A.8). Women are significantly more likely to score high across all dimensions. By contrast, the older participants are the less they care about risk and differing in their contributions from the other player.

Table A.8: OLS and tobit models. Determinants of risk, sucker, and free-rider aversion

	Risk Aversion		Sucker aversion		Free-rider aversion	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	1.25***	1.31***	0.44***	0.59***	0.74***	1.15***
	(0.15)	(0.17)	(0.11)	(0.15)	(0.12)	(0.19)
Age	0.02***	0.02***	-0.03***	-0.03***	-0.01***	-0.02***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)
Education (baseline=no formal degree)						
Secondary school	-0.12	-0.29	-0.31	-0.63	-0.41	-0.62
	(0.53)	(0.62)	(0.41)	(0.54)	(0.39)	(0.67)
University/ college	-0.68	-0.82	-0.39	-0.71	-0.72*	-1.13*
	(0.52)	(0.61)	(0.41)	(0.53)	(0.38)	(0.66)
Prefer not to say	-0.22	-0.25	-0.13	-0.45	-1.16*	-1.67
	(1.03)	(1.09)	(0.50)	(0.93)	(0.60)	(1.18)
Constant	4.75***	4.86***	5.80***	6.52***	4.82***	5.13***
	(0.55)	(0.64)	(0.43)	(0.56)	(0.41)	(0.69)
N observations	1188	1188	1188	1188	1188	1188
(Pseudo) R^2	0.07		0.06		0.04	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.
Note. The dependent variables are measured on a Likert scale from 1 to 7. Models (1), (3), and (5) are OLS regressions. Models (2), (4) and (6) are tobit regressions, accounting for the censored nature of the data.

Analogously to the differential effect of personal values across different environments, we find that sucker, free-rider, and risk aversion have a larger effect on contributions in u-shaped as compared to low variance environments (see Table A.9). This holds even though we control for personal values and their interaction with the different environments. When comparing high variance with low variance conditions, there is no significant difference although the signs of the coefficients go in the same direction as for the u-shaped conditions.

Table A.9: Effect of sucker, free-rider, and risk aversion on contributions in Part II across environments.

	OLS	Tobit
High mean	0.68***	0.98***
	(0.07)	(0.12)
Variance (baseline = low)		
High variance	-0.13	-0.29
	(0.32)	(0.58)
U-shaped	0.21	0.42
	(0.39)	(0.62)
Sucker aversion	-0.11***	-0.17***
	(0.03)	(0.06)
Sucker aversion x high variance	-0.01	-0.03
	(0.04)	(0.08)
Sucker aversion x u-shaped	-0.09*	-0.25***
	(0.05)	(0.08)
Free-rider aversion	0.11***	0.18***
	(0.02)	(0.05)
Free-rider aversion x high variance	0.01	0.02
	(0.04)	(0.07)
Free-rider aversion x u-shaped	0.11***	0.28***
	(0.04)	(0.07)
Risk aversion	-0.04**	-0.07**
	(0.02)	(0.03)
Risk aversion x high variance	-0.02	-0.04
	(0.03)	(0.05)
Risk aversion x u-shaped	-0.05*	-0.14***
	(0.03)	(0.05)
Personal values in part I	0.34***	0.51***
	(0.05)	(0.09)
PVs in part I x high variance	0.13*	0.30**
	(0.07)	(0.12)
PVs in part I x u-shaped	0.09	0.36***
	(0.08)	(0.13)
Constant	1.33***	1.05**
	(0.22)	(0.43)
N observations	1203	1203
(Pseudo)R^2	0.32	0.11

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors in parentheses.
Note. High mean is a binary variable with 0 = low and 1 = high mean. *Variance* is a categorical variable with 0 = low variance, 1 = high variance and 2 = u-shaped. *Personal values* can take values between 0 and 4. Sucker, free-rider, and risk aversion are measured on a Likert scale from 1 to 7. All regressions control for order effects.

B Instructions

Welcome

Thank you very much for participating in this study! This study consists of two parts and a questionnaire. Upon completion you will receive $1.70 for your participation plus an additional bonus of up to $2.36 that depends both on your decisions and the decisions of other participants. **In both parts you will face a situation in which you will be matched with one other, real participant**. On the next page we will describe this situation to you in more detail.

Instructions (1/2)

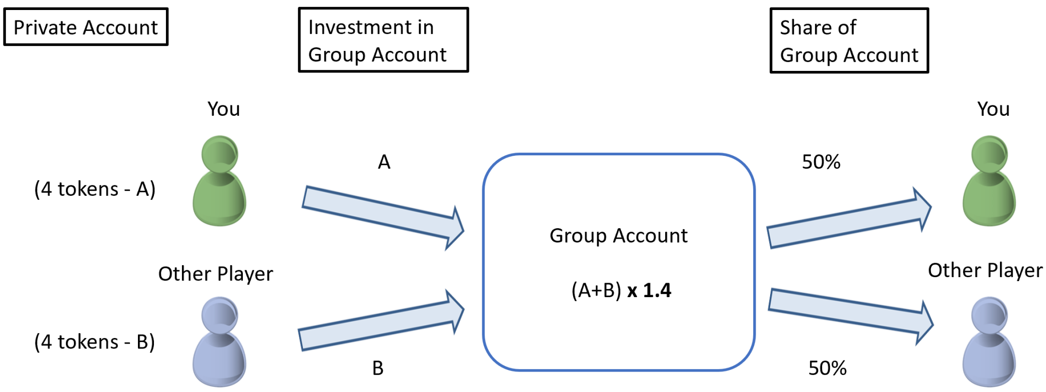
In this study, you will be anonymously paired with another participant. You will each start with **4 token** in your personal **private accounts**. In addition to the private accounts, there is a **group account**. You have to decide how many of your token you want to invest in the group account (either 0, 1, 2, 3 or 4 token). The amount leftover will remain in your private account. The other player has to make the same decision.

Your income from the private account

The amount in the private account is yours to keep. The other player doesn't earn anything from the token you keep in your private account. For example, if you keep 2 token in your private account, this will be your income from this account.

Your income from the group account

The amount invested in the group account will be multiplied by 1.4. That is, each token invested in the group account will yield 1.4 token for the group. The total amount in the group account will be split equally between you and your partner regardless of your individual investments. That is, each player receives half (50%) of the total amount in the group account.



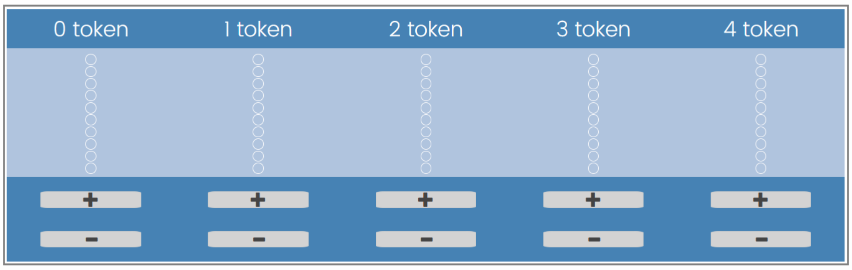
If, for example, the sum of all investments in the group account by you and the other player is 6 token (A+B), then the group account yields 6 x 1.4 = 8.4 token. Both you and the other player would then receive 0.5 x 8.4 = 4.2 token from this account.

Your total income

Please note that for logistic reasons you are not interacting with other participants in real time. Once we collected all responses, we will match you with another person to calculate your and the other's total income. The latter consists of **all the token you kept in your private account plus half of the token** that you and that other participant invested **in the group account**. **Your total income will then determine your bonus payment**, with each token being worth \$0.10. Whatever income you earned in token will be converted at this rate into actual money at the end of the experiment and paid out as a bonus.

Instructions (2/2)

In addition to making an investment decision in this situation, we will ask you to state **your beliefs about other participants**. You will be paid for these tasks according to how accurate your beliefs are.
A brief explanation follows: let us assume, we ask you to make a guess about how many token the participant you have been matched with invested in the group account. In this case, you would have to indicate **how likely you think it is that the other participant invested 0, 1, 2, 3 or 4 token**. To make your choices you will see a screen like the one below.



To make your decision you have to allocate a total of 10 points across options by clicking on the plus and minus buttons. The points you allocate need to add up to 10 and **the more likely you think one option is, the more points you would allocate to it**. The points you allocate to each option will naturally reflect your beliefs about the other participant's behavior.
The amount of money you can earn depends on how you allocated your points and what is actually true. If you put all points on the correct option, you will earn \$1 if you put all points on a wrong option you will earn \$0. In general, the more points you allocate to a correct option, the higher your earnings and the more points you allocate to a wrong option the lower your earnings. **The way your earnings are determined ensures that your best strategy is to carefully and honestly answer these questions.** If you want to have a closer look at how your earnings will be calculated click **here**.
Let's for example assume that you think it is equally likely that the other participant invested 2 or 4 token and you put 5 points on each option. If the other participant really invested either 2 or 4 token, you would in each case earn \$0.75. If they invested 0, 1 or 3 token you would earn \$0.
What if you had instead put all your eggs in one basket and allocated 10 points on the other participant investing 2 token? If the other participant indeed invested 2 token, you earn the maximum bonus of \$1. But if any of the other options is the correct one, you would earn nothing in this task. It is thus up to you to balance the strength of your personal beliefs with the risk of them being wrong.

In total, we will ask you to state your belief on **five** different questions throughout this study. In the end, a lottery will decide **one of them to be chosen for payment**. The amount you earned in the chosen question will then be added to your bonus payment.

If participants click to get more information about payoffs, they see the following pop-up:

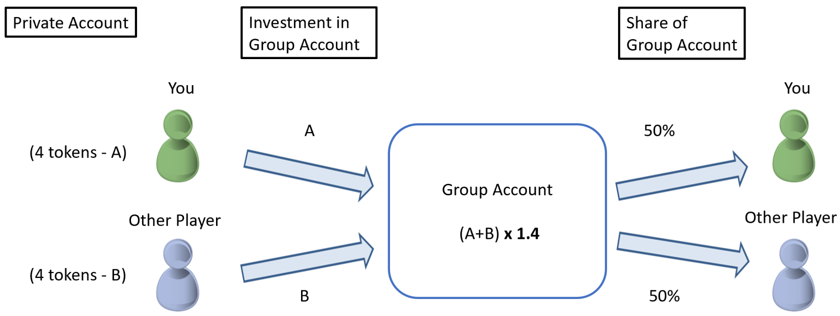
Your earnings are calculated on the basis of the table below. The more points you put on the correct option the higher your earnings. For each wrong option to which you allocate points your earnings will be reduced. The reduction is larger the more points you allocated to that option.

Points put on the correct option	**Earnings from the correct option**	**Points put on a wrong option**	**Costs from a wrong option**
10	100¢	10	50¢
9	99.5¢	9	40.5¢
8	98¢	8	32¢
7	95.5¢	7	24.5¢
6	92¢	6	18¢
5	87.5¢	5	12.5¢
4	82¢	4	8¢
3	75.5¢	3	4.5¢
2	68¢	2	2¢
1	59.5¢	1	0.5¢
0	50¢	0	0¢

Part 1

We are now going to ask you a number of questions that relate to the situation that you previously read (see image below). It is important that you answer these questions truthfully and as accurately as possible.[34]

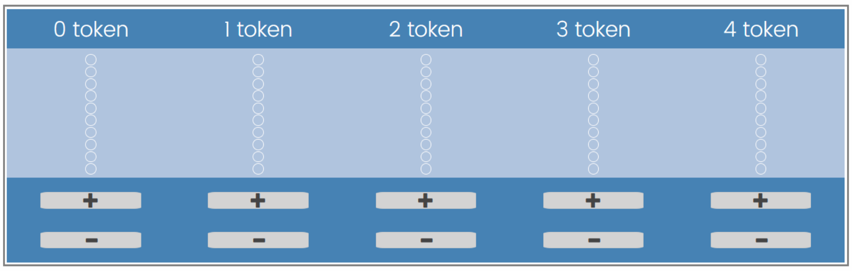
[34]Either normative questions or ABC questions are asked first. The three normative questions appear in randomized order.



1) We asked other participants what they believe is the **most appropriate amount to invest** in the **group account**. What do you believe was the most common answer?

Appropriate here means what you personally consider to be "correct" or "moral". You can allocate up to 10 points to an option by clicking on the plus and minus buttons below to indicate your guess. The more likely you think one option is, the more points you would allocate to it. Your guesses need to add up to 10.

Most people believe it is appropriate to invest...

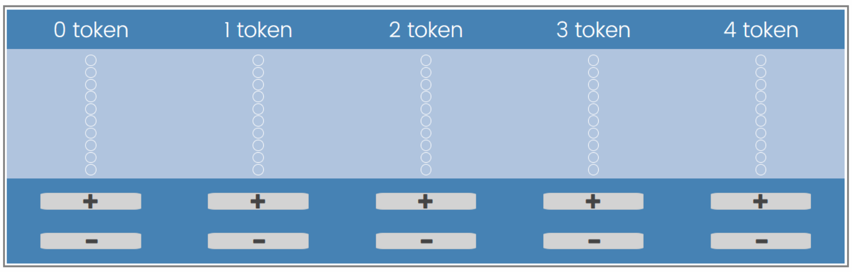


How confident are you in your response above? (0 not very confident, 100 very confident)

2) We asked other participants to make an investment decision in this situation. How many token do you believe most people **actually invested** in the group account?

Appropriate here means what you personally consider to be "correct" or "moral". You can allocate up to 10 points to an option by clicking on the plus and minus buttons below to indicate your guess. The more likely you think one option is, the more points you would allocate to it. Your guesses need to add up to 10.

Most people actually invested...



How confident are you in your response above? (0 not very confident, 100 very confident)

3) According to your own opinion and independent of the opinion of others, what is the **most appropriate amount to invest** in the **group account**?

Appropriate here means what you personally consider to be "correct" or "moral".

- 0 token
- 1 token
- 2 token
- 3 token
- 4 token

For the next section of Part 1, you will be matched with one other participant. You will only interact once with this person and you will never learn each other's identity.
Your and the other participant's bonus payment for Part 1 will depend on your decisions and the decisions of this participant.

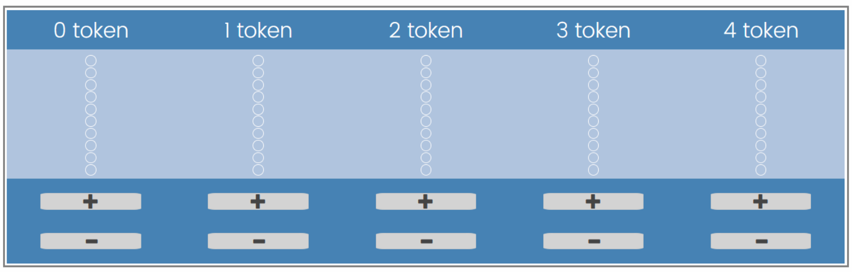
1) How many token do you want to **invest** in the **group account**?

- 0 token
- 1 token
- 2 token
- 3 token
- 4 token

2) How many token do you believe the participant you are matched with **invested** in the **group account**?

You can allocate up to 10 points to an option by clicking on the plus and minus buttons below to indicate your guess. The more likely you think one option is, the more points you would allocate to it. Your guesses need to add up to 10.

The participant you are matched with invested...



How confident are you in your response above? (0 not very confident, 100 very confident)

3) We are also interested in how many token you want to invest in the group account if you could know the other's choice beforehand. This means **you can condition** your investment on your group member's choice.
For one of you, the **unconditional choice** that you took before will count as the investment decision. For the other, the **conditional choice** (according to the table below) will count as the investment decision. Should the conditional choice be selected for you and the other participant invested x token in their unconditional choice, your decision for that scenario will determine your investment and thus matter for your bonus.
To determine your conditional choice, please tell us what you **want to invest** in the **group account** if:

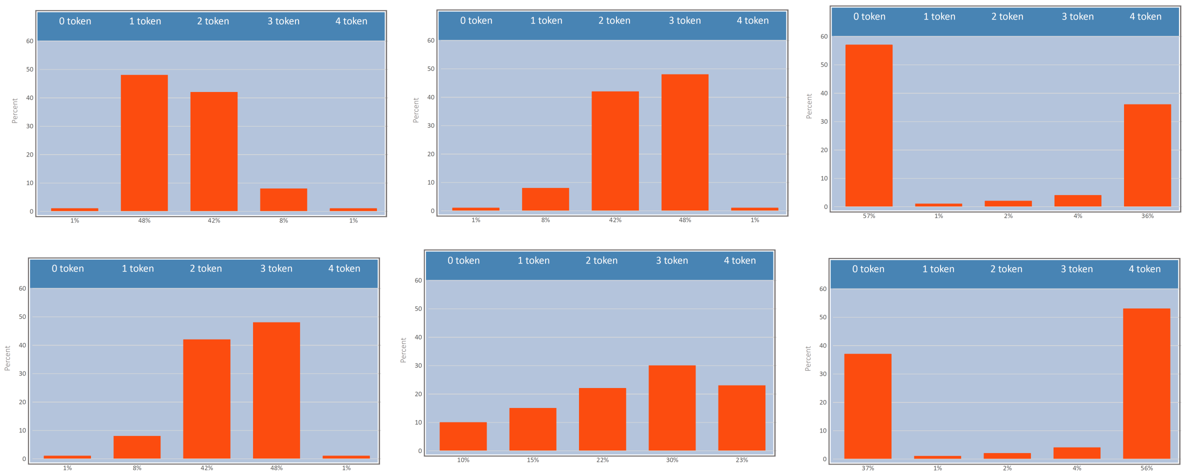
- The other player invests 0 token: ______ token
- The other player invests 1 token: ______ token
- The other player invests 2 token: ______ token
- The other player invests 3 token: ______ token
- The other player invests 4 token : ______ token

Part 2

In a previous study we asked over 600 participants to **make an investment decision** in the same situation. The possible choices were to invest 0, 1, 2, 3 or 4 token in the **group account**. From their answers we constructed different sub-groups. The graph below shows the percentage of people choosing each option in one randomly selected sub-group.

What previous participants invested in the group account:

(Participants are randomly shown one of the following six pictures.)



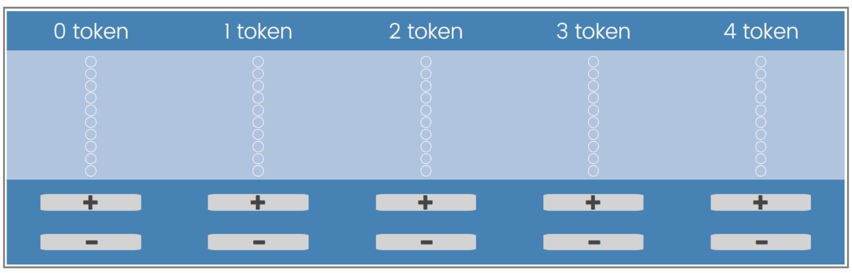
For Part 2 of the experiment you are matched with **one of the participants from the sub-group above**. You will only interact once with this person and you will never learn each other's identity.

Your and the other participant's **bonus payment for Part 2** will depend on your decisions and the decisions of this participant.[35]

1) We asked other participants from the previous study what they believe is the **most appropriate amount to invest** in the **group account**. What do you believe was the most common answer?

Appropriate here means what you personally consider to be "correct" or "moral". You can allocate up to 10 points to an option by clicking on the plus and minus buttons below to indicate your guess. The more likely you think one option is, the more points you would allocate to it. Your guesses need to add up to 10.

Most people believe it is appropriate to invest...



[35]We randomise whether participants are first asked about contributions and beliefs or about personal values and normative expectations.

How confident are you in your response above? (0 not very confident, 100 very confident)

2) Think again about the investment decision itself. According to your own opinion and independent of the opinion of others, what is the **most appropriate amount to invest** in the **group account**?

Appropriate here means what you personally consider to be "correct" or "moral".

- 0 token
- 1 token
- 2 token
- 3 token
- 4 token

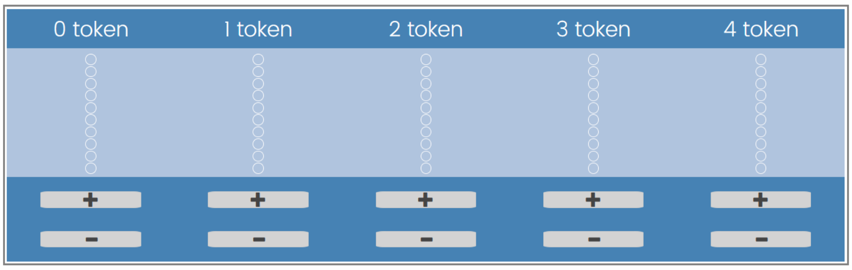
3) How many token do you want to **invest** in the **group account**?

- 0 token
- 1 token
- 2 token
- 3 token
- 4 token

4) How many token do you believe the participant you are matched with **invested** in the **group account**?

You can allocate up to 10 points to an option by clicking on the plus and minus buttons below to indicate your guess. The more likely you think one option is, the more points you would allocate to it. Your guesses need to add up to 10.

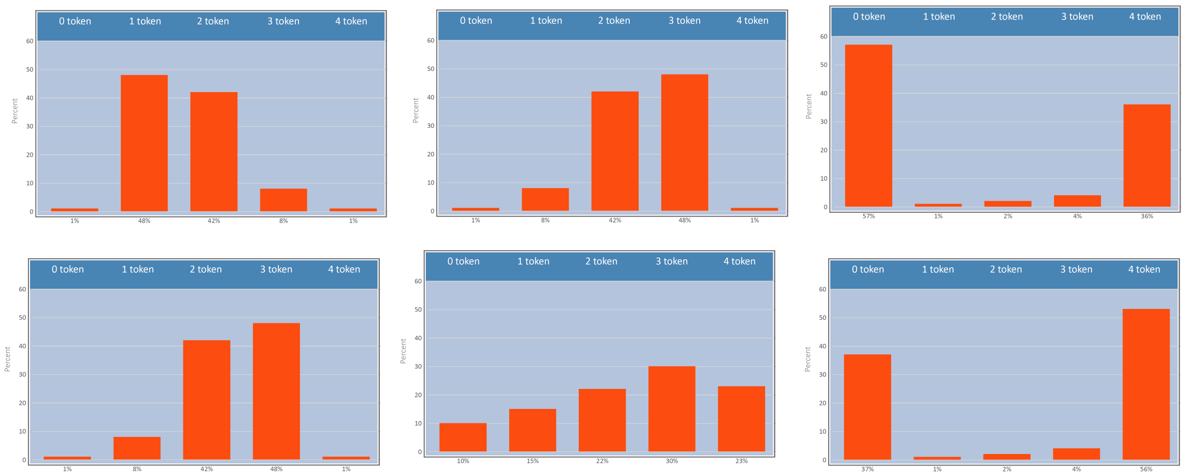
The participant you are matched with invested...



How confident are you in your response above? (0 not very confident, 100 very confident)

Questionnaire (1/2)

In this survey we showed you how many token a sub-group of other participants **invested** in the **group account**. Their answers are represented by the graph below.
What previous participants invested in the group account: *(Participants are randomly shown one of the following six pictures.)*



We will now ask you a few questions about the graph.

1) What are your thoughts on the behavior shown above?

---

2) Would you say the graph shows that overall

- people invest most of their token in the group account
- people invest half of their token in the group account
- people keep most of their token in their private account

3) Would you say the graph shows that overall

- there is a strong tendency for people to invest similar amounts in the group account
- there is a moderate tendency for people to invest similar amounts in the group account
- investments in the group account are very mixed

4) How common do you think the distribution of behavior shown above would be in other groups? (1 very rare, 7 very common)

5) How difficult was it for you to interpret the graph in Part 2, which is also shown above? (1 very easy, 7 very difficult)

6) How upset would you be if you invested everything in the group account and discovered that the participant you have been matched with invested nothing? (1 not at all upset, 7 very upset)

7) How ashamed would you be if you invested nothing in the group account and discovered that the participant you have been matched with invested everything? (1 not at all ashamed, 7 very ashamed)

Questionnaire (2/2)

1) Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?

- Need to be very careful
- Don't know
- Most people can be trusted

2) In how far do you agree with the following statement: "When someone does me a favour, I will return it." (1 don't agree at all, 7 completely agree)

3) In how far do you agree with the following statement: "If I am treated very unjustly, I will take revenge, even if there is a cost to do so." (1 don't agree at all, 7 completely agree)

4) Please tell me, in general, how willing or unwilling you are to take risks. (1 very unwilling to take risks, 11 very willing to take risks)

5) What is your age? ______ token

6) Which gender do you identify with?

- Female
- Male
- Non-binary
- Other
- Prefer not to say

7) What is the highest level of schooling you completed?

- No formal qualifications
- Secondary school
- University/ college degree
- Prefer not to say

Thanks a lot for participating in this survey! If you have any feedback for us you can write it here:

____