Altruism through Empathy: Evidence from the Field*

Elif Kubilay†

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Abstract

We study how random wealth shocks affect altruistic behavior within a controlled field experiment. Specifically, we analyze whether children who have experienced losses in a risky decision context are more or less likely to behave altruistically later on. We find that on average losers are more likely to donate than winners. This result is driven by individuals who were less exposed to disadvantages earlier in their life: (i) children from mid/high SES groups and (ii) children in classes with a high share of mid/high SES children. Moreover, not only own experiences but also peers' experiences affect donations. These findings suggest that negative experiences motivate altruistic behavior through increasing awareness of other people's needs, i.e. their level of empathy.

JEL Categories: *C90, C93, D64.*

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†Institute for Social and Economic Research University of Essex, Wivenhoe Park, Colchester, CO4 3SQ, United Kingdom (email: elif.kubilay@essex.ac.uk)

1 Introduction

Economic research has long acknowledged that private transfers are not only driven by selfish motives. That is, a transfer may well occur because individuals care about the recipient's well-being, often referred to as an "altruism-driven transfer". Altruistic behavior can explain many factors governing a society from redistributional policies to voter turnout (e.g. Andreoni (1989) and Fowler (2006)). While most economic models take the extent to which an individual cares about the recipient as exogenously given, there is vast evidence suggesting that altruistic behavior is not invariant to time or experiences. However, how altruism evolves over time and which factors shape other-regarding preferences are still questions to be answered. The aim of this paper is to analyze the effects of random wealth shocks on children's prosocial behavior and to explore the underlying mechanism within a controlled field experiment.

Life experiences can significantly affect prosocial behavior. *The world giving index*[1] is a combined measure of donations, the willingness to help strangers and volunteering time. This index indicates increased giving behavior in post-conflict countries such as Malaysia, where inhabitants suffered from Typhoon Haiyan (Yolanda) or Sri Lanka, which endured a long-lasting civil war.[2][3] One of the conclusions drawn with this index is that there is "little correlation between economic prosperity and generosity", i.e. being wealthy does not necessarily imply higher donations. The impact of political unrest and natural disasters on altruistic behavior have been extensively studied in the literature. Castillo and Carter (2011) document high levels of cooperation in rural Honduras after Hurricane Mitch and show a shift towards other regarding preferences for moderately affected people. Moreover, Voors et al. (2012) find that people who are more exposed to the civil war in rural Burundi have become more altruistic.[4] Here, the observed change in behavior is long lasting as the measurements took place 6 years after the end of civil war. Similarly, Bauer et al. (2014) show that wars in the

[1]See World Giving Index 2014 by Charities Aid Foundation.

[2]According to Lum and Margesson (2014) "Haiyan was one of the strongest typhoons to strike land on record" and United Nations (UN) has reported that 14.1 million people has been affected.

[3]UN estimates show that between 80,000 and 100,000 people were killed during the Sri Lankan civil war which lasted for 27 years.

[4]They also show that exposure to civil war makes people less risk averse and less patient.

Republic of Georgia and Sierra Leone motivated egalitarian behavior of individuals between the ages of 7 and 20 toward their in-group. From a macroeconomic perspective, Giuliano and Spilimbergo (2014) show that people who experience a recession during their youth tend to support redistributive policies by the government and left-wing parties. Jakiela et al. (2015) analyze the effects of human capital on the respect for property rights, a dimension of social preferences, in Kenya within a lab experiment. The results show that women with better academic outcomes are less likely to act selfish toward another productive individual who is known to increase the social surplus. All this evidence points to the fact that altruism cannot be taken as exogenously given. Events that people experience either individually or as a group, may lead to changes in their behavior throughout the course of life.

Identifying the causal effect of experiences on altruistic behavior is challenging because often it is a selected sample that is more exposed to shocks, which potentially biases results. For example, in the case of hurricanes, the people who are most affected might be the ones who are less risk averse and therefore choose to live in more dangerous places. Similarly, people more badly affected by civil wars might be the ones with insufficient resources. An identification problem might arise in the case of altruism as well. If a poor family is more likely to be affected by a negative shock, donation levels cannot be attributed solely to the type of the shock. Another example is that an altruistic individual's urge to help others increases the likelihood of getting hurt at the time of civil wars or natural disasters.[5] In this paper, we study the effects of random wealth shocks on the development of altruistic behavior in children. Specifically, we explore whether negative experiences increase people's willingness to give in the context of a field experiment with elementary school children between the ages of 9 and 11. The shocks are induced through random outcomes in a lottery, which allows us to avoid the before mentioned selection problems.

The main result of the paper is that children who experience losses are more altruistic. We explain this result with the hypothesis that the link runs through empathy: if experiencing

[5] Rand and Epstein (2014) argue that extreme altruists, who help others under dangerous situations act fast and intuitively rather than to first think about the consequences of their actions to themselves.

losses can help one gain a higher awareness of other people's needs, it can motivate giving and prosocial behavior. Particularly, unlucky children who lost part of their endowment due to a random wealth shock feel empathy for the children who do not have any gifts at all. By contrast, lucky children, who did not lose gifts are less aware of how a child without any gifts might feel. Consequently, the one who suffers is the one who is more likely to help others.

We present three further pieces of evidence supporting the hypothesis that increased donations come about in response to losses because children are building empathy. First, after splitting the sample into different wealth groups we see that children in higher SES groups are the ones whose decisions are most affected by the shock. This finding also supports the hypothesis because children from poor backgrounds are more likely to have already experienced situations that allow them to empathize with children who did not receive any gifts. On the contrary, wealthy families are better able to protect their children from a shock, and children may not have had a chance to know what it feels like to have little resources. The other set of evidence on the effect of past experiences is that children who possibly lack empathy can develop this skill through their environment, i.e. their classroom in the present study. First, children in classes dominated by peers from poor families are less affected by the shock than children in classes that are not dominated by the poor. Second, having loser peers in a classroom significatly affects the donation levels of children: as the number of peers who lose increases, the level of individual donations increases. These results suggest that spending time with peers with lower SES or with bad experiences helps higher SES children acquire empathetic skills, therefore their donation behavior is not affected by the negative wealth shock in our experimental setting.

Finally, we propose a potential mechanism on how negative experiences may trigger higher empathy levels with a skill production function proposed by Cunha et al. (2010). Empathy, the ability to understand and relate to other people's state of mind, is a skill that is both cognitive and non-cognitive. The production function of this skill has two components: the initial level of empathy and costly cognitive effort. We take the initial level of empathy as given. Every individual can exert effort subject to a cognitive cost. That is, even if a rich child is not empathetic enough to understand a child on the street instantly, he can start imagining about the hardships of being on the street. We believe that the negative experience in our framework gives a sense of being poor, which in turn decreases the cognitive cost of imagining the unlucky. The effort exerted to understand others in our paper is in the spirit of Becker and Mulligan (1997) in which an agent can spend time and effort to understand his future selves more and appreciate future consumption.

Related Literature. To our knowledge, this paper is the first to study the development of altruism in children in response to positive and negative experiences in an environment with random shocks, and link altruistic behavior to the development of empathy. There are several papers discussing the empathy-altruism link. For example, one related study is Andreoni et al. (2017) in which the effects of verbal and non-verbal ask for a donation on the altruistic behavior is analyzed within a randomized controlled trial. Specifically, they place solicitors at the entrance of a market where donations are either asked verbally or by ringing a bell. The verbal ask has shown to increase both the amount and the prevalence of donations dramatically. The authors discuss that the underlying mechanism behind this result might be empathy. When people are verbally asked to donate, this could stimulate empathy and consequently an increase in altruistic behavior. Moreover, Andreoni and Rao (2011) investigate whether "putting allocators in receivers' shoes" in a dictator game can substitute for full communication between a receiver and an allocater in a lab experiment. They achieve this by asking participants about their choices for both roles and then randomly assigning some to be an allocator and some to be a receiver. The idea is that before becoming an allocator, stating your choice in case you are a receiver makes you see the situation from the recipient's perspective. They find that allocators' giving levels are similar to the levels where there is communication between the allocator and the receiver. In another paper, Rao (2014) exploits a policy change in India where private schools are required to open up quotas for poor children. The results show substantial effects of having poor classmates on rich students' behavior. In particular, rich students in classes where poor children are present have become more generous and prosocial than the students in earlier cohorts in which the policy is not present.

It is important to note that we explore one specific channel that motivates altruistic behavior, i.e. negative experiences. There may well be other channels inducing prosocial behavior. For example, according to Kosse et al. (2016), children who spend time with mentors develop stronger prosocial skills, i.e. they focus on a rather positive channel in the form of assistance by mentors to children. They find that poor children in their framework are more affected by this intervention, whereas it has no effect on rich children. This result is intuitive and consistent with the findings of the present paper. Since poor children are less likely to be exposed to positive experiences such as having a mentor taking care of them, they are building higher prosocial skills than the rich. Likewise, we find that since higher SES children are less likely to experience a negative wealth shock prior to the experiment, they are more affected by it than the poor.

Research in the social psychology literature shows that empathy helps people to become aware of the negative consequences of not helping and the positive consequences of helping. Therefore, it induces altruistic behavior (Aderman and Berkowitz (1970), Batson et al. (1981), Batson (1990)). Moreover, Morishima et al. (2012) explore the role of brain structures, which can explain differences in people' s altruism levels. Their evidence suggests that the volume of gray matter in the temporoparietal junction, a part of the brain related to perspective-taking and theory of mind (also referred to as cognitive empathy), is positively correlated with the level of altruism. The "perception-action model" also emphasizes the importance of past experiences on other-regarding behavior (e.g. Preston (2007)). When people experience certain events such as losing a parent or having a car accident, the level of empathy towards another individual with similar experiences increases. This mechanism also works in the other direction: having no similar past experiences makes people less empathetic and less helpful towards each other. It seems as if when observing other agents' actions or states, people look for a similar experience, and a matching experience makes them put more weight on the other agents' payoffs. This paper provides evidence that is consistent with such a mechanism.

Further, neurological evidence suggests that the altruism levels depend on experiences and the observed experiences of others. Mirror neurons found in various parts of brain are fired when we execute an action or when we observe someone executing an action.[6] This neuron system has been linked to empathy: more empathetic people have a higher activation in the mirror neuron system (Decety and Jackson (2004), Gallese (2001), Schulte-Rüther et al. (2008)). Mirror neurons act as bridges between human beings by connecting the states of mind and emotions, thereby helping people to understand each other.

Understanding the development of altruism in children is important for two reasons. First, the late elementary school phase (the sample used in this paper) is a period where children begin to understand "guilt or positive effect about the consequences of one's behavior for others, self-reflective sympathy and perspective taking" (Eisenberg (2005)). Second, there is a large literature that emphasizes the importance of the childhood period for the development of cognitive and non-cognitive skills.[7] Our design allows us to produce a proxy for real life experiences through the consequences of children's investment decisions in a risk preference elicitation task. Randomly generated wealth shocks, coming from wins and losses rule out the possibility of selection bias. Moreover, our design involves negative as well as positive random shocks, which differentiates this paper from Kosse et al. (2016), where children were assigned to enriched environments only.

The rest of the paper is structured as follows: Section 2 introduces the background and the experimental design. Section 3 presents the results, Section 4 provides a discussion and Section 5 concludes.

2 Background and Experimental Design

In this paper, we exploit a data set from a larger field experiment where the impact of various educational interventions is measured. The data has been collected from public primary

[6]The parts of brain with mirror neurons are premotor cortex, the supplementary motor area, the primary somatosensory cortex, and the inferior parietal cortex.

[7]See Shonkoff and Phillips (2000), Carneiro and Heckman (2003), Cunha et al. (2006), Heckman (2006), Cunha and Heckman (2007).

schools located in different districts of Istanbul with the approval of the Ministry of National Education of Turkey and the institutional review board of Koc University. In addition, informed consent by parents was obtained for all the students in our sample. Subjects used pen-and-paper in the experiments, which were conducted during regular class hours with the permission of the teachers. Note that as a result of high rates of migration inflows over the years, the population of Istanbul has become quite heterogeneous in terms of birth place, therefore it provides a good representation of Turkey's population.

The experimental setup consists of two visits, one in December 2013 and the other in May 2014.[8] In the first visit, students' risk attitudes were elicitied by an individual decision-making task. In particular, students could decide how risky they could invest their experimental wealth and the risky part of their investment was exposed to a random wealth shock. In the second visit subjects' altruistic preferences were elicited by a simple dictator game. All the experiments were incentivized by gifts such as toys and attractive stationery materials.[9] Given that there are at least three months between the two visits, we are able to analyze the long-term effects of random wealth shocks on the giving behavior of children.

2.1 Individual Risk Elicitation Task

In the individual risk elicitation task, children are presented an investment decision à la Gneezy and Potters (1997). All students are given 5 tokens, each corresponding to a gift of equal value. The investment is in the form of a lottery, in which there are equal chances of losing and tripling the tokens. The students decide on how much to bet where the amount, which they do not invest, is safe. Hence, the more they bet, the more risk loving they are. After the decision, the outcome of the investment decision is determined by a draw from a black urn containing one yellow and one purple ball. If the yellow ball is drawn students win

[8] For the first visit, only one school has been visited in February 2014 due to organizational constraints. For the second visit, some schools were visited in the last week of April.

[9] A rich variety and quantity of gifts was provided in order to be equally appealing to boys and girls. Gifts included, for example, jumping ropes, footballs, money purses printed with pictures of barbie dolls as well as emblems of soccer teams. Moreover, different types of gifts were selected in the second visit to keep incentivization strong.

and triple their tokens. If the purple ball is drawn they lose everything they invested. Each individual draw constitutes our first treatment variable in the form of random wealth shocks.[10] After the draws, students are paid according to the outcome of the game and the number of tokens invested. Since all the draws were made in front of the class, all students were informed not only about the consequences of their own decision but also about their peers' outcomes. This is essential for the design as it allows us to analyze whether experiences of peers affect the giving behavior of children. Therefore, our second treatment variable is the percentage of peers who lost within the classroom.

It is worthwhile to discuss why it makes sense to expect an effect of random wealth shocks on the donation decision of children in this particular setting. One might think that in comparison to the literature where the impact of experiences such as natural shocks, conflicts and economic distress on behavior is analyzed, the wealth shocks generated in this study are weak. In fact, if we were to have adults or even adolescents in our sample we would not expect significant results. However, as already documented, our sample consists of children in public primary schools and childhood is a period in one's life time where cognitive and non-cognitive skills are mallable and sensitive to interventions.[11] Therefore, we conjecture that it is plausible to expect children, especially those coming from a relatively poor part of society and facing a shock in an entirely different setting to be affected. Another objection could be that since the duration between the wealth shocks and the measurement of altruism is considerably long, children might have already forgotten what they have experienced in the first place. In order to understand whether outcomes are still memorized by children, we ask whether they remember the color of the ball they drew. It is important to note that this question has been posed to an entirely different sample which is not a part of the analysis in this paper. The results show that 89% of the subjects remember their draws indicating that these wealth shocks are memorized in the long run.

[10]The expected amount from the investment is $(5 - R) + 0.5 * 3R$, given that a student chooses to invest $R \in \{0, \ldots, 5\}$. The full payment scheme is available at Table A.1 in Appendix.

[11]For the importance of early childhood period on non-cognitive and cognitive skills see Shonkoff and Phillips (2000), Carneiro and Heckman (2003), Cunha et al. (2006), Heckman (2006). For the effect of educational interventions on non-cognitive skills see Alan et al. (2016)and Alan and Ertac (2017b).

2.2 Dictator Game

At least three months later, a second visit is made to the same pool of students. In this visit, students play a simple dictator game, where they are given an additional 4 tokens. Note that the tokens provided in the second visit are independent from the gifts obtained in the first visit, i.e. they have a whole new budget. Students are asked to allocate these tokens between themselves and other students who are in the first grade and could not participate in our field study. Students do not have any further information about the recipients.[12] All decisions are made in complete privacy.

Two features of the current experimental setup are particularly important for the question asked in this paper. First, recipients' poorness is generated by bad luck. In other words, subjects are made clear that we are not able to pay a visit to the recipients. Therefore, recipients are not able to participate in our games, i.e. they are not even given the opportunity to play. Secondly, in the risky investment game, conditional on investing, students either gain or lose by chance. We expect students who lose and/or who are exposed to an environment with many losers to gain an awareness of how it is like to have low resources due to bad luck. Therefore, they will potentially be more able to relate to anonymous recipients. A match of experience might decrease the cognitive cost of effort to imagine recipients' situation. For winners, on the other hand, it will be comparatively harder to empathize with the poor recipients as their experience do not match.

There are papers in which the relation between various sources of poorness and altruistic behavior is analyzed. For example, Alan and Ertac (2017a) include both effort and luck as a source of recipient poorness and study the effects of this variation on donation levels. In Cassar and Klein (2017) both potential donors and recipients can become poor due to bad luck or low effort. The results show that low income subjects are more likely to help if the recipient is poor for the same reason. However, effort does not play a role in our setting and

[12]The recipients in our study are completely anonymous to the subjects as we do not aim to analyze the difference between in-group favoritism, i.e. parochialism, and out-group hostility as in Voors et al. (2012) and Fehr et al. (2013).

we only focus on the luck component as a genarator of wealth.

All the instructions for the individual decision-making task and the dictator game are provided in Appendix.

3 Results

3.1 Data and Descriptive Statistics

Our sample consists of students from the 4th grade and predominantly aged between 9 and 11 years. One (1) student is dropped from the sample due to cognitive difficulties reported by the teacher.

We use several covariates with a potential of high predictive power on prosocial behavior obtained from surveys administered to both students and teachers in our analyses. In particular, we use students' SES level provided by teachers. One characteristic of the Turkish education system is that teachers stay with the same students during the first four years of primary school. Therefore, teachers are well acquainted with their students and their families after several years of interaction. This gives us confidence on the reliability of the information given by teachers on each of their students. We also include the number of older and younger siblings reported by students in our analysis as these are found to be significant predictors of altruism in several studies such as Fehr et al. (2013).

Note that in the current setting receiving a wealth shock is conditional on investing at least one token. Consequently, subjects who choose to keep all their tokens are exposed to neither a positive nor a negative shock. Therefore, children who play safe are dropped in the analysis since they are not treated. Although selection bias is a natural concern, we think it is not an issue in our specific setting for two reasons. First, these children account only for 5.5% of the sample and secondly the difference between the mean donations of children who invested at least one token and who did not invest at all is not statistically significant (p-value = 0.561). An additional concern may be missing observations on several covariates. This is largely driven by the SES level of children as we lack of information on this covariate from 26.6% of our overall sample. In order to overcome this problem we impute missing values of this covariate and provide the main results without imputation in the Appendix (see tables A.2-A.4).[13] After dropping students with no treatment status and imputing missing values for the SES levels, we have a sample size of 608. Throughout the analysis we cluster standard errors at the classroom level to account for intra-cluster correlations.

Our main treatment variable is the outcome of the individual risk game which equals to 0 in case of a win and equals to 1 in case of a loss. 54.5% of the random shocks received by the children are positive, therefore we have an almost balanced sample of winners and losers. The second treatment variable is the percentage of losers within one's class. Figure 1 depicts the variation of the loser share within a class. While on average the loser share is naturally close to 50%, there is enough variation across classrooms that we can exploit. Our outcome variable is a three-category dummy variable constructed as follows: Children who donated (1) nothing, (2) exactly one token and (3) more than one token.[14] On average, losers donated 2.21 of their tokens whereas winners donated 2.03 tokens and the difference in average donation levels is significant (p-value = 0.01). This observation suggests that random wealth shocks are correlated with children's decision to donate.

3.2 Effect of Self Experience on Altruistic Behavior

Table 1 presents the ordered logit regression results, in which the donation is taken as the dependent variable and the outcome of the risk task is the treatment variable. Column (1) shows the main result of the paper: after being exposed to a negative shock, we expect a 0.35 unit increase in the log-odds of donating more. Moreover, this result is robust when we control for potential covariates of altruism such as risk tolerance, number of younger and older siblings, gender and the SES level of the family (see columns (2) to (5)).[15]

[13]In order to impute SES levels we use the measure of intelligence obtained by the results of raven's progressive matrices because of high correlation between the two.

[14]We pool the students who donated more than one token because of the low rates of donations of 3 and 4.

[15]The SES level of the family is obtained from the surveys filled out by teachers on a 5-item scale.

Another covariate that stands out is the number of young siblings. An additional young sibling is associated with a higher level of donation. Indeed, it has been found in the literature that children with a higher number of siblings perform better in theory of mind tasks, which are used to measure the understanding of others' mental states and beliefs.[16] We also see that boys are less altruistic than girls, however this difference does not reach statistical significance.

Figure 2 gives a clearer interpretation of the coefficients obtained in Table 1. In this figure, based on the estimated coefficients in column (5) of Table 1, predicted probabilities of donating 0, 1 and more than 1 token are calculated both from winners and losers. The probability of not donating is almost 39% for winners, whereas for losers it is around 28%. By contrast, the probability of donating more than one token is only about 25% for winners but 35% for losers. The predicted probabilities of donating one token for winners and losers are very close.

Standard models of altruism predict that a negative wealth shock should lead children to donate less. However, our first result contradicts this prediction: losers are more likely to donate higher levels than winners. Moreover, the SES level of the family is not significantly correlated with children's donation levels (see Table 1). Given these results, we check whether the effect of the treatment variable is heterogeneous over different SES groups. In Table 2, we partition the sample into two SES groups, low SES and mid/high SES children. Then, we run the same regression for each of these two groups separately. We observe that the random wealth shock has no significant effect on the donation levels for those children whose families belong to the low SES group (see column (1)). However, children in medium- and high- SES groups are significantly affected by the shock (see column (2)). In order to test whether the random wealth shock affected the mid/high SES group significantly more than the low SES group, we estimate the following empirical model:

$$y_i = \alpha_0 + \alpha_1 Loser_i + \alpha_2 LowSES_i + \alpha_3 Loser_i * LowSES_i + X_i'\gamma + \varepsilon_i,$$

where y_i is the donation of student i, $Loser_i$ is a dummy equal to 1 if student i loses in

[16] See, for example, Perner et al. (1994), Jenkins and Astington (1996) and Cassidy et al. (2005).

the risk task, $LowSES_i$ is a dummy equal to 1 if student i belongs to the low SES group and X_i is a vector of individual characteristics. The coefficient of interest, α_3, shows the change in donation levels between losers and winners as we move from the low SES group to the mid/high SES group. The results indicate that the coefficient is statistically significant and negative, i.e. random wealth shock affects the behavior of mid/high SES children more than of low SES children (see column (3) of Table 2).

Figure 3 shows how the predicted probability of donation changes between these two wealth categories separately for losers and winners. As we move to the mid/high SES level, the probability of donating decreases for winners but increases for losers. Further, the gap in donation levels widens substantially: For the low SES, the difference in the probability of donation is about 4.5 percentage points, whereas this gap increases to 15 percentage points in the mid/high SES group. Overall, this result is intuitive in the sense that poorer families are possibly more exposed to adverse shocks both in magnitude and frequency. Moreover, wealthy families are able to smooth out exogenous shocks, i.e. shocks are to a lesser extent transmitted to their children. Therefore, the behavior is affected rather in high and medium SES children. Since empathy is an ability that can be developed by past experiences, low SES children are possibly already more empathetic than medium and high SES children. The former are therefore less affected by an additional random shock brought by the experimental setup.

We interpret losing as gaining an understanding or information on other people's states. Another way to obtain this information is sharing an environment with others on a regular basis. In this regard, we investigate whether exposure to different environments affects the donations of winners and losers differently. Especially, for children in medium- and high-SES groups, an appropriate environment can fill this gap. First, we know that one's wealth level appears to be an important factor of empathy. Being exposed to an environment where there are many peers from the low SES group might help one develop empathy and in turn might induce higher altruism levels as shown by Rao (2014). Consequently, we expect that a random wealth shock bears less effect on the donation level of children in poor classes. In order to understand whether this prediction holds, we exploit the exogenous variation in SES levels in classrooms. In particular, we categorize a class as low SES class if a high share of the class is composed of low SES children and mid/high SES class otherwise.[17] The first two columns of Table 3 document the ordered logit results for these two categories exclusively. First, we see that being a loser significantly increases the likelihood of high donations in both types of environments. The coefficients suggest that the size of the effect is bigger for children in mid/high SES classes with odd logs of donating a higher level being almost two times higher. Therefore, in order to see the differential effects of treatment we estimate the following empirical model:

$$y_i = \alpha_0 + \alpha_1 Loser_i + \alpha_2 LSSC_i + \alpha_3 Loser_i * LSSC_i + X_i'\gamma + \varepsilon_i.$$

Low SES in class (LSSC) is a continuous variable constructed by the percentage of children from the low SES group within class. The coefficient of intereset in this model is α_3 with which the differential effect of the treatment can be observed as we move from a classroom with a few low SES students to a classroom with many. The result of this model is given in the last column of Table 3. The interaction between being a loser and the low SES share in class is negative and significant. This indicates the following: as the share of low SES children in a class decreases, it is more likely that a negative shock is going to induce higher levels of donation.

Figure 4 shows in visual clarity how the increase of low SES share in class affects the predicted probabilities for each donation category by the outcome of the game. In the first panel we see that having more peers from the low SES group on average decreases the probability of not donating both for winners and losers. This observation is in accordance with the assumption that such an environment improves students' prosocial skills. Although the predicted probability of not donating decreases on average, this decrease is more drastic for winners. Consequently, the gap between winners and losers shrinks as a class becomes more

[17] In Turkish public schools, there is no structured student tracking system, in which students are sorted into classrooms by their abilities or SES groups. The distribution of share of low SES children in classes can be found in Figure 5.

and more populated with low SES children. Predicted probabilities for the donation of one token do not change significantly among losers and winners as the percentage of poor increases in class. The last panel nearly depicts a mirror image of the first panel. As the share of poor increases the predicted probability of donating more than one token increases on average and this effect is more prominent for winners.

The first piece of evidence documented in this section shows that experiencing a random wealth shock affects the donation levels. The second and third pieces of evidence indicate that the random wealth shock is more effective if the subject (1) comes from mid/high SES group or (2) shares an environment with a few peers from low SES group. In other words, we do not observe an effect on donation levels of children who already developed a high level of empathy prior to the experiment.

3.3 Effect of Peers' Experiences on Altruistic Behavior

Since empathy is a skill which can be developed not only by own experiences but also through observing others we also analyze how the share of losers in a class affects individual donations. As mentioned before, our experimental setup allows students to observe peers' outcomes within a class.[18] Since all draws are random and independent from each other, we obtain an exogenous variation in the number of students who lost in the risk task for each class. It is as if we assign each class a random number of peers with an unlucky outcome. Therefore, we are able to assess the causality of peers' experiences on the individual donation behavior. The questions we pose here are the following: (1) Does the random wealth shock of one's classmate affect own donation behavior and if so, in which direction? (2) Do we observe heterogeneous treatment effects across SES groups as in the case of individual experiences? We turn to Table 4 to answer these questions. Our treatment variable is the "Loser Share in Class (LSC)", which is the percentage of peers within a class who lost. When we divide the sample into low SES and mid/high SES children, we see that our treatment variable is

[18] For each student, we excluded student's own experience (outcome of the risk game) when calculating the share of losers in a class.

significant only for the mid/high SES group (see column (2)). For low SES children peers' outcomes are not a significant driver of the donation level and if anything it looks as if a larger fraction of losing peers reduces the likelihood of high donations. We propose the following econometric model to see the heterogeneous effects of our treatment variable:

$$y_i = \alpha_0 + \alpha_1 Loser_i + \alpha_2 LSC_i + \alpha_3 LowSES_i + \alpha_4 LSC_i * LowSES_i + X_i'\gamma + \varepsilon_i,$$

where the coefficient of interest is α_4. Column 3 in Table 4 shows that the loser percentage in a class affects the donation behavior of mid/high SES children more than that of low SES children. We obtain the predicted probabilities of donations using the coefficient estimates given in column (3). Figure 6 depicts the movement of these probabilities as we randomly include more losers in a class for low SES and mid/high SES children exclusively. For mid/high SES children the predicted probability of not donating decreases from 48% to 18% and in a similar manner the predicted probability of donating more than one token increases from 19% to 50% as the share of losers increases from 0 to 100. On the other hand, for low SES children there is relatively little variation in the donation as the share of losers changes.. The probability of donating one token is almost constant as the loser share increases, on average 40% and 34% respectively for low and mid/high SES children. These findings confirm the main hypothesis of the paper. An environment in which students observe peers' unlucky outcomes can lead to prosocial behavior that of children who were less exposed to unfortunate shocks in their lives, i.e. mid/high SES children.

3.4 Self Experience and Peers' Experiences

One important question is how the relationship between own and peers' experiences affects donation behavior. How someone is affected by others' experiences might be conditional on own experience. Table 5 documents the ordered logit results for two subsamples, losers and winners, in the first two columns. We see that an increase in the loser share of a class increases the likelihood of donating only for children who lost in the risk task. On the other hand for winners there is no significant effect of others' experiences. The interaction term between losing and the fraction of loser peers shows that the difference in difference is significant (see column (3)).

However, it is hard to make any further inference about the underlying mechanism as there are many potential scenarios on what it could be. From the perspective of losers, experiencing a negative wealth shock together with peers may amplify the effect of the shock on donation behavior. Moreover, experiencing a negative shock while many peers experience a positive shock might lead to resentment and consequently to a decrease in donations. From the perspective of winners, a potential scenerio could be that observing others' unlucky draws might help develop empathy and could lead to an increase in donations. Alternatively, winners could be completely oblivious to their surrounding and not likely to develop empathy by observing others. Identification of the exact mechanism between self and peers' experiences should be further explored in the future.

4 Discussion

We explain the difference in donation levels between control and treatment groups with the effect of random wealth shock on the development of empathy. The next question is the following: How does the random wealth shock affect empathy? In a standard model of altruism an individual i with an initial endowment w faces the problem

$$\max_{d} u_i(w-d) + \alpha u_j(d).$$

He derives utility from his own consumption $u_i(.)$ and from the consumption of individual j, $u_j(.)$. The extent of altruism towards individual j is represented by $\alpha \in [0,1]$. The first order condition

$$u_i^{'}(w-d^*) = \alpha u_j^{'}(d^*)$$

describes that the optimal donation level d^* is chosen in order to equate the marginal utility of individual i's own consumption and the discounted marginal utility of the recipient's consumption. In our experimental setup, at the time of the donation decision every student is endowed with the same number of tokens. Further, we expect two randomly chosen groups to have similar utility from own consumption, u_i, on average. As we give the same information on recipients to all our subjects we also expect them to have similar perceptions on the recipients' utility from consumption. Therefore, a significant difference in observed donation levels between treatment and control groups can not be attributed to differences in u_i, u_j and w.

Instead, we propose a model in which the altruism parameter is a function of empathy, a skill that helps individuals understand others' mental states:

$$\max_d u_i(w-d) + \alpha(\xi) u_j(d)$$

where $\alpha(\xi) > 0$, $\alpha'(\xi) > 0$, and $\alpha''(\xi) < 0$ for $\xi > 0$. $\alpha(.)$ is increasing as one's empathy level increases, however, the concavity assumption asserts that additional increases in empathy will increase altruism less and less.

Empathy is a skill with two dimensions, cognitive and non-cognitive. An individual is endowed with a certain stock of empathy which depends on many factors emanating both from nature and nurture. In addition to the already existing stock of empathy, one can exert costly cognitive effort to relate to others. Following Cunha et al. (2010), we can write down the technology of skill production with constant elasticity of substitution as

$$\xi_2^t = \left[\gamma \xi_1^\rho + \delta E^\rho\right]^{1/\rho},$$

where ξ_1 is the pre-treatment empathy level and E is the costly effort exerted to imagine other's needs. Our treatment, the random wealth shock, potentially affected the coefficient of effort exerted. In other words, mental cost of effort is relatively lower for unlucky individuals in the experiment. On the other hand, lucky individuals have to exert higher effort to relate to the recipients' situation. Therefore, the post-treatment empathy level will be higher for losers, i.e. $\xi_2^l > \xi_2^w$ and consequently $\alpha(\xi_2^l) > \alpha(\xi_2^w)$. Since losers discount the marginal utility of the recipient less than winners, they will end up donating more.

5 Conclusion

This paper studies the effects of random wealth shocks on children's giving behavior. The results reveal that a negative shock, i.e. losing in a risky investment game, leads to increases in altruistic behavior. The hypothesis is that the change in altruistic behavior is because of changes in empathy. Specifically, experiencing negative shocks increases the empathy towards "poor" children, which in turn increases donations.

The first piece of evidence is that negative experiences make children more willing to donate. At first glance this result seems counter-intuitive since one would expect wealthier people to donate more. However, experiencing negative wealth shocks can change people's perception of poorer individuals, by making them more vividly understand their situation and building empathy. This result is twofold: (1) We find that wealth shocks only increase donations in medium and high SES children. Low SES children may have already built a certain level of empathy toward individuals, who do not have gifts, because of their lifetime experience. On the other hand, medium and high SES children may not have such experiences. Therefore, we observe effects only in the medium and high SES groups, (2) Random wealth shocks have no effect on the donation behavior of children in classes with many peers from the low SES group. We conjecture that interacting with peers from a poor background helps students to develop a certain a level of empathy and consequently, we do not observe any effect.

The second piece of evidence is that observing peers' experiences can also change donation behavior. In particular, we show that an increase in the number of peers with negative experiences in a class leads to increases in individual donations. Again, this result is driven by students with mid/high SES backgrounds. Findings in neurobiology show that mirror neurons are activated when we observe others' actions, which might be the underlying mechanism behind this result. Mirror neurons in the brain of a child, who observes his friends' negative experiences, fire up so that it feels like the experience of a friend belongs to the child.

Taken together, these results confirm our hypothesis that a motivator of altruism is empathy, which develops through both own experiences and observing others. There are various channels through which one can develop prosocial skills and in this paper we focus on the effect of experiences on the development of empathy. This channel is fairly new to higher SES children who were more protected in their life.

The evidence put forward in this paper offers a way to understand heterogeneity in other-regarding preferences. Since experiences vary among people, the results provide insight into why people exhibit different levels of altruism. In addition, the paper provides a possible explanation on why we observe an increase in altruistic behavior in the years following civil wars or natural disasters that are documented in the literature. The findings of this paper suggest that further research should take into account the effect of exogenous shocks on altruistic behavior. In particular, dynamic models with altruistic preferences should account for the fact that these preferences are changing as people experience wealth shocks. Moreover, the extent and nature of variation in altruistic preferences due to experiences should be analyzed further. For example, an interesting research question related to neuroeconomics might be whether random wealth shocks cause differences in brain structures associated with understanding other people's perspectives and in the functioning of the mirror neuron system. Finally, the paper is related to the growing literature on the importance of educational interventions aiming to enhance not only cognitive, but also non-cognitive skills. An OECD report stresses that these skills "are not traits set in stone at birth and determined solely by genes. They can be fostered." (Kautz et al. (2014)). For example, "Dialogue in the Dark", founded in 1989, is an exhibition with the objective of increasing awareness toward blind people. People going to this exhibition are subjected to complete darkness, which gives an experience of visual impairment, and therefore develops a better understanding of the blind.

Our results suggest a way to foster prosocial behavior through empathy, in particular perspective taking. An implication might be to consider an educational intervention, where children can be exposed to stories or games which can help them understand how they would feel in a negative situation. This can be especially helpful to foster prosocial behavior for children who are not exposed to such stimuli in their daily lives.

Tables

Table 1: Determinants of Altruism

	(1)	(2)	(3)	(4)	(5)
Loser (=1)	0.355***	0.352***	0.371***	0.468***	0.478***
	(0.106)	(0.106)	(0.107)	(0.108)	(0.109)
Risk Tolerance		0.023	0.017	0.037	0.041
		(0.044)	(0.043)	(0.043)	(0.043)
High SES (=1)			0.045	0.092	0.072
			(0.187)	(0.200)	(0.199)
Low SES (=1)			0.140	0.120	0.106
			(0.135)	(0.145)	(0.143)
Number of Young Siblings				0.143**	0.139**
				(0.056)	(0.058)
Number of Old Siblings				0.003	0.001
				(0.039)	(0.039)
Male (=1)					-0.235
					(0.165)
Constant cut1	-0.525***	-0.462**	-0.392*	-0.148	-0.264
	(0.114)	(0.189)	(0.203)	(0.227)	(0.239)
Constant cut2	1.038***	1.101***	1.166***	1.412***	1.301***
	(0.118)	(0.187)	(0.207)	(0.234)	(0.251)
Observations	670	670	662	608	608
Pseudo R^2	0.00420	0.00434	0.00529	0.0119	0.0137

Reported estimates are coefficients from ordered logit regressions where the dependent variable is the categorical donation choice. Risk tolerance equals to the number of tokens invested. The standard errors are clustered at the classroom level. * p<0.10, ** p<0.05, *** p<0.01.

Table 2: Heterogeneous Treatment Effects across SES Groups

	(1) Low SES	(2) Mid/High SES	(3) Full Sample
Loser (=1)	0.228	0.667***	0.675***
	(0.191)	(0.145)	(0.148)
Risk Tolerance	0.087	0.008	0.037
	(0.090)	(0.052)	(0.043)
Number of Young Siblings	0.261**	0.084	0.141**
	(0.113)	(0.074)	(0.056)
Number of Old Siblings	0.061	-0.027	0.000
	(0.064)	(0.054)	(0.039)
Male (=1)	-0.027	-0.392	-0.249
	(0.274)	(0.254)	(0.169)
Low SES (=1)			0.298
			(0.205)
Loser*Low SES			-0.473*
			(0.262)
Constant cut1	-0.126	-0.406	-0.221
	(0.367)	(0.293)	(0.239)
Constant cut2	1.619***	1.058***	1.349***
	(0.376)	(0.287)	(0.256)
Observations	247	361	608
Pseudo R^2	0.0152	0.0197	0.0154

Reported estimates are odd log ratios from logit regressions where the dependent variable is the categorical donation choice. The standard errors are clustered at the classroom level. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Low SES Share in Class and Altruistic Behavior

	(1) Low SES Classes	(2) Mid/High SES Classes	(3) Full Sample
Loser (=1)	0.341**	0.650***	0.760***
	(0.162)	(0.148)	(0.180)
Risk Tolerance	0.106	0.032	0.057
	(0.072)	(0.045)	(0.043)
High SES (=1)	0.283	-0.046	0.057
	(0.361)	(0.239)	(0.201)
Low SES (=1)	0.154	-0.252	-0.143
	(0.298)	(0.192)	(0.171)
Number of Old Siblings	0.010	-0.035	-0.016
	(0.047)	(0.061)	(0.037)
Number of Young Siblings	0.103	0.168	0.123**
	(0.077)	(0.106)	(0.055)
Male (=1)	-0.348	-0.132	-0.253
	(0.262)	(0.237)	(0.177)
Low SES Share in Class (LSSC)			1.233***
			(0.315)
LSSC*Loser			-0.591*
			(0.354)
Constant cut1	-0.381	-0.120	0.141
	(0.491)	(0.290)	(0.255)
Constant cut2	1.217**	1.466***	1.733***
	(0.495)	(0.311)	(0.261)
Observations	278	329	607
Pseudo R^2	0.0138	0.0200	0.0224

Reported estimates are odd log ratios from logit regressions where the dependent variable is the categorical donation choice. The standard errors are clustered at the classroom level. * p<0.10, ** p<0.05, *** p<0.01.

Table 4: Loser Share in Class and Altruistic Behavior

	(1) Low SES	(2) Mid/High SES	(3) Full Sample
Loser (=1)	0.213	0.642***	0.459***
	(0.199)	(0.147)	(0.114)
Risk Tolerance	0.078	-0.003	0.032
	(0.090)	(0.054)	(0.044)
Number of Young Siblings	0.256**	0.083	0.134**
	(0.111)	(0.073)	(0.057)
Number of Old Siblings	0.064	-0.037	-0.001
	(0.065)	(0.055)	(0.041)
Male (=1)	-0.048	-0.365	-0.232
	(0.283)	(0.257)	(0.168)
Loser Share in Class (LSC)	-0.095	1.638*	1.700*
	(1.040)	(0.905)	(0.920)
Low SES (=1)			0.988*
			(0.533)
LSC*Low SES			-1.933*
			(1.069)
Constant cut1	-0.200	0.341	0.483
	(0.600)	(0.473)	(0.470)
Constant cut2	1.539***	1.805***	2.046***
	(0.557)	(0.476)	(0.488)
Observations	245	360	605
Pseudo R^2	0.0143	0.0232	0.0156

Reported estimates are odd log ratios from logit regressions where the dependent variable is the categorical donation choice. The standard errors are clustered at the classroom level. * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Own and Other's Experiences

	(1) Losers	(2) Winners	(3) Full Sample
Risk Tolerance	0.031	-0.007	0.013
	(0.068)	(0.081)	(0.048)
High SES (=1)	0.368	0.106	0.225
	(0.301)	(0.316)	(0.168)
Low SES (=1)	-0.030	0.189	0.081
	(0.225)	(0.234)	(0.163)
Number of Young Siblings	0.195**	0.115	0.154**
	(0.095)	(0.086)	(0.066)
Number of Old Siblings	-0.001	0.000	0.003
	(0.098)	(0.059)	(0.046)
Male (=1)	-0.102	-0.312	-0.211
	(0.217)	(0.269)	(0.178)
Loser Share in Class (LSC)	1.543*	-0.267	-0.487
	(0.912)	(1.076)	(1.050)
Loser (=1)			-0.507
			(0.458)
LSC*Loser			2.102**
			(0.976)
Constant cut1	0.003	-0.531	-0.544
	(0.568)	(0.574)	(0.517)
Constant cut2	1.667***	0.966*	1.025**
	(0.563)	(0.551)	(0.504)
Observations	254	299	553
Pseudo R^2	0.0149	0.00661	0.0157

Reported estimates are odd log ratios from logit regressions where the dependent variable is the categorical donation choice. The standard errors are clustered at the classroom level. * p<0.10, ** p<0.05, *** p<0.01.

Figures

Figure 1: Distribution of Loser Share in Class

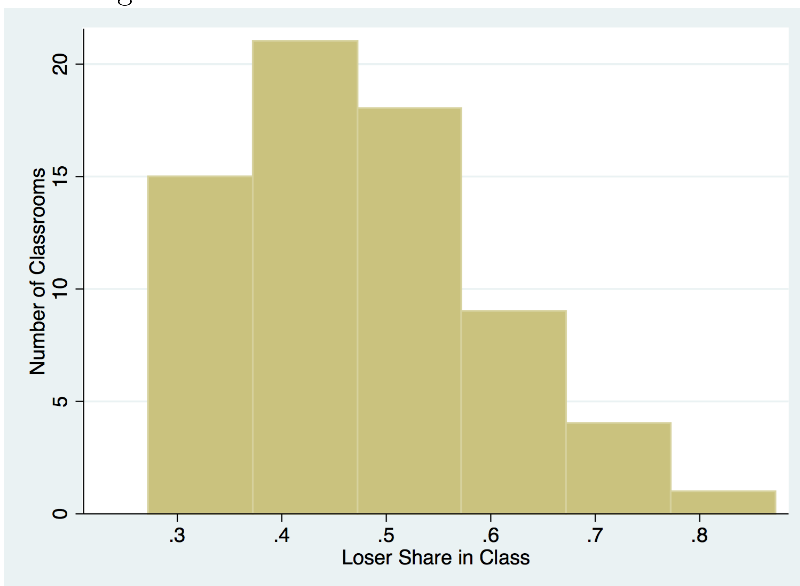

Figure 2: Predicted Probabilities of Donations by the Outcome of the Risk Task

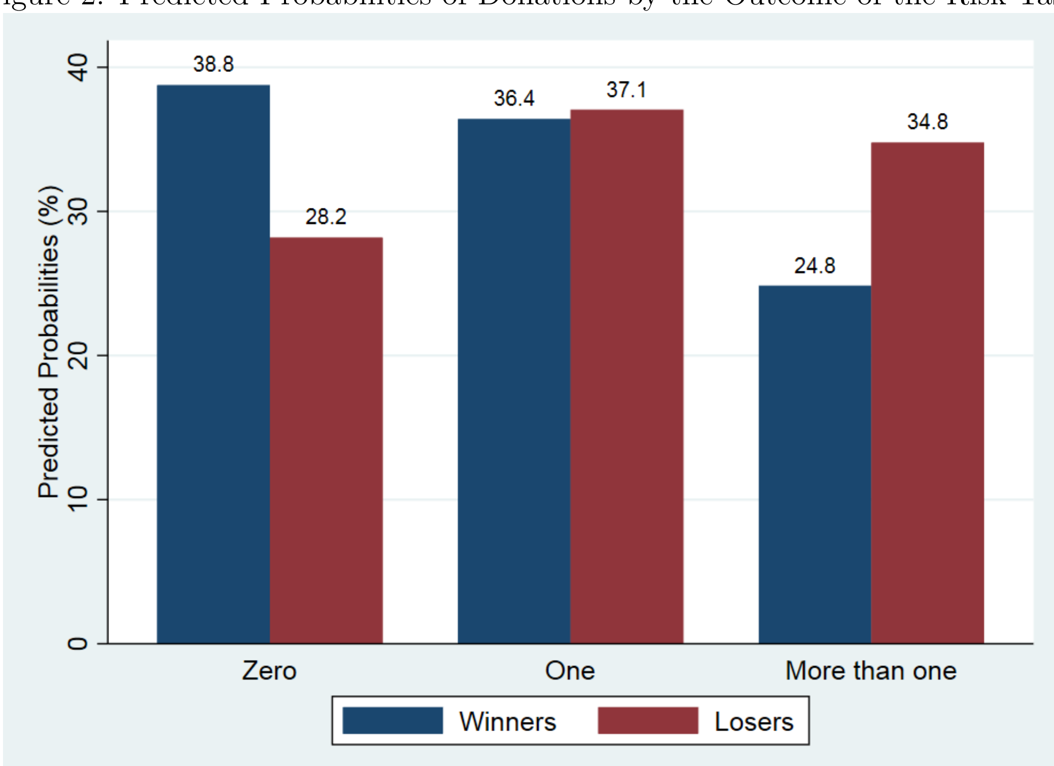

Figure 3: Predicted Probability of Donating across SES Groups

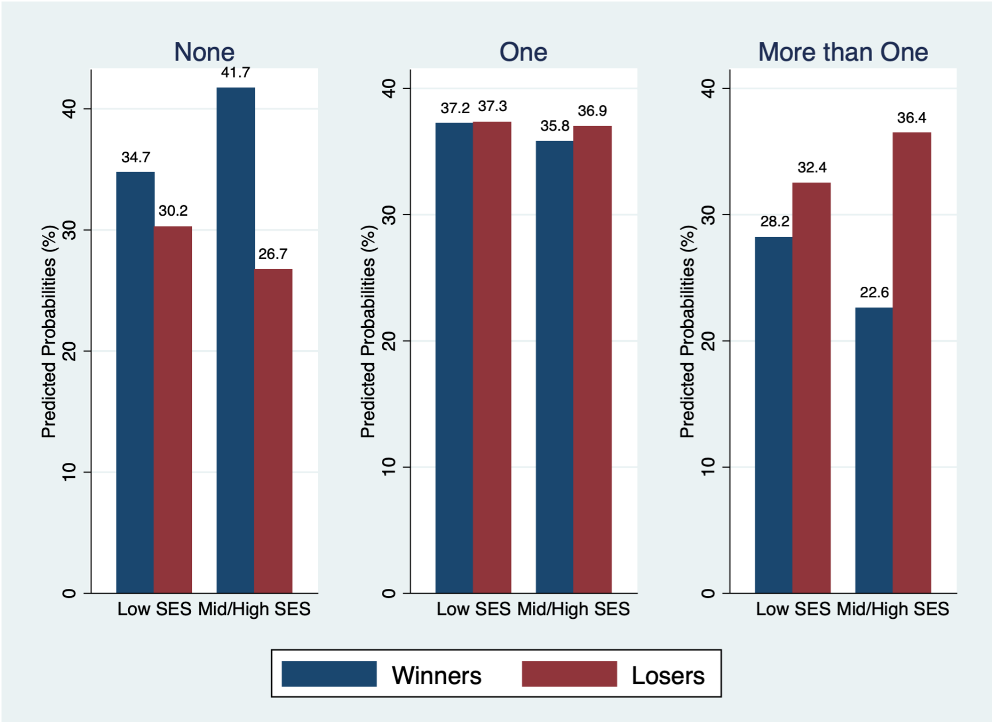

Figure 4: Predicted Probabilities of Donations and Low SES Share in Class

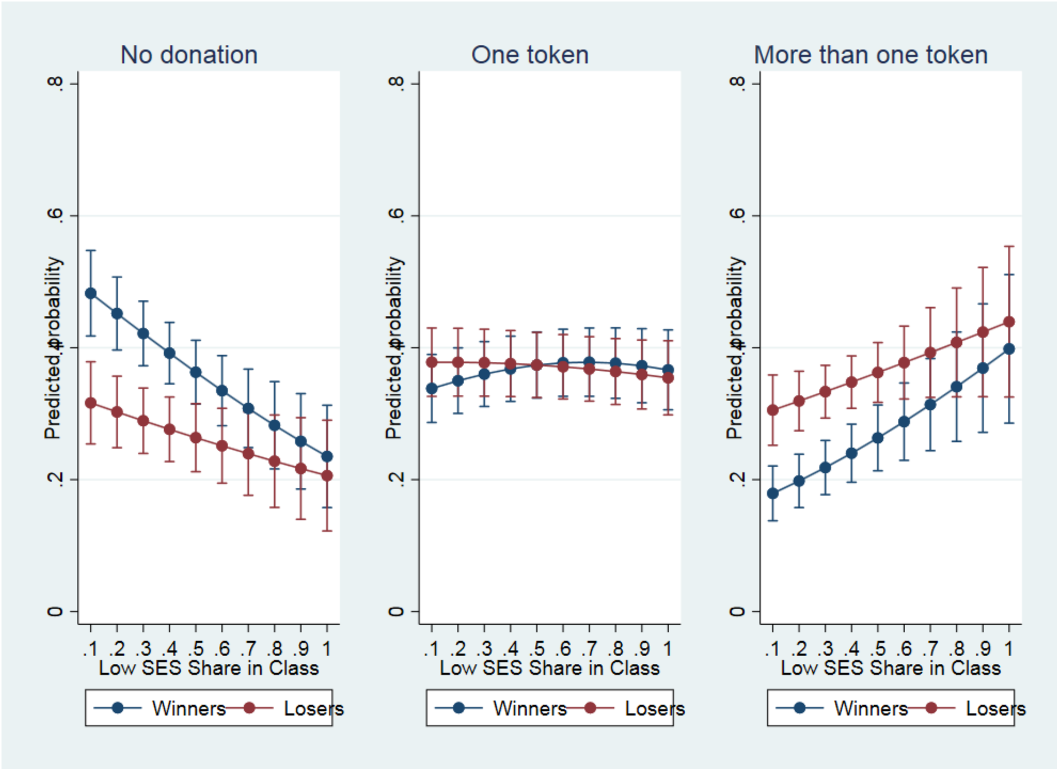

Figure 5: Distribution of Low SES Children in Class

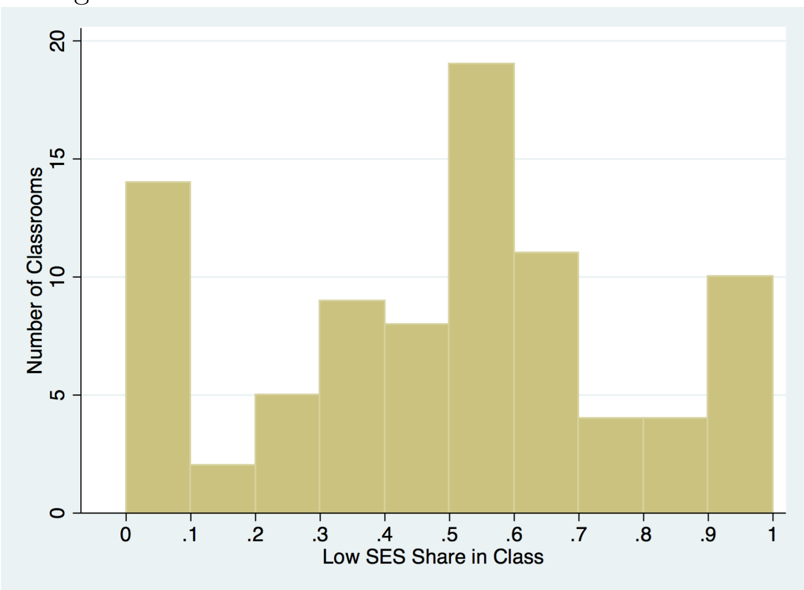

Figure 6: Predicted Probabilities of Donations by SES Groups and Loser Share in Class

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Appendix

Instructions for the Individual Risk Task

We are going to play different games with you today. Depending on your decisions in these games, you will earn gifts of your choice from our gift basket. As you can see we have many kinds of gifts that you might like [show different gifts from the gift basket]. Now, listen to the rules and make your decisions very carefully.

Your rewards will be based on the decisions you make in this game, if this game is randomly selected at the end of the lecture. Please be very quiet while the rules are being explained. If you have a question, please raise your hand. Also note that there are no right or wrong decisions in the games we will play today. In this game, each one of you will have 5 tokens. Each token corresponds to a gift equal value. For example, one token corresponds to 1 gift, two tokens correspond to 2 gifts, three tokens to 3 gifts etc. How many tokens you have will determine how many gifts you will get at the end of the game.

Now here is a bowl [draw a bowl on the board]. You can put as many tokens as you want in this bowl. The tokens you do not put in the bowl are yours to keep. What will happen to the tokens you put in the bowl depends on chance. These tokens will either multiply or they will be lost. How? Here is a bag with two balls in it, one of them is yellow and the other one is purple [show bag and balls]. If this game is selected, you will draw a ball without looking. The yellow ball is the good ball: If you draw this ball, the tokens you put in the bowl will triple. The purple ball is the bad ball: If you draw this ball, all of the tokens you put in the bowl will be lost. That is, depending on the color of the ball you draw, you have a 50-50 chance of losing or winning. If this game is selected at the end, you will draw the ball and the color of the ball along with how many tokens you put in the bowl will determine how many coupons you will get. Now we will go over some examples to make sure that everyone understood the rules:

Assume that you did not put any tokens in the bowl [Draw all 5 tokens outside of the bowl, on the board]. Then, since you kept all of your five tokens you get 5 gifts for sure. Assume that you put one token in the cup and kept 4 [Draw one token in the bowl on the board, draw the remaining ones outside]. Assume that you draw the purple ball. You lose all of your tokens in the bowl. Since you had kept 4 of your tokens, you get 4 gifts. Now assume that you draw the yellow ball, then the one token in the cup triples and becomes three tokens [Draw two more tokens in the cup]. You had already kept 4 tokens, so in total you have 7 tokens. Therefore, you will get 7 gifts.

Assume that you put 4 tokens in the bowl and kept one of them [Draw on the board]. Assume that you draw the purple ball. You lose all of your tokens in the bowl. Since you had kept one of your tokens, you get 1 gift. Now assume that you draw the yellow ball. The 4 tokens in the bowl triple and become 12 tokens. You had kept one token, so in total you have 13 tokens which correspond to 13 gifts.

Assume that you put all of your tokens in the bowl [Draw on the board]. Assume that you draw the purple ball. Then you lose all the tokens in the bowl and since you did not keep any, you get 0 gift. Now, assume that you draw the yellow ball. Then your tokens in the bowl triple and you get 15 tokens in total, which correspond to 15 gifts.

Did you understand the rules of the game? Any questions? [The decision-making will not start until the students answer the following questions correctly]

Assume that you put two tokens in the bowl and keep three tokens. Assume that you draw the yellow ball. How many gifts would you get? [Correct answer is 9]. Assume that you draw the purple ball; how many gifts would you get? [Correct answer is 3].

Assume that you put three tokens in the bowl and you keep two tokens. Assume that you draw the yellow ball. How many gifts would you get? [Correct answer is 11]. Assume that you draw the purple ball; how many gifts would you get? [Correct answer is 2].

Now, each one of you will get a decision sheet. You will mark the number of tokens that you want to put in the bowl on your decision sheet. If this game is selected, the rewards you will get will be determined based on this decision and the color of the ball that you draw. Make your decision quitely and do not show your decision sheet to anyone. [Decision sheets are distributed, students write their names and make their decisions, sheets are collected]

Table A.1: Payment Scheme in Individual Risk Elicitation Task

Amount invested	Winner	Loser
0	5	5
1	$1 \times 3 + 4 = 7$	$1 \times 0 + 4 = 4$
2	$2 \times 3 + 3 = 9$	$2 \times 0 + 3 = 3$
3	$3 \times 3 + 2 = 11$	$3 \times 0 + 2 = 2$
4	$4 \times 3 + 1 = 13$	$4 \times 0 + 1 = 1$
5	$5 \times 3 + 0 = 15$	$5 \times 0 = 0$

Instructions for the Dictator Game

Subjects are asked to make a decision in the following decision sheet:

You will get at least four gifts from our games today. If you would like, you can donate some of your gifts to children in first grade, who otherwise will not get any gifts. Donating is voluntary; you do not have to donate. How many gifts, if any, would you like to donate?

○ I prefer to give none of my gifts.

○ I prefer to give one out of 4.

○ I prefer to give two out of 4.

○ I prefer to give three out of 4.

○ I prefer to give four out of 4.

Main Results without Missing Data Imputation

Table A.2: Determinants of Altruism

	(1)	(2)	(3)	(4)	(5)	(6)
Loser (=1)	0.355***	0.352***	0.535***	0.613***	0.622***	0.627***
	(0.106)	(0.106)	(0.136)	(0.142)	(0.150)	(0.149)
Risk Tolerance		0.023	-0.022	-0.005	0.005	0.006
		(0.044)	(0.050)	(0.051)	(0.053)	(0.052)
High SES (=1)			-0.152	-0.122	-0.082	-0.084
			(0.182)	(0.212)	(0.215)	(0.215)
Low SES (=1)			0.093	0.055	0.150	0.140
			(0.164)	(0.175)	(0.212)	(0.206)
Number of Young Siblings				0.140**	0.131**	0.128**
				(0.059)	(0.056)	(0.057)
Number of Old Siblings				0.004	-0.004	-0.006
				(0.038)	(0.044)	(0.042)
IQ Level					-0.001	-0.004
					(0.088)	(0.087)
Male (=1)						-0.106
						(0.218)
Constant cut1	-0.525***	-0.462**	-0.388*	-0.170	-0.086	-0.142
	(0.114)	(0.189)	(0.220)	(0.254)	(0.265)	(0.286)
Constant cut2	1.038***	1.101***	1.091***	1.334***	1.391***	1.336***
	(0.118)	(0.187)	(0.226)	(0.255)	(0.267)	(0.293)
Observations	670	670	492	470	441	441
Pseudo R^2	0.00420	0.00434	0.0105	0.0174	0.0180	0.0183

Reported estimates are odd log ratios from logit regressions where the dependent variable is the categorical donation choice. The standard errors are clustered at the classroom level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.3: Heterogeneous Treatment Effects across SES Groups

	(1) Low SES	(2) Medium SES	(3) High SES
Loser (=1)	0.457	0.704***	0.702***
	(0.302)	(0.156)	(0.160)
Low SES (=1)			0.271
			(0.233)
loser*loww			-0.232
			(0.337)
Risk Tolerance	0.018	-0.003	0.004
	(0.135)	(0.061)	(0.052)
Number of Young Siblings	0.236	0.096	0.132**
	(0.153)	(0.078)	(0.059)
Number of Old Siblings	0.065	-0.033	-0.007
	(0.070)	(0.065)	(0.042)
IQ Level	0.042	-0.019	-0.007
	(0.170)	(0.107)	(0.087)
Male (=1)	0.279	-0.262	-0.107
	(0.364)	(0.291)	(0.221)
Constant cut1	0.054	-0.236	-0.085
	(0.612)	(0.333)	(0.297)
Constant cut2	1.576**	1.234***	1.394***
	(0.620)	(0.313)	(0.298)
Observations	134	307	441
Pseudo R^2	0.0212	0.0197	0.0186

Reported estimates are odd log ratios from logit regressions where the dependent variable is the categorical donation choice. The standard errors are clustered at the classroom level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.4: Low SES Share in Class and Altruistic Behavior

	(1) Low SES Classes	(2) Mid/High SES Classes	(3) Full Sample
Loser (=1)	0.259	0.977***	1.035***
	(0.242)	(0.160)	(0.217)
Risk Tolerance	0.035	-0.005	0.002
	(0.082)	(0.051)	(0.051)
High SES (=1)	-0.041	-0.113	-0.024
	(0.263)	(0.278)	(0.207)
Low SES (=1)	-0.064	0.203	0.016
	(0.286)	(0.298)	(0.211)
Number of Old Siblings	-0.068	0.032	-0.006
	(0.064)	(0.063)	(0.043)
Number of Young Siblings	0.053	0.142	0.117*
	(0.100)	(0.099)	(0.061)
IQ Level	-0.055	0.081	0.015
	(0.134)	(0.118)	(0.088)
Male (=1)	-0.405	0.026	-0.132
	(0.332)	(0.321)	(0.231)
Low SES Share in Class (LSSC)			1.273***
			(0.475)
LSSC*Loser			-1.251**
			(0.600)
Constant cut1	-0.713	0.180	0.208
	(0.627)	(0.325)	(0.285)
Constant cut2	0.614	1.816***	1.696***
	(0.598)	(0.311)	(0.288)
Observations	184	255	439
Pseudo R^2	0.00950	0.0359	0.0240

Reported estimates are odd log ratios from logit regressions where the dependent variable is the categorical donation choice. The standard errors are clustered at the classroom level. * p<0.10, ** p<0.05, *** p<0.01.