Children's rationality, risk attitudes and field behavior

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Abstract: We investigate the relationship between risk attitudes, choice consistency and field behavior of children by conducting economic experiments with 1,275 8th graders. Choices are not completely consistent with any of the economic theories we consider, however, they are not random either. We use our experimental data to structurally estimate risk preferences and correct for decision error. Using a measure constructed from the estimates and individual choices, we find that risk preferences do predict future field behavior. Children who are more risk averse are less likely to receive disciplinary referrals one and two years after the experiment and are more likely to graduate from high school, even controlling for economic rationality, family background, scholarly achievement and past misbehavior. Accounting for decision error turns out to be important as a simple aggregate measure of risk is not found to be correlated with field behavior.

1. Introduction

According to the Center for Disease Control (CDC), 29,551 individuals aged 15-24 died in 2010. Of those deaths, 20.7 percent were due to accidental discharge of firearms, accidental poisoning, exposure to noxious substances, and assault. By comparison, the frequency of these causes of death in the rest of the population is 1.5 percent. As reported by childrenstats.gov, the percent of 8th graders who admit using drugs is 7.7, and of the 47.4 percent who say they have had sex, three-quarters did not use contraceptives and 40 percent did not use a condom. While many of these behaviors may be viewed as imprudent, some could be considered economically rational if, for example, the returns to illegal activities are high or a child is willing to take risks. We investigate these type of behaviors more generally by asking two questions: (1) Are children's choices over risky outcomes rational, in that they are consistent with economic theory? and (2) Do risk preferences predict field behavior? We address these by collecting experimental and field behavior on 1,275 8th graders.

Several reasons motivate studying the nature of children's preferences and their relationship with field behavior. First, children make many decisions on their own, independent of their parents, and these decisions have important consequences for future economic outcomes. For instance, recent studies from labor economics show that misbehavior during childhood and adolescence have long term consequences on earnings (Segal, 2013; Heckman et al., 2006). Second, economic theory (Freeman, 1999) suggests that children's behavior must respond to both the relative costs to human capital accumulation and their preferences. So, examining the link between preferences and field behavior should be fruitful. Third, measurement error may be important when relating experimental estimates of preferences to outcomes. Children's misbehavior and high school graduation status are relevant outcomes that can be used to test the extent of the error and our proposed methodology to correct for it.

We aim to improve our understanding of risk preferences, economic rationality and field behavior by using several data collection methods. Information on the child's household environment is gathered with a survey. High school graduation, past and future misbehavior come from school records, and risk preferences are measured using incentivized economic experiments. Measuring preferences with experiments is advantageous because this allows us to observe the behavior of children from various backgrounds over identical choice sets. Similarly, data on household environment are potentially informative of the barriers some children might face in attempting to accumulate human capital.[1] An important component of our study is a brief survey on family structure completed by children participating in the experiment. This drastically reduces the loss of information due to non-response from mailed surveys to parents and allows us to control for variables that might be correlated with behavior in the experiment and the field. To control for the influence of cognitive and non-cognitive abilities (Heckman et al., 2006), we use standardized test scores and disciplinary referrals prior to the experiment.[2]

We look at the effect of children's risk preferences on field behavior, as measured by disciplinary referrals one to two years after the experiment and high school graduation five years later. While field behavior is likely to be influenced by many factors that are difficult to measure, we add various controls to reduce the potential for omitted variables.

Before relating measures of risk preferences to field behavior, however, it is crucial to determine what these experimental measures of risk reveal. It would be inappropriate to interpret choices in experiments as a measure of preferences if they are made randomly and are not consistent with theory. Even if children possess well-behaved preferences over risky prospects, they might be distorted in experiments because the child is not paying attention or makes execution mistakes. This measurement error could make it difficult to detect a relationship between preferences and field behavior even if one exists. To address these issues, our experimental design is constructed specifically to detect rational behavior through a series of lottery decisions. The generated data permit us to structurally estimate a decision model and identify whether children's choices are consistent with various theories of decision-making under risk and to what extent choices are noisy. We test consistency with expected utility theory, but also with less restrictive models of behavior such as Neilson (1992a), Diecidue et al. (2004), and cumulative prospect theory.

We have several key results. First, children's choices systematically deviate from decision patterns predicted by the theories of decision-making under risk we consider,

[1]For instance, children in two-parent households might face higher costs to misbehaving. While personality might also be important in explaining behavior, we do not have these measures. Instead, we control for household environment and past misbehavior.

[2]While disciplinary referrals and test scores are imperfect measures of cognitive and non-cognitive abilities (Heckman et al., 2006), achievement tests have been found to be correlated with personality traits (see Borghans et al. (2011)). A more complete approach would take into consideration measurement error in risk preferences as well as skills (Cunha et al., 2010). We examine measurement error in the former but not the latter.

including expected utility, as well as non-expected utility theory. While choices are not completely consistent with these theories, children are not choosing randomly. For example, we estimate that the proportion of children who make decisions consistent with expected utility theory is almost three times larger than the proportion that would be consistent if decisions were made randomly. Using the approach of Harless and Camerer (1994), we find that, once we allow for errors in decision making and compare across theories, expected utility performs no worse than other models (Vuong, 1989).

Second, looking at demographic heterogeneity in consistency and risk preferences, we find no particularly strong or robust patterns across the theories of decision making we consider. In terms of field behavior, we find that boys, children living with a single or no parent and children eligible for free or reduced price school meals have more disciplinary referrals and are less likely to graduate from high school. The opposite is true for children who are first born and have higher standardized math scores. These results are consistent with previous research on children's behavior (Bertrand and Pan, 2013; Segal, 2013; Currie and Tekin, 2006) and demonstrate that our sample is not atypical.

Third, we introduce a new estimate of risk preferences that corrects for measurement error due to decision mistakes. Assuming an expected utility model of decision making, we structurally estimate the conditional probability that a child has a certain set of preferences given the pattern of errors in the population and the actual choices made by the child in the experiment. The estimates from the structural model are then used to construct a risk preference measure that corrects for decision error.

Fourth, as predicted by economic theory, when our constructed risk preference measure is correlated with field behavior, we find that a child who is more risk averse is less likely to have future disciplinary referrals and more likely to graduate high school. This holds even controlling for economic rationality, past disciplinary referrals, scholastic performance and family background. The magnitude of the effect of risk preferences on high school graduation is large (e.g. equivalent to a one standard deviation change in 8th grade math scores). These findings are important because they show that our constructed measure can significantly explain some of the variation in field behavior, even controlling for other relevant covariates. It is worth noting that the disciplinary referrals we use in the analysis occurred one and two years after the children completed our experiment and high school graduation occurred five years later. This means that our results show a relationship between an estimated risk preference measure and future behavior.[3]

Finally, having a measure of preferences that accounts for decision error turns out to be crucial to uncover a relationship with field behavior. The correlation between risk aversion and disciplinary referrals is only statistically and economically significant if we use our estimate of risk preferences that corrects for measurement error. If we ignore error and use an aggregate measure of lottery choices or each separate lottery decision to explain discipline, we find no significant correlation. Similar correlation patterns exist for high school graduation as well. These results highlight that experimental measures could be imprecise due to measurement error (see Kimball et al. (2006, 2008); Gillen et al. (2015); Beauchamp et al. (2011)).

Very little is known about whether children's decisions under risk are consistent with economic theory broadly defined. Harbaugh et al. (2002) examine the risk attitudes of children and test for deviations from expected utility, but they do not test for consistency with other economic theories of decision-making under uncertainty. Our findings are consistent with studies using adults (Harless and Camerer, 1994) and a similar instrument. Consistent with previous research (Jacobson and Petrie (2009); Ashraf et al. (2006)), we find that a significant proportion of choices in a risky setting can be attributed to decision error.

A main contribution of our study is to show the importance of measurement error when estimating children's risk preferences and correlating them with future field behavior. If individuals make mistakes when choosing among risky alternatives, then it would be important to account for this when estimating risk preferences.[4] Underlying relationships with field behavior could be obscured with a preference measure that does not account for decision error. In addition, our findings contribute to the small but growing body of results showing significant correlations between choices in experiments and future field behavior (Buser et al., 2014; Castillo et al., 2011).[5]

[3]We note that precedence does not necessarily resolve the reverse causality problem since current behavior might depend on expected future behavior and incentives. We did not collect information on children's expectations.

[4]In general, error has been shown to be important in estimating preferences (Kimball et al., 2006, 2008; von Gaudecker et al., 2011). Beauchamp et al. (2011) use data from adults to show that once measurement error is accounted for risk preferences predict field behavior. More generally, there is growing evidence that measurement error is an issue when estimating preferences from experimental data. Gillen et al. (2015) present compelling evidence that error in experimental measures of risk preferences can severely underestimate its importance in explaining behavior.

[5]Several studies have examined the correlation between experimental preference measures and contemporaneous outcomes. Sutter et al. (2013) control for both risk and time preferences of children when correlating with field behavior and find time preferences to be a stronger predictor

Our results also speak to policy design. Incentive schemes in schools designed to promote investment in human capital are likely to have a differential impact across children if the decision to participate reflects a child's underlying preferences. If misbehavior is positively correlated with impatience and risk taking behavior, it is unclear if those who might benefit the most from an incentive would be more or less likely to take advantage of it. If they are less likely, then incentives tied to a target level of performance could merely be a transfer to children who would have invested in human capital anyway in the absence of the incentives. The recent experience providing children monetary payments to improve scholarly performance (Angrist and Lavy, 2009; Fryer, 2011) provides a cautionary tale. Preferences may interact in important ways with offered incentives and would then have an impact on the success of policies. Our study suggests that children might be tolerant of incentive schemes that bear significant risks (e.g. tournaments). Policies aimed at fostering human capital accumulation might bear this in mind.

The paper is organized as follows. Section 2 describes the risk instrument used in the experiments and how it can detect irrational behavior relative to the theories we consider. The section also describes the experimental implementation. Section 3 presents results, including summary statistics, a description of rational behavior, an estimation of risk preferences, the relationship between theories of rationality and individual characteristics, and the correlation between rationality, risk preferences, disciplinary referrals and high school graduation. Section 4 concludes.

2. Experimental Design and Implementation

In this section, we describe the experimental design and implementation. We also show how the design can be used to measure risk preferences and test for consistency with alternative models of decision-making under uncertainty.

2.1. Design

The experimental design, based on Chew and Waller (1986), requires three ordered payoffs, $x_L < x_M < x_H$, two alternative lotteries, $A = (x_M, 1)$ and $B =$

than risk. Angerer et al. (2015) explore the relationship between both risk and time preferences and donations to a real charity among children and find risk and time preferences to have a nonlinear relationship with donations. Survey measures of risk preferences have also been correlated with field behavior in adults (Dohmen et al., 2011; Kimball et al., 2008; Jaeger et al., 2010; Bonin et al., 2007; Burks et al., 2009).

$(x_H, \alpha; x_L, 1-\alpha)$, and a parameter $0 < \beta < 1$ which specifies how the A and B lotteries and payoffs are combined into new lotteries used in the experiment.[6] Subjects make five decisions, and each decision consists of choosing one out of two lotteries. The lotteries used in the five decisions are constructed from the three payoffs, the A and B lotteries and β.[7] The five-decision design has the advantage of being simple for the children and gives us data that allow for a robust test of rationality.[8] A simpler design of choosing one lottery from many options (e.g. Binswanger (1981)) or a multiple price list of binary lottery choices (e.g. Holt and Laury (2002)) would not provide data rich enough to distinguish between various models of behavior.

We have two designs, the on-border design and the off-border design, which only differ in the possibility of receiving a certain payoff. We will first discuss the set-up of the on-border design. The off-border design is very similiar and discussed later in this section. In the on-border design, $x_L = \$0$, $x_M = \$30$, $x_H = \$40$, $\alpha = 0.8$ and $\beta = 0.25$.[9] The off-border design shares the same ordered payoffs and β.

Figure 1 presents the lotteries used in both of our designs in the Marshack-Machina (MM) triangle (Machina, 1987). The left panel shows the on-border design, and the right panel shows the off-border design. Figure 2 shows the decision sheets used in the on-border design treatment, and Figure 3 shows the decision sheets used in the off-border design treatment.[10] For the on-border design, in Figure 1 (left-panel), each decision is represented by two solid dots connected by a line. The dots represent the two lottery options for that decision. The five decisions which subjects make are labelled D1, D2, D3, D4 and D5 in the figures. By construction, along each line, the bottom left lottery is the safer (S) option, and the upper right lottery is the riskier (R) option. In Figures 2 and 3, for each decision, option A is the safer

[6]Lotteries A and B are referred to as pair O. Chew and Waller (1986) called their design HILO, from high (H), intermediate (I) and low (L) outcomes plus lottery O.

[7]These are devised such that we can test for Allais' paradox (the common consequence effect) and the common ratio property of expected utility. Allais' paradox is tested by comparing what we call decisions D1 and D2, and the common ratio property is tested by comparing choices in decision D3 and D2.

[8]An alternative design could have been Choi et al. (2007), however, this would have been much more difficult to implement in our setting since it requires more decisions and computer terminals. Our design uses only paper and pencil, and more importantly, it allows us to examine a larger set of theories of behavior (see Polisson and Quah (2013)). This is important because we would like to distinguish between systematic deviations from theory and noisy behavior.

[9]The five decisions used in the experiment are constructed as follows. D1 compares $\beta A \oplus (1-\beta)x_M$ and $\beta B \oplus (1-\beta)x_M$. D2 compares $\beta A \oplus (1-\beta)x_L$ and $\beta B \oplus (1-\beta)x_L$. D3 compares A and B. D4 compares $\beta B \oplus (1-\beta)x_M$ and B. D5 compares $\beta A \oplus (1-\beta)x_H$ and $\beta B \oplus (1-\beta)x_H$.

[10]The decision sheets used by subjects to make their decision in the experiment are included in Appendix B.

lottery.

An expected utility maximizer would choose either all safe or all risky options since his/her indifference curves are linear and parallel (Mas-Colell et al., 1995). The possible choice patterns over the five decisions for an expected utility maximizer would be $SSSSS$ or $RRRRR$. Other choice patterns are possible if we consider alternative models of behavior. For instance, linear, but not parallel, indifference curves as in (Dekel, 1986; Gul, 1991; Neilson, 1992a) require only that choices satisfy expected utility along each separate line. This property is called betweenness. Models of preferences for certainty like that of (Diecidue et al., 2004) and (Bleichrodt and Schmidt, 2002) predict that behavior will follow expected utility theory except for lottery A which gives \$30 with certainty. Other models, like (Neilson, 1992b) and cumulative prospect theory, produce richer patterns of behavior. We consider six theories of behavior under uncertainty, including expected and non-expected utility, and the choice patterns each theory predicts. These are detailed in Table A1 in Appendix A.[11]

Our on-border design has the advantage of being simple and compact. However, as noted by Sopher and Gigliotti (1993) and Conslik (1989), this design might overstate departures from expected utility if choices are different when certain options are available than when none are available. That is, the on-border design might reject the null hypothesis of expected utility too often. To test the robustness of the results, we created our off-border design. This design only has pairs of lotteries which do not include a certain option. These are based on lotteries $A^\star = (x_H, 0.16; x_M, 0.8; x_L, 0.04)$ and $B^\star = (x_H, 0.64; x_M, 0.2, x_L, 0.16)$.[12]

None of the lotteries in the off-border design involve complete certainty, and all are within the borders of the Marshack-Machina triangle. These lotteries are presented in the right-side panel in Figure 1 as open dots. Notice that the two options available for each decision in either the on-border or off-border designs lie on the same line. The on-border decisions (solid dots) may include options where a certain payoff is available, and the off-border decisions (open dots) have no options

[11]The theories considered are betweenness, Neilson (1992b), Diecidue et al. (2004), cumulative prospect theory with convex weighting function, cumulative prospect theory with concave weighting function, and expected utility theory.

[12]The five new decisions are created in a similar manner to the on-border design, using the following rule: $A_i^\star = \beta A^\star \oplus (1-\beta)x_i$ and $B_i^\star = \beta B^\star \oplus (1-\beta)x_i$ for $i = L, M, H$. In particular, D1* compares $\beta A^\star \oplus (1-\beta)x_M$ and $\beta B^\star \oplus (1-\beta)x_M$. D2* compares $\beta A^\star \oplus (1-\beta)x_L$ and $\beta B^\star \oplus (1-\beta)x_L$. D3* compares $A^\star$ and $B^\star$. D4* compares $\beta B^\star \oplus (1-\beta)x_M$ and $B^\star$. D5* compares $\beta A^\star \oplus (1-\beta)x_H$ and $\beta B^\star \oplus (1-\beta)x_H$. These lotteries are constructed using the same value of β as the original lotteries.

with certain payoffs.

2.2. Implementation and Data Collection

In each experimental session, subjects are assigned a unique identification code. This code is private, and subjects do not know the identification codes of other subjects. Instructions are given orally by reading from a script, and a bingo cage with numbered balls is used to represent probabilities (e.g. out of 20 balls, those numbered 1-15 pay \$30 and those numbered 16-20 pay \$40).[13] During the instructions, several written examples are used to make sure subjects understand probabilities, to show that payoffs are tied to probabilities and to make clear the nature of the decision task. To maximize comprehension, subjects write down the answers to the examples, and any questions are addressed.

Upon completion of the instructions and questions, subjects make their choices privately by circling option A or option B on the decision sheet for each of the five decisions.[14] Only one decision is shown on each page, and subjects are free to move back and forth between pages when making their choices. After completing their choices, a subject puts her decision sheets in an envelope with her identification code written discretely on the bottom and the envelopes of all subjects are collected. Subjects then complete a short survey about family structure, parent's education and number of siblings. This survey is put in a separate envelope with the identification code and also collected.

Once all the envelopes are collected, one of the decisions is chosen at random for payment by taking index cards with the decision numbers written on them, shuffling them in front of the subjects, presenting them "face down," and asking a subject to choose one card. The number on the selected card is the decision number to be paid for the three subjects in each session who are randomly chosen to receive payment. Upon selecting a decision to be paid, the bingo cage is turned to select a ball numbered between 1 and 20. The selected ball determines the payoff corresponding to the subject's choice (A or B) for that decision.[15] For example, if decision 1 (D1)

[13]The decision sheet the subject sees has numbers next to various payments. The number on the ball that comes out of the bingo cage determines which payment is realized.

[14]Subjects made an additional lottery decision that is not analyzed in this paper. The additional decision varied across classrooms and is therefore controlled for with classroom fixed effects in the regression results. The decision sheets the subjects used to make their choices in the on-border and off-border designs, as well as the survey, are in Appendix B.

[15]In the on-border design, the bingo cage had 20 numbered balls to make the decision task simpler.

in the on-border design was chosen for payment, and the number chosen from the bingo cage was 18, the subject would earn \$30 if she chose option A and \$40 if she chose option B.

After determining the decision to be paid and the amount to be paid for choosing option A or option B, all the envelopes with the decision sheets are shuffled in front of the subjects, and three envelopes are chosen for payment. This is done in each session. The identification codes of those chosen to receive payment are written on the blackboard. Because identification codes are kept private by each subject, no other subject knows which subjects have been chosen to receive payment. Those who are chosen to receive payment are paid with a Wal-Mart gift card within a few days of the experiment.[16] The subjects who are chosen to be paid go privately to the principal's office to pick up their gift cards, and their names and payment are kept confidential. Subjects know all of these procedures before making their decisions.

All experiments were conducted by the authors. In total, 1,275 8th-grade students participated. One hundred and twenty two students were randomly chosen to be paid, and the average payment was \$34.55. The experiments were conducted during the school day in the home-room classrooms of the entire 8th-grade cohort of a county in Georgia, USA during the 2008-2009 and 2011-2012 school years. All experimental sessions in a particular school were completed sequentially during one morning or afternoon to minimize the chance that students spoke to one another about the experiment across sessions within a school.[17] The experiment took 30 minutes to complete, and the participation rate was very high, with about 95% of each 8th-grade cohort completing the experiment.[18] Subject characteristics are presented in more detail in the next section.

The experimental data provide a measure of risk preferences, and the survey

In the off-border design, because we had probabilities of less than 5%, there were 100 numbered balls.

[16]In order to minimize using up classroom time, we paid subjects a day or two later. We chose to pay with a Wal-Mart gift card because it minimizes potential problems associated with giving children cash and it can be transformed into many goods that children desire, so it is very similar to cash. In addition, it cannot be used for alcohol, tobacco, or firearms purchases by anyone. The school administration did not want us to use cash.

[17]Spillover across sessions was extremely unlikely. The children were kept in their home rooms while the experiments were conducted and were not allowed to interact with children seated in other classrooms either waiting to participate in the experiment or having completed the experiment. The children did not know the exact nature of the experiment prior to our arrival in the room to conduct the session.

[18]Non-participation was primarily due to absence on the day the experiments were implemented. We had only a handful of students across the three times the experiments were implemented who declined to participate.

data collected from the subjects after the experiment provide information on family background and structure. In addition, the school district supplied information from the student's school records on gender, race, standardized math and reading scores, whether the student qualified for free or reduced price school meals, high school graduation status (graduated or not) and the number of disciplinary referrals the student received in 7th, 8th and 9th grades.

A disciplinary referral happens when an offending student is sent to the administrative office (by a teacher, administrator or bus driver) and the behavior is entered into the student's official record (i.e. reprimand, detention, suspension, etc.). This measure does not include referrals to the office that do not result in a recorded entry in the student's record. Because students move from middle school to high school between 8th and 9th grades, the outcome measure of disciplinary referrals is from two different sets of teachers and administrators. 7th and 8th grade referrals are from middle school, and 9th grade referrals are from high school. This is an advantage for our analysis because disciplinary referrals in 8th grade are an independent measure of misbehavior from those in 9th grade.

All the data, from the school and the experiment, were anonymized to protect students' privacy.

3. Results

In this section we summarize the survey and school record data and describe the experimental results and evidence of deviations from rational behavior. We correlate rational behavior to individual characteristics, present our estimate of risk preferences, and explore the relationship between rationality, risk preferences and field behavior.

3.1. Description of the sample

Summary statistics of our sample are shown in Table 1. One half of the children are male, and 44% are given a racial classification by the school district as black and 48% as white. The average age is 13.8 years, and 34% of children report living with one or no parent. These numbers hide the fact that 49% of black children report living with one or no parent while only 22% of white children do. About two thirds of children qualify for free or reduced price school meals. The average number of disciplinary referrals is 1.56 in the 7th grade, 2.06 in the 8th grade and 1.33 in the 9th grade. While the number of referrals is highly correlated across 7th and 8th grades ($\rho = 0.5778$, p-value < 0.0001), they are statistically significantly different (t-test = -3.9976, p-value = 0.0001). The correlation between 8th and 9th disciplinary referrals is 0.5695 (p-value < 0.0001)]. Figure 4 shows that the distribution of referrals for 7th, 8th and 9th grades is skewed towards zero. For any grade year, between 65 and 78 percent of children receive no referrals. Some 73% of children in our sample are confirmed to have graduated high school.

3.2. Are choices consistent with theory or random?

The distributions of choices for each of the five decisions in the on-the-border and off-the-border designs are presented in Table 2. These are significantly different across the two designs (χ^2 test of equality of distributions p-value = 0.000). The modal choice is risk averse. In total, safe options (S) are chosen about three-fifths of the time across both designs. Across decisions, the distribution is not uniform within either design. This is contrary to what would be predicted by expected utility theory. For example, the proportion of times the safe option is chosen in the on-border design varies from 51 to 69 percent across the five decisions. Also, consistent with previous experiments, when the option of $30 for sure is available, as in D1 and D3 of the on-the-border design, children are more likely to choose it (69% in D1 and 63% in D3). The common consequence effect (or Allais Paradox) can be evaluated using D1 and D2. The pattern typically found in previous experiments is for subjects to choose S more frequently than R in D1 compared to D2. Table 2 shows that this pattern is present in the on-the-border design, but the opposite pattern (from R to S) emerges in the off-the-border design.

We turn now to examining whether choices are consistent with theory or random.[19] Harbaugh et al. (2001) have shown that children as young as eight years old satisfy the Generalized Axiom of Revealed Preferences (GARP) when choosing between two certain goods and that this behavior is statistically significantly different

[19]Our measure of consistency with theory is valid independent of the underlying distribution of preferences. Individual risk attitudes affect the distribution of patterns of behavior, but not whether a person acts consistently. While the experimental design might not be well calibrated to capture individual differences in risk attitudes, our design is still powerful enough to detect deviations from behavior consistent with theory. For example, under expected utility theory, the calibration of the experiment might affect whether a subject chose always S or always R, but not that he only chose one of these two patterns. The distribution of underlying preferences, however, does affect the power of the test of alternative theories of behavior under risk. That is, the calibration might affect the relative, but not the absolute, performance of a particular model in rationalizing the data.

from random choice. Our design allows us to examine if this holds when choices are made over uncertain outcomes.

We consider six theories of decision-making under uncertainty. While the list of models is not exhaustive, some of the theories deviate significantly from expected utility and therefore increase the chance of detecting whether choices are consistent more broadly.[20] The theories include (1) a model that requires behavior satisfies betweenness, (2) Neilson (1992a)'s model that allows for different utilities over certain and uncertain payoffs depending on the cardinality of the prospect, (3) Diecidue et al. (2004)'s model that allows for different utilities over certain and uncertain payoffs only, (4) cumulative prospect theory (CPT) with a convex weighting function, (5) CPT with a concave weighting function and (6) expected utility theory.

The property of betweennes was introduced by Dekel (1986) and requires that an individual's indifference curve be linear, but not necessarily parallel. Individuals satisfying this property can behave in a way consistent with the common ratio and common consequence effects. Neilson (1992a)'s model modifies the utility function over money to reflect the cardinality of a lottery (the number of different possible outcomes). This theory can explain a preference for certain outcomes, and it allows for violations of the independence axiom when compound lotteries have more outcomes than the originals. Diecidue et al. (2004)'s model is similar to Neilson's with the additional restriction that only two utility functions are used, one for certain payments and one for uncertain payments, regardless of their cardinality. Cumulative prospect theory allows for individuals to distort probabilities and value prizes depending on their rank. This means that in the Marshack-Machina triangle representing the lotteries in our experiments, indifference curves can be convex (with a concave probability weighting function) or concave (with a convex probability weighting function).

Table 3 shows the predicted frequency of patterns of behavior if children chose at random and the observed frequency of such patterns in the data for the six theories we consider. The first row shows that a child choosing at random would satisfy betweenness 25 percent of the time while behavior consistent with betweenness oc-

[20]Following the convention in the literature, we compare patterns of behavior to random choice. Other patterns of "irrational" behavior could manifest, such as choosing all A's. If so, it would be difficult to distinguish this pattern from adherence to expected utility. For this reason, we examine five additional theories that produce further patterns of behavior. Also, we might expect to see this type of "irrationality" when the decision problem is more complex, e.g. in the off-border design. However, the proportion of children choosing all A's is not significantly different in the off-border and on-border designs (13.2% in the on-border and 12.0% in in the off border, p-value=0.528).

curred 38.6 percent of the time in the on-the-border design and 38.9 percent in the off-the-border design. The z-scores testing differences in means corresponding to these comparisons are 7.98 and 8.05 and show that behavior in the experiment is significantly different from random choice when we assume preferences satisfy betweenness.[21] Indeed, for five of the six theories we examine, the patterns of choices made by children are significantly different from what random decision-making would predict. The only exception is cumulative prospect theory with a concave weighting function.

Additional statistical tests confirm that children's choices are not just noise. The scale reliability coefficient (Cronbach's alpha) is a measure of internal consistency or how related are a set of items in a group (similar to a correlation). This coefficient for the choices in the five lotteries is 0.31 – it would be about 0.08 if the data were generated at random. Similarly, the largest eigenvalue corresponding to the five decisions using factor analysis is 0.508, while the largest eigenvalue, if the data were generated at random, would be 0.076 (Horn, 1965).

3.3. Consistency with alternative behavioral theories and individual characteristics

Next, we examine whether individual characteristics are correlated with the predicted patterns of behavior for each theory. This is examined in Table 4 which presents a linear probability model of a variable that equals 1 if a child's choice pattern is consistent with a pattern predicted by a particular theory and equals 0 otherwise on individual characteristics.[22] For instance, column 7 in Table 4 presents the linear probability model corresponding to expected utility theory. For expected utility theory, the dependent variable equals 1 if a child always chose S or always R, yielding a choice pattern of $SSSSS$ or $RRRRR$. For the other columns, the dependent variable equals 1 if the choice pattern is one of those listed in Table A1 in the Appendix and 0 otherwise. In the first column of Table 4, we show an Ordinary Least Squares regression using the number of safe choices made across the five lotteries as the dependent variable. This is a measure of the individual level of risk aversion. All the estimations include fixed-effects at the classroom level to account for unobserved heterogeneity.

[21]For an observed and predicted frequency x and y the z-score is calculate as $z = \frac{x-y}{\sqrt{\frac{y(1-y)}{n}}}$ where n is the sample size.

[22]Estimates using a logit specification with fixed effects at the classroom level produce qualitatively similar results.

The first column in Table 4 shows that younger children within the cohort and children who perform better in standardized reading tests are more likely to choose safe options.[23] Columns 2-7 look at consistency with predicted patterns of behavior for each theory and show that older children within the cohort tend to be less likely to choose consistently, but this is not significant for all theories considered. Children whose father's highest level of education is high school are less likely to act rationally, but again, this is not robust.

We also examine an alternative measure of rationality: the number of decisions that need to be changed to make a choice pattern consistent with a particular behavioral theory. For instance, an individual choosing a pattern predicted by theory will have a cost of zero while an individual who would conform to theory by changing at most one decision will have a cost of one. In general, we find that this alternative measure reproduces the same results as Table 4, but the correlation between individual characteristics and costs to rationality is even weaker.[24]

So, while some individual characteristics are correlated with making rational decisions, no consistent relationships exist across the various theories we consider.

3.4. Estimation of risk preferences

Thus far, we have seen that the decisions of children are noisy but not random and individual characteristics are not strong predictors of consistency with theory. Ultimately, we would like to see how risk preferences and rationality correlate with field behavior, however, to do so, we need to take into account possible noise in decision-making. In this section, we introduce a structural approach to estimate risk preferences that accounts for error in decision-making. In the following section, we present the estimates that are used with individual choice data to construct a new risk measure that we correlate with field behavior.

The number of patterns of behavior predicted by the theories we consider ranges from two to thirteen. To put the various models on the same footing, we use the approach of Harless and Camerer (1994). They model the observed patterns of

[23]Note that the effect of age in any of our results is not due to older children (e.g. those > 14 years old) who may have been held back and are repeating 8th grade. The effect is solely due to natural age variation within a grade cohort. A potential reason for age effects is hormonal changes, however, we do not have a direct way to test this hypothesis.

[24]Table A5 in Appendix A shows these results. In addition, Table A3 shows that, for the case of expected utility, the propensity to deviate from rational behavior is correlated with age, father's education and math scores.

behavior as the result of adherence to a theory with probability $(1 - \omega)$ or random choice with probability ω. For instance, suppose pattern $SSSSS$ is chosen with probability p and pattern $RRRRR$ is chosen with probability $1 - p$, then if a person makes a mistake with probability ω then the probability of observing pattern $SSSSS$ according to this theory of behavior is $p(1-\omega)^5 + (1-p)\omega^5$. That is, $SSSSS$ could have been chosen without making errors or because a person switched from the desired pattern $RRRRR$ by making a mistake.

Since for a given p and ω this approach allows us to calculate the likelihood of observing any pattern of behavior, we can use maximum likelihood methods to estimate the parameters of this model or any theory that predicts a subset of all possible patterns. The number of parameters of a theory so defined is then equal to the number of patterns of behavior predicted by the theory.[25] Note that this approach treats all mistakes as equal regardless of the absolute difference in the expected value of the lotteries considered. This should not be an issue in our case, however, because we do not find evidence that children are less likely to make mistakes the larger the difference in the expected value of the lotteries.[26] Table A2 in the Appendix presents estimates for the theories we consider. All theories have large levels of error, and these error rates are on the higher side of those reported for adults in Harless and Camerer (1994).

Comparison of the six models shows that expected utility does just as well at explaining the data as any of the alternative theories we consider. This is confirmed with a Vuong (1989) test for model selection and is consistent with results from experiments with adults (Harless and Camerer, 1994).[27] Thus, we use the estimates from an expected utility model to construct our new measure of risk preferences which we correlate with field behavior.

An alternative approach to the one described above is the framework of random

[25]Because probabilities add up to one, there are the number of patterns minus one parameter. The noise parameter adds one more, which makes the total number of parameters equal to the number of patterns.

[26]We test if decision errors are sorted according to the difference in expected value between lotteries by allowing decision errors to decrease with the difference in expected value between lotteries. We cannot reject the hypothesis that errors are not sorted in this manner ($\chi^2(1) = 1.13$, p-value = 0.2881). The test restricts decision errors to be the same across all participants, but allows the propensity to choose risk aversely to depend on covariates.

[27]We conduct pairwise comparisons of all six theories using Vuong (1989)'s test. This is similar to the AIC test for model selection, but it allows for non-nested models. We use this test because the patterns of behavior predicted by these models are not always nested. Except for betweenness, expected utility never does worse than any other model. Statistical comparison of these models are available from the authors upon request.

utility theory. For instance, we could assume that children either choose according to a constant absolute risk aversion utility function with some probability or choose completely at random otherwise. Our approach uses the data more thoroughly. Estimates are based on the population data and the individual decisions of a child and provide a more precise measure of individual preferences.[28] The random utility model would allow for this if we assume that individual preferences are characterized by a distribution rather than a singleton. Our data, however, are not rich enough to satisfy this assumption.[29] Instead, the approach outlined above addresses the issue of idiosyncratic heterogeneity in preferences, independent of covariates, subject to the data generated by our experimental design.

3.5. Rationality, risk attitudes and field behavior

3.5.1. Disciplinary referrals

We now turn to the relationship between risk attitudes, rationality and field behavior. We start with disciplinary referrals as these are acts that have been shown to predict economic outcomes later in life, such as education achievement and lower wages (Bowles et al., 2001; Heckman et al., 2006; Lang and Ruud, 1986; Segal, 2013), as well as high school drop-out rates (Alexander et al., 1997; Rumberger, 1995). Disciplinary referrals are therefore a good benchmark to evaluate the influence of preferences on behavior and to test the ability of experiments to uncover them.[30]

[28]That is, our approach allows an estimation of the conditional probability an individual has risk averse preferences given his specific choices in the experiment and not just on his individual characteristics. This approach assumes the existence of idiosyncratic differences in preferences and uses individual decisions to best guess what these are.

[29]Such an approach is proposed by von Gaudecker et al. (2011) and ours is a discrete version of it. von Gaudecker et al. (2011) assume that individuals either evaluate lotteries according to a parametrically specified expected utility function or choose at random. To model heterogeneity across individuals, and in the spirit of mixed logit models, they characterize preference parameters as drawn from a continuous parametric distribution function. For any given set of parameters, an estimate of an individual's expected utility parameters can be constructed based on observed choices and the individual's characteristics. We have attempted this approach in our data but could not obtain estimates of the model either using a constant relative risk aversion or a constant absolute risk aversion utility function. This suggests that our experimental design is not rich enough to estimate underlying preferences using this approach.

[30]Time preference may also be important, however, we do not have a measure of this for all children to include in the regressions. There is a small overlap of students (n=218) who participated in the time preference experiments reported in Castillo et al. (2011) and the risk experiments reported in this paper during the 2008-2009 school year. Using this subsample, we rerun the regressions reported in Table 7 and find similar results. When we add time preferences to the specifications in Table 7, the coefficient on the posterior risk measure is reduced (by 8-12%) and remains significant for 8th grade referrals. The coefficient on time preferences, however, is not significant.

Following Freeman (1999), we expect disciplinary referrals to be negatively correlated with risk aversion.

Tables 5-7 present negative binomial regressions of disciplinary referrals on three different measures of risk preferences. All regressions include a measure of rationality as defined by expected utility theory and covariates. We use a negative binomial specification because disciplinary referrals are a count variable and many children have no referrals (see Figure 4 for the distribution of referrals across 7th, 8th and 9th grades). Our control for rationality is a dummy variable indicating choices consistent with expected utility because, as shown in Section 3.4, it is as good at explaining the data as other theories and has been used frequently in the literature. All reported results in this section hold using any of the alternative theories to define rationality.[31] The regressions include fixed effects at the classroom level to account for any variation due to experimental implementation or selection of students into classrooms.

We look at disciplinary referrals at the end of the 8th grade, 9th grade and the sum of the two. Eighth grade referrals occurred in middle school, and 9th grade referrals occurred in high school. Having referrals for the same child from two different schools provides two separate, independent measures of misbehavior. This allows for a stress test on our results because these are two different sets of school administrators deciding whether to record the discipline infraction on the student's permanent record. These referrals occurred up to 2 years after the experiments were conducted. All the regressions also control for disciplinary referrals in the 7th grade. While our results are qualitatively similar whether this variable is included or not, including past misbehavior diminishes the omitted variable problem due to unobservable conditions that might influence an individual's behavior in the field and in the experiment.

We examine whether our first risk preference measure, a simple aggregate of the total number of safe choices across the five decisions, can explain disciplinary referrals. Table 5 shows these results for referrals in 8th, 9th and 8th and 9th grades combined.[32]

Consistent with previous research on the behavior of children (Bertrand and Pan, 2013), we find that male and black children are more likely to have disciplinary re-

[31] These results are reported in Tables A6-A14 in Appendix A.

[32] Tables A6-A8 in Appendix A show the same results for all six of the theories we consider. These tables show that the results reported in the paper are robust to our use of expected utility to define rationality.

ferrals.[33] Children who qualify for free or reduced price school meals are also more likely to have disciplinary referrals. The opposite is true for children living in a two-parent household, first-born children, an only child in the household, and children who perform better on standardized math tests, although some of these results are not robust across years. Past disciplinary referrals are a strong predictor of future disciplinary referrals. This is consistent with disciplinary referrals being the product of unobserved personality traits, conditions faced by the child or expectations.[34] In the absence of additional individual information on these factors, we cannot distinguish between these hypotheses.

Looking at the effect of risk preferences on referrals, columns 1-3 in Table 5 show that, using our first measure of risk, the more safe choices a child makes, the fewer disciplinary referrals she receives. However, this is only significant when 8th and 9th grade referrals are combined (column 3). Table 6 reports the effect of our second risk preference measure on referrals. This measure looks at each decision separately and equals one if the riskier option was chosen. Only one of the decisions, D1, is significantly correlated with referrals and only in 8th grade and 8th and 9th grades combined. The results from Tables 5 and 6 show that our first two measures of risk preferences are not significantly correlated with disciplinary referrals.

For our third measure of risk preferences, we construct a new measure that accounts for decision error. Using the results and approach outlined in the previous section, we estimate a structural model that predicts that a person adheres to expected utility with probability $1-\omega$ and reverses her preferences (makes a mistake) with probability ω. Recall that, in our experiment, expected utility permits only two choice patterns ($SSSSS$ or $RRRRR$, i.e. *all safe* or *all risky*). We allow the probability p of choosing $SSSSS$ and the probability of making a mistake (ω) to depend on the characteristics of the individual. Using the entire sample, we then estimate these parameters and use them to calculate a posterior probability that a person chooses all safe options. e.g. $SSSSS$.[35]

[33]In our data, boys have 2.59 disciplinary referrals and girls have 1.51 disciplinary referrals (p-value < 0.000). Black children have 2.99 disciplinary referrals on average and non-black children have 1.32 disciplinary referrals (p-value < 0.000).

[34]The school system follows a progressive discipline policy so that after one referral the consequences of the next become greater. After one referral the administrator may not have the option to not record a second referral whereas until one referral is entered the administrator has the discretion to not enter referrals.

[35]The results of these estimations are shown in Table A3 in Appendix A and are largely consistent with previous research. For example, boys are less likely to choose all safe options, but this is not significant. Those with higher math scores are less likely to choose all safe and have lower error

We illustrate how the posterior probability is determined with an example. Suppose we want to know the probability that a child of characteristics x, absent making decision mistakes, would have chosen pattern $SSSSS$ instead of the observed pattern $SSRRR$. Suppose also that the structural estimate of the probability a child choose pattern $SSSSS$ is $Pr(SSSSS|x) = p_S(x)$ and the structural estimates of the probability of making a decision error is $e(x)$. We can calculate the posterior probability that a child choosing $SSRRR$ has preferences $SSSSS$ using Bayes rule as $Pr(SSSSS|SSRRR, x) = \frac{p_S(x)(1-e(x))^3 e(x)^2}{p_S(x)(1-e(x))^3 e(x)^2 + (1-p_S(x))(1-e(x))^2 e(x)^3}$. We use this formula to produce the estimate of an individual's preferences given the model estimates and their actual choices. We refer to this new measure of risk attitudes that corrects for measurement error as $Pr(AAAAA|Choice)$ in the regression table.

Table 7 shows the results of using this third measure. Now, we see that future disciplinary referrals are significantly and negatively correlated with risk aversion, even controlling for demographics, household characteristics and rationality. Children who are more risk averse are less likely to receive disciplinary referrals up to two years in the future. The effect is large, consistent with theory and holds in both 8th and 9th grades, when the child is in the last year of middle school and the first year of high school. The average difference in the likelihood of being risk averse between those who chose always S and those who chose always R is 0.5. This implies that the effect of risk preferences on disciplinary referrals in 9th grade (0.5×-0.65 = -0.325) is half the effect of being black and almost three times the effect of being a boy. For the sum of referrals in 8th and 9th grades, the effect of choosing always safe options versus risky is the same as the effect of being a boy or three quarters the effect of being black. Rationality, however, does not explain referrals.[36] Finally, the negative and significant effect of risk aversion on misbehavior is robust to alternative specifications.[37]

rates. The off-border design (partially proxied by the dummy variable "Experiment run in 2011") yields higher error rates.

[36]Results using alternative definitions of rationality can be seen in Tables A12-A14 in Appendix A. These results show that, with the exception of Diecidue et al. (2004), none of the theories of decision making under uncertainty explain misbehavior. It is interesting to note that Diecidue et al. (2004) allow for certainty baises (people value certain payoff more than uncertain ones) and uncertainty biases (people value uncertain payoff more than certain ones). It is the presence of uncertainty biased children that explains the positive correlation between rationality and disciplinary referrals. These confirm that whether risk attitudes are measured by the concavity of the utility function or through a distortion of expected utility, it is the propensity to take risky actions that is correlated with disciplinary referrals.

[37]If instead of the number of disciplinary referrals, we use as the dependent variable a binary variable that equals 1 if the child has had any disciplinary referrals > 0 and equals 0 if the child

This third measure of risk aversion is an estimate and therefore is likely to be affected by sampling error. Table A4 in Appendix A presents the distribution of the estimated effect of risk aversion on disciplinary referrals in the 8th grade, 9th grade and 8th and 9th grades combined based on 1,000 bootstrap replications of the estimates. As expected, sampling error is important, nonetheless, the estimates of risk aversion are still significantly negatively correlated with future disciplinary referrals in 9th grade and 8th and 9th grades combined. So, even taking into account sampling error, our result that more risk averse children are less likely to have disciplinary referrals up to two years in the future is still robust.

The results in this section show that repeated measures of risk preferences are advantageous as they allow us to construct estimates that correct for measurement error. Without taking into account decision error, we would have concluded that there is no significant relationship between preferences and disciplinary referrals. With our constructed measure of risk preferences, however, we are able to uncover that children who are more risk averse are significantly less likely to receive disciplinary referrals two years in the future.

3.5.2. High School completion

We now consider the relationship between risk attitudes and high school graduation. The current definition for an on-time graduation by the state of Georgia (see www.gadoe.gov) is completing all high school requirements in four years, and this is commonly used in the education literature (Murnane, 2013). The school district provided us with high school graduation status data, however, there is missing information for about 27 percent of the children. These children transferred to other schools outside the district or dropped out of the system.[38] So, we cannot determine with certainty if they finished high school in four years or not.

To address this issue, we build on Eckstein and Wolpin (1999)'s approach to studying the dynamics of educational attainment through credits earned in each

has had no referrals and rerun all the specifications in Table 8, we get the same results. Risk averse children have a lower probability of having at least one disciplinary referral. The effect is roughly 11 percent in 8th grade and 16 percent in 9th grade and 8th and 9th grades combined. The effect is significant at the 5-percent level for 9th grade and 8th and 9th grades combined and at the 15-percent level for 8th grade.

[38]Of the children who participated in the experiment, 64.0% are confirmed to have graduated in four years, 9.6% are confirmed to have "dropped out" (e.g. due to being expelled, lack of attendance, still enrolled in high school, incarcerated, low grades/school failure), and the remaining 26.5% have an uncertain graduation status. Of those who graduated, 2.8% obtained high school graduation in an *Academy*. Academies are private high schools that accept students who cannot pass the tests required by public schools to graduate.

year of high school. We construct an outcome variable that equals one if the child finished or was on track to finish high school in four years at the date of the last administrative record. It is coded as zero otherwise. The variable is constructed using the cumulative number of credits earned because this reveals the child's progress towards an on-time graduation. The advantage of this approach is that the data on credits earned are available for all children even if graduation status is not.

For those children for whom we have confirmed graduation status records, the on-track to graduate in four years variable equals one if the child graduated in no more than four years. For the children whose graduation status is not confirmed, we know when they started high school and the date they left the school system. If the cumulative credits earned in high school on the last record date for the child is greater than or equal to the number of credits they should have earned by that date to be on track to finish high school in four years, they are given a value of one. If they are not on track, they are given a value of zero. A child needs to earn at least 5 credits to complete 9th grade, 11 credits to complete 10th grade, 17 credits to complete 11th grade and 23 credits to complete 12th grade. For children who left in the Fall semester of a school year, we check whether they had completed the required credits to be enrolled in that grade. For children who left in the Spring semester, we check whether they had earned an additional 3 credits.

To evaluate if our "on-track" measure provides a reliable proxy for finishing high school on time, we perform a placebo test of the measure on the sub-sample of children for whom we have graduation status. In particular, we calculate the "on-track" variable based on data at the end of the 9th, 10th and 11th grade and compare it with the observed high school outcome (i.e. graduate on time or not). We find that our on-track proxy and the actual graduation status are highly and significantly correlated (correlations are 0.746 using 9th grade data, 0.806 using 10th grade data and 0.800 using 11th grade data). This shows that our measure, while not perfect, is highly predictive of actual high school completion. With this proxy measure, 74.8% of children are classified as being on track to graduate on time. This is comparable with the state level graduation rate of 71%.

Table 8 shows the relationship between risk preferences, other covariates and being on track to graduate high school. All the regressions include dummy variables 'SAFE_i' that equal 1 if the number of safe decisions is 'i' and 0 otherwise. The omitted category is choosing always risky. The regressions also include indicators of academic performance in the 8th grade, household background variables and the number of disciplinary referrals in 7th grade as a control of past behavioral problems.

We report probit regressions with classroom random effects and logit regressions with classroom fixed effects for the entire sample and the subsample for whom graduation status is known.[39] Table 8 shows that a child who makes safe choices in the experiment is more likely to graduate high school, and this relationship appears to be nonlinear. This holds in the entire sample, the subsample of children with confirmed graduation status and when we use a stricter measure of high school completion (e.g. academy graduates are counted as not completing high school).

To assess the magnitude of the effect of risk attitudes on high school completion, Table 9 reports regressions with a dummy variable that equals 1 if the number of risky decisions is 5 and 0 otherwise. The size of the effect is large. Column 1 of Table 9 shows that the coefficient is -0.610 while the coefficient on the standardized math test is 0.023. Given that the standard deviation of the standardized math test is 32.3, we conclude that always choosing the risky alternatives is close in magnitude to a one standard deviation change in math scores. Comparable calculations hold using estimates from alternative specifications.

In the previous section, we showed that accounting for measurement and decision error in analyzing the relationship between risk preferences and disciplinary referrals is crucial. Table 10 shows that the same is true for high school completion. To capture the nonlinearity of the relationship between high school completion and risk preferences we estimate the coefficients of a polynomial of degree three on the posterior probability of choosing all safe decisions.[40] Table 10 confirms that naive measures might underestimate the importance of individual preferences on field behavior and provides evidence of the robustness of our results. This is consistent with the effect size of risk attitudes on high school completion of being similar to that of academic performance.

3.5.3. Robustness checks

We investigate whether a more standard, and perhaps simpler, approach to measurement error produces similar results to those provided in the previous sections. To do this, we recast the problem of measuring individual preference as one of measuring a linear latent factor model for which we have five measures.

[39]The results using probit specifications are similar and more significant if we include dummy variables to control for classroom instead of random effects. The same is true if we estimate linear probability models.

[40]This nonlinear effect is illustrated in Figure A1 which graphs the estimates for different hypothetical values of the posterior compared to the effect of different proportions of safe decisions. Estimates are based on column 1 of Tables 8 and 10.

Suppose child i is an expected utility maximizer with utilities for lottery outcomes H, M and L equal to H_i, M_i and 0. It can be shown that, in our on-border design, a child chooses the risk lottery if $0.8H_i - M_i \geq 0$. Similarly, in our off-border design, a child chooses the risk lottery if $0.6(0.8H_i - M_i) \geq 0$. Let f_i denote the amount $0.8H_i - M_i$ and let ε_j be a random component of utility. Then a child will choose the risky decision in lottery k if $\lambda_k f_i + \varepsilon_k \geq 0$ in the on-border lotteries and $0.6\lambda_k f_i + \varepsilon_k \geq 0$ in the off-border lotteries. The parameter λ_k captures all the factors that make the decision in a particular lottery more or less salient. Under the assumption that random utility terms are independent across lotteries ($Cov(\varepsilon_k, \varepsilon_l) = 0$), this is equivalent to a linear latent factor model, where the latent factor is the difference in utility $0.8H_i - M_i$. The model can be estimated without making assumptions on the parametric form of the utility function, and some features of preferences ($0.8H_i - M_i$) are identified while others will not be (e.g. the coefficient of relative risk aversion). Our off-border design is expected to produce noisier measures of individual preferences. Estimates of the latent factor f_i therefore provide an alternative approach to measure decision error.

Tables A15 and A16 in the Appendix show the coefficient estimates on disciplinary referrals and high school graduation using estimates of latent factor f_i instead of the posterior probability of choosing all safe decisions.[41] To put the factor model on equal footing with our proposed approach, we estimate it under the assumption that lottery decisions depend on individual characteristics as well. We find that estimates of the latent factor using maximum likelihood methods is significantly correlated with our posterior estimates ($\rho = -0.596, p-value < 0.0001$). However, Tables A15 and A16 show that this latent factor is not predictive of either future disciplinary referrals or high school graduation. Since the main difference between this model and the one proposed in the previous section is that inconsistencies are not due to small variations in utility but to the tendency to choose at random, we conclude that how the underlying motivations of children are modeled is crucial in obtaining precisely measured results. This robustness check lends additional support to our preferred approach.

[41]The parameters of the factor model are also non-parametrically identified if variables are continuous rather than discrete. The estimates using this nonparametric approach, albeit technically incorrect, provide similar results to those based on maximum likelihood estimates.

4. Conclusions

We set out to investigate the relationship between children's rationality, risk preferences and field behavior. Our study is motivated by economic theory which suggests that misbehavior and educational outcomes are, ceteris paribus, correlated with the willingness to take risks. One of the main findings is that children who are more risk averse are less likely to receive disciplinary referrals up to two years after the experiment and are more likely to graduate high school five years later. That is, risk attitudes not only significantly correlate with behavior in the field but also with behavior in the future. More importantly, our estimates show that risk preferences have an effect on behavior separate from rationality, cognitive abilities, household environment and past behavior. Overall, we find that the size of the effect of risk attitudes on field behavior is as large as a one standard deviation change in standardized math scores. Risk preferences are therefore important for understanding the heterogeneity of children's field behavior and could interact with how children respond to policy.

A main contribution of our paper is a direct test of the rationality of children in risky environments under alternative models of behavior. Our data suggest that children's behavior is noisier than that of adults, but otherwise is informative. That is, children are not always rational, as defined by various theories, but their choices are not random either. These results suggest that similar issues are likely to emerge in less educated populations as well and that the study of the effect of preferences in other context may require appropriately addressing measurement problems.

Our paper also contributes to the discussion on the external validity of experimental measures of preferences by showing that the relationship between experimental data and field behavior may be obscured by measurement error. In our data, simple aggregate measures of risk preferences do not correlate strongly with future field behavior, but an estimate of risk preferences that corrects for measurement error does. In addition, we control for past field behavior when examining the relationship between future field behavior and our estimated risk measure. This allows us to examine the correlation of risk preferences with important educational outcomes separately from the child's history.

If preferences largely determine responses to incentives, policies designed to foster investment in human capital among children are likely to have heterogeneous effects in the population. In the extreme, if those more likely to take risks are also less likely to take advantage of these type of incentives, rewards for good behavior might just be a transfer to children that would have invested optimally in the absence of the incentive. Our findings lend insight into the limited effectiveness of incentives that reward achieving a certain level of performance on standardized tests. Optimal policies might ultimately require differential treatment across individuals. Our results certainly suggest that designs of incentives for children to accumulate human and non-human capital may need to take into consideration heterogeneity of preferences and the desire of some children to take risks.

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6. Figures and Tables

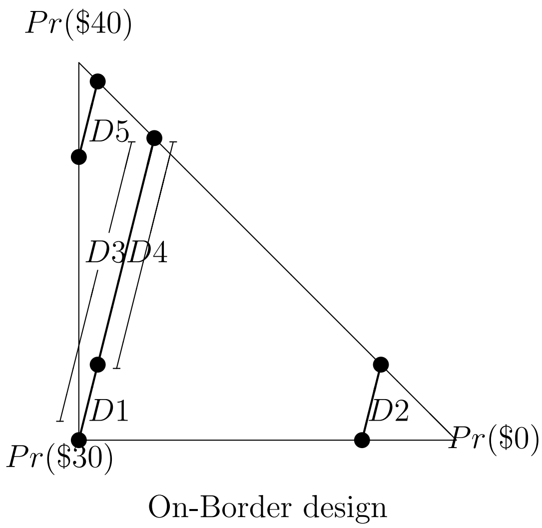

Figure 1: Experimental design represented in the Marschak-Machina triangle

The thicker lines connect the two lottery options available for each of the five decisions (D1, D2, D3, D4, D5). Solid dots represent options for the on-border design, and open dots are for the off-border design. The dot located on the lower left along the thicker line is the safer option (S) and the one on the upper right is the riskier option (R).

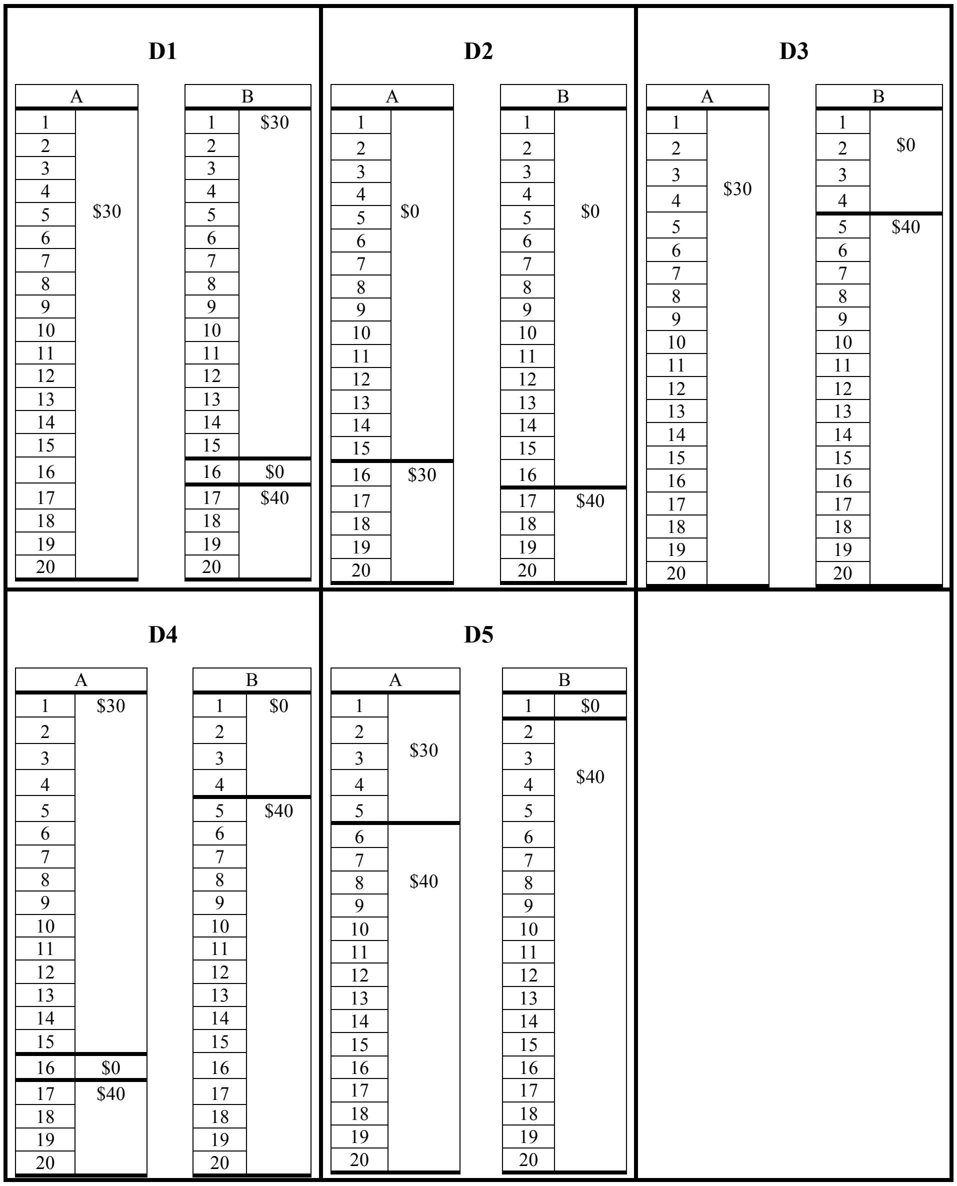

Figure 2. Decisions in the on-border design as represented to subjects

For each of the five decisions (D1, D2, D3, D4, D5), subjects chose either A or B . A is the safer option (S) and B is the riskier option (R). For each option, payoffs are associated with numbers, from 1-20. These represent the probability of receiving that payment. Payment is determined by choosing one numbered ball (numbered from 1-20) from a bingo cage.

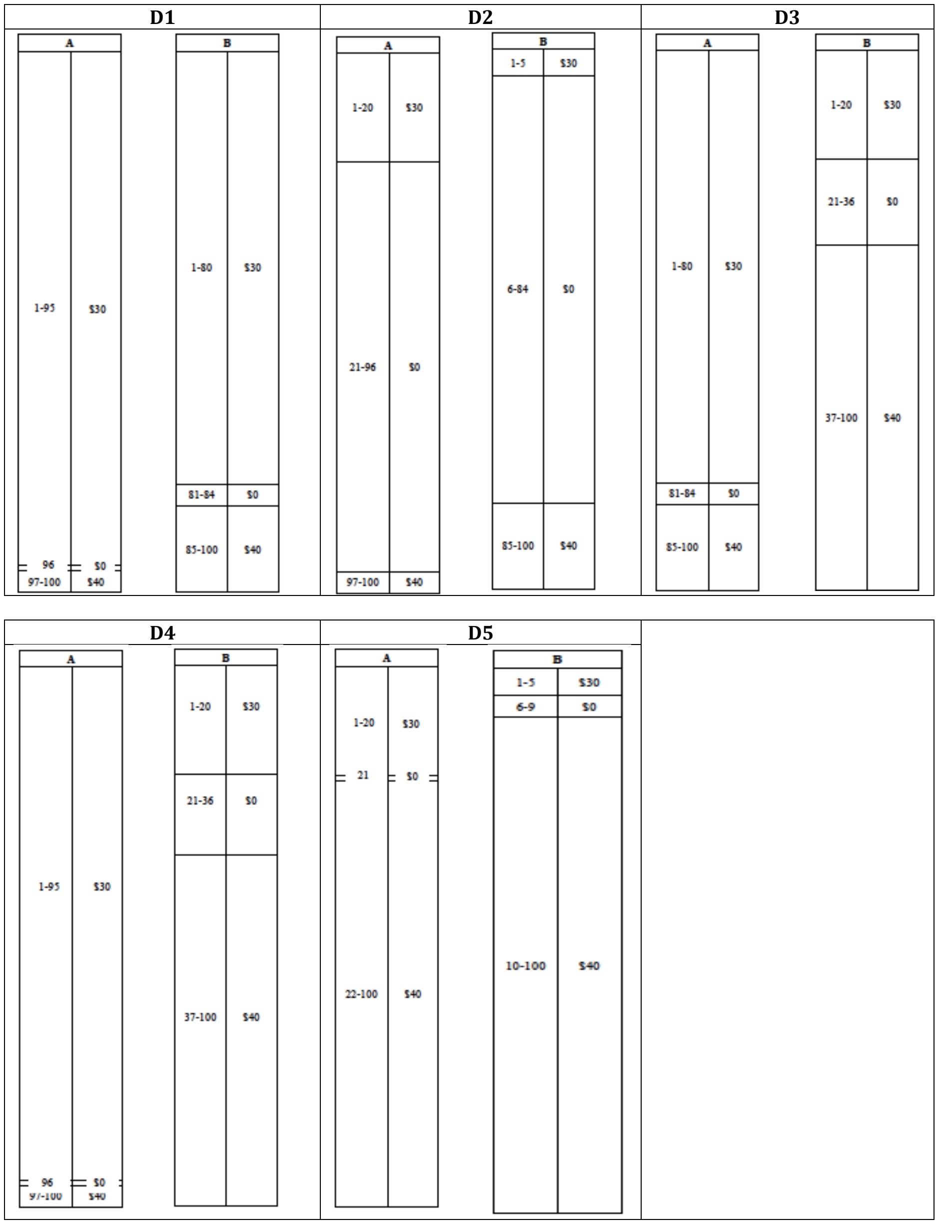

Figure 3. Decisions in the off-border design as represented to subjects

For each of the five decisions (D1, D2, D3, D4, D5), subjects chose either A or B . A is the safer option (S) and B is the riskier option (R). For each option, payoffs are associated with numbers, from 1-100. These represent the probability of receiving that payment. Payment is determined by choosing one numbered ball (numbered from 1-100) from a bingo cage.

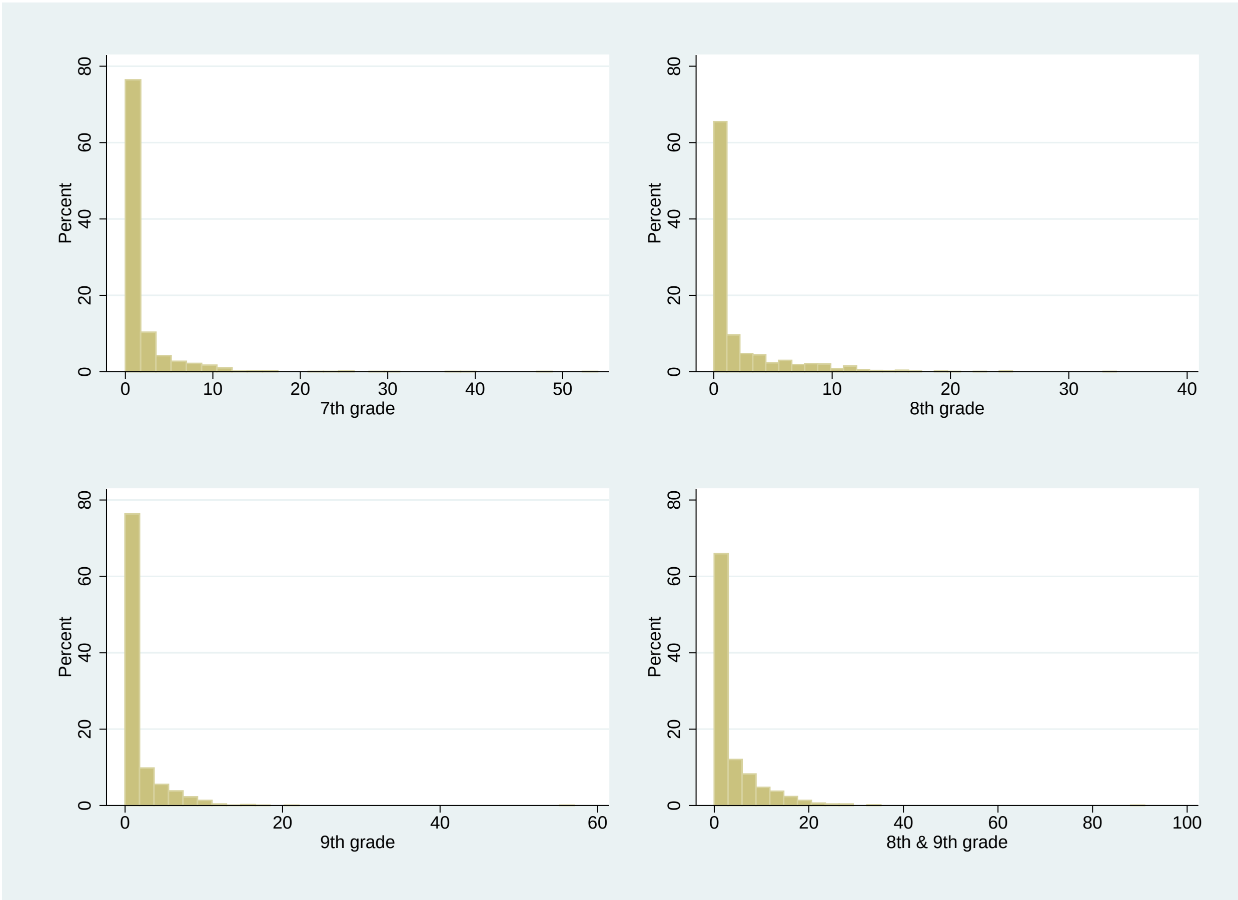

Figure 4. Distribution of Disciplinary referrals

For 7th, 8th, 9th and 8th/9th grades.

Table 1. Descriptive statistics

	% or Mean	s.d.	N
Total			1,275
Male (%)	50.82		648
Black (%)	44.16		563
White (%)	48.16		614
Age in years	13.78	0.64	
Two-parent household (%)	66.00		
Mother finished high school (no college) (%)	39.02		
Father finished high school (no college) (%)	35.35		
Mother has college degree (%)	32.56		
Father has college degree (%)	23.26		
First born (%)	37.80		
No older sibling in household (%)	48.63		
Math score (8th grade)	812.51	32.31	
Reading score (8th grade)	831.27	23.00	
Free and reduced price lunch (%)	64.84		
# of Disciplinary referrals (7th grade)	1.56	3.92	
# of Disciplinary referrals (8th grade)	2.06	3.55	
# of Disciplinary referrals (9th grade)	1.33	3.00	
Graduated high school (%)	73.0		

Some children are missing data on age, test scores (because they left the school system between the experiment and testing), household characteristics (because they failed to answer a post-experiment survey question) or graduation status (because they left the school system prior to 12th grade).

Table 2. Distribution of lottery decisions (percent in parentheses)

	On-border lotteries		Off-border lotteries	
	Safe	Risky	Safe	Risky
D1	447 (68.98)	201 (31.02)	379 (60.45)	248 (39.55)
D2	384 (59.26)	264 (40.74)	420 (66.99)	207 (33.01)
D3	411 (63.43)	237 (36.57)	410 (65.39)	217 (34.61)
D4	394 (60.80)	254 (39.20)	374 (59.65)	253 (40.35)
D5	332 (51.23)	316 (48.77)	289 (46.09)	338 (53.91)
Total	1,968 (60.74)	1,272 (39.26)	1,872 (59.71)	1,263 (40.29)

Test of equality of distributions: $\chi^2(31) = 65.7085$, p-value = 0.000

Table 3. Observed behavior versus random behavior (in percent)

	On-the-border design			Off-the-border design		
Theory (# of patterns)	Observed	Random	z-score	Observed	Random	z-score
Betweenness (8)	38.58	25.00	7.98	38.92	25.00	8.05
Neilson (1992) (5;2)	26.70	15.63	7.76	13.56	6.25	7.56
Diecidue et al. (2004) (6;2)	27.62	18.75	5.79	13.56	6.25	7.56
CPT w/convex weights (13)	61.42	40.63	10.78	52.47	40.63	12.48
CPT w/concave weights (13)	40.43	40.63	-0.10	44.50	40.63	1.97
Expected utility (2)	16.51	6.25	10.79	13.56	6.25	7.56

If the number of predicted patterns differ in the on-border and off-border designs, they are listed as (x;y). The z-score is the test statistic comparing observed to random behavior for the on-border or off-border designs.

Table 4. Linear probability model of rationality as defined by various theories

Variables	(1) Number of safe decisions	(2) Betweenness	(3) Neilson (1992)	(4) Preference for certainty	(5) CPT convex w.	(6) CPT concave w.	(7) Expected utility
Male	-0.112	-0.009	-0.038	0.007	-0.001	-0.000	-0.001
	[0.077]	[0.031]	[0.031]	[0.025]	[0.025]	[0.031]	[0.022]
Black	-0.040	-0.061*	-0.058	-0.012	-0.026	0.031	-0.025
	[0.090]	[0.036]	[0.036]	[0.029]	[0.029]	[0.036]	[0.026]
Age in years	-0.230***	-0.041	-0.023	-0.048*	-0.056**	-0.032	-0.057**
	[0.078]	[0.031]	[0.031]	[0.025]	[0.025]	[0.031]	[0.022]
Two-parent household	0.043	-0.045	-0.007	-0.013	-0.021	0.001	-0.012
	[0.088]	[0.035]	[0.035]	[0.028]	[0.028]	[0.035]	[0.025]
Mother's highest education is high school	0.043	0.008	0.073*	0.031	-0.003	0.077*	0.023
	[0.105]	[0.042]	[0.042]	[0.034]	[0.034]	[0.043]	[0.030]
Father's highest education is high school	-0.042	-0.045	-0.073*	-0.062**	-0.054*	-0.056	-0.064**
	[0.098]	[0.039]	[0.039]	[0.031]	[0.031]	[0.040]	[0.028]
Mother's highest education is college	-0.021	0.036	0.091*	0.009	-0.023	0.051	0.011
	[0.118]	[0.047]	[0.047]	[0.037]	[0.038]	[0.048]	[0.034]
Father's highest education is college	0.150	-0.020	0.000	-0.011	0.000	-0.024	-0.025
	[0.116]	[0.046]	[0.046]	[0.037]	[0.037]	[0.047]	[0.033]
First born	-0.029	0.035	0.040	0.042	0.031	-0.009	0.028
	[0.092]	[0.037]	[0.037]	[0.029]	[0.030]	[0.037]	[0.026]
Only child in household	0.052	-0.046	-0.011	-0.016	-0.012	0.047	-0.007
	[0.091]	[0.036]	[0.036]	[0.029]	[0.029]	[0.037]	[0.026]
Math score (8th grade)	-0.001	0.001	0.000	0.000	0.000	-0.000	0.000
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Reading score (8th grade)	0.005**	0.001	0.000	0.000	0.001	-0.000	0.001
	[0.002]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Free & reduced price meal	0.025	-0.043	0.024	-0.056*	-0.041	0.018	-0.037
	[0.096]	[0.038]	[0.038]	[0.031]	[0.031]	[0.039]	[0.028]
Constant	2.703	-0.761	0.175	0.332	0.349	1.328	-0.017
	[2.335]	[0.932]	[0.932]	[0.743]	[0.750]	[0.943]	[0.672]
Observations	1,065	1,065	1,065	1,065	1,065	1,065	1,065
R-squared	0.024	0.021	0.015	0.018	0.018	0.009	0.024
Number of classrooms	65	65	65	65	65	65	65

Dependent variable in columns 2-7 equals 1 if the observed decision pattern is predicted by the theory. Fixed effects at the classroom level. Robust standard errors in brackets. Off-border design is controlled for with classroom fixed effects. *** p<0.01, ** p<0.05, * p<0.10.

Table 5. Fixed effects negative binomial regression on number of disciplinary referrals using number of safe decisions as risk measure

	(1) 8th grade	(2) 9th grade	(3) 8th & 9th grade
Number of safe decisions	-0.050	-0.067	-0.057*
	[0.034]	[0.044]	[0.032]
Consistent with EU	0.146	0.238	0.161
	[0.124]	[0.158]	[0.117]
Disciplinary referrals (7th grade)	0.060***	0.054***	0.055***
	[0.005]	[0.006]	[0.004]
Male	0.449***	0.143	0.288***
	[0.079]	[0.101]	[0.074]
Black	0.259***	0.586***	0.355***
	[0.093]	[0.121]	[0.088]
Age (years)	-0.134*	-0.085	-0.134*
	[0.077]	[0.099]	[0.073]
Two-parent household	-0.193**	0.022	-0.146*
	[0.084]	[0.110]	[0.080]
Mother's highest education is high school	-0.041	0.007	-0.015
	[0.103]	[0.132]	[0.097]
Father's highest education is high school	-0.048	-0.112	-0.074
	[0.098]	[0.126]	[0.093]
Mother's highest education is college	0.026	0.079	0.023
	[0.119]	[0.153]	[0.113]
Father's highest education is college	-0.211*	-0.267*	-0.158
	[0.123]	[0.160]	[0.115]
First born	-0.210**	-0.230*	-0.217**
	[0.097]	[0.123]	[0.090]
Only child in household	-0.174*	-0.046	-0.132
	[0.093]	[0.119]	[0.087]
Math score (8th grade)	-0.010***	-0.009***	-0.011***
	[0.002]	[0.003]	[0.002]
Reading score (8th grade)	-0.003	-0.004	-0.003
	[0.003]	[0.003]	[0.002]
Free & reduced price meal	0.277***	0.328**	0.261***
	[0.106]	[0.139]	[0.099]
Constant	11.599***	10.462***	12.144***
	[2.504]	[3.191]	[2.338]
Observations	1,060	1,055	1,060
Number of classrooms	62	60	62
Log-Likelihood	-1453	-1145	-1833

Fixed effects at the classroom level. Robust standard errors in brackets. Off-border design is controlled for with classroom fixed effects. *** p<0.01, ** p<0.05, * p<0.10.

Table 6. Fixed effects negative binomial regression on number of disciplinary referrals using each individual decision separately as risk measure. Numbers in table are coefficients on each decision.

	(1) 8th grade	(2) 9th grade	(3) 8th & 9th grade
Risk taking in D1	0.156*	0.082	0.133*
	[0.083]	[0.108]	[0.079]
Risk taking in D2	0.018	0.132	0.044
	[0.083]	[0.107]	[0.079]
Risk taking in D3	0.030	0.013	0.040
	[0.084]	[0.109]	[0.079]
Risk taking in D4	0.098	0.144	0.120
	[0.081]	[0.105]	[0.077]
Risk taking in D5	-0.017	0.010	-0.017
	[0.084]	[0.109]	[0.079]
Covariates inlcuded?	yes	yes	yes
Observations	1,060	1,055	1,060
Number of classrooms	62	60	62

Full regression results are reported in Tables A9-A11 in Appendix A. Fixed effects at the classroom level. Robust standard errors in brackets. Off-border design is controlled for with classroom fixed effects. *** p<0.01, ** p<0.05, * p<0.10.

Table 7. Fixed effects negative binomial regression on disciplinary referrals using estimated risk measure

	(1) 8th grade	(2) 9th grade	(3) 8th & 9th grade
$Pr(AAAAA\|Choice)^+$	-0.464**	-0.651**	-0.584***
	[0.231]	[0.299]	[0.213]
Consistent with EU	0.098	0.172	0.104
	[0.118]	[0.150]	[0.111]
Disciplinary referrals (7th grade)	0.061***	0.055***	0.056***
	[0.005]	[0.006]	[0.004]
Male	0.439***	0.128	0.274***
	[0.079]	[0.102]	[0.074]
Black	0.300***	0.648***	0.408***
	[0.096]	[0.125]	[0.090]
Age (years)	-0.134*	-0.080	-0.133*
	[0.077]	[0.099]	[0.073]
Two-parent household	-0.194**	0.024	-0.145*
	[0.083]	[0.109]	[0.079]
Mother's highest education	-0.021	0.037	0.009
is high school	[0.104]	[0.134]	[0.097]
Father's highest education	-0.012	-0.064	-0.030
is high school	[0.099]	[0.128]	[0.094]
Mother's highest education	0.042	0.103	0.042
is college	[0.119]	[0.154]	[0.113]
Father's highest education	-0.194	-0.242	-0.135
is college	[0.124]	[0.161]	[0.116]
First born	-0.257**	-0.290**	-0.273***
	[0.100]	[0.127]	[0.093]
Only child in household	-0.152	-0.023	-0.106
	[0.093]	[0.120]	[0.087]
Math score (8th grade)	-0.011***	-0.011***	-0.012***
	[0.002]	[0.003]	[0.002]
Reading score (8th grade)	-0.002	-0.003	-0.002
	[0.003]	[0.003]	[0.002]
Free & reduced price meal	0.281***	0.335**	0.264***
	[0.106]	[0.139]	[0.099]
Constant	12.199***	11.023***	12.809***
	[2.510]	[3.194]	[2.342]
Observations	1,060	1,055	1,060
Number of classrooms	62	60	62
Log-Likelihood	-1452	-1143	-1831

^+Pr(Observed choice) $= Pr$(Observed choice$|\alpha, \epsilon)\alpha + Pr$(Observed choice$|1-\alpha, \epsilon)(1-\alpha)$, $\alpha = Pr(AAAAA)$. $Pr(AAAAA|$Observed choice$) = \frac{Pr(ObservedChoice|\alpha,\epsilon)\alpha}{Pr(ObservedChoice)}$.

Fixed effects at the classroom level. Robust standard errors in brackets. Off-border design is controlled for with classroom fixed effects. *** p<0.01, ** p<0.05, * p<0.10.

Table 8. Effect of number of safe decisions on graduating high school

	Academy graduates included				Academy graduates counted as dropouts			
	Probit		Logit		Probit		Logit	
	Random Effects		Fixed Effects		Random Effects		Fixed Effects	
VARIABLES	All	Known	All	Known	All	Known	All	Known
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1 Safe decision	0.769**	1.019**	1.517**	2.049**	0.499	0.630	1.088*	1.452*
	[0.373]	[0.441]	[0.671]	[0.848]	[0.366]	[0.420]	[0.646]	[0.775]
2 Safe decisions	0.712**	0.986**	1.394**	2.064**	0.573*	0.783*	1.122*	1.635**
	[0.344]	[0.410]	[0.627]	[0.804]	[0.342]	[0.400]	[0.609]	[0.740]
3 Safe decisions	0.574*	0.836**	1.169*	1.807**	0.406	0.566	0.877	1.275*
	[0.341]	[0.405]	[0.617]	[0.790]	[0.339]	[0.393]	[0.601]	[0.727]
4 Safe decisions	0.557	0.831**	1.042*	1.608**	0.508	0.704*	0.965	1.337*
	[0.343]	[0.409]	[0.622]	[0.797]	[0.342]	[0.399]	[0.607]	[0.739]
5 Safe decisions	0.598*	1.010**	1.228*	2.124**	0.501	0.790*	0.998	1.560**
	[0.361]	[0.436]	[0.660]	[0.864]	[0.359]	[0.423]	[0.642]	[0.790]
Disciplinary referrals (7th grade)	-0.104***	-0.102***	-0.176***	-0.182***	-0.113***	-0.099***	-0.185***	-0.165***
	[0.019]	[0.023]	[0.034]	[0.045]	[0.019]	[0.022]	[0.035]	[0.041]
Male	-0.201*	-0.017	-0.334*	-0.061	-0.132	0.023	-0.196	0.029
	[0.108]	[0.138]	[0.196]	[0.261]	[0.105]	[0.128]	[0.186]	[0.236]
Black	0.330***	0.449***	0.560**	0.732**	0.264**	0.311**	0.440**	0.510*
	[0.124]	[0.162]	[0.227]	[0.318]	[0.120]	[0.148]	[0.215]	[0.281]
Age (years)	-0.188*	-0.426***	-0.333*	-0.893***	-0.190**	-0.380***	-0.329*	-0.733***
	[0.099]	[0.129]	[0.179]	[0.246]	[0.097]	[0.121]	[0.173]	[0.223]
Two-parent household	0.266**	0.213	0.444**	0.405	0.222**	0.156	0.358*	0.317
	[0.116]	[0.150]	[0.208]	[0.287]	[0.112]	[0.138]	[0.199]	[0.255]
Mother's highest education	0.412***	0.462***	0.590**	0.737**	0.477***	0.558***	0.699***	0.815***
is high school	[0.137]	[0.170]	[0.247]	[0.327]	[0.133]	[0.159]	[0.238]	[0.294]
Father's highest education	0.197	0.260	0.343	0.451	0.106	0.095	0.157	0.139
is high school	[0.134]	[0.169]	[0.245]	[0.313]	[0.129]	[0.154]	[0.233]	[0.286]
Mother's highest education	0.267*	0.272	0.362	0.352	0.320**	0.338*	0.446*	0.352
is college	[0.155]	[0.200]	[0.282]	[0.387]	[0.150]	[0.185]	[0.270]	[0.343]
Father's highest education	0.128	0.236	0.394	0.525	0.208	0.293	0.525*	0.683*
is college	[0.162]	[0.221]	[0.294]	[0.428]	[0.159]	[0.207]	[0.285]	[0.390]
First born	0.119	0.183	0.173	0.331	0.137	0.214	0.240	0.438
	[0.128]	[0.163]	[0.230]	[0.312]	[0.123]	[0.150]	[0.220]	[0.282]
Only child in household	0.131	0.180	0.233	0.360	0.110	0.091	0.192	0.169
	[0.124]	[0.159]	[0.223]	[0.302]	[0.120]	[0.146]	[0.214]	[0.272]
Math score (8th grade)	0.023***	0.025***	0.042***	0.048***	0.022***	0.024***	0.039***	0.042***
	[0.003]	[0.004]	[0.006]	[0.008]	[0.003]	[0.004]	[0.006]	[0.007]
Reading score (8th grade)	0.006*	0.011**	0.015**	0.028***	0.005	0.008*	0.011*	0.018**
	[0.004]	[0.005]	[0.007]	[0.010]	[0.003]	[0.004]	[0.006]	[0.008]
Free & reduced price meal	-0.203	-0.221	-0.215	-0.340	-0.151	-0.154	-0.131	-0.194
	[0.137]	[0.183]	[0.251]	[0.359]	[0.131]	[0.166]	[0.238]	[0.313]
Observations	1,016	820	844	613	1,016	820	844	624
Number of classrooms	63	62	52	48	63	62	52	49
log-likelihood	-381.1	-237.3	-275.5	-146.1	-411.2	-276.3	-300.6	-181.4

s.e. in brackets, *** p<0.01, ** p<0.05, * p<0.10. "All" includes the entire sample, and "Known" is the known graduation status subsample.

Table 9. Effect of choosing "all risky" on graduating high school

	Academy graduates included				Academy graduates counted as dropouts			
	Probit		Logit		Probit		Logit	
	Random Effects		Fixed Effects		Random Effects		Fixed Effects	
VARIABLES	All	Known	All	Known	All	Known	All	Known
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Always chose risky	-0.598*	-1.014**	-1.234*	-2.156**	-0.503	-0.793*	-1.006	-1.576**
	[0.361]	[0.436]	[0.662]	[0.859]	[0.359]	[0.422]	[0.644]	[0.789]
Consistent with EU	-0.030	0.116	0.001	0.295	0.012	0.125	0.012	0.164
	[0.167]	[0.225]	[0.308]	[0.442]	[0.163]	[0.208]	[0.296]	[0.395]
Disciplinary referrals (7th grade)	-0.104***	-0.101***	-0.175***	-0.182***	-0.112***	-0.097***	-0.185***	-0.164***
	[0.019]	[0.023]	[0.034]	[0.044]	[0.019]	[0.022]	[0.035]	[0.041]
Male	-0.197*	-0.012	-0.323*	-0.022	-0.133	0.020	-0.192	0.047
	[0.108]	[0.138]	[0.195]	[0.258]	[0.104]	[0.127]	[0.186]	[0.234]
Black	0.329***	0.456***	0.551**	0.759**	0.266**	0.319**	0.441**	0.538*
	[0.124]	[0.161]	[0.226]	[0.317]	[0.120]	[0.147]	[0.214]	[0.279]
Age (years)	-0.186*	-0.422***	-0.327*	-0.894***	-0.187*	-0.369***	-0.324*	-0.718***
	[0.099]	[0.128]	[0.179]	[0.246]	[0.097]	[0.120]	[0.173]	[0.222]
Two-parent household	0.267**	0.215	0.436**	0.385	0.224**	0.165	0.359*	0.323
	[0.115]	[0.149]	[0.207]	[0.281]	[0.112]	[0.138]	[0.198]	[0.254]
Mother's highest education	0.400***	0.459***	0.575**	0.746**	0.467***	0.547***	0.690***	0.812***
is high school	[0.136]	[0.170]	[0.246]	[0.325]	[0.133]	[0.159]	[0.238]	[0.293]
Father's highest education	0.194	0.259	0.335	0.468	0.096	0.080	0.142	0.128
is high school	[0.133]	[0.168]	[0.243]	[0.312]	[0.128]	[0.154]	[0.232]	[0.284]
Mother's highest education	0.256*	0.273	0.337	0.332	0.316**	0.338*	0.439	0.349
is college	[0.154]	[0.199]	[0.280]	[0.385]	[0.150]	[0.184]	[0.269]	[0.342]
Father's highest education	0.108	0.220	0.355	0.518	0.201	0.284	0.504*	0.655*
is college	[0.161]	[0.220]	[0.292]	[0.426]	[0.158]	[0.207]	[0.283]	[0.388]
First born	0.124	0.192	0.176	0.325	0.143	0.220	0.250	0.447
	[0.128]	[0.163]	[0.229]	[0.309]	[0.123]	[0.149]	[0.219]	[0.281]
Only child in household	0.127	0.170	0.228	0.357	0.108	0.081	0.184	0.149
	[0.124]	[0.158]	[0.221]	[0.298]	[0.120]	[0.145]	[0.213]	[0.270]
Math score (8th grade)	0.023***	0.025***	0.042***	0.047***	0.023***	0.024***	0.039***	0.041***
	[0.003]	[0.004]	[0.006]	[0.008]	[0.003]	[0.003]	[0.006]	[0.007]
Reading score (8th grade)	0.006*	0.011**	0.014**	0.028***	0.005	0.008*	0.011*	0.018**
	[0.003]	[0.005]	[0.007]	[0.009]	[0.003]	[0.004]	[0.006]	[0.008]
Free & reduced price meal	-0.213	-0.227	-0.234	-0.345	-0.160	-0.170	-0.145	-0.219
	[0.136]	[0.182]	[0.250]	[0.355]	[0.131]	[0.165]	[0.237]	[0.310]
Observations	1,016	820	844	613	1,016	820	844	624
Number of classrooms	63	62	52	48	63	62	52	49
log-likelihood	-382.1	-237.9	-276.8	-146.9	-411.9	-277.2	-301.1	-182.0

s.e. in brackets, p-values in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.10$. "All" includes the entire sample, and "Known" is the known graduation status subsample.

Table 10. Effect of estimated risk on graduating high school

	Academy graduates included				Academy graduates counted as dropouts			
	Probit		Logit		Probit		Logit	
	Random Effects		Fixed Effects		Random Effects		Fixed Effects	
VARIABLES	All	Known	All	Known	All	Known	All	Known
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Pr(AAAAA\|Choice)^{+}$	6.691*	12.737***	15.745**	34.422***	6.552*	11.349***	15.686**	28.615***
	[3.806]	[4.749]	[7.559]	[10.304]	[3.637]	[4.307]	[6.869]	[8.915]
$Pr(AAAAA\|Choice)^{2,+}$	-12.958*	-25.234***	-29.608**	-64.676***	-11.970*	-21.701**	-28.100**	-52.591***
	[7.456]	[9.492]	[14.468]	[20.074]	[7.153]	[8.626]	[13.290]	[17.457]
$Pr(AAAAA\|Choice)^{3,+}$	7.018*	13.984**	15.867*	34.527***	6.322	11.850**	14.714*	27.761***
	[4.246]	[5.431]	[8.118]	[11.243]	[4.086]	[4.956]	[7.519]	[9.837]
Consistent with EU	-0.135	-0.118	-0.244	-0.179	-0.062	-0.033	-0.150	-0.127
	[0.170]	[0.226]	[0.307]	[0.430]	[0.166]	[0.210]	[0.296]	[0.390]
Disciplinary referrals (7th grade)	-0.104***	-0.104***	-0.177***	-0.185***	-0.112***	-0.099***	-0.186***	-0.166***
	[0.019]	[0.023]	[0.034]	[0.045]	[0.019]	[0.022]	[0.036]	[0.041]
Male	-0.193*	0.017	-0.302	0.047	-0.128	0.045	-0.173	0.098
	[0.109]	[0.141]	[0.197]	[0.264]	[0.106]	[0.131]	[0.188]	[0.239]
Black	0.335***	0.454***	0.553**	0.779**	0.260**	0.304**	0.424*	0.534*
	[0.127]	[0.165]	[0.232]	[0.319]	[0.122]	[0.150]	[0.220]	[0.282]
Age (years)	-0.180*	-0.418***	-0.317*	-0.904***	-0.184*	-0.366***	-0.314*	-0.729***
	[0.100]	[0.132]	[0.181]	[0.250]	[0.098]	[0.123]	[0.176]	[0.227]
Two-parent household	0.270**	0.242	0.449**	0.509*	0.227**	0.186	0.373*	0.388
	[0.115]	[0.150]	[0.208]	[0.286]	[0.112]	[0.139]	[0.199]	[0.257]
Mother's highest education is high school	0.399***	0.428**	0.556**	0.633*	0.463***	0.527***	0.677***	0.783***
	[0.137]	[0.171]	[0.248]	[0.328]	[0.134]	[0.160]	[0.240]	[0.298]
Father's highest education is high school	0.204	0.268	0.332	0.470	0.096	0.075	0.128	0.126
	[0.136]	[0.172]	[0.248]	[0.317]	[0.132]	[0.158]	[0.237]	[0.290]
Mother's highest education is college	0.253	0.234	0.330	0.237	0.310**	0.308*	0.427	0.293
	[0.154]	[0.198]	[0.281]	[0.383]	[0.150]	[0.184]	[0.271]	[0.344]
Father's highest education is college	0.104	0.210	0.321	0.537	0.193	0.264	0.481*	0.673*
	[0.165]	[0.226]	[0.299]	[0.436]	[0.162]	[0.213]	[0.290]	[0.399]
First born	0.110	0.186	0.153	0.258	0.143	0.235	0.254	0.436
	[0.132]	[0.172]	[0.238]	[0.329]	[0.128]	[0.157]	[0.228]	[0.297]
Only child in household	0.128	0.159	0.242	0.385	0.106	0.065	0.189	0.163
	[0.126]	[0.162]	[0.225]	[0.306]	[0.122]	[0.148]	[0.217]	[0.277]
Math score (8th grade)	0.023***	0.025***	0.041***	0.047***	0.023***	0.024***	0.039***	0.041***
	[0.003]	[0.004]	[0.006]	[0.009]	[0.003]	[0.004]	[0.006]	[0.007]
Reading score (8th grade)	0.006*	0.011**	0.014**	0.029***	0.005	0.008*	0.011*	0.019**
	[0.004]	[0.005]	[0.007]	[0.010]	[0.003]	[0.004]	[0.006]	[0.008]
Free & reduced price meal	-0.213	-0.222	-0.234	-0.294	-0.160	-0.167	-0.142	-0.166
	[0.137]	[0.184]	[0.251]	[0.360]	[0.131]	[0.167]	[0.238]	[0.314]
Observations	1,016	820	844	613	1,016	820	844	624
Number of classrooms	63	62	52	48	63	62	52	49
log-likelihood	-381.8	-236.9	-276.3	-144.4	-411.2	-275.4	-299.7	-178.7

s.e. in brackets, p-values in parentheses, *** p<0.01, ** p<0.05, * p<0.10. "All" includes the entire sample, and "Known" is the known graduation status subsample.

7. Appendix A - Not Intended for Publication

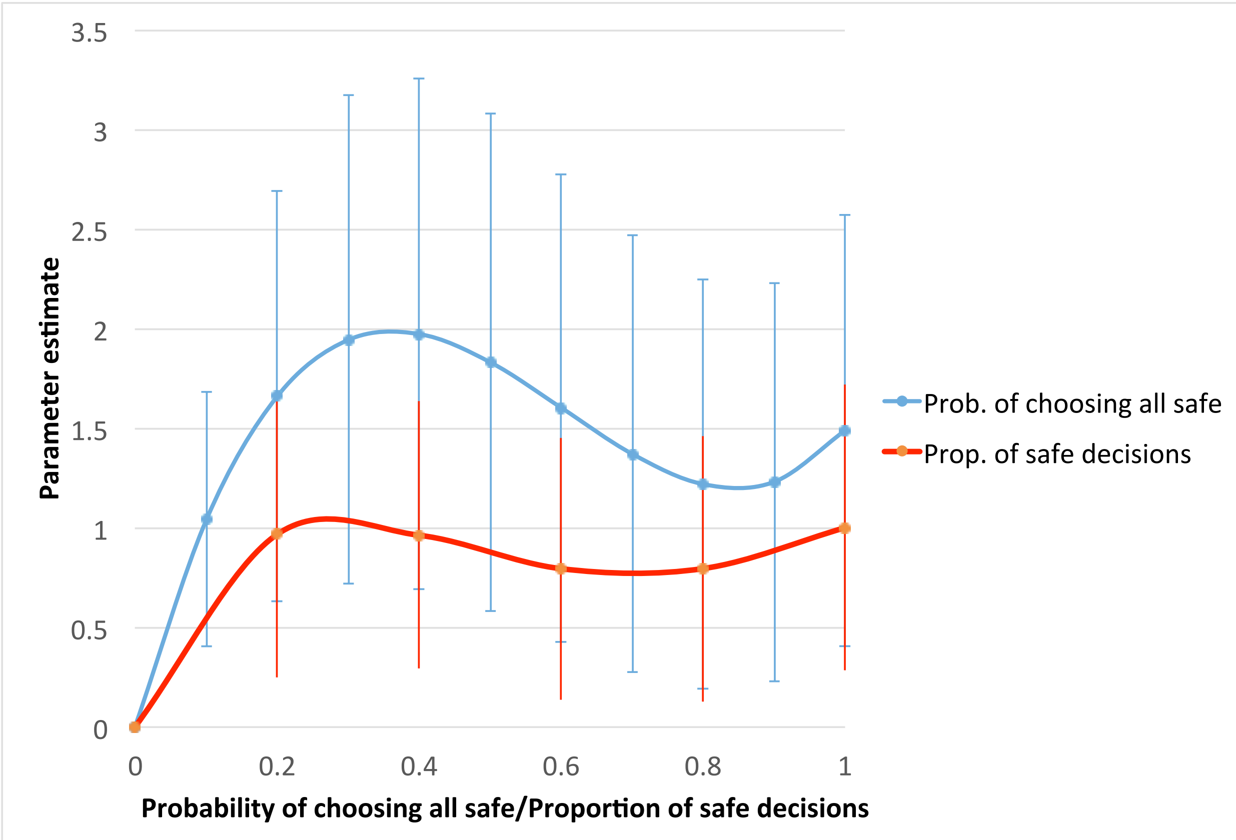

Figure A1. Estimated effect of risk attitudes on graduation

Table A1. Choice patterns across the five lotteries in the on-border and off-border designs as predicted by each theory of behavior under risk

	Assumption/Model					
Choice Pattern	Betweenness	Diecidue et al. (2004)	Neilson's (1992)	CPT w/convex weights	CPT w/concave weights	EUT
SSSSS	Yes	Yes	Yes	Yes	Yes	Yes
SSSSR	Yes	No	No	Yes	No	No
SSSRS	No	No	Yes/No	Yes	No	No
SSSRR	No	No	No	Yes	No	No
SSRSS	No	No	No	No	No	No
SSRSR	No	No	No	No	No	No
SSRRS	No	No	No	Yes	No	No
SSRRR	No	No	No	Yes	No	No
SRSSS	Yes	No	No	Yes	No	No
SRSSR	Yes	No	No	Yes	No	No
SRSRS	No	No	No	Yes	No	No
SRSRR	No	Yes/No	Yes/No	Yes	No	No
SRRSS	No	No	No	No	No	No
SRRSR	No	No	No	No	No	No
SRRRS	No	No	No	Yes	No	No
SRRRR	No	Yes/No	Yes/No	Yes	No	No
RSSSS	No	Yes/No	No	No	Yes	No
RSSSR	No	No	No	No	Yes	No
RSSRS	No	No	No	No	No	No
RSSRR	No	No	No	No	No	No
RSRSS	No	Yes/No	No	No	Yes	No
RSRSR	No	No	No	No	Yes	No
RSRRS	Yes	No	No	No	Yes	No
RSRRR	Yes	No	No	No	Yes	No
RRSSS	No	No	No	No	Yes	No
RRSSR	No	No	No	No	Yes	No
RRSRS	No	No	No	No	No	No
RRSRR	No	No	No	No	No	No
RRRSS	No	No	No	No	Yes	No
RRRSR	No	No	No	No	Yes	No
RRRRS	Yes	No	No	No	Yes	No
RRRRR	Yes	Yes	Yes	Yes	Yes	Yes

If a choice pattern of choosing the safer (S) or riskier (R) options across the five decisions is predicted by a theory, the column entry is "Yes" and if not it is "No." In the case that the theoretical prediction differs for the on-border and off-border designs, the column entry is x/y, with x being whether the pattern is predicted in the on-border design and y being whether it is predicted in the off-border design. Theories considered in the table are Betweenness, Neilson's (1992) model, Diecidue et al's (2004) model, Cumulative prospect theory (CPT) with convex weighting function, Cumulative prospect theory (CPT) with concave weighting function, and Expected utility theory (EUT)

Table A1 summarizes the patterns of behavior inconsistent with several assumptions about decision making under risk. The first column presents the patterns that violate betweenness. Lotteries I, III and IV allow to test for the betweenness axiom (or any theory that relies on the linearity of indifference curves). Betweenness implies simultaneously that preferences are quasi-concave and quasi-convex. Quasi-concavity implies that a lottery that is a linear combination of two other lotteries will be preferred to the least preferred lottery of the two and quasi-convexity implies that a lottery that is a linear combination of two other lotteries will be less preferred to the most preferred of the two lotteries. Both properties imply that decisions in lotteries I, III and IV should be the same. Betweenness allows only eight possible choice patterns in our experiment.

A set of theories suggests that violation of expected utility theory is due to the fact that individuals judge certain and risky prospects differently (Neilson, 1992a; Diecidue et al., 2004;

Bleichrodt and Schmidt, 2002). These theories can be roughly separated between those that allow for violation of stochastic dominance (Neilson, 1992b; Diecidue et al., 2004) and those that allow for violation of transitivity (Bleichrodt and Schmidt, 2002). As shown by Diecidue et al. (2004), theories that allow for a taste for gambling will violate stochastic dominance due to the fact that they assume that certain prospects and risky prospects are evaluated by different utility functions. Diecidue et al. (2004) show that if the independence axiom is assumed to hold among all risky prospects, preferences can be represented by two functions over money u and v such that one is the equal to the sum of the other plus a cost of gambling that is defined on either the certain amount of money or the probabilities defining the gamble. Since Diecidue et al. (2004) assume that the independence axiom holds on strictly risky gambles we have that their theory predicts that decisions in lotteries II, IV and V should coincide. In addition, since their theory allows for a utility representation of preferences that is menu-independent, we have that transitivity must hold as well. The second column of Table A1 shows that their theory allows six choice patterns.

Neilson (1992a) proposes a theory based on the cardinality of the risky prospects. In particular, Neilson proposes the use of a utility function u^n that depends on the cardinality of the prospect, n. In addition, he suggests a boundary condition implying that $|u^i(x)| \geq |u^j(x)|$ for all x, if $i < j$. Since utility representation of preferences are menu-independent, we have that Neilson (1992a) theory exclude intransitive choices. Since expected utility holds for lotteries of the same cardinality, we have that choices in lotteries II and V should coincide. The boundary condition implies additional restrictions in choices. In particular, a person choosing prospect $(\beta, x_L; 1-\beta, x_M)$ over prospect $(\beta, x_L; 1-\beta, (x_L, 1-\alpha; x_H, \alpha))$, both with the same cardinality, will reveal that $\beta u^2(x_L) + (1-\beta)u^2(x_M) \geq \beta u^2(x_L) + (1-\beta)[u^2(x_L)(1-\alpha) + u^2(x_H)\alpha]$. Or, $u^2(x_M) \geq u^2(x_L)(1-\alpha) + u^2(x_H)\alpha$ which implies that $u^1(x_M) \geq u^2(x_M) \geq u^2(x_L)(1-\alpha) + u^2(x_H)\alpha$. That is, the choice of S in lottery II implies the choice of S in lottery III. The boundary condition also implies that $u^2(x_L)(1-\alpha) + u^2(x_H)\alpha \geq u^3(x_L)(1-\alpha) + u^3(x_H)\alpha$ and $u^1(x_M) \geq u^3(x_M)$. That is, a choice of S in lottery II must be accompanied of a choice of S in lottery I. Suppose instead that prospect $(\beta, x_L; 1-\beta, (x_L, 1-\alpha; x_H, \alpha))$ in lottery II is chosen over prospect $(\beta, x_L; 1-\beta, x_M)$. This implies that $u^2(x_M) \leq u^2(x_L)(1-\alpha) + u^2(x_H)\alpha$ and consequently $\beta u^3(x_M) + (1-\beta)[u^3(x_L)(1-\alpha) + u^3(x_H)\alpha] \leq u^2(x_L)(1-\alpha) + u^2(x_H)\alpha$. That is, a choice of R in lottery II must be accompanied of a choice of R in lottery IV. In sum, Neilson (1992a) theory allows only five possible choice patterns in our experiment (see column 3 in Table A1).

(Bleichrodt and Schmidt, 2002) propose an alternative theory that prevents violations of stochastic dominance at the cost of allowing intransitivities. (Bleichrodt and Schmidt, 2002) suggest that a person evaluating a certain outcome $(x, 1)$ against a strictly risky lottery $(p, y; 1-p, z)$ uses a utility functional v that is a concave transformation of a function u that is used to evaluate two strictly risky prospects. This implies that expected utility holds among strictly risky prospects but fails when certain and risky prospects are compared. Since comparisons are menu-dependent, their theory can generate intransitivities. Our design, however, prevents intransitivities. To see this, recall that the three prospects used in lotteries I, III and IV are: A, $\beta(x_L, 1-\alpha; x_H, \alpha) + (1-\beta)A$ and $(x_L, 1-\alpha; x_H, \alpha)$. Any intransitive choice pattern necesitates that a person choose differently in lottery I and in lottery III. However, $A \preceq (\succeq)\beta(x_L, 1-\alpha; x_H, \alpha) + (1-\beta)A$ requires that $v(A) \leq (\geq)\beta[v(x_L)(1-\alpha) + v(x_H)\alpha] + (1-\beta)v(A)$ which is equivalent to $v(A) \leq (\geq)v(x_L)(1-\alpha) + v(x_H)\alpha$.[42] This implies that the theory proposed by Bleichrodt and Schmidt (2002) will exclude intransitive choices in our environment and therefore coincides with Diecidue et al. (2004) predictions.

We finally consider two variants of rank dependent expected utility (RDEU), RDEU with convex weighting function (RDEU-cave) and RDEU with concave weighting function (RDEU-vex). As shown in Harless (1992) the RDEU-cave generates concave indifference curves that fan out at the base of the triangle and fan in along the left side of the triangle. RDEU-vex implies quasiconvex preferences and RDEU-cave generates quasiconcave preferences. These preferences are necessarily transitive. Moreover, a person with quasiconvex preferences will choose S in lottery I if he chooses S in lottery III and will choose R in lottery IV if he instead chooses R in lottery III. And, a person

[42] Note that the same argument holds if we start by comparing lottery A to lottery B.

with quasiconcave preferences will choose S in lottery IV if he chooses S in lottery III and will choose R in lottery I if he instead chooses R in lottery III. These restrictions plus the pattterns of fanning implied by the theory are summarized in columns 4 and 5 of Table A1.

Table A2. Estimates of alternative decision models using Harless and Camerer's (1994) error choice model

	Assumption/Model					
Choice	Between.	Diecidue et al. (2004)	Neilson (1992)	CPT w/conv. weights	CPT w/conc. weights	EUT
SSSSS	0.4615	0.7502	0.7502	0.4660	0.6973	0.8039
SSSSR	0.1881			0.1464		
SSSRS			0.0000			
SSSRR				0.0933		
SSRSS						
SSRSR						
SSRRS						
SSRRR				0.0639		
SRSSS	0.0143			0.0000		
SRSSR	0.1331			0.0965		
SRSRS				0.0114		
SRSRR		0.1154	0.1154	0.0000		
SRRSS						
SRRSR						
SRRRS						
SRRRR		0.0273	0.0273			
RSSSS		0.0000			0.0000	
RSSSR					0.0000	
RSSRS						
RSSRR						
RSRSS		0.0000			0.0000	
RSRSR					0.0000	
RSRRS						
RSRRR				0.1636		
RRSSS					0.0000	
RRSSR					0.0809	
RRSRS						
RRSRR						
RRRSS					0.0000	
RRRSR					0.0178	
RRRRS						
RRRRR	0.0558	0.1071	0.1071	0.1225	0.0404	0.1961
error rate	0.2800	0.3251	0.3251	0.2799	0.3084	0.3358
log-likelihood	-4194.5	-4247.0	-4247.0	-4199.8	-4237	-4255.3
observations	1,275	1,275	1,275	1,275	1,275	1,275

If a choice pattern of choosing the safer (S) or riskier (R) option across the five decisions is predicted by a theory, the column entry reports the maximum likelihood estimate of the probability that such a pattern exists in the data for the error rate level reported in row "error rate." For instance, column "Betweenness" shows that the probability that a person has pattern *SSSSS* is 0.4615 and column EUT shows that such pattern is estimated to be 0.8039 according to expected utility theory. All estimates combine data from the on-border and off-border design. Neilson's (1992) model and Diecidue et al's (2004) estimation in the off-border design re-assigns probability to patterns *SSSSS* and *RRRRR* according to the preponderances of safe and risky decisions.

Table A3. Harless and Camerer (1994) error choice model Maximum Likelihood estimation of irrational behavior assuming expected utility theory

	$Pr(SSSSS)$		ϵ	
Variables	coefficient	S.E.	coefficient	S.E.
Male	-0.2787	0.4116	0.0634	0.0801
Black	0.7798	0.7003	0.1676*	0.0978
Age in years	-0.1924	0.4642	0.1873**	0.0898
Two-parent household	0.0885	0.4636	0.0187	0.0890
Mother's highest educ. is high sch.	0.3413	0.5977	-0.0147	0.1072
Father's highest educ. is high sch.	0.7075	0.6447	0.1832*	0.0971
Mother's highest educ. is college	0.2469	0.6095	0.0375	0.1177
Father's highest educ. is college	0.5834	0.5054	-0.1060	0.1061
First born	-0.9272	0.4787*	-0.1348	0.0945
No older siblings in household	0.5472	0.5225	-0.0143	0.0883
Math score (8th grade)	-0.0138	0.0068**	-0.0036**	0.0016
Reading score (8th grade)	0.0101	0.0100	-0.0017	0.0022
On-border design	0.1706	0.4908	0.0213	0.1104
Free/reduced price meal	0.1294	0.4424	0.0012	0.0906
Experiment run in 2011	0.7026	0.6643	0.3019***	0.1156
Constant	6.3610	10.1483	0.9333	2.2585
Observations			1,065	
Log-likelihood			-3,518.2	

Because of the nonlinearity of the estimation, dummies for year in which the experiment was conducted and the on-border design are included in lieu of the 62 classroom dummy variables.

Table A4. Bootstrap estimation of the effect of estimated risk aversion on disciplinary referrals (1000 reps) - using specification in Table 8

Parameter Statistics	No controls	Betweenness	Neilson (1992)	Diecidue et al. (2004)	CPT convex weights	CPT concave weights	EUT
				Disciplinary referrals 8th grade			
Mean	-0.315	-0.316	-0.321	-0.327	-0.307	-0.277	-0.323
S.E.	0.006	0.006	0.005	0.005	0.006	0.005	0.005
$q_{0.05}$	-0.549	-0.550	-0.550	-0.553	-0.546	-0.512	-0.554
$q_{0.95}$	0.014	0.014	0.003	-0.014	0.026	0.043	0.008
				Disciplinary referrals 9th grade			
Mean	-0.463	-0.461	-0.473	-0.480	-0.486	-0.448	-0.477
S.E.	0.007	0.007	0.007	0.007	0.007	0.007	0.007
$q_{0.05}$	-0.832	-0.831	-0.835	-0.843	-0.851	-0.820	-0.831
$q_{0.95}$	-0.074	-0.070	-0.092	-0.098	-0.095	-0.058	-0.094
				Disciplinary referrals 8th & 9th grade			
Mean	-0.411	-0.410	-0.420	-0.427	-0.416	-0.381	-0.419
S.E.	0.005	0.006	0.005	0.005	0.006	0.005	0.005
$q_{0.05}$	-0.657	-0.658	-0.658	-0.661	-0.666	-0.624	-0.659
$q_{0.95}$	-0.084	-0.080	-0.103	-0.114	-0.084	-0.058	-0.094

Estimated risk aversion (calculated posteriors) for each child in the sample are recalculated 1,000 using bootstrapped samples of the population. $q_{0.05}$ is the estimate for the 5th percentile, and $q_{0.95}$ is the estimate for the 95th percentile.

Table A5. Negative binomial regression on cost to rationality

Variables	Betweenness	Neilson (1992)	Diecidue et al (2004)	CPT convex w.	CPT concave w.	EUT
Male	0.045	0.037	0.051	0.041	-0.039	0.041
	[0.044]	[0.034]	[0.033]	[0.058]	[0.074]	[0.030]
Black	0.082	0.066*	0.024	0.116	-0.099	0.048
	[0.051]	[0.038]	[0.036]	[0.079]	[0.101]	[0.034]
Age in years	0.008	0.057*	0.027	0.019	0.081	0.042
	[0.042]	[0.033]	[0.035]	[0.059]	[0.070]	[0.031]
Two-parent household	0.028	0.045	0.052	0.052	0.029	0.039
	[0.056]	[0.045]	[0.043]	[0.074]	[0.083]	[0.036]
Mother's highest education	-0.091	-0.048	-0.039	-0.021	-0.163*	-0.027
is high school	[0.058]	[0.041]	[0.043]	[0.079]	[0.096]	[0.037]
Father's highest education	0.104*	0.097**	0.096**	0.101	0.099	0.088**
is high school	[0.055]	[0.046]	[0.044]	[0.063]	[0.102]	[0.041]
Mother's highest education	-0.126*	-0.058	-0.024	-0.080	-0.019	-0.041
is college	[0.075]	[0.050]	[0.056]	[0.093]	[0.111]	[0.051]
Father's highest education	-0.028	0.056	0.040	0.057	-0.011	0.036
is college	[0.083]	[0.052]	[0.056]	[0.085]	[0.139]	[0.047]
First born	-0.076	-0.059	-0.071	-0.019	-0.055	-0.061
	[0.054]	[0.043]	[0.045]	[0.070]	[0.093]	[0.042]
No older siblings in household	0.017	0.005	0.002	0.076	-0.063	0.021
	[0.055]	[0.043]	[0.044]	[0.064]	[0.078]	[0.040]
Math score (8th grade)	-0.001	-0.002**	-0.001	-0.002	-0.001	-0.001*
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Reading score (8th grade)	-0.001	-0.001	-0.001	-0.001	-0.000	-0.001
	[0.002]	[0.001]	[0.001]	[0.002]	[0.002]	[0.001]
Free/reduced price meal	-0.050	0.032	0.077	-0.004	-0.010	0.019
	[0.058]	[0.050]	[0.048]	[0.071]	[0.090]	[0.043]
On-border design	-0.013	-0.215***	-0.455***	0.084	-0.213**	0.010
	[0.060]	[0.062]	[0.060]	[0.086]	[0.104]	[0.054]
Experiment run in 2011	0.044	0.080	0.078	0.123	-0.032	0.075
	[0.057]	[0.057]	[0.056]	[0.096]	[0.101]	[0.055]
Constant	0.439	1.772*	1.159	1.407	-0.754	1.246
	[1.300]	[0.961]	[0.953]	[1.514]	[2.020]	[0.846]
Observations	1,065	1,065	1,065	1,065	1,065	1,065
Log-Likelihood	-971.4	-1334	-1254	-1098	-923.3	-1371

Robust standard errors in brackets, clusters at the classroom level. Dummy variables for on-border design and year in which experiment was run are included in lieu of dummy variables per classroom. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A6. Fixed effects negative binomial regression on number of disciplinary referrals (8th grade)

Number of safe decisions	-0.038	-0.040	-0.048	-0.055*	-0.037	-0.034	-0.050
	[0.034]	[0.034]	[0.034]	[0.033]	[0.035]	[0.033]	[0.034]
Betweenness		0.023					
		[0.084]					
Neilson (1992)			0.149				
			[0.103]				
Diecidue et al. (2004)				0.257**			
				[0.100]			
CPT w/ convex weights					-0.008		
					[0.084]		
CPT w/ concave weights						0.115	
						[0.082]	
Expected utility							0.146
							[0.124]
Disciplinary referrals (7th grade)	0.060***	0.060***	0.060***	0.060***	0.060***	0.060***	0.060***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Male	0.450***	0.451***	0.451***	0.449***	0.450***	0.456***	0.449***
	[0.079]	[0.079]	[0.079]	[0.079]	[0.079]	[0.079]	[0.079]
Black	0.255***	0.256***	0.256***	0.261***	0.255***	0.264***	0.259***
	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]
Age in years	-0.141*	-0.140*	-0.137*	-0.139*	-0.141*	-0.132*	-0.134*
	[0.077]	[0.077]	[0.077]	[0.077]	[0.077]	[0.077]	[0.077]
Two-parent household	-0.194**	-0.193**	-0.192**	-0.188**	-0.194**	-0.193**	-0.193**
	[0.084]	[0.084]	[0.084]	[0.084]	[0.084]	[0.084]	[0.084]
Mother's highest education	-0.041	-0.042	-0.045	-0.041	-0.041	-0.044	-0.041
is high school	[0.103]	[0.103]	[0.103]	[0.103]	[0.103]	[0.103]	[0.103]
Father's highest education	-0.051	-0.050	-0.047	-0.047	-0.051	-0.043	-0.048
is high school	[0.098]	[0.098]	[0.098]	[0.098]	[0.098]	[0.098]	[0.098]
Mother's highest education	0.024	0.025	0.023	0.028	0.025	0.023	0.026
is college	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]
Father's highest education	-0.214*	-0.214*	-0.213*	-0.212*	-0.214*	-0.212*	-0.211*
is college	[0.123]	[0.123]	[0.123]	[0.123]	[0.123]	[0.123]	[0.123]
First born	-0.207**	-0.207**	-0.211**	-0.213**	-0.207**	-0.210**	-0.210**
	[0.097]	[0.097]	[0.097]	[0.097]	[0.097]	[0.097]	[0.097]
No older sibling in household	-0.175*	-0.175*	-0.172*	-0.180*	-0.175*	-0.173*	-0.174*
	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]
Math score (8th grade)	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Reading score (8th grade)	-0.003	-0.003	-0.002	-0.003	-0.003	-0.003	-0.003
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Free/reduced priced meal	0.274**	0.273**	0.281***	0.285***	0.273**	0.273**	0.277***
	[0.106]	[0.106]	[0.106]	[0.106]	[0.106]	[0.106]	[0.106]
Constant	11.697***	11.681***	11.552***	11.572***	11.700***	11.554***	11.599***
	[2.501]	[2.501]	[2.512]	[2.512]	[2.501]	[2.497]	[2.504]
Observations	1,060	1,060	1,060	1,060	1,060	1,060	1,060
Number of classrooms	62	62	62	62	62	62	62
Log-Likelihood	-1454	-1454	-1453	-1451	-1454	-1453	-1453

Robust standard errors in brackets. Fixed effects at the classroom level. *** p<0.01, ** p<0.05, * p<0.10

Table A7. Fixed effects negative binomial regression on number of disciplinary referrals (9th grade)

Number of safe decisions	-0.046	-0.045	-0.066	-0.067	-0.057	-0.044	-0.067
	[0.043]	[0.044]	[0.042]	[0.043]	[0.045]	[0.043]	[0.044]
Betweenness		-0.013					
		[0.109]					
Neilson (1992)			0.282**				
			[0.134]				
Diecidue et al. (2004)				0.281**			
				[0.132]			
CPT w/ convex weights					0.083		
					[0.110]		
CPT w/ concave weights						0.059	
						[0.106]	
Expected utility							0.238
							[0.158]
Disciplinary referrals (7th grade)	0.054***	0.054***	0.054***	0.054***	0.054***	0.053***	0.054***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Male	0.144	0.143	0.147	0.145	0.143	0.145	0.143
	[0.101]	[0.101]	[0.101]	[0.101]	[0.101]	[0.101]	[0.101]
Black	0.582***	0.582***	0.582***	0.586***	0.579***	0.588***	0.586***
	[0.122]	[0.122]	[0.121]	[0.122]	[0.122]	[0.122]	[0.121]
Age in years	-0.091	-0.091	-0.083	-0.084	-0.090	-0.087	-0.085
	[0.099]	[0.099]	[0.099]	[0.100]	[0.099]	[0.099]	[0.099]
Two-parent household	0.026	0.026	0.025	0.029	0.029	0.027	0.022
	[0.109]	[0.109]	[0.109]	[0.110]	[0.110]	[0.110]	[0.110]
Mother's highest education	0.008	0.008	0.009	0.012	0.003	0.006	0.007
is high school	[0.132]	[0.132]	[0.132]	[0.132]	[0.132]	[0.132]	[0.132]
Father's highest education	-0.120	-0.120	-0.111	-0.108	-0.123	-0.114	-0.112
is high school	[0.126]	[0.126]	[0.126]	[0.127]	[0.126]	[0.127]	[0.126]
Mother's highest education	0.076	0.076	0.087	0.096	0.073	0.074	0.079
is college	[0.153]	[0.153]	[0.153]	[0.154]	[0.153]	[0.153]	[0.153]
Father's highest education	-0.274*	-0.274*	-0.273*	-0.269*	-0.276*	-0.272*	-0.267*
is college	[0.160]	[0.160]	[0.159]	[0.159]	[0.160]	[0.160]	[0.160]
First born	-0.223*	-0.222*	-0.234*	-0.232*	-0.221*	-0.226*	-0.230*
	[0.123]	[0.123]	[0.123]	[0.123]	[0.123]	[0.124]	[0.123]
No older sibling in household	-0.051	-0.051	-0.036	-0.044	-0.052	-0.049	-0.046
	[0.119]	[0.120]	[0.119]	[0.119]	[0.119]	[0.120]	[0.119]
Math score (8th grade)	-0.009***	-0.009***	-0.010***	-0.009***	-0.009***	-0.009***	-0.009***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Reading score (8th grade)	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Free/reduced priced meal	0.320**	0.321**	0.341**	0.335**	0.324**	0.320**	0.328**
	[0.139]	[0.139]	[0.140]	[0.140]	[0.139]	[0.139]	[0.139]
Constant	10.424***	10.427***	10.411***	10.326***	10.430***	10.405***	10.462***
	[3.188]	[3.188]	[3.200]	[3.198]	[3.190]	[3.187]	[3.191]
Observations	1,055	1,055	1,055	1,055	1,055	1,055	1,055
Number of classrooms	60	60	60	60	60	60	60
Log-Likelihood	-1146	-1146	-1144	-1143	-1145	-1145	-1145

Robust standard errors in brackets. Fixed effects at the classroom level. *** p<0.01, ** p<0.05, * p<0.10

Table A8. Fixed effects negative binomial regression on number of disciplinary referrals (total in 8th and 9th grade)

Number of safe decisions	-0.043	-0.042	-0.057*	-0.064**	-0.046	-0.040	-0.057*
	[0.032]	[0.032]	[0.031]	[0.031]	[0.033]	[0.031]	[0.032]
Betweenness		-0.004					
		[0.079]					
Neilson (1992)			0.190*				
			[0.098]				
Diecidue et al. (2004)				0.281***			
				[0.095]			
CPT w/ convex weights					0.027		
					[0.080]		
CPT w/ concave weights						0.100	
						[0.077]	
Expected utility							0.161
							[0.117]
Disciplinary referrals (7th grade)	0.055***	0.055***	0.055***	0.055***	0.055***	0.054***	0.055***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Male	0.288***	0.288***	0.291***	0.288***	0.288***	0.292***	0.288***
	[0.074]	[0.074]	[0.074]	[0.074]	[0.074]	[0.074]	[0.074]
Black	0.349***	0.349***	0.353***	0.358***	0.349***	0.360***	0.355***
	[0.088]	[0.088]	[0.087]	[0.088]	[0.088]	[0.088]	[0.088]
Age in years	-0.141*	-0.141*	-0.133*	-0.133*	-0.141*	-0.133*	-0.134*
	[0.073]	[0.073]	[0.073]	[0.073]	[0.073]	[0.074]	[0.073]
Two-parent household	-0.147*	-0.147*	-0.143*	-0.139*	-0.145*	-0.145*	-0.146*
	[0.080]	[0.080]	[0.080]	[0.080]	[0.080]	[0.080]	[0.080]
Mother's highest education	-0.016	-0.015	-0.017	-0.013	-0.017	-0.018	-0.015
is high school	[0.097]	[0.097]	[0.097]	[0.097]	[0.097]	[0.097]	[0.097]
Father's highest education	-0.078	-0.078	-0.073	-0.072	-0.079	-0.070	-0.074
is high school	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]
Mother's highest education	0.022	0.022	0.024	0.031	0.021	0.019	0.023
is college	[0.113]	[0.113]	[0.113]	[0.113]	[0.113]	[0.113]	[0.113]
Father's highest education	-0.163	-0.163	-0.162	-0.159	-0.164	-0.158	-0.158
is college	[0.115]	[0.115]	[0.115]	[0.115]	[0.115]	[0.115]	[0.115]
First born	-0.213**	-0.213**	-0.219**	-0.220**	-0.213**	-0.218**	-0.217**
	[0.090]	[0.090]	[0.090]	[0.090]	[0.090]	[0.090]	[0.090]
No older sibling in household	-0.134	-0.134	-0.129	-0.136	-0.135	-0.131	-0.132
	[0.087]	[0.087]	[0.087]	[0.087]	[0.087]	[0.087]	[0.087]
Math score (8th grade)	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Reading score (8th grade)	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Free/reduced priced meal	0.256***	0.256***	0.266***	0.268***	0.257***	0.256***	0.261***
	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]
Constant	12.207***	12.209***	12.074***	12.022***	12.204***	12.092***	12.144***
	[2.336]	[2.336]	[2.344]	[2.345]	[2.337]	[2.335]	[2.338]
Observations	1,060	1,060	1,060	1,060	1,060	1,060	1,060
Number of classrooms	62	62	62	62	62	62	62
Log-Likelihood	-1834	-1834	-1832	-1830	-1834	-1833	-1833

Robust standard errors in brackets. Fixed effects at the classroom level. *** p<0.01, ** p<0.05, * p<0.10

Table A9. Fixed effects negative binomial regression on number of disciplinary referrals (8th grade)

Risk taking in D1	0.156*				
	[0.083]				
Risk taking in D2		0.018			
		[0.083]			
Risk taking in D3			0.030		
			[0.084]		
Risk taking in D4				0.098	
				[0.081]	
Risk taking in D5					-0.017
					[0.084]
Expected utility	0.117	0.091	0.092	0.112	0.079
	[0.119]	[0.120]	[0.120]	[0.120]	[0.124]
Disciplinary referrals (7th grade)	0.060***	0.060***	0.061***	0.060***	0.060***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Male	0.456***	0.450***	0.450***	0.451***	0.451***
	[0.079]	[0.079]	[0.079]	[0.079]	[0.079]
Black	0.263***	0.258***	0.260***	0.254***	0.259***
	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]
Age in years	-0.123	-0.129*	-0.131*	-0.129*	-0.128*
	[0.077]	[0.077]	[0.077]	[0.077]	[0.077]
Two-parent household	-0.202**	-0.199**	-0.198**	-0.194**	-0.199**
	[0.083]	[0.084]	[0.084]	[0.084]	[0.084]
Mother's highest education	-0.041	-0.047	-0.044	-0.037	-0.046
is high school	[0.103]	[0.103]	[0.103]	[0.103]	[0.103]
Father's highest education	-0.038	-0.043	-0.046	-0.050	-0.044
is high school	[0.098]	[0.098]	[0.098]	[0.098]	[0.098]
Mother's highest education	0.026	0.022	0.024	0.027	0.022
is college	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]
Father's highest education	-0.212*	-0.216*	-0.217*	-0.214*	-0.217*
is college	[0.123]	[0.123]	[0.123]	[0.123]	[0.124]
First born	-0.209**	-0.208**	-0.208**	-0.208**	-0.208**
college	[0.096]	[0.097]	[0.097]	[0.097]	[0.097]
No older siblings in household	-0.172*	-0.175*	-0.173*	-0.170*	-0.173*
college	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]
Math score (8th grade)	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Reading score (8th grade)	-0.003	-0.003	-0.003	-0.003	-0.003
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Free/reduced price meal	0.278***	0.282***	0.280***	0.288***	0.282***
	[0.106]	[0.106]	[0.106]	[0.106]	[0.106]
Constant	11.424***	11.649***	11.671***	11.629***	11.713***
	[2.498]	[2.514]	[2.503]	[2.506]	[2.500]
Observations	1,060	1,060	1,060	1,060	1,060
Number of classrooms	62	62	62	62	62
Log-Likelihood	-1453	-1454	-1454	-1454	-1454

Robust standard errors in brackets. Fixed effects at the classroom level. *** p<0.01, ** p<0.05, * p<0.10

Table A10. Fixed effects negative binomial regression on number of disciplinary referrals (9th grade)

	(1)	(2)	(3)	(4)	(5)
Risk taking in D1	0.082				
	[0.108]				
Risk taking in D2		0.132			
		[0.107]			
Risk taking in D3			0.013		
			[0.109]		
Risk taking in D4				0.144	
				[0.105]	
Risk taking in D5					0.010
					[0.109]
Expected utility	0.172	0.188	0.158	0.195	0.159
	[0.152]	[0.153]	[0.152]	[0.153]	[0.157]
Disciplinary referrals (7th grade)	0.054***	0.053***	0.055***	0.055***	0.055***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Male	0.145	0.145	0.143	0.149	0.142
	[0.101]	[0.101]	[0.101]	[0.101]	[0.102]
Black	0.594***	0.583***	0.590***	0.585***	0.589***
	[0.122]	[0.121]	[0.121]	[0.121]	[0.121]
Age in years	-0.074	-0.072	-0.076	-0.077	-0.076
	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]
bothparents	0.017	0.021	0.019	0.022	0.018
	[0.109]	[0.109]	[0.110]	[0.109]	[0.109]
Mother's highest education	-0.002	-0.010	-0.005	0.011	-0.005
is high school	[0.132]	[0.132]	[0.132]	[0.132]	[0.132]
Father's highest education	-0.102	-0.113	-0.108	-0.115	-0.107
is high school	[0.127]	[0.127]	[0.127]	[0.126]	[0.126]
Mother's highest education	0.070	0.073	0.070	0.081	0.070
is college	[0.153]	[0.153]	[0.153]	[0.153]	[0.153]
Father's highest education	-0.278*	-0.288*	-0.284*	-0.279*	-0.283*
is college	[0.159]	[0.160]	[0.159]	[0.159]	[0.160]
First born	-0.227*	-0.221*	-0.226*	-0.225*	-0.226*
	[0.123]	[0.124]	[0.123]	[0.123]	[0.123]
No older siblings in household	-0.051	-0.062	-0.052	-0.046	-0.053
	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]
Math score (8th grade)	-0.009***	-0.009***	-0.009***	-0.010***	-0.009***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Reading score (8th grade)	-0.004	-0.004	-0.004	-0.004	-0.004
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Free/reduced price meal	0.325**	0.322**	0.326**	0.342**	0.327**
	[0.139]	[0.139]	[0.139]	[0.139]	[0.139]
Constant	10.339***	10.144***	10.419***	10.314***	10.433***
	[3.187]	[3.189]	[3.186]	[3.189]	[3.186]
Observations	1,055	1,055	1,055	1,055	1,055
Number of classrooms	60	60	60	60	60
Log-Likelihood	-1145	-1145	-1146	-1145	-1146

Robust standard errors in brackets. Fixed effects at the classroom level. *** p<0.01, ** p<0.05, * p<0.10

Table A11. Fixed effects negative binomial regression on number of disciplinary referrals (total in 8th and 9th grade)

Risk taking in D1	0.133*				
	[0.079]				
Risk taking in D2		0.044			
		[0.079]			
Risk taking in D3			0.040		
			[0.079]		
Risk taking in D4				0.120	
				[0.077]	
Risk taking in D5					-0.017
					[0.079]
Expected utility	0.117	0.099	0.096	0.122	0.081
	[0.112]	[0.113]	[0.112]	[0.113]	[0.116]
Disciplinary referrals (7th grade)	0.055***	0.055***	0.056***	0.056***	0.056***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Male	0.293***	0.289***	0.289***	0.292***	0.290***
	[0.074]	[0.074]	[0.074]	[0.074]	[0.074]
Black	0.361***	0.354***	0.357***	0.350***	0.355***
	[0.088]	[0.088]	[0.088]	[0.087]	[0.088]
Age in years	-0.123*	-0.127*	-0.130*	-0.127*	-0.126*
	[0.073]	[0.073]	[0.073]	[0.073]	[0.073]
Two-parent household	-0.153*	-0.149*	-0.149*	-0.145*	-0.150*
	[0.080]	[0.080]	[0.080]	[0.079]	[0.080]
Mother's highest education	-0.019	-0.025	-0.020	-0.011	-0.022
is high school	[0.097]	[0.097]	[0.097]	[0.097]	[0.097]
Father's highest education	-0.061	-0.069	-0.071	-0.077	-0.068
is high school	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]
Mother's highest education	0.019	0.017	0.020	0.026	0.018
is college	[0.113]	[0.113]	[0.113]	[0.113]	[0.113]
Father's highest education	-0.159	-0.169	-0.168	-0.166	-0.170
is college	[0.115]	[0.115]	[0.115]	[0.115]	[0.116]
First born	-0.217**	-0.213**	-0.215**	-0.213**	-0.213**
	[0.090]	[0.090]	[0.090]	[0.090]	[0.090]
No older siblings in household	-0.132	-0.138	-0.133	-0.132	-0.135
	[0.087]	[0.087]	[0.087]	[0.087]	[0.087]
Math score (8th grade)	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Reading score (8th grade)	-0.003	-0.003	-0.003	-0.003	-0.003
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Free/reduced price meal	0.261***	0.263***	0.263***	0.274***	0.265***
	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]
Constant	11.973***	12.071***	12.125***	12.066***	12.170***
	[2.335]	[2.340]	[2.337]	[2.339]	[2.333]
Observations	1,060	1,060	1,060	1,060	1,060
Number of classrooms	62	62	62	62	62
Log-Likelihood	-1833	-1834	-1834	-1833	-1834

Robust standard errors in brackets. Fixed effects at the classroom level. *** p<0.01, ** p<0.05, * p<0.10

Table A12. Fixed effects negative binomial regression of disciplinary acts (8th grade)

$Pr(AAAAA \mid Choice)^{+}$	-0.459**	-0.459**	-0.461**	-0.465**	-0.454*	-0.408*	-0.464**
	[0.233]	[0.233]	[0.230]	[0.228]	[0.237]	[0.235]	[0.231]
Betweenness		0.008					
		[0.082]					
Neilson (1992)			0.118				
			[0.101]				
Diecidue et al. (2004)				0.224**			
				[0.098]			
CPT w/ convex weights					-0.008		
					[0.081]		
CPT w/ concave weights						0.097	
						[0.083]	
Expected utility							0.098
							[0.118]
Disciplinary referrals (7th grade)	0.060***	0.060***	0.061***	0.061***	0.060***	0.060***	0.061***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
Male	0.439***	0.440***	0.440***	0.438***	0.440***	0.446***	0.439***
	[0.079]	[0.079]	[0.079]	[0.079]	[0.079]	[0.079]	[0.079]
Black	0.297***	0.297***	0.299***	0.303***	0.297***	0.300***	0.300***
	[0.096]	[0.096]	[0.096]	[0.095]	[0.096]	[0.096]	[0.096]
Age in years	-0.140*	-0.139*	-0.135*	-0.134*	-0.140*	-0.131*	-0.134*
	[0.076]	[0.077]	[0.077]	[0.077]	[0.076]	[0.077]	[0.077]
Two-parent household	-0.193**	-0.192**	-0.193**	-0.190**	-0.193**	-0.193**	-0.194**
	[0.083]	[0.083]	[0.083]	[0.083]	[0.084]	[0.083]	[0.083]
Mother's highest education	-0.020	-0.021	-0.024	-0.021	-0.020	-0.025	-0.021
is high school	[0.104]	[0.104]	[0.104]	[0.104]	[0.104]	[0.104]	[0.104]
Father's highest education	-0.016	-0.015	-0.011	-0.009	-0.016	-0.012	-0.012
is high school	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]
Mother's highest education	0.041	0.041	0.040	0.044	0.041	0.039	0.042
is college	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]	[0.119]
Father's highest education	-0.195	-0.195	-0.195	-0.195	-0.195	-0.196	-0.194
is college	[0.124]	[0.124]	[0.124]	[0.123]	[0.124]	[0.124]	[0.124]
First born	-0.254**	-0.254**	-0.258***	-0.259***	-0.254**	-0.252**	-0.257**
	[0.100]	[0.100]	[0.100]	[0.100]	[0.100]	[0.100]	[0.100]
No older sibling in household	-0.153	-0.153	-0.150	-0.157*	-0.153	-0.154*	-0.152
	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]
Math score (8th grade)	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Reading score (8th grade)	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Free/reduced price meal	0.278***	0.278***	0.284***	0.290***	0.277***	0.277***	0.281***
	[0.106]	[0.106]	[0.106]	[0.106]	[0.106]	[0.106]	[0.106]
Constant	12.242***	12.239***	12.151***	12.174***	12.237***	12.055***	12.199***
	[2.508]	[2.507]	[2.516]	[2.517]	[2.508]	[2.508]	[2.510]
Observations	1,060	1,060	1,060	1,060	1,060	1,060	1,060
Number of classrooms	62	62	62	62	62	62	62
Log-Likelihood	-1453	-1453	-1452	-1450	-1453	-1452	-1452

$^{+}Pr(Choice) = Pr(Choice|\alpha,\epsilon)\alpha + Pr(Choice|1-\alpha,\epsilon)(1-\alpha)$, $\alpha = Pr(AAAAA)$. $Pr(AAAAA|Choice) = \frac{Pr(Choice|\alpha,\epsilon)\alpha}{Pr(Choice)}$

Robust standard errors in brackets. Fixed effects at the classroom level. *** p<0.01, ** p<0.05, * p<0.10.

Table A13. Fixed effects negative binomial regression of disciplinary acts (9th grade)

$Pr(AAAAA\|Choice)^{+}$	-0.644**	-0.644**	-0.642**	-0.653**	-0.681**	-0.627**	-0.651**
	[0.304]	[0.306]	[0.298]	[0.298]	[0.306]	[0.309]	[0.299]
Betweenness		-0.033					
		[0.106]					
Neilson (1992)			0.234*				
			[0.131]				
Diecidue et al. (2004)				0.238*			
				[0.128]			
CPT w/ convex weights					0.078		
					[0.106]		
CPT w/ concave weights						0.033	
						[0.107]	
Expected utility							0.172
							[0.150]
Disciplinary referrals (7th grade)	0.054***	0.054***	0.055***	0.055***	0.055***	0.054***	0.055***
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
Male	0.129	0.127	0.131	0.129	0.128	0.130	0.128
	[0.102]	[0.102]	[0.102]	[0.102]	[0.101]	[0.102]	[0.102]
Black	0.643***	0.642***	0.644***	0.648***	0.644***	0.645***	0.648***
	[0.125]	[0.125]	[0.125]	[0.125]	[0.125]	[0.125]	[0.125]
Age in years	-0.087	-0.089	-0.077	-0.077	-0.085	-0.085	-0.080
	[0.099]	[0.099]	[0.099]	[0.099]	[0.098]	[0.099]	[0.099]
Two-parent household	0.029	0.029	0.026	0.029	0.031	0.029	0.024
	[0.109]	[0.109]	[0.109]	[0.109]	[0.109]	[0.109]	[0.109]
Mother's highest education	0.040	0.042	0.038	0.041	0.035	0.038	0.037
is high school	[0.134]	[0.134]	[0.134]	[0.134]	[0.134]	[0.134]	[0.134]
Father's highest education	-0.071	-0.072	-0.062	-0.059	-0.071	-0.070	-0.064
is high school	[0.128]	[0.128]	[0.128]	[0.128]	[0.128]	[0.129]	[0.128]
Mother's highest education	0.102	0.102	0.109	0.118	0.099	0.101	0.103
is college	[0.154]	[0.154]	[0.154]	[0.155]	[0.155]	[0.154]	[0.154]
Father's highest education	-0.243	-0.242	-0.248	-0.245	-0.245	-0.242	-0.242
is college	[0.161]	[0.161]	[0.160]	[0.160]	[0.161]	[0.161]	[0.161]
First born	-0.284**	-0.284**	-0.292**	-0.292**	-0.286**	-0.284**	-0.290**
	[0.127]	[0.127]	[0.127]	[0.127]	[0.127]	[0.127]	[0.127]
No older sibling in household	-0.025	-0.026	-0.014	-0.020	-0.025	-0.024	-0.023
	[0.120]	[0.120]	[0.120]	[0.120]	[0.120]	[0.120]	[0.120]
Math score (8th grade)	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***	-0.011***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Reading score (8th grade)	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Free/reduced price meal	0.330**	0.331**	0.347**	0.343**	0.333**	0.329**	0.335**
	[0.139]	[0.139]	[0.139]	[0.139]	[0.139]	[0.139]	[0.139]
Constant	10.980***	10.988***	10.988***	10.927***	11.031***	10.952***	11.023***
	[3.193]	[3.193]	[3.202]	[3.201]	[3.195]	[3.194]	[3.194]
Observations	1,055	1,055	1,055	1,055	1,055	1,055	1,055
Number of classrooms	60	60	60	60	60	60	60
Log-Likelihood	-1144	-1144	-1143	-1142	-1144	-1144	-1143

$^{+}Pr(Choice) = Pr(Choice|\alpha,\epsilon)\alpha + Pr(Choice|1-\alpha,\epsilon)(1-\alpha)$, $\alpha = Pr(AAAAA)$. $Pr(AAAAA|Choice) = \frac{Pr(Choice|\alpha,\epsilon)\alpha}{Pr(Choice)}$

Robust standard errors in brackets. Fixed effects at the classroom level. *** p<0.01, ** p<0.05, * p<0.10.

Table A14. Fixed effects negative binomial regression of disciplinary acts (total from 8th and 9th grades)

$Pr(AAAAA\|Choice)^{+}$	-0.579***	-0.579***	-0.582***	-0.586***	-0.592***	-0.541**	-0.584***
	[0.216]	[0.217]	[0.213]	[0.211]	[0.218]	[0.219]	[0.213]
Betweenness		-0.021					
		[0.077]					
Neilson (1992)			0.150				
			[0.095]				
Diecidue et al. (2004)				0.240***			
				[0.092]			
CPT w/ convex weights					0.025		
					[0.077]		
CPT w/ concave weights						0.076	
						[0.078]	
Expected utility							0.104
							[0.111]
Disciplinary referrals (7th grade)	0.056***	0.056***	0.056***	0.056***	0.056***	0.055***	0.056***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Male	0.275***	0.274***	0.277***	0.275***	0.274***	0.279***	0.274***
	[0.074]	[0.074]	[0.074]	[0.074]	[0.074]	[0.074]	[0.074]
Black	0.404***	0.403***	0.407***	0.412***	0.404***	0.408***	0.408***
	[0.090]	[0.090]	[0.090]	[0.090]	[0.090]	[0.090]	[0.090]
Age in years	-0.139*	-0.140*	-0.130*	-0.128*	-0.138*	-0.133*	-0.133*
	[0.073]	[0.073]	[0.073]	[0.073]	[0.073]	[0.073]	[0.073]
Two-parent household	-0.144*	-0.144*	-0.143*	-0.140*	-0.143*	-0.143*	-0.145*
	[0.079]	[0.079]	[0.079]	[0.079]	[0.079]	[0.079]	[0.079]
Mother's highest education	0.010	0.011	0.007	0.010	0.009	0.006	0.009
is high school	[0.098]	[0.098]	[0.097]	[0.097]	[0.098]	[0.098]	[0.097]
Father's highest education	-0.034	-0.035	-0.028	-0.025	-0.033	-0.031	-0.030
is high school	[0.094]	[0.094]	[0.094]	[0.094]	[0.094]	[0.094]	[0.094]
Mother's highest education	0.042	0.042	0.042	0.048	0.040	0.039	0.042
is college	[0.113]	[0.113]	[0.113]	[0.113]	[0.113]	[0.113]	[0.113]
Father's highest education	-0.137	-0.136	-0.138	-0.137	-0.137	-0.135	-0.135
is college	[0.116]	[0.116]	[0.116]	[0.115]	[0.116]	[0.116]	[0.116]
First born	-0.271***	-0.270***	-0.275***	-0.276***	-0.271***	-0.270***	-0.273***
	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]	[0.093]
No older sibling in household	-0.107	-0.108	-0.103	-0.109	-0.107	-0.107	-0.106
	[0.088]	[0.088]	[0.087]	[0.087]	[0.088]	[0.088]	[0.087]
Math score (8th grade)	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***	-0.012***
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Reading score (8th grade)	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Free/reduced price meal	0.260***	0.261***	0.270***	0.273***	0.262***	0.260***	0.264***
	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]	[0.099]
Constant	12.838***	12.846***	12.752***	12.710***	12.854***	12.701***	12.809***
	[2.341]	[2.341]	[2.347]	[2.348]	[2.342]	[2.343]	[2.342]
Observations	1,060	1,060	1,060	1,060	1,060	1,060	1,060
Number of classrooms	62	62	62	62	62	62	62
Log-Likelihood	-1831	-1831	-1830	-1828	-1831	-1831	-1831

$^{+}Pr(Choice) = Pr(Choice|\alpha,\epsilon)\alpha + Pr(Choice|1-\alpha,\epsilon)(1-\alpha)$, $\alpha = Pr(AAAAA)$. $Pr(AAAAA|Choice) = \frac{Pr(Choice|\alpha,\epsilon)\alpha}{Pr(Choice)}$

Robust standard errors in brackets. Fixed effects at the classroom level. *** p<0.01, ** p<0.05, * p<0.10.

Table A15. Fixed effects negative binomial regression on disciplinary referrals using estimated risk measure (latent factor)

	(1) 8th grade	(2) 9th grade	(3) 8th & 9th grade
Empirical Bayes means for f_i	0.055	0.049	0.061
	[0.052]	[0.067]	[0.049]
Consistent with expected utility theory	0.112	0.187	0.123
	[0.123]	[0.156]	[0.116]
Disciplinary referrals in 7th grade	0.060***	0.054***	0.055***
	[0.005]	[0.006]	[0.004]
Male	0.450***	0.145	0.289***
	[0.079]	[0.101]	[0.074]
Black	0.258***	0.589***	0.356***
	[0.094]	[0.121]	[0.088]
Age	-0.128*	-0.075	-0.126*
	[0.077]	[0.099]	[0.073]
Two-parent household	-0.199**	0.019	-0.151*
	[0.084]	[0.109]	[0.080]
Mother's highest education	-0.047	-0.002	-0.021
is high school	[0.103]	[0.132]	[0.097]
Father's highest education	-0.043	-0.108	-0.069
is high school	[0.098]	[0.126]	[0.093]
Mother's highest education	0.027	0.074	0.023
is college	[0.119]	[0.153]	[0.113]
Father's highest education	-0.218*	-0.282*	-0.167
is college	[0.123]	[0.159]	[0.115]
First born	-0.202**	-0.226*	-0.211**
	[0.097]	[0.123]	[0.090]
No older siblings in household	-0.180*	-0.052	-0.138
	[0.093]	[0.119]	[0.087]
Math score 8th grade	-0.010***	-0.009***	-0.011***
	[0.002]	[0.003]	[0.002]
Reading score 8th grade	-0.003	-0.004	-0.003
	[0.003]	[0.003]	[0.002]
Free/reduced price meal	0.276***	0.325**	0.259***
	[0.107]	[0.139]	[0.099]
Constant	11.559***	10.359***	11.996***
	[2.520]	[3.187]	[2.350]
Observations	1,058	1,055	1,058
Number of classrooms	61	60	61
log-likelihood	-1452	-1145	-1831

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.

Table A16. Effect of estimated risk latent factor on graduating high school

	Academy graduates included				Academy graduates counted as dropouts			
	Probit		Logit		Probit		Logit	
	Random Effects		Fixed Effects		Random Effects		Fixed Effects	
VARIABLES	All	Known	All	Known	All	Known	All	Known
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Empirical Bayes means for f_i	-0.015	-0.043	-0.031	-0.211	0.005	0.064	-0.010	0.034
	[0.151]	[0.191]	[0.277]	[0.373]	[0.146]	[0.177]	[0.264]	[0.333]
	(0.919)	(0.823)	(0.911)	(0.572)	(0.972)	(0.718)	(0.969)	(0.919)
f_i^2	-0.110	0.050	-0.150	0.090	-0.127	0.037	-0.123	0.058
	[0.176]	[0.227]	[0.316]	[0.433]	[0.172]	[0.212]	[0.305]	[0.391]
	(0.534)	(0.826)	(0.634)	(0.835)	(0.460)	(0.863)	(0.686)	(0.882)
f_i^3	0.023	-0.076	0.012	-0.082	-0.004	-0.150	-0.039	-0.212
	[0.138]	[0.174]	[0.253]	[0.342]	[0.135]	[0.163]	[0.243]	[0.306]
	(0.870)	(0.664)	(0.962)	(0.811)	(0.976)	(0.357)	(0.873)	(0.488)
Disciplinary ref. in 7th grade	-0.106***	-0.105***	-0.178***	-0.188***	-0.113***	-0.100***	-0.186***	-0.168***
	[0.019]	[0.023]	[0.034]	[0.043]	[0.019]	[0.022]	[0.035]	[0.041]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Math standardized sc. in 8th grade	0.022***	0.025***	0.041***	0.045***	0.022***	0.024***	0.039***	0.041***
	[0.003]	[0.004]	[0.006]	[0.008]	[0.003]	[0.004]	[0.006]	[0.007]
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Read. standardized sc. in 8th grade	0.006*	0.012**	0.014**	0.029***	0.006	0.008**	0.011*	0.019**
	[0.003]	[0.005]	[0.007]	[0.009]	[0.003]	[0.004]	[0.006]	[0.008]
	(0.065)	(0.013)	(0.032)	(0.002)	(0.102)	(0.050)	(0.080)	(0.023)
Male	-0.191*	-0.010	-0.317	-0.010	-0.128	0.021	-0.189	0.056
	[0.107]	[0.137]	[0.194]	[0.258]	[0.104]	[0.127]	[0.185]	[0.233]
	(0.076)	(0.942)	(0.102)	(0.969)	(0.218)	(0.866)	(0.308)	(0.809)
Black	0.267**	0.403***	0.467**	0.632**	0.218*	0.280**	0.388*	0.471*
	[0.119]	[0.156]	[0.217]	[0.300]	[0.115]	[0.142]	[0.206]	[0.269]
	(0.025)	(0.010)	(0.031)	(0.035)	(0.058)	(0.049)	(0.060)	(0.080)
Age (years)	-0.206**	-0.463***	-0.360**	-0.978***	-0.207**	-0.409***	-0.356**	-0.783***
	[0.099]	[0.129]	[0.179]	[0.248]	[0.097]	[0.121]	[0.174]	[0.222]
	(0.038)	(0.000)	(0.045)	(0.000)	(0.034)	(0.001)	(0.040)	(0.000)
Two-parent HH.	0.271**	0.221	0.440**	0.386	0.227**	0.177	0.363*	0.328
	[0.116]	[0.149]	[0.207]	[0.280]	[0.112]	[0.138]	[0.199]	[0.254]
	(0.019)	(0.137)	(0.033)	(0.168)	(0.043)	(0.200)	(0.067)	(0.196)
Mother has HS	0.422***	0.480***	0.589**	0.758**	0.487***	0.572***	0.703***	0.843***
	[0.136]	[0.169]	[0.246]	[0.327]	[0.132]	[0.158]	[0.237]	[0.294]
	(0.002)	(0.004)	(0.017)	(0.020)	(0.000)	(0.000)	(0.003)	(0.004)
Father has HS	0.220*	0.302*	0.347	0.504	0.111	0.104	0.150	0.153
	[0.133]	[0.166]	[0.243]	[0.309]	[0.128]	[0.152]	[0.231]	[0.282]
	(0.098)	(0.069)	(0.153)	(0.103)	(0.384)	(0.493)	(0.517)	(0.588)
Mother has college	0.292*	0.294	0.361	0.343	0.349**	0.360**	0.453*	0.351
	[0.153]	[0.196]	[0.278]	[0.379]	[0.148]	[0.182]	[0.267]	[0.339]
	(0.056)	(0.135)	(0.194)	(0.365)	(0.019)	(0.048)	(0.090)	(0.301)
Father has college	0.152	0.300	0.383	0.623	0.228	0.335*	0.518*	0.717*
	[0.158]	[0.215]	[0.288]	[0.419]	[0.156]	[0.202]	[0.280]	[0.382]
	(0.335)	(0.163)	(0.183)	(0.137)	(0.142)	(0.098)	(0.064)	(0.060)
First born	0.117	0.189	0.170	0.305	0.138	0.214	0.243	0.432
	[0.127]	[0.162]	[0.228]	[0.307]	[0.123]	[0.149]	[0.218]	[0.279]
	(0.357)	(0.242)	(0.456)	(0.320)	(0.262)	(0.150)	(0.266)	(0.121)
Only child in HH	0.128	0.180	0.230	0.353	0.107	0.098	0.186	0.162
	[0.124]	[0.159]	[0.222]	[0.298]	[0.120]	[0.146]	[0.214]	[0.272]
	(0.304)	(0.257)	(0.300)	(0.236)	(0.373)	(0.502)	(0.384)	(0.551)
Consistent with EU	-0.037	-0.172	-0.106	-0.366	0.029	-0.071	-0.095	-0.259
	[0.229]	[0.297]	[0.418]	[0.578]	[0.224]	[0.277]	[0.403]	[0.518]
	(0.872)	(0.564)	(0.801)	(0.527)	(0.898)	(0.796)	(0.814)	(0.617)
	[0.834]	[0.818]			[0.674]	[0.778]		
	(0.000)	(0.003)			(0.000)	(0.001)		
Observations	1,016	820	844	613	1,016	820	844	624
Number of class rooms	63	62	52	48	63	62	52	49
log-likelihood	-384.3	-240.4	-278.6	-149.2	-412.8	-278.1	-301.9	-183.1

s.e. in brackets, p-values in parentheses, *** p<0.01, ** p<0.05, * p<0.10. "All" includes the entire sample, and "Known" is the subsample for whom graduation status is known.

8. Appendix B - Subject Decision Sheets and Survey - Not Intended for Publication

On-border Design Decision Sheet

DECISION 2

Below are 2 options showing you what you can earn when a numbered ball is chosen from the bingo cage. Choose the one you like best (A or B) by drawing a circle around it. CHOOSE ONLY ONE.

CHOOSE ONLY ONE OPTION

CIRCLE THE ONE OPTION THAT YOU LIKE BEST

A		B	
1		1	$30
2		2	
3		3	
4		4	
5	$30	5	
6		6	
7		7	
8		8	
9		9	
10		10	
11		11	
12		12	
13		13	
14		14	
15		15	
16		16	$0
17		17	$40
18		18	
19		19	
20		20	

REMEMBER: Only one of these six decisions will count. Treat each decision seriously and separately.

You don't know which one will count until you have made all your decisions.

Each page should have one (1) circle on it when you're done.

DECISION 3

Below are 2 options showing you what you can earn when a numbered ball is chosen from the bingo cage. Choose the one you like best (A or B) by drawing a circle around it. CHOOSE ONLY ONE.

CHOOSE ONLY ONE OPTION

CIRCLE THE ONE OPTION THAT YOU LIKE BEST

A		B	
1	$0	1	$0
2		2	
3		3	
4		4	
5		5	
6		6	
7		7	
8		8	
9		9	
10		10	
11		11	
12		12	
13		13	
14		14	
15		15	
16	$30	16	
17		17	$40
18		18	
19		19	
20		20	

REMEMBER: Only one of these six decisions will count. Treat each decision seriously and separately.

You don't know which one will count until you have made all your decisions.

Each page should have one (1) circle on it when you're done.

3

DECISION 4

Below are 2 options showing you what you can earn when a numbered ball is chosen from the bingo cage. Choose the one you like best (A or B) by drawing a circle around it. CHOOSE ONLY ONE.

CHOOSE ONLY ONE OPTION

CIRCLE THE ONE OPTION THAT YOU LIKE BEST

<table>
<tr><th colspan="2">A</th></tr>
<tr><td>1</td><td rowspan="20">$30</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td></tr>
<tr><td>6</td></tr>
<tr><td>7</td></tr>
<tr><td>8</td></tr>
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<tr><td>16</td></tr>
<tr><td>17</td></tr>
<tr><td>18</td></tr>
<tr><td>19</td></tr>
<tr><td>20</td></tr>
</table>

<table>
<tr><th colspan="2">B</th></tr>
<tr><td>1</td><td rowspan="4">$0</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td><td rowspan="16">$40</td></tr>
<tr><td>6</td></tr>
<tr><td>7</td></tr>
<tr><td>8</td></tr>
<tr><td>9</td></tr>
<tr><td>10</td></tr>
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<tr><td>18</td></tr>
<tr><td>19</td></tr>
<tr><td>20</td></tr>
</table>

REMEMBER: Only one of these six decisions will count. Treat each decision seriously and separately.

You don't know which one will count until you have made all your decisions.

Each page should have one (1) circle on it when you're done.

DECISION 5

Below are 2 options showing you what you can earn when a numbered ball is chosen from the bingo cage. Choose the one you like best (A or B) by drawing a circle around it. CHOOSE ONLY ONE.

CHOOSE ONLY ONE OPTION

CIRCLE THE ONE OPTION THAT YOU LIKE BEST

A	
1	$30
2	
3	
4	
5	
6	
7	
8	
9	
10	
11	
12	
13	
14	
15	
16	$0
17	$40
18	
19	
20	

B	
1	$0
2	
3	
4	
5	$40
6	
7	
8	
9	
10	
11	
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REMEMBER: Only one of these six decisions will count. Treat each decision seriously and separately.

You don't know which one will count until you have made all your decisions.

Each page should have one (1) circle on it when you're done.

5

DECISION 6

Below are 2 options showing you what you can earn when a numbered ball is chosen from the bingo cage. Choose the one you like best (A or B) by drawing a circle around it. CHOOSE ONLY ONE.

CHOOSE ONLY ONE OPTION

CIRCLE THE ONE OPTION THAT YOU LIKE BEST

<table>
<tr><th colspan="2">A</th></tr>
<tr><td>1</td><td rowspan="5">$30</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td></tr>
<tr><td>6</td><td rowspan="15">$40</td></tr>
<tr><td>7</td></tr>
<tr><td>8</td></tr>
<tr><td>9</td></tr>
<tr><td>10</td></tr>
<tr><td>11</td></tr>
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<tr><td>16</td></tr>
<tr><td>17</td></tr>
<tr><td>18</td></tr>
<tr><td>19</td></tr>
<tr><td>20</td></tr>
</table>

<table>
<tr><th colspan="2">B</th></tr>
<tr><td>1</td><td>$0</td></tr>
<tr><td>2</td><td rowspan="19">$40</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td></tr>
<tr><td>6</td></tr>
<tr><td>7</td></tr>
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<tr><td>18</td></tr>
<tr><td>19</td></tr>
<tr><td>20</td></tr>
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REMEMBER: Only one of these six decisions will count. Treat each decision seriously and separately.

You don't know which one will count until you have made all your decisions.

Each page should have one (1) circle on it when you're done.

6

Off-border Design Decision Sheet

DECISION 2

Below are 2 options showing you what you can earn when a numbered ball is chosen from the bingo cage. Choose the one you like best (A or B) by drawing a circle around it. CHOOSE ONLY ONE.

CIRCLE THE ONE OPTION (A or B) THAT YOU LIKE BEST

A	
1-95	$30
96	$0
97-100	$40

B	
1-80	$30
81-84	$0
85-100	$40

REMEMBER: Only one of these six decisions will count. Treat each decision seriously and separately. You don't know which one will count until you have made all your decisions.

This page should have one (1) circle on it when you're done.

DECISION 3

Below are 2 options showing you what you can earn when a numbered ball is chosen from the bingo cage. Choose the one you like best (A or B) by drawing a circle around it. CHOOSE ONLY ONE.

CIRCLE THE ONE OPTION (A or B) THAT YOU LIKE BEST

A	
1-20	$30
21-96	$0
97-100	$40

B	
1-5	$30
6-84	$0
85-100	$40

REMEMBER: Only one of these six decisions will count. Treat each decision seriously and separately. You don't know which one will count until you have made all your decisions.

This page should have one (1) circle on it when you're done.

DECISION 4

Below are 2 options showing you what you can earn when a numbered ball is chosen from the bingo cage. Choose the one you like best (A or B) by drawing a circle around it. CHOOSE ONLY ONE.

CIRCLE THE ONE OPTION (A or B) THAT YOU LIKE BEST

A	
1-80	$30
81-84	$0
85-100	$40

B	
1-20	$30
21-36	$0
37-100	$40

REMEMBER: Only one of these six decisions will count. Treat each decision seriously and separately. You don't know which one will count until you have made all your decisions.

This page should have one (1) circle on it when you're done.

DECISION 5

Below are 2 options showing you what you can earn when a numbered ball is chosen from the bingo cage. Choose the one you like best (A or B) by drawing a circle around it. CHOOSE ONLY ONE.

CIRCLE THE ONE OPTION (A or B) THAT YOU LIKE BEST

A	
1-95	$30
96	$0
97-100	$40

B	
1-20	$30
21-36	$0
37-100	$40

REMEMBER: Only one of these six decisions will count. Treat each decision seriously and separately. You don't know which one will count until you have made all your decisions.

This page should have one (1) circle on it when you're done.

DECISION 6

Below are 2 options showing you what you can earn when a numbered ball is chosen from the bingo cage. Choose the one you like best (A or B) by drawing a circle around it. CHOOSE ONLY ONE.

CIRCLE THE ONE OPTION (A or B) THAT YOU LIKE BEST

A	
1-20	$30
21	$0
22-100	$40

B	
1-5	$30
6-9	$0
10-100	$40

REMEMBER: Only one of these six decisions will count. Treat each decision seriously and separately. You don't know which one will count until you have made all your decisions.

This page should have one (1) circle on it when you're done.

Post-experiment survey

Please do not talk to the other students while completing this survey.

Please complete the following 7 questions. Put an X next to the answer that best answers the question for you.

Please complete all the questions to the best of your ability.

Remember your answers are confidential and no one from your school or your home will see your responses to these questions.

1. Put an X next to the answer that best describes you. Choose only one answer:
   Your mother's only child_________
   Your mother's first-born child ____
   Your mother's last-born child ____
   A middle child (not your mother's oldest child, but not her youngest, either) ______

2. Do you have any older brothers, sisters, step-brothers or step-sisters who live with you now?
   Yes_____ No_____

3. How many of your parents live with you? Include step-parents in your answer.
   0______ 1______ 2______

4. Did your mother graduate from high school?
   Yes____ No_____ I don't know_______

5. Did your mother graduate from college?
   Yes_____ No____ I don't know_______

6. Did your father graduate from high school?
   Yes____ No_____ I don't know_______

7. Did your father graduate from college?
   Yes_____ No____ I don't know_______