# (De-)Biasing *on a Roll*: Changing Gambling Behavior through Experiential Learning

Martin Abel*
Shawn Cole†
Bilal Zia‡§

August 2016

**Abstract**

This paper tests experiential learning as a debiasing tool against gambling behavior in South Africa. We implement a simple, interactive game that simulates the odds of winning the national lottery through dice rolling. Participants roll one and two dice until they obtain simultaneous sixes and are then informed that the odds of winning the jackpot is equivalent to rolling all sixes with nine dice. Individuals who need many (few) attempts play the lottery significantly less (more) than the control group in the following year. We find suggestive evidence that the debiasing affected sensitivity to varying winning odds. These changes cannot be explained by changes in entertainment utility or risk preferences; rather results are consistent with changes in risk beliefs.

**JEL Codes: D03, D12, D81, G02**
**Keywords: Debiasing, Experiential Learning, Behavioral Economics, Financial Education**

---

*Harvard University. Email: abel@fas.harvard.edu. Corresponding author. 79 John F. Kennedy Street, Cambridge, MA 02138, United States. Phone: (207) 319 2967

†Harvard Business School and NBER. Email: scole@hbs.edu

‡World Bank. Email: bzia@worldbank.org

§Acknowledgments: This paper greatly benefited from discussions with and comments from Xavier Gine, David Laibson, David McKenzie, Matthew Rabin, Julius Rüschenpöhler, Andrei Shleifer, Richard Zeckhauser, and conference participants at Yale University, the University of Cape Town, the University of California San Diego, the Rotterdam Behavioral Finance Conference, and the World Bank. Megan Blair, Reinhard Schiel, and Sarah van Vliet provided excellent research assistance. Special thanks to Luke Crowley for creative contibutions to the debiasing intervention. We also thank the International Labor Organization and the World Bank for financial support. All errors and omissions are our own.

# 1 Introduction

Gambling is an ancient human activity practiced in many world cultures and serves as an important everyday pastime in both developed and developing countries (Custer and Milt (1985); McMillen (1996)).[1] The popularity of gambling poses a challenge to the classical theory of decision-making under risk and uncertainty, which posits that risk-averse individuals should avoid gambles with negative expected value (Tversky and Wakker (1995)).

One explanation for gambling that is consistent with rational utility maximization is that individuals understand winning probabilities, but receive utility from gambling which offsets the negative expected payout of the lottery (Kearney (2005)). An alternative set of explanations argues that individuals have cognitive biases that lead to systematic misjudgments of risk, in particular overestimation of small probability events (Tversky and Kahneman (1992); Barberis (2013)). This strand of literature shows that people's risk *beliefs* are affected by heuristics that rely on psychological cues such as ease of retrieval, familiar scenarios, or personal similarities (Jones et al. (1995)). One example particularly relevant for assessing winning probabilities of gambling is the availability heuristic – the tendency to "*assess the likelihood of an event... by assessing the ease with which the relevant mental operation of retrieval, construction, or association can be carried out*" (Kahneman and Tversky (1979)). While availability is generally a useful cue for assessing probabilities as more frequent events are usually recalled better and faster, it can easily lead to the overestimation of the likelihood of emotionally arousing (Nisbett and Ross (1980)) or unusual and salient events (Miller and McFarland (1986); Plous (1993); Bordalo et al. (2012)). This phenomenon is readily apparent in the gambling industry – advertisements of lotteries often emphasize large jackpots, casinos typically have bells that ring if somebody wins a major prize, and betting houses strategically place slot machines in large clusters so gamblers can hear the sound of others winning (Clotfelter and Cook (1989)).[2]

Distinguishing between these explanations is important not only for assessing welfare effects of gambling but for designing interventions aimed at changing gambling behavior. In this paper, we address this important area of research by studying the impact and discerning mechanisms of a gambling debias experiment in a sample of 840 poor households in the Eastern Cape and KwaZulu-Natal province of South Africa.

Our debiasing tool was an experiential dice game which started by asking participants to roll a six-sided die until they obtained a six. We then handed them two dice and asked them to roll till they obtained two sixes, which on average took them much longer. This iteration offered them a

[1] Gambling can be defined as "the act of risking a sum of money on the outcome of a game or event that is determined by chance" (Bolen and Boyd (1968)). It takes many forms, from betting on cockfights in the Philippines, to playing mahjong for money in China, to buying lottery tickets virtually in any part of the world.

[2] Three advertisement schemes are particularly common in the lottery industry in the U.S. (Clotfelter and Cook (2013)): (i) advertizing the size of the jackpot, (ii) emphasizing the fun and excitement of playing, and (iii) highlighting lifestyles of past winners. Example radio advertisement in Arizona: "Every single second, the lottery makes someone very happy. Every single second, someone is cashing a winning ticket."

concrete experience on assessing probabilities. Moreover, depending on how fast participants were able to roll two sixes, they could reflect and update their beliefs about winning odds. We then informed them that the chance of winning the South African national lottery jackpot was smaller than them rolling *nine* dice with all nine showing up sixes.

Our research design features two levels of exogenous variation. First, half the study sample was randomly assigned to receive the debias treatment at the end of a baseline survey on financial access, while the other half received a more traditional financial education module on avoiding expensive credit. Both the debiasing and credit modules took an average of 10 minutes and covered mutually exclusive topics. Second, the number of rolls it took for participants in the treatment group to get two sixes provides additional variation in what we refer to as treatment intensity: the longer it took to roll two sixes, the clearer it became to the participants that their chance of winning was low. This research design allows us not only to report primary impacts of experiential learning on gambling, but importantly to shed light on mechanisms of impact. Specifically, we can test whether impacts were driven by changes in entertainment utility or risk preferences versus changes in risk beliefs. If the debiasing treatment resulted in a general change in risk preferences, we would expect to observe a change in gambling decisions regardless of treatment intensity and regardless of the lotteries' winning odds.

We find support for heuristic-based belief updating in our analysis. Specifically, there is substantial variation in outcomes based on treatment intensity – individuals who needed more than the median number of rolls to obtain two sixes (high intensity) gambled 19 percent less in a lottery offered after the debiasing intervention and were 34 percent less likely to have played the lottery after one year compared to the control group. Conversely, the group with below median number of rolls (low treatment intensity) gambled 29 percent more in a lottery offered immediately after the intervention and was 45 percent more likely than the control group to have played the lottery after one year. These differences are statistically significant at the 5 percent level.

Moreover, our study design allows us to test whether the treatment changed individuals' sensitivity to winning odds. Orthogonal to original treatment status, half the sample was offered a lottery with very low winning odds and the other half was offered a lottery with higher winning odds after six months. Employing a difference-in-difference strategy, we find that the high (low) treatment intensity group indeed showed greater (lower) sensitivity to winning odds than the control group. While these coefficients are large in magnitude they are estimated imprecisely and are not statistically significant at conventional levels. Nonetheless, these results provide some suggestive evidence that the channel of belief updating was through greater understanding of odds rather than simply a changed entertainment utility or perception of luck.

As a third mechanism test, we investigate changes in gambling behavior other than the national lottery. If the lottery effect is driven by a change in overall entertainment utility from gambling or by participants inferring from the dice rolling that they are a lucky or unlucky 'type', we would expect changes in playing the lottery and other forms of gambling to be positively correlated. In fact, we find that participants *substitute* between different forms of gambling and that the overall prevalence of (any) gambling does not differ by treatment intensity, corroborating the conclusion that the debiasing changed beliefs of winning odds – albeit narrowly for the national lottery.

Finally, the analysis addresses the important complementary question of how individuals learn. Specifically, we exploit the exogenous variation in the number of rolls in both the first and second round of dice rolling to study whether the reinforcement effect (difficulty rolling sixes in both rounds) led to a stronger impact than the exponential learning effect (easy first round followed by difficult second round). We find that the debiasing effect is larger for participants with a reinforcing treatment of needing many rolls to get sixes in both rounds compared to those experiencing the more complex lesson that rolling sixes is disproportionally more difficult with each die added.

Our study adds to a rich literature in decision theory that compares decision-making in two contexts: choice alternatives fully described to subjects as probability distributions over potential outcomes versus learning about unknown probability distributions through sampling (repeated draws with replacement) before making decisions (Abdellaoui et al. (2011)). Existing studies typically employ lab experiments in which college students conduct abstract tasks. Our study is among the very first to test experiential learning through a field study that measures real world (gambling) behavior over a longer time period. The lab-based literature finds a robust 'description-experience gap': people who sample outcome distributions act as if they underweight true objective probability of rare events (Barron and Erev (2003); Hertwig et al. (2004), for a review see Hertwig and Erev (2009)). In contrast, our study finds that the effect of experiential learning depends on the actual (random) experience. One possible explanation for this discrepancy is that learning about probability distributions in lab studies is costless and subjects can in a short amount of time gain extensive experience about chance events. Our study exogenously varies the amount of experience where some subjects experience extreme events – this is a more realistic scenario in a world where obtaining feedback from small probability events is often infrequent and costly.

We also contribute to the literature on gambling prevention. Most studies in this area assess information-based programs in schools and universities and find that such interventions can be effective in improving knowledge and reducing misconceptions about gambling (Williams and Connolly (2006)), but fail to reduce gambling behavior (for a review see Ladouceur et al. (2013)). Our study is among the first to employ debiasing techniques to address gambling and to follow participants' behavior over a longer time horizon. One limitation of our setting is that the prevalence of pathological gamblers is very low in our sample, so we cannot test the effect on individuals suffering from gambling disorder. There is reason to believe that treatment effects may differ for this population as addictive gambling behavior has been linked to neurobiological and genetic factors (Clark and Limbrick-Oldfield (2013), for a review see Hodgins et al. (2011)).

Overall, our research is one of the first field studies that shows experiential learning in general and experiential debiasing in particular have the potential to be promising alternatives to the traditional method of conveying information. Insights from educational theory suggest that experiential learning may be a particularly promising strategy in the context of developing countries. The four-stage learning cycle model used in the psychology literature posits that learning is most effective if participants can test relationships between experiential learning (e.g. dice rolling) and abstract concept (winning probabilities) through active experimentation (Zull (2002)). To the extent that developing country economies have less division of labor, agents may be more likely to observe the relationship between actions and outcomes (Hanna et al. (2014)). Finally, experiential learning is less taxing on cognitive resources, which is conducive in environments where people are less likely to have developed analytical skills in school (Bell et al. (1988)).

# 2 Experiential Learning and Game Design

## 2.1 Debiasing through Experiential Learning

The effectiveness of teaching financial concepts in standard classroom settings is often constrained by limited numeric skills, low arithmetic intuition, and general lack of interest among participants. As a result, many evaluations of financial education programs have found only limited impacts on financial outcomes (see Fernandes et al. (2014); Xu and Zia (2013); Miller et al. (2014) for literature reviews).

While standard financial education has failed to establish a stronghold in the literature on savings and credit decisions, the domain of gambling presents an even greater hurdle as understanding the pitfalls of gambling requires knowledge of probabilities. In developing countries where poor individuals have limited or no formal schooling, even understanding simple math problems is a substantial challenge (see for example Cole et al. (2011)). Insights from behavioral economics, however, can help design interventions that address cognitive biases rather than focusing on pure knowledge transmission (Fischhoff (1982)). One of the main insights of this literature is that a wide range of factors such as framing or context affect individuals' assessment and internalization of knowledge. Consequently, it is unlikely that there is '*one way to perfect intuitive judgment*' (Griffin and Buehler (1999)). Rather than finding a general method to improve decision making, Heath et al. (1998) conclude that different interventions may be effective in different circumstances. These insights are important in the context of financial decision making, where simply telling people about their cognitive biases has not proven to be effective. Debiasing interventions have tried three types of methods (for a review see Soll et al. (2014): (i) repeat interaction with immediate unambiguous feedback, (ii) consider the opposite, and (iii) counter-biasing (Willis (2008); Jolls and Sunstein (2006)).[3]

The first method of immediately providing feedback on an action has been used successfully in

[3] One additional method previously proposed by supporters of the 'ecological rationality' theory is to specifically address poor understanding of probabilities is to use frequencies rather than probabilities to communicate odds (Hoffrage and Gigerenzer (1998)). Hoffrage and Gigerenzer (1998) called this "*the strongest and most consistent debiasing method known today*". However, other research has shown that under most real-life circumstances, intuitive judgments are equally biased regardless of whether are presented in frequencies or probabilities (Griffin and Buehler (1999)).

the lab to address overconfidence (Lichtenstein and Frischhoff (1980)). However, getting feedback on financial decision making in a classroom setting has not proven to be effective (Prabhu and Tellis (2000)). Likewise, applying this method through educational financial games has led to some improvement in financial knowledge, but does not appear to have translated into improvements in financial decision making (Mandell (2006)). The 'consider the opposite' method has been implemented by asking participants to list alternative choices before making a financial decision. Theory predicts that participants place increasing weight on these alternatives as they become more mentally available. However, the few studies that have tested the effectiveness of this method have found little or no results (Trout (2005)). The third method of 'counter-biasing' builds on the premise that cognitive biases may be used to induce desired behavior (Jolls and Sunstein (2006)). One example is the well-known 'save-more-tomorrow plan' that is built on the premise that people do not change saving rates they initially chose as a default (Thaler and Benartzi (2004)).

The experiential learning approach contrasts to traditional forms of financial education based on cognitive learning theories that '*emphasize cognition over effect*' (Boyatzis et al. (1999)). Kolb (1984) argues that '*learning is not just the result of cognition,* [it] *involves the integrated functioning of the total person - thinking, feeling, perceiving, behaving.*" This insight is captured in the concept of the four-stage learning cycle which posits that learning is most effective if it involves four aspects: an (i) immediate experience forms the basis for (ii) observations and reflections which are then (iii) distilled into abstract concepts (Boyatzis et al. (1999); Zull (2002)). These concepts are subsequently (iv) actively tested which leads to new experiences.[4]

Lecture-based learning is less likely to activate all stages in the learning cycle. Traditional forms of financial education interventions may only convey abstract concept that are not actively tested and thus do not lead to new experiences. A reflection on the lesson learned is unlikely and the content may be quickly forgotten amidst the daily challenges and obligations people face.

### 2.2 Game Design

In this study we play a simple dice game with participants to provide an experience-based learning forum to convey low probabilities of gambling. Gambling prevalence is often explained by the fact that individuals do not understand how low probabilities translate into the frequency of winning as probabilities such as 14 million to one are unlikely to lie within the range of everyday experiences (Smith and Walker (1993)). Hence, our game was meant to provide an intuitive mapping of probabilities through active experimentation.

The game used regular six-sided dice as props and was administered in the field at the conclusion of a baseline survey on financial access. The game was administered by our trained staff and at the

[4]Neuroscience research shows that the different stages of the cycle of experiential learning corresponds to the structure and process of brain functioning. Zull (2002: 18-19) explains that "*...concrete experiences come through the sensory cortex, reflective observations involves the integrative cortex at the back, creating new abstract concepts occurs in the frontal integrative cortex, and active testing involves the motor brain. In other words, the learning cycle arises from the structure of the brain.*"

individual respondent level (see Appendix A for the exact protocol used). We first let participants roll one die until they obtained a six. Then we added another die and let them roll until they simultaneously obtained two sixes, which took them much longer. The participants were then told the equivalence of number of dice and the odds of winning different prizes in the lottery. The chance of having four right numbers in the lottery, for example, was equivalent to rolling all sixes with five dice and the odds of winning the jackpot was smaller than getting all sixes with nine dice.

The study sample consisted of 840 individuals from the Eastern Cape and KwaZulu-Natal province of South Africa. Half the study sample was randomly assigned to receive the debias treatment while the other half received a more traditional financial education module on avoiding expensive credit. (For the expensive credit treatment protocol see Appendix B.) Both the debiasing and credit modules took an average of 10 minutes and did not have any overlapping content.

In contrast to lecture-based learning, the starting point of our intervention is the active experience of rolling dice and the game incorporates elements from each of the learning models discussed above. Rolling dice provides the participants with immediate feedback on probabilities of winning in a lottery (presented by getting a certain number of sixes) and the intervention serves as a memorable event that can form the basis of a new decision heuristic. Participants are able to reflect on the difficulty of obtaining sixes and the facilitator explains the link between dice rolling and the abstract concept of lottery winning probabilities. Likewise, playing a game with dice allows the complex notion of probability to be conveyed in a low-key setting without taxing the cognitively heavy systems of attention and memory.

# 3 Empirical Setting and Identification

## 3.1 Gambling in South Africa

Since the legalization of gambling in 1996,[5] the South African gaming industry has grown substantially with gross revenues more than doubling between 2001 and 2009 to 18.13 billion Rand (1.57 billion USD) (Nzimande et al. (2010)). The prevalence of gambling is also quite skewed – a 2003 survey found that while 43% of the population participated in some form of gambling, poorer household spent a significantly higher percentage of total income on it (Smith and Walker (1993)). Further research in the country has shown that gambling is most prevalent among blacks, with 56.7% of urban residents reporting that they gambled at least occasionally (Kincaid et al. (2013)). When asked why they gamble, 85% of respondents mentioned the chance of winning a large prize. This study also highlighted that gambling is quite socially acceptable in South Africa with 69% of respondents reporting that either some or all forms of gambling 'was ok'. We focus on one particular form of gambling, the national lotto. A 2009 regional study in the Eastern Cape showed that playing the lottery was by far the most common form of gambling in the area – 49%

[5]During apartheid, all forms of gambling were prohibited under the 1965 National Gambling Act (no 15). The National Party denounced gambling as an "immoral evil" undermining the work ethic by encouraging reliance upon luck rather than hard work and skill (Lotter 1994, p.192).

of respondents had tried it at least once and active gamblers played an average of 3.5 times per month (TNS (2009)).[6]

### 3.2 Study Sample and Outcome Measures

This study was part of a broader program that delivered classroom based financial education to individuals in rural and peri-urban areas.[7] Participants were organized in burial societies and women borrowing groups.[8] We conducted surveys in 13 geographic clusters in the Eastern Cape and KwaZulu Natal, two of South Africa's most populous provinces.

A total sample of 840 individuals was drawn from 27 women borrowing groups and 45 burial societies. Baseline characteristics of the sample were measured between July and November 2011 and are reported in Table 1. As the majority of burial society members were female, our sample consists of almost 90% women. Our sample is also older (53 years vs. the national average of 39 years), less educated (6.4 vs. 7.5 years), and less likely to be employed (7.3% vs. 23.4%). At the time of the baseline survey, 15% of the sample reported that they had previously gambled. This figure is considerably lower than the national average, likely because gambling is less common among women and older individuals in rural areas.

During the course of the study we measured gambling outcomes at three stages, immediately after the treatment during baseline, after six months, and after one year.

i) Immediate outcome: Following the baseline survey, participants received 10 Rand ($1.00) and were offered to spend part of this compensation in the following game. First, they were shown a bag with fifty balls, in which five balls were red. Participants were then offered the opportunity to pay 1 Rand from their show-up fee to draw a ball (which was replaced after each round). If they drew a red ball they would receive 5 Rand in return. They were allowed to play up to ten times. On average, participants played 0.8 rounds. 57% of people decided not to play this gamble.

ii) Midterm outcome: About six months after the debiasing treatment, participants were contacted via cell phone to collect an intermediate gambling outcome. Participants were offered the choice of a lottery in which they could win R250 or to receive R15 for certain (all prizes were delivered as cell phone airtime). To mimic the experience of playing the lottery, participants were asked to guess which six numbers between 1 and 49 were drawn at the national lottery at an undisclosed particular date over the past six months. The winning odds were randomly assigned within each group:[9] half of the participants were told they would win if they picked all six numbers correctly

[6] The lottery has distinctive features that distinguish it from other forms of gambling: it has large prizes and very low winning odds, is cheap to play, fair in the sense that it does not depend on skills, and regarded one of most socially acceptable forms of gambling (Rogers (1998)).

[7] As part of a different study, half of the group in the sample received a half-day financial education training between March and June 2012. As the gambling debias was randomly assigned at the individual level, these two treatments are orthogonal. In addition, the financial education curriculum did not include any information on gambling. All estimations in this study control for whether participants received the financial education program.

[8] Burial Societies are a common form of associations to save for the typically large costs of funerals in South Africa.

[9] Within the treatment group, random assignment was stratified along treatment intensity (above vs. below median number of rolls).

(odds 1:9,355,819), while the other half were told they would win if they picked at least four correct numbers (odds 1:800). These exact winning odds were not disclosed to participants. Overall, 26.6% of the participating sample chose to play the lottery, of which nobody won.

iii) Endline outcome: Between June and November 2012, approximately one year after the debiasing treatments were administered, an in-person endline survey was administered that collected data on gambling behavior of participants in the last six months. Information was also collected on a range of financial behaviors and attitudes. Note that although endline outcome measures are self reported, our empirical strategy exploits variation in the intensity of treatment rather than the binary effects of treatment. Since all respondents in this sample received the same treatment (but experienced different intensity due to the roll of dice) we are not concerned about reporting biases.

### 3.3 Empirical Strategy and Identification

In the spirit of Crepon et al. (2013), this study employs two stages of exogenous variation. In the first stage, participants were randomly assigned to receive either the gambling debias or credit information treatment. In the second stage, the number of rolls it took treated participants to roll two sixes provided additional random variation in treatment intensity. For instance, participants who, by chance, rolled two sixes on the third try received a less intense debiasing treatment than participants who needed thirty rolls. We take advantage of this exogenous variation in treatment intensity to test the various theories of behavior change discussed in Section 5.2.

The control group received a treatment on credit to allay concerns of Hawthorne effects (see Appendix B for details). The two interventions were unrelated in content – the gambling intervention did not mention hire purchase credit, or even interest rates; and the credit intervention did not discuss lotteries, odds, or gambling.[10] However, since the unit of randomization was the individual rather than the village, there may be knowledge spillovers. Participants may have talked about their particular intervention with individuals in the same saving or borrowing group who were part of the control group. Any learning spillovers within a group would also lead to a downward bias of our results. Since we cannot rule this out, our results should be interpreted as a lower bound of the true effect.

In Table 1 we test for balance across the treatment groups and find that the random assignment at the two stages resulted in groups that were balanced across a range of observable baseline characteristics. The left panel in Table 1 reports the sample means and p-value of a test of equal means between the gambling debiasing group (T) and credit information participants who served as the control group (C). Of the 15 baseline characteristics tested, only one difference in means is (marginally) significant.

[10]We designed the hire purchase intervention as a form of 'placebo treatment'. While it is theoretically possible that a better understanding of compound interest rates would also affect comprehension of low probabilities, this would only bias our treatment effects downwards. Another potential concern might be if the hire purchase debiasing intervention had a large effect on participants monthly expenditure: we may then observe increases or decreases in gambling due to wealth or liquidity effects. However, we do not observe changes in financial behavior or in discretionary income as a result of the hire purchase intervention.

Figure A.1 (Appendix) shows the distribution of number of rolls it took people in the sample to get two 6s. While the distribution is roughly normal, there are spikes at 15, 20, and 25 rolls. This resulted from field workers using different stopping rules, i.e. some stopped the demonstration after 15 or 20 rolls if the participant had not rolled two sixes by then. We will therefore divide the sample into two treatment intensity groups depending on whether they needed more than the median (N=12) number of rolls. The rationale is that there are no clear excess mass in the distribution below the median, e.g. at 5 or 10 rolls. The assignment to the low vs. high intensity treatment group is therefore independent of the stoppage rule used by field workers. The key question for the identification strategy is whether the assignment to treatment intensity within the gambling debiasing group is orthogonal to the baseline characteristics.

The right panel of Table 1 reports a balance test of the randomization resulting from dice rolls. The first two columns report average baseline characteristics of the low intensity (below median rolls) and high intensity (above median) treatment groups. The last column reports p-values of a test of equal means between the control and two treatment groups. Similar to the previous test, only the difference in share of women between the different groups are statistically significant. When we simultaneously control for all covariates in a regression with the number of rolls to get two sixes or an indicator variable for high intensity as the dependent variable, none of the baseline characteristics are statistically significant.[11]

While other differences in baseline characteristics are not statistically significant, some may still be economically meaningful. In particular, 14% of people in the high intensity treatment group had gambled before compared to 11% in the low intensity group. With a marginally higher share of gamblers in the high intensity group, a simple comparison of means may underestimate the true treatment effect. In the empirical analysis we therefore report results with and without controlling for these covariates.

Attrition was not an issue for the immediate outcome measure since it was captured immediately after the baseline survey. For the midterm outcome data collection, we successfully reached 74% of the sample via phone, of which 78.4% agreed to participate. Results from a linear probability regression (Table 2, Columns 1-4) show that both the probability of reaching individuals and their decision to respond to the survey were not systematically correlated with treatment assignment, nor with the number of die rolls they required to obtain two sixes. As an additional test, we find that the decision to participate in the midterm survey was not significantly correlated with the gambling decision in the immediate outcome measure. This supports the view that attrition does not bias results.

Overall attrition in the endline was 30.4%. This attrition rate is relatively high, however, it was primarily due to a hardware failure: all data from certain clusters was lost when the digital devices used to conduct the surveys failed to synchronize. This reduces the precision with which we can

[11] Simulation exercises (not reported) shows that our observed median value is lower than the simulated median value suggesting that some surveyors may have stopped even before reaching 15 rolls, which would bias our results towards zero.

estimate outcome measures collected at the endline. However, Table 2 shows that the attrition rates did not vary significantly between treatment and control groups (Column 5) or between the treatment intensity groups (Column 6).

### 3.4 Estimation

Our main regression specification is as follows:

$$y_i = \alpha_0 + \beta_1 T_{low} + \beta_2 T_{high} + \gamma X_i + e_i \quad (1)$$

$y_i$ refers to the outcome of person $i$. $T_{low}$ and $T_{high}$ are indicator variables for gambling debiasing participants that took below and above median number of rolls to get two 6s, respectively. Coefficient $\beta_1$ and $\beta_2$ estimate the average effect of being in the low and high intensity treatment group compared to the control group, respectively. $X_i$ is a vector of baseline covariates including gender, age, education levels, income level, and indicator variables for whether the person gambled before and uses formal financial services. We control for these covariates to increase the precision of treatment estimates. Regressions are estimated using robust standard errors $e_i$. We also report F-Test p-values of equality between $\beta_1$ and $\beta_2$.

As further discussed in Section 5.2, we test whether treated individuals became more sensitive to changing winning odds of a lottery. We do so by estimating the following specification:

$$y_i = \alpha_0 + \beta_1 T_{low} + \beta_2 T_{high} + \eta odd_g + \delta_1 T_{low} * odds_g + \delta_2 T_{high} * odds_g + \gamma X_i + e_i \quad (2)$$

The variable $odds_g$ refers to the randomly assigned better winning odds in the midterm outcome. Estimates of $\delta_1$ ($\delta_2$) show how the odds sensitivity of the low (high) intensity treatment group compare to the control group. F-test p-values of equal coefficients ($\delta_1 = \delta_2$) are also reported.

## 4 Results

### 4.1 Gambling Behavior

The analysis takes advantage of the fact that we have gambling outcome variables for individuals at three points in time, as described in the previous section. Hence, to maximize statistical power, we aggregate outcomes for individuals across time and create an index of lottery outcomes, following Kling et al. (2007).[12]

Table 3 reports regression results using both the lottery index and individual survey measures as the dependent variables. Column 1 shows that the average treatment effect is close to zero and statistically insignificant. This suggests that in the aggregate, gambling behavior did not change in

[12]The index is created by adding values for the two indicator outcomes (midterm , endline) and a standardized measure of the number of rounds played (immediate).

the treatment group. Columns 2 to 4 report results of regression model 1 that estimates differential treatment effects between the high and low treatment groups. Column 2 shows that results vary significantly between the two groups – the low intensity group, where individuals needed fewer attempts to get two sixes, gambled significantly *more* than the control group, while the high intensity group gambled significantly *less*. The treatment coefficients (compared to the control group) are statistically significant at the 5% and 10% level, respectively. The difference between the high and low treatment coefficients is also significant at the 1% level as indicated by the p-value of the F-test reported in the bottom row of Table 3. Results do not change in magnitude or statistical significance when we control for additional baseline covariates in columns 3 and 4.

Table 3 also reports results of the same regression specification estimated separately for the three gambling outcomes that comprise the lottery index. All gambling outcomes show a consistent picture: the high treatment intensity group gambled less and the low treatment group gambled more relative to the control group. Estimated effects are large in magnitude. Individuals in the high treatment group gambled 29% less in a lottery offered after the debiasing intervention while the low treatment intensity group gambled 19% more compared to the control group in a lottery offered immediately after the intervention. It is noteworthy that the effects persist one year after the intervention – in the final follow-up, 10.7% of people in the low treatment intensity group reported playing the lottery compared to 7.4% in the control group. The equivalent figure for the high treatment intensity group was 4.7%. The p-values on the F-tests are statistically significant, hence showing that the differences between high and low intensity groups are significantly different from each other.

As discussed earlier, our main specification divides the treatment intensity into above and below median, because of differential stoppage rules. We can nevertheless examine how decisions vary when using all available variation in treatment intensity. Figure A.2 shows the relationship between the full distribution of treatment intensity and the lottery index non-parametrically. Fitting a local polynomial function using a Epanechikov kernel confirms a relatively monotonic negative relationship between the number of rolls and gambling behavior.

## 4.2 Odds Sensitivity

Next we explore whether the debiasing treatment led to a change in the sensitivity to winning odds. As described above, our study design randomly varied the winning odds of gambles offered to the sample at midterm. Figure 2 shows the effect of improving the winning odds (from having to get all six numbers right to having to get at least four right) on the probability that a participant chooses the lottery over a certain amount, separately for the high and low treatment intensity groups. Improving winning odds induces individuals in the high intensity group to increase the take-up of the lottery from 13% to 30% (middle panel), whereas there was no such change for the low intensity group (right panel).

Table 5 reports these results in a regression framework. Column 1 shows that when we pool winning probabilities in the full sample, higher winning odds are associated with a higher probability of choosing the lottery. As shown in the graph, the low intensity group was more likely and the high intensity group was less likely to choose the gamble compared to the control group. While large in magnitude these estimates are not significant at conventional levels. The p-value of a test of equal coefficients between the two treatment groups is 0.175. The specification in Column 2 includes interaction terms between the treatment groups and the better odds dummy. The coefficients on these interaction terms suggest that the low intensity group was less sensitive and the high intensity group was more sensitive to changing winning odds than the control group. However, the test of equal coefficients of these interaction terms ($\delta_1$ and $\delta_2$) cannot be rejected at significant levels (p-value=0.178). While we lack the statistical power to provide conclusive evidence, these results provide some suggestive evidence that at the change in gambling behavior can at least partly be explained by a change in sensitivity to winning odds. This question should be explored in future research.

# 5 Mechanisms

## 5.1 Framework

The intuition and conceptual framework of our study builds on Kahneman and Tversky's prospect theory. A decade after introducing the concept of heuristics and cognitive biases, Kahneman and Tversky (1982) suggested a second reason for why people systematically misjudge probabilities. Analyzing data on gambling, they noticed that the increase in winning odds from 0% to 5% had a larger effect on the inclination to gamble than the increase from 30 to 35% which in turn had a lower effect than an increase in odds from 95% to 100%. They concluded that the "*psychophysics of chance induce over-weighting of sure things and of improbable events, relative to events of moderate probability*" (Kahneman and Tversky 1982), and introduced the concept of a probability weighting function that translates objective probabilities $p$ into weights $\pi(p)$ used in decision making.[13]

Gonzalez and Wu (1999) note that there are two distinct features that characterize the probability weighting function: the degree of curvature and the elevation (level). The curvature of the weighting function, also referred to as *discriminability* in the psychophysics literature, reflects how sensitive people's decisions are to a change in (objective) probabilities $p$. A flatter slope than 45% degree line means that people are too insensitive to a change in probability. Conversely, the steeper the curvature of the weighting functions the more sensitive individuals are to changing probabilities. The observed inverse-S-shape of the probability function implies diminishing sensitivity to proba-

[13]Figure 1 shows the shape of the decision weighting function that corresponds to Kahneman and Tversky's observations. Decision weights lower than objective probability values near $p = 1$ corresponds to the tendency to be risk averse in dealing with unlikely losses. By contrast, decisions weights higher than actual probability values near $p = 0$ reflect that the tendency to be risk seeking in dealing with improbable gains such as winning the lottery. Several subsequent empirical studies have provided evidence consistent with this shape of the probability weighting function (Tversky and Kahneman (1992); Gonzalez and Wu (1999); Camerer and Ho (1994)). Quiggin (1982) pointed out that KT's originally proposed probability weighting function can lead to violations of stochastic dominance. Subsequently, the concept of cumulative prospect theory was developed in which agents transform cumulative instead of individual probabilities and base decisions on the ranking of outcomes (Tversky and Kahneman (1992)).

bilities further away from the two reference points of uncertainty ($p = 0$) and certainty ($p = 1$). The level of the weighting function, referred to as *attractiveness*, can be interpreted as the interpersonal preference of individuals to take risk and bet on chance events (Gonzalez and Wu (1999)).[14] The concepts of attractiveness and discriminability are two independent psychological properties. This distinction helps understand different mechanisms through which debiasing interventions may reduce people's inclinations to gamble.

## 5.2 Changing Beliefs or Preferences?

Kahneman and Tversky (1979) observe that people have "*limited ability to comprehend and evaluate extreme probabilities.*" It is commonly overlooked that this statement captures two distinct concepts: comprehension and evaluation of unlikely events. Fox et al. (1996) model decision making as a two-step framework: first, individuals assess the probability of events and second, they make decisions based on the assessed likelihood (Barberis (2013)). In the context of our study, the question is whether people changed their beliefs of winning odds and/or whether, conditional on assessed probabilities, participants over-weighted the chances of this event in their decision-making. The difference between these two mechanisms is visualized in Figure 1. We may observe a decrease in gambling because people change their *beliefs* about the odds of winning (depicted by a change from $b$ to $a$ due to a change in assessed probability $p$) or because participants change their risk *preference* for given winning odds (depicted by a change from $a$ to $c$ and $b$ to $d$ due to a vertical change in decision weight $\pi(p)$).

The distinction between changes in beliefs and preferences is important because "*overestimation is a mistake; it is less clear that over-weighting is a mistake*" (Barberis (2013)). These two mechanisms have different predictions. A change in *risk preference* would be regarded as a change in the decision weights or the inclination of people to accept any lottery ('attractiveness').[15] Importantly, the treatment effect would be observed across varying treatment intensities and range of (low probability) winning odds. Alternatively, changes in *beliefs* or risk perception would affect people's sensitivity to winning odds ('discriminability'), i.e. individuals' inclination to base gambling decision on the odds offered. The behavioral economics literature offers concrete explanations why our treatment may affect *beliefs* of winning the lottery (e.g. availability heuristic, discussed in Section 6). Importantly, the direction of belief updating underlying these behavioral mechanisms would depend on the intensity of treatment.

[14] There may also be intra-personal difference of chance domains: holding winning odds constants, individuals may prefer betting on sporting events compared to outcomes of political elections (Heath and Tversky (1991)). This is related to the concept of 'illusion of control' (Langer (1975)): gamblers prefer to choose their own numbers in a lottery rather than playing with assigned numbers even though the winning odds of each combination is identical.

[15] Attractiveness may also be affected by changes in salience bias (Bordalo et al. (2012); Gennaioli and Shleifer (2010)). Bordalo et al. (2012)Bordalo et. al's (2012) salience theory is consistent with agents who comprehend (small) probabilities, but whose risk attitudes are affected by the salience of lottery payoffs. However, since the salience of lottery prices did not differ between treatment groups and the control group in our study, it is unlikely that this mechanism explains our results.

### 5.3 Evidence

The first test to shed light on the underlying mechanism is whether behavior change varies across treatment intensities; indeed, we find that the treatment effect goes in polar opposite directions depending on the treatment intensity (Section 4.1) providing evidence against a change in risk preference as the driving mechanism of behavior change. Second, we test whether the debiasing treatment affects individuals' sensitivity to winning odds. Half the sample was offered a lottery with very low winning odds ($p_l$) and the other half were offered a lottery with higher winning odds ($p_h$). As per Table 4, the difference between cells $[a, b]$ and $[c, d]$ shows how the debiasing treatment affected the odds sensitivity, with a larger difference in $d - c$ relative to $b - a$ indicating a greater change in risk beliefs for given risk preferences (Figure 1). The difference-in-difference strategy employed in Section 4.2 finds large effects (albeit not statistically significant) on the odds sensitivity, correlated with treatment intensity.

Finally, we can directly observe whether the debiasing led to a substitution to other forms of gambling. If the lottery effect is driven by a change in overall entertainment utility from gambling or by participants inferring from the dice rolling that they are a lucky or unlucky 'type', we would expect prevalence of other forms of gambling to move in the same direction as changes in playing the lottery. Conversely, if individuals update beliefs on lotteries through a new heuristic or changed odds sensitivity, they may decide to substitute to other forms of gambling (e.g. scratch cards) that do not deal with lottery odds. Results reported in Table A.1 show that individuals indeed substituted between different types of gambling based on treatment intensity. The low intensity treatment group was more likely than the control group to play the lottery but less likely to play scratch cards while the high intensity treatment group was significantly more likely to switch and play scratch cards instead of the lottery. This substitution between different forms of gambling further corroborates that the intervention changed beliefs of winning odds (albeit narrowly for the national lottery).

Taken together, these three tests point to changes in risk *beliefs* rather than general risk *preferences* as the mechanism of impact on gambling outcomes.

## 6 Discussion

### 6.1 What Can Explain the Large Effects?

Given that most previous studies in the financial education and debiasing literature have found modest results, it may be surprising that a simple experiential debiasing treatment that did not take more than ten minutes led to large and persistent treatment effects. The gambling treatment may have been more effective in changing beliefs on gambling winning odds for at least three reasons. First, as pointed out by Heath et al. (1998), while debiasing techniques that build on preexisting knowledge make behavior changes less costly, they also do not create much enthusiasm and are more likely to get ignored. Our study implemented debiasing techniques through experiential learning combining both novel and familiar elements: while participants were generally familiar with the concept of rolling dice, they were unfamiliar with linking it to winning probabilities of the lottery. This explanation is supported by experiences from field workers who reported that most participants were intrigued by the dice game. As discussed in Section 2, the intervention may have thus activated more stages of the learning cycle.

Second, we may observe large effects because the treatment had elements of a 'counter-biasing' strategy (Jolls and Sunstein (2006). The experience of getting all sixes in both the one die and two dice round with only few rolls combined with information that the chances of winning the lottery jackpot are equivalent to adding 'only' seven additional dice may have caused a strong emotional reaction. This memorable event may have become the basis of a new availability bias: study participants that needed many rolls and thus memorize the difficulty of winning gamble less than the control group, while low treatment intensity participants remember the ease of winning and gamble more.[16] Along similar lines, Griffin and Tversky (1992) and Fischhoff and Hall (1992) show that people are imperfect when updating their beliefs with new evidence: the strength of the evidence tends to dominate its weight compared to predictions of a Bayesian model. For example, when testing the bias of a coin, people make their judgment primarily by the proportion of tails and heads in the sample with insufficient consideration of the sample size (Slovic and Lichtenstein (1971); Rabin (2002)). Consequently, people are overconfident in evidence generated by small samples.

Third, our study sample is very different from those of previous studies, which in most cases conducted lab experiments in developed countries. Our sample of women in rural South Africa with relatively little formal education may have been particularly receptive to the interactive and intuitive nature of learning about probabilities. This explanation is supported by earlier research showing that debiasing techniques tend to be more effective if they are simple as they do not tax cognitive resources like memory or attention (Bell et al. (1988)).

Next, we discuss whether there are reasons to believe that our results translate to other populations or whether there was something particular about our sample that made participants particularly receptive to the debiasing intervention.

### 6.2 External Validity: How Did Individuals Learn?

A natural question that arises is whether our intervention would yield similar effects among other samples and in different setting. The education literature indeed finds that individuals have different

[16]Finding of earlier research showing that emotional events are particularly effective in creating cognitive biases (Nisbett and Ross (1980)), is supported by the fact that the effects of the low intensity treatment (which may have led to an overestimation of the jackpot winning odds) are consistently larger in magnitude than effects of high treatment intensity.

optimal learning styles and a teaching method that worked well in rural South Africa may not be effective in a different environment. Specifically, learning styles can be categorized along two dimensions: (i) modes of grasping experience and (ii) modes of processing experience. In grasping experience, some learn new information best through "*experiencing the concrete, tangible, felt qualities of the world, relying on our sense*" whereas others absorb new information through abstract conceptualization that includes contemplating and analyzing experiences (Kolb and Kolb (2005)). Similarly, individuals differ in how they process experience: some favor reflective observations that include careful observation of peers while others prefer active experimentation.

While optimal learning styles were initially believed to be individual specific and fixed, recent studies have argued that they are instead dynamic and depend on the environment and past life experiences. It seems likely that the environment poor individuals in developing countries face would favor a learning style that focuses on concrete experiencing and active experimentation. First, there is less division of labor so individuals observe the relationship between actions and outcomes without needing to reason about the underlying mechanism or complexity. For example, observing the behavior of seaweed farmers in Indonesia, Hanna et al. (2014) note that farmers unintentionally experiment in the production process by varying pod sizes. Second, individuals with less schooling may be less likely to develop analytical skills needed for abstract conceptualization and reflective observations. Hence, experiential learning interventions may be particularly relevant for individuals with such accommodating learning styles who primarily learn from 'hands-on' experience and tend to act on 'gut' feelings instead of logical analysis (Boyatzis et al. (1999)).

The data in our study allows us to shed some light on how individuals learn, which helps address the external validity question. We are particularly interested in whether participants with little formal education gained an intuitive understanding of the relatively sophisticated debiasing concept that rolling additional sixes gets *exponentially* more difficult with each die added. We take advantage of the fact that we have two independent treatment indicators for each participant: the number of times to get a six with one die (round 1) and the number of times to get all sixes with two dice (round 2). To provide intuition for our test of learning mechanisms, imagine two participants who both needed 15 rolls to get both sixes in round two. Person A took ten times to get the six in round 1 whereas it took Person B only two times. In theory, the overall treatment could be more effective for either person. For person A, both rounds convey the same message that it is very difficult to get sixes. For person B, the treatment may be more effective because the larger difference in number of attempts in the two rounds better conveys the message that getting all sixes becomes increasingly difficult with each additional die. This is particularly relevant because our treatment message, comparing the odds of winning the lottery jackpot to the odds of rolling all sixes with nine dice, is based on the concept of this exponential increase in difficulty as dice are added.

To distinguish between these two possible learning mechanisms, we divide the sample in each round along the median number of rolls and compare the four possible combinations of treatments. Table 6 shows the results of this analysis. Column (2) reports results of the previous analysis of round two (two dice). Column (1) shows results of the same econometric specification using only the information of round 1 (one die). The coefficients are of the same sign as for round 2 but not statistically significant. It is also reassuring that the coefficient is much smaller as the treatment is weaker compared to rolling two dice. Column (3) reports results of the previously discussed analysis with the treatment groups divided into four groups depending on whether participants needed above or below median number of rolls in the two rounds. The only significant coefficients are for people that had the same outcome in both rounds (</<and >/>) which provides evidence in support of the theory that reinforcement is more effective. Comparing participants in our motivating example corroborates this conclusion. Person B (>/>) gambles less than person A (</>). The difference in coefficient is statistically significant at the 10 percent level as reported in an F-test in the last row.

Overall, these results suggest that reinforcement of the same lesson in both rounds is the most effective treatment. Taken at face value, this finding confirms that experiential learning may be most effective for people without strong abstract reasoning skills as the concept of an exponential increase in difficulty is more sophisticated than the concept of reinforcement.

## 7 Concluding Remarks

In this paper, we test whether experiential learning about lottery odds through a simple and interactive dice game can lead to meaningful impacts on gambling behavior. We find significant heterogeneity in impacts based on the intensity of treatment with the high (low) intensity treatment group exhibiting reductions (increases) in gambling behavior and increased (reduced) sensitivity to winning odds. These results are consistent with a model where individuals update their beliefs about lottery winning odds through the experience of the game.

Our study is one of the first pieces of field research that shows experiential learning in general and experiential debiasing in particular have the potential to be a promising alternative to the traditional method of conveying information, especially for people with little formal education. Yet, the perverse results for the low intensity treatment group serve as a caution that debiasing instruments can potentially backfire. Future programs should be designed to take into account and minimize this risk. In our specific game design, this perverse outcome could easily have been mitigated, for instance by adding a third die to the game. Future research should also explore whether similar interventions prove to be effective in changing behavior in domains like technology adoption or financial decision making in which lecture-based provision of information has been shown to be ineffective.

## References


Abdellaoui, M., O. L'Haridon, and C. Paraschiv (2011). Experienced vs. Described Uncertainty: Do we need two Prospect Theory Specifications? *Management Science 57*, 1879–1895. 4

Barberis, N. (2013). The psychology of tail events: Progress and challenges. *American Economic Review 103*(3), 611–616. 2, 14

Barron, G. and I. Erev (2003). Small feedback-based decisions and their limited correspondence to description-based decisions. *Journal of Behavioral Decision Making 16*, 215–233. 4

Bell, D., H. Raiffa, and A. Tversky (1988). *Decision making: Descriptive, normative, and prescriptive interactions.* 5, 16

Bolen, D. and W. Boyd (1968). Gambling and the gambler: A review and preliminary findings. *Archives of General Psychiatry 18*(5), 617–630. 2

Bordalo, P., N. Gennaioli, and A. Shleifer (2012). Salience theory of choice under risk. *The Quarterly Journal of Economics*, 1243–1285. 2, 14

Boyatzis, R., D. A. Kolb, and C. Mainemelis (1999). Experiential Learning Theory: Previous Research and New Directions. *Working Paper*. 6, 17

Camerer, C. and T.-H. Ho (1994). Violations of the betweenness axiom and nonlinearity in probability. *Journal of risk and uncertainty 8*(2), 167–196. 13

Clark, L. and E. Limbrick-Oldfield (2013). Disordered gambling: a behavioral addiction. *Current Opinion in Neurobiology 23*(4), 655–659. 4

Clotfelter, C. and P. Cook (1989). The demand for lottery products. *NBER Working Paper* (2928). 2

Clotfelter, C. T. and P. J. Cook (2013). On the Economics of State Lotteries. *Journal of Economic Perspectives 4*(4), 105–119. 2

Cole, S., T. Sampson, and B. Zia (2011). Prices or Knowledge? What Drives Demand for Financial Services in Emerging Markets? *Journal of Finance 66*(6), 1933–1967. 5

Crepon, B., E. Duflo, M. Gurgand, R. Rathelot, and P. Zamora (2013). Do labor market policies have displacement effects? Evidence from a clustered randomized experiment. *The Quarterly Journal of Economics 128*(2), 531–580. 9

Custer, R. and H. Milt (1985). *When luck runs out: Help for compulsive gamblers and their families.* New York. 2

Fernandes, D., J. Lynch, and R. G. Netemeyer (2014). Financial Literacy, Financial Education, and Downstream Financial Behaviors. *Management Science*. 5

Fischhoff, B. (1982). Debiasing. In *Judgment under uncertaint: Heuristics and biases*. New York: Cambridge University Press. 5

Fischhoff, B. and J. Hall (1992). The Weighing of Evidence and the Determinants of Confidence. *411435*, 411–435. 16

Fox, C., B. Rogers, and A. Tversky (1996). Options traders exhibit subadditive decision weights. *Journal of Risk and Uncertainty1 13*(1), 5–17. 14

Gennaioli, N. and A. Shleifer (2010). What comes to mind. *Quarterly Journal of Economics 125*(4), 1399–1433. 14

Gonzalez, R. and G. Wu (1999). On the shape of the probability weighting function. *Cognitive psychology 166*, 129–166. 13, 14

Griffin, D. and R. Buehler (1999). Frequency, probability, and prediction: Easy solutions to cognitive illusions? *Cognitive psychology 38*(1), 48–78. 5

Griffin, D. and A. Tversky (1992). The weighing of evidence and the determinants of confidence. *Cognitive psychology 24*(3), 411–435. 16

Hanna, R., S. Mullainathan, and Schwartzstein (2014). Learning by Noticing: Theory and Evidence through a Field Experiment. *Quarterly Journal of Economics*, 1311–1353. 5, 17

Heath, C., R. Larrick, and J. Klayman (1998). Cognitive repairs: How organizational practices can compensate for individual shortcomings. *Review of Organizational Behavior 20*. 5, 15

Heath, C. and A. Tversky (1991). Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of Risk and Uncertainty 4*(1), 5–28. 14

Hertwig, R., G. Barron, E. Weber, and I. Erev (2004). Decisions from experience and the effect of rare events in risky choice. *Psychological Science 15*, 534–539. 4

Hertwig, R. and I. Erev (2009). The description-experience gap in risky choice. *Trends in Cognitive Sciences 13*, 517–523. 4

Hodgins, D., J. Stea, and J. Grant (2011). Gambling disorders. *The Lancet 378*(9806), 1874–1884. 4

Hoffrage, U. and G. Gigerenzer (1998). Using natural frequencies to improve diagnostic inferences. *Academic Medicine 73*(5), 538–540. 5

Jolls, C. and C. Sunstein (2006). The law of implicit bias. *California Law Review 94*(4), 969–996. 5, 6, 16

Jones, S., K. T. Jones, and D. Frisch (1995). Biases of probability assessment: A comparison of frequency and single-case judgments. *Organizational Behavior and Human Decision Processes*. 2

Kahneman, D. and A. Tversky (1979). Prospect Theory: An analysis of decision under uncertainty. *Econometrica*, 263–291. 2, 14

Kahneman, D. and A. Tversky (1982). The psychology of preferences. *Scientific America*, 160–173. 13

Kearney, M. (2005). State lotteries and consumer behavior. *Journal of Public Economics* (October), 1–40. 2

Kincaid, H., R. Daniels, A. Dellis, A. Hofmeyr, J. Rousseau, C. Sharp, and D. Ross (2013). A taxometric analysis of problem gambling data from a South African national urban sample. *Journal of Gambling Studies 29*(3). 7

Kling, J., J. Liebman, and L. Katz (2007). Experimental analysis of neighborhood effects. *Econometrica 75*(1), 83–119. 11

Kolb, A. Y. and D. A. Kolb (2005). Learning Styles and Learning Spaces : Enhancing Experiential Learning in Higher Education. *Academy of Management Learning & Education 4*(2), 193–212. 17

Kolb, D. A. (1984). *Experiential Learning: Experience as the source of learning and development.* New Jersey: Prentice-Hall. 6

Ladouceur, R., A. Goulet, and F. Vitaro (2013). Prevention programmes for youth gambling: a review of the empirical evidenc. *International Gambling Studies 13*(2), 141–159. 4

Langer, E. (1975). The illusion of control. *Journal of personality and social psychology 32*(2). 14

Lichtenstein, S. and B. Frischhoff (1980). Training for Calibration. *Organizational Behavior and Human Performance*, 149–150. 6

Mandell, L. (2006). Financial Literacy, Improving Education: National JumpStart Survey. 6

McMillen, J. (1996). *Gambling Cultures: Studies in History and Interpretation.* London: Routledge. 2

Miller, D. and C. McFarland (1986). Counterfactual Thinking and Victim Compensation A Test of Norm Theory. *Personality and Social Psychology Bulletin 12*(4), 513–519. 2

Miller, M., N. Godfrey, B. Levesque, and E. Stark (2014). The Case for Financial Literacy in Developing Countries: Promoting Access to Finance by Empowering Consumers. *World Bank*. 5

Nisbett, R. and L. Ross (1980). *Human Inference: Strategies and shorcomings of human judgement.* Englewood Cliffs, NJ: Prentice Hall. 2, 16

Nzimande, S., S. Louw, C. Mannya, A. Bodasing, and A. Ludin (2010). Review of the South African gambling industry and its regulation A report prepared by the Gambling Review Commission. (September). 7

Plous, S. (1993). The Psychology of Judgement and Decision Making. New York: McGraw-Hill. 2

Prabhu, J. and G. J. Tellis (2000). Do Consumers Ever Learn? An Analysis of Segment Behavior in Experimental Markets. *Journal of Bhavioral Decision Making 13*(1), 19–34. 6

Quiggin, J. (1982). A Theory of Anticipated Utility. *Journal of Economic Behavior and Organization 3*(4), 323–343. 13

Rabin, M. (2002). Inference by Believers in the Law of Small Numbers. *Quarterly Journal of Economics 117*(3), 775–816. 16

Rogers, P. (1998, jan). The Cognitive Psychology of Lottery Gambling: A Theoretical Review. *Journal of gambling studies 14*(2), 111–134. 8

Slovic, P. and S. Lichtenstein (1971). Comparison of Bayesian and regression approaches to the study of information processing in judgment. *Organizational Behavior and Human Decision Processes 6*(6), 649–744. 16

Smith, V. and J. Walker (1993). Monetary Rewards and Decision Cost in Experimental Economics. *Economic Inquiry 31*(2), 245–261. 6, 7

Soll, J., K. Milkman, and J. Payne (2014). A user's guide to debiasing. In G. Keren and G. Wu (Eds.), *Wiley-Blackwell Handbook of Judgment and Decision Making.* 5

Thaler, R. and S. Benartzi (2004). Save More Tomorrow: Using behavioral economics to increase employee saving. *Journal of Political Economy 112*(1), 164–187. 6

TNS (2009). Socio-economic impact of gambling in the Eastern Cape. 8

Trout, J. (2005). Paternalism and cognitive bias. *Law and Philosophy 24*(4), 393–434. 6

Tversky, A. and D. Kahneman (1992, oct). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*(4), 297–323. 2, 13

Tversky, A. and P. Wakker (1995). Risk attitudes and decision weights. *Econometrica: Journal of the Econometric Society 63*(6), 1255–1280. 2

Williams, R. and D. Connolly (2006). Does learning about the mathematics of gambling change gambling behavior? *Psychology of Addictive Behaviors 20*(1). 4

Willis, L. (2008). Against financial literacy education. *Iowa Law Review 94*(1), 197–285. 5

Xu, L. and B. Zia (2013). Financial Literacy in the Developing World. *Policy Research Working Paper. World Bank*. 5

Zull, J. (2002). *The art of changing the brain: Enriching teaching by exploring the biology of learning.* Stylus Publishing. 5, 6

## Figures and Tables

Table 1: Balance Test

| | *Assignment to Gambling Debiasing* | | | *Intensity of Treatment (# of dice rolls)* | | |
|---|---|---|---|---|---|---|
| | Control | Treatment | p-value (C=T) | above median | below median | p-value (C=T1=T2) |
| Age | 52.99 | 52.96 | .978 | 51.67 | 54.06 | .288 |
| Married | .464 | .465 | .974 | .461 | .468 | .991 |
| Female | .84 | .88 | .099 | .918 | .849 | .036 |
| Education (yrs) | 6.27 | 6.47 | .465 | 6.42 | 6.52 | .746 |
| Played Lottery | .12 | .127 | .755 | .11 | .141 | .612 |
| Understand English | .422 | .422 | .999 | .415 | .428 | .968 |
| Owns TV | .672 | .643 | .397 | .646 | .641 | .695 |
| Owns Radio | .6 | .601 | .998 | .612 | .591 | .91 |
| 1st income quartile | .22 | .208 | .67 | .19 | .222 | .672 |
| 2nd income quartile | .368 | .352 | .63 | .353 | .351 | .89 |
| 3rd income quartile | .171 | .196 | .363 | .207 | .187 | .579 |
| Has bank account | .569 | .551 | .609 | .538 | .563 | .776 |
| Employed | .074 | .071 | .86 | .082 | .063 | .751 |
| Has savings | .503 | .5 | .92 | .511 | .491 | .919 |
| Has a loan | .352 | .377 | .458 | .418 | .342 | .213 |
| N | 432 | 409 | | 214 | 195 | |

Note: The Table reports compares baseline characteristics between the low treatment intensity (T1:<median), high intensity (T2:>median) and control (C) group. P-values reported of a test of equal means.

Table 2: Linear Probability Model: Attrition Analysis

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | reached (mid) | reached (mid) | particip (mid) | particip (mid) | Attrit (end) | Attrit (end) |
| Gambling debias | -0.002 | | -0.014 | | -0.014 | |
| | (0.034) | | (0.034) | | (0.032) | |
| Above median rolls | | -0.016 | | -0.056 | | -0.040 |
| | | (0.041) | | (0.041) | | (0.037) |
| Below median rolls | | 0.016 | | 0.039 | | 0.018 |
| | | (0.044) | | (0.044) | | (0.040) |
| N | 832 | 832 | 832 | 832 | 832 | 832 |

Standard errors in parentheses. $^{*}$ $p < 0.10$ , $^{**}$ $p < 0.05$ , $^{***}$ $p < 0.01$

Columns refer to whether participants were reached in the midterm phone survey (1-2), and whether those reached agreed to participate in the survey (3-4). Column (5-6) measure attrition in the endline survey.

Table 3: Gambling Analysis

| | Lottery Index | | | | Immediate Outcome | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Gambling Debias | -0.0014 | | | | 0.0294 | | |
| | (0.040) | | | | (0.092) | | |
| Above median rolls | | -0.085** | -0.081** | -0.083* | | -0.146 | -0.126 |
| | | (0.040) | (0.040) | (0.058) | | (0.095) | (0.094) |
| Below median rolls | | 0.103* | 0.101* | 0.097* | | 0.241* | 0.230* |
| | | (0.059) | (0.058) | (0.058) | | (0.132) | (0.130) |
| Control Variables | Y | N | Y | Y | Y | N | Y |
| Financial Education | Y | N | N | Y | Y | N | Y |
| R-square | 0.001 | 0.013 | 0.081 | 0.082 | 0.001 | 0.011 | 0.056 |
| N | 813 | 813 | 813 | 813 | 813 | 813 | 813 |
| Control Mean | 0.065 | 0.065 | 0.065 | 0.065 | 0.775 | 0.775 | 0.775 |
| $\beta_1$=$\beta_2$ (p-value) | | 0.001 | 0.001 | 0.002 | | 0.004 | 0.007 |
| | **Intermediate Outcome** | | | | **Endline Outcome** | | |
| | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
| Gambling Debias | 0.0433 | | | | -0.001 | | |
| | (0.058) | | | | (0.022) | | |
| Above median rolls | | -0.028 | -0.032 | -0.037 | | -0.026 | -0.026 |
| | | (0.065) | (0.065) | (0.055) | | (0.023) | (0.023) |
| Below median rolls | | 0.119 | 0.100 | 0.044 | | 0.034 | 0.039 |
| | | (0.079) | (0.091) | (0.060) | | (0.032) | (0.033) |
| Control Variables | Y | N | Y | Y | Y | N | Y |
| Financial Education | Y | N | Y | Y | Y | N | Y |
| R-square | 0.003 | 0.019 | 0.161 | 0.079 | 0.001 | 0.006 | 0.120 |
| N | 193 | 193 | 193 | 384 | 585 | 585 | 585 |
| Control Mean | 0.176 | 0.176 | 0.176 | 0.236 | 0.074 | 0.074 | 0.074 |
| $\beta_1$=$\beta_2$ (p-value) | | 0.093 | 0.182 | 0.226 | | 0.071 | 0.053 |

Notes:

Standard errors in parentheses. * $p < 0.10$ , **$p < 0.05$ , ***$p < 0.01$ . The lottery index measures the average value of the (standardized) immediate, intermediate and endline outcome measure. Column 5-7 measures the treatment effect on the number of rounds that participants decide to gamble immediately after the intervention. Column 8-10 report outcomes for the subset of the sample offered the low winning odds lottery which presents the odds of winning the lottery jackpot. Column 11 pools lottery choices of participants with low and better winning odds. The endline outcome (column 12-14) measures whether people played the national lottery in the past 6 months. Control variables include all covariates listed in Table 1. P-values are reported of a test of equal coefficient for the above and below median treatment group.

Table 4: Test of Odds Discriminability

| | Winning Odds | |
|---|---|---|
| | Low ($p_l$) | High ($p_h$) |
| Control | $a$ | $b$ |
| Treatment | $c$ | $d$ |

Table 5: Odds Sensitivity (Midline Survey)

| | (1) | (2) |
|---|---|---|
| | 1=lottery, 0=airtime | 1=lottery, 0=airtime |
| 1=Better Odds | 0.086* | 0.111* |
| | (0.044) | (0.060) |
| Above median rolls | -0.0433 | -0.061 |
| | (0.053) | (0.063) |
| Below median rolls | 0.047 | 0.118 |
| | (0.059) | (0.087) |
| Better Odds x above median | | 0.039 |
| | | (0.106) |
| Better Odds x below median | | -0.140 |
| | | (0.117) |
| Financial education | 0.040 | 0.041 |
| | (0.046) | (0.046) |
| Control Variables | Y | Y |
| R-squared | 0.068 | 0.074 |
| N | 381 | 381 |
| Control Mean | 0.236 | 0.236 |
| $\beta_1$=$\beta_2$ | 0.175 | 0.045 |
| $\beta_1$=$\delta_1$ (>median) | | 0.512 |
| $\beta_2$=$\delta_2$ (<median) | | 0.173 |
| $\delta_1$=$\delta_2$ (equal Interaction) | | 0.178 |

Notes: Standard errors are reported in parentheses. $^{*}$ $p < 0.10$ , $^{**}$ $p < 0.05$ , $^{***}$ $p < 0.01$
The table shows results of regression specification (2):
$y_i = \alpha_0 + \beta_1 T_{low} + \beta_2 T_{high} + \eta odd_g + \delta_1 T_{low} * odds_g + \delta_2 T_{high} * odds_g + \gamma X_i + e_i$
The bottom rows show p-values of an F-test of equal coefficients. Coefficients refer to specification (2). The depend variable is an indicator variable measuring whether participants chose the lottery over airtime in the mid-line.

Table 6: Learning Mechanism Analysis

| y=lottery index | | | |
|---|---|---|---|
| | First Die | Two Dice | Interaction |
| (one / two dice) | (1) | (2) | (3) |
| <median rolls | 0.057 | 0.155$^{*}$ | |
| | (0.066) | (0.083) | |
| >median rolls | -0.033 | -0.104$^{*}$ | |
| | (0.070) | (0.054) | |
| <median / <median | | | 0.144$^{*}$ |
| | | | (0.087) |
| >median / <median | | | 0.174 |
| | | | (0.148) |
| <median / >median | | | -0.045 |
| | | | (0.080) |
| >median / >median | | | -0.144$^{**}$ |
| | | | (0.057) |
| R-squared | 0.049 | 0.059 | 0.060 |
| N | 825 | 825 | 825 |
| Control Mean DepVar | 0.484 | 0.484 | 0.484 |
| p-value:<med.=>med. | 0.251 | 0.002 | |
| p-value:</<= >/> | | | 0.001 |
| p-value:</>= >/> | | | 0.089 |

Regressions control for gender, age, marital status, years of education, and WDB vs. burial society group.

$^{*}$ $p < 0.10$ , $^{**}$ $p < 0.05$ , $^{***}$ $p < 0.01$

Figure 1: Probability Weighting Function

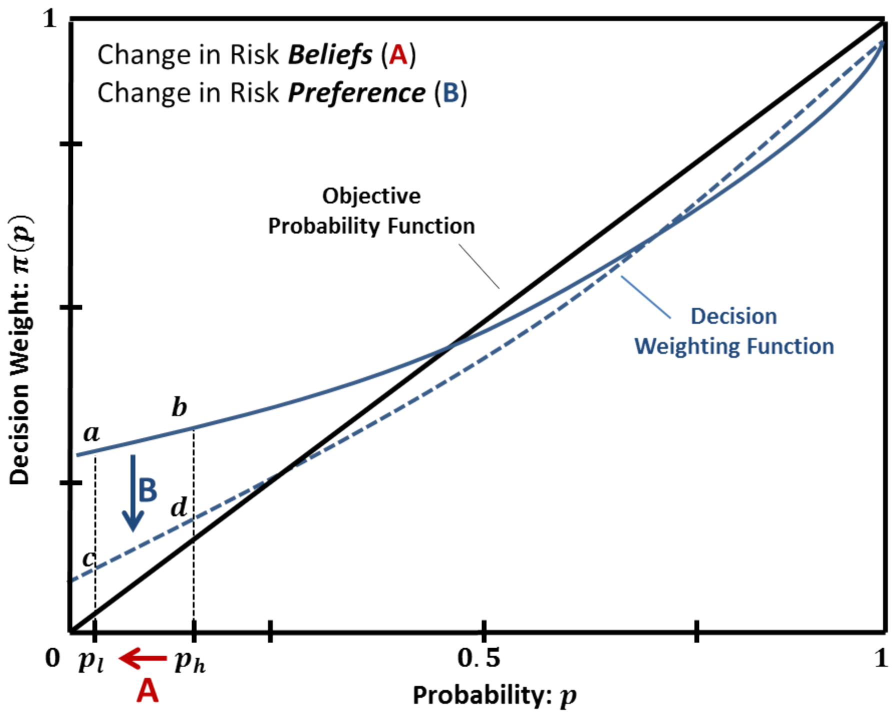
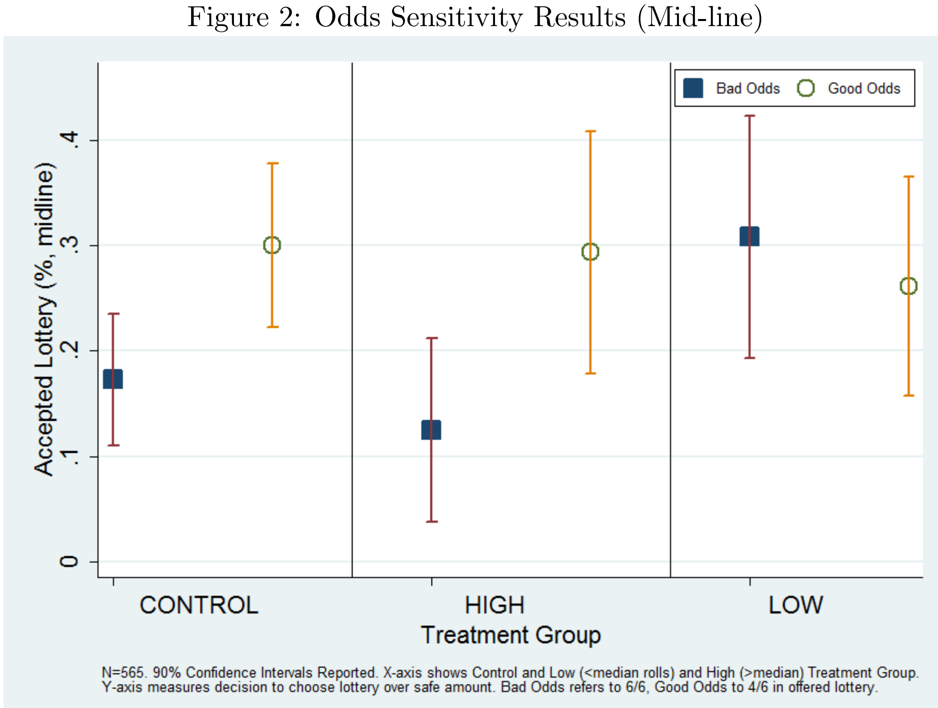



Figure 2: Odds Sensitivity Results (Mid-line)



# Appendix

## A Gambling Debias Treatment

**Gambling Debias Treatment Protocol** (*Instructions for Enumerator*)

1. Start by asking the respondent to roll one die and count how many throws it takes to get a 6 (enumerator must keep count aloud).
2. Make a note of how many times it took them to get it on one die and then hand them another and ask them to roll them together until they get two 6's simultaneously (again, enumerator keeps count –if they take more than 25 times you can stop them).
3. Remark on how much longer it took to get all 6's on 5 dice simultaneously and that the chance of getting all 6's on 5 dice takes more than 7000 throws.
4. Tell the chances of getting all 6's on 5 dice on the first try, is the same as the chance of buying a lotto ticket and getting 4 numbers right in the draw.
5. Tell participant that the chance of winning the grand jackpot (6 right numbers), are 1 in 14 000 0000 and that they have a better chance of being able to throw 6's on 9 dice all in one go on the first try than they do of winning the lotto grand jackpot.

Table A.1: Forms of Gambling - Endline

| | Lottery | | | Other gambling | | | Any gamble | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Gambling debias | -0.0006 | | | 0.0018 | | | 0.0043 | | |
| | (-0.03) | | | (0.10) | | | (0.16) | | |
| below median rolls | | 0.0336 | 0.0347 | | -0.0305 | -0.0285 | | 0.0139 | 0.0185 |
| | | (1.05) | (1.07) | | (-1.80) | (-1.65) | | (0.39) | (0.52) |
| above median rolls | | -0.0256 | -0.0250 | | 0.0253 | 0.0248 | | -0.0027 | -0.0017 |
| | | (-1.14) | (-1.09) | | (1.07) | (1.04) | | (-0.09) | (-0.05) |
| Control Var | Y | N | Y | Y | N | Y | Y | N | Y |
| R-squared | 0.000 | 0.006 | 0.039 | 0.000 | 0.008 | 0.027 | 0.000 | 0.000 | 0.029 |
| N | 585 | 585 | 585 | 585 | 585 | 585 | 583 | 583 | 583 |
| Control mean | | 0.074 | 0.074 | | 0.047 | 0.047 | | 0.111 | 0.111 |
| $\beta_1$=$\beta_2$ (p-value) | | 0.071 | 0.072 | | 0.017 | 0.025 | | 0.669 | 0.605 |

$t$ statistics in parentheses$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Figure A.1: Treatment Intensity Distribution

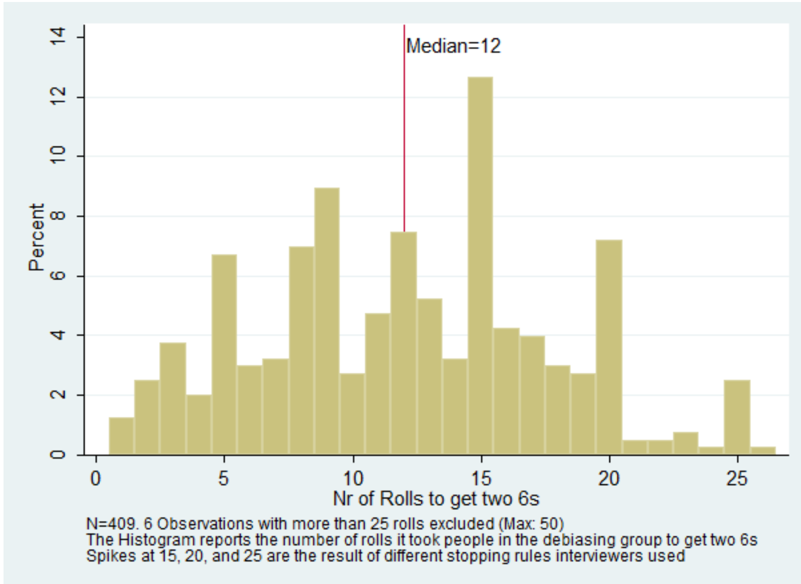
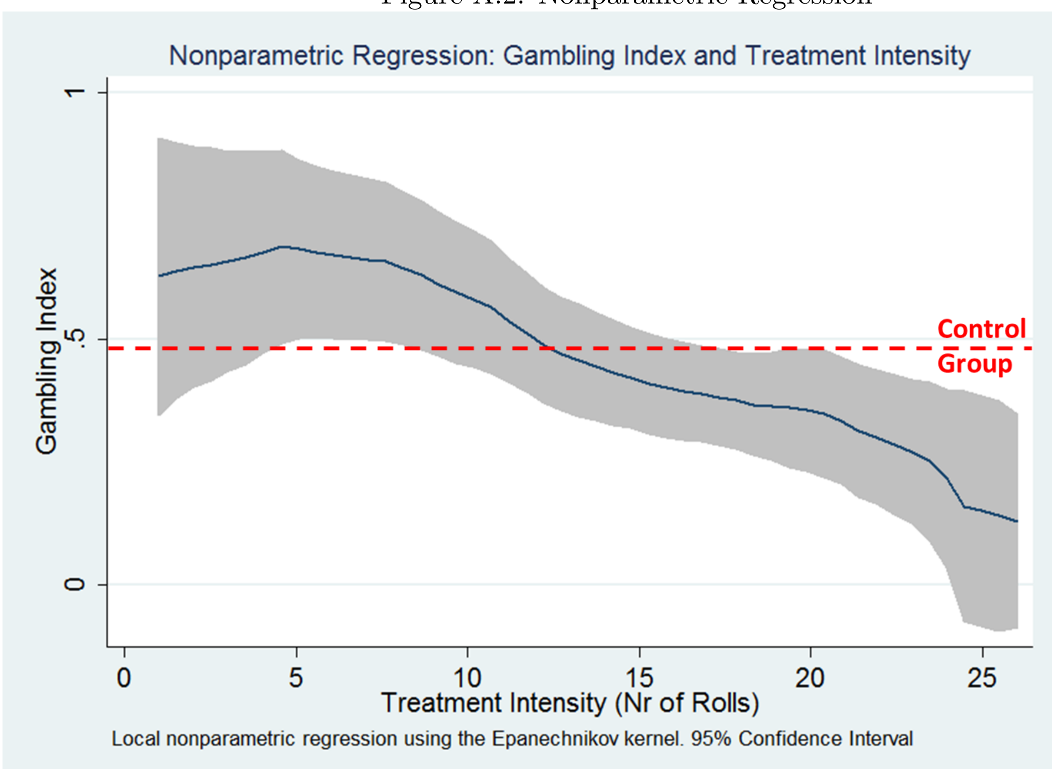



Figure A.2: Nonparametric Regression



# B Hire Purchase Treatment

## B.1 Treatment

Hire purchase, also known as 'rent-to-own' arrangements in the United States, is a method of buying goods through making installment payments over time. Under the hire purchase agreement, buyers are leasing the goods and do not obtain ownership until the full amount of the contract is paid. Some have argued that the prevalence of hire purchase and similar arrangements has contributed to a problem of over-indebtedness in poor households in South Africa. The National Credit Act of 2005 brought more stringent regulation to bear on the consumer credit market, setting caps on the interest rate and initiation fee. Yet, even with these caps, the implied APR can be in excess of 400%. Many stores advertise the small monthly payment rates of items without providing details on initiation fees and agreement lengths.

Initial qualitative field work found that a poor understanding of (compound) interest rates is likely to be one of the reasons for the prevalence of hire purchase agreements, especially among people with lower income levels. The intervention attempted to communicate the cost of this behavior relative to plausible alternatives by by visually demonstrating that finding alternative cheaper loan products (e.g. micro-loans) allows for the purchase of the desired item, plus an additional good, for the same payment stream. We also show that saving and postponing consumption will allow the purchase of extra items. We base our calculation on actual hire purchase and micro-loan interest rates.

Figure A.3: Hire Purchasing Debiasing Material

## B.2 Results

Table A.2 reports the effect of the debiasing on a range of questions measuring the attitude towards and knowledge of hire purchasing collected in the endline survey. We also collected data on whether people accepted hire purchase agreements when offered by stores between the time of treatment and endline as well as the length of any agreements made. Overall, we find little evidence that the hire purchase debiasing was effective. Treatment participants were less likely to agree that HP is convenient. However, they were also less likely to agree that HP should only be used for necessary purchases. Likewise, we observe only very modest changes in HP knowledge. The treatment group was more likely to give a correct answer for only one of the three questions. While the analysis of actual HP behavior is limited by the small number of people who were offered a HP between baseline and endline (N=43), there is no evidence that people in the HP treatment group were less likely to accept it or entered a shorter HP contract (Column 8-9).

Table A.2: Hire Purchase Outcomes

| | HP Attitudes | | | | HP Knowledge | | | HP Behavior | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | convenient | necessary | helpful | longerbetter | test TV | test bed | test sizeTV | Accept HP | HP Length |
| HP debias | -0.066* | -0.087** | -0.057 | -0.042 | 0.022 | 0.082** | 0.027 | 0.001 | -0.280 |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.002) | (0.204) |
| financial educ | -0.068* | -0.064 | -0.068* | -0.062 | 0.033 | 0.095** | 0.093** | 0.001 | -0.295 |
| | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.009) | (0.323) |
| used HP (basel.) | 0.003 | -0.005 | -0.000 | 0.019 | 0.039 | 0.009 | 0.108** | -0.001 | 0.116 |
| | (0.04) | (0.05) | (0.04) | (0.04) | (0.04) | (0.04) | (0.04) | (0.009) | (0.395) |
| Control Variables | Y | Y | Y | Y | Y | Y | Y | Y | Y |
| R-squared | 0.039 | 0.018 | 0.036 | 0.025 | 0.037 | 0.054 | 0.037 | | |
| N | 578 | 578 | 578 | 578 | 578 | 578 | 578 | 578 | 578 |
| Control Mean | 0.33 | 0.48 | 0.31 | 0.32 | 0.69 | 0.62 | 0.61 | 0.86 | 20.4 |

Notes: Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01
Attitude questions report the share of people that agreed with the statement. HP Knowledge questions report the share that answered the question correctly. The HP behavior quesions measure the effect on accepting HP agreements conditional on receiving a HP offer (Column 8) and the length of the agreement measured in months.