Debiasing *On a Roll*: Changing Gambling Behavior through Experiential Learning

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Abstract

Cognitive biases such as the availability heuristic or a systematic overestimation of small probabilities may partly explain the prevalence of gambling observed in many countries. To test whether experiential learning can debias gambling behaviors, we design an interactive game in which the odds of winning the national lottery are presented through dice rolling. Participants are first asked to roll a die until they get 1 six. Upon success, a second die is added and people roll until they get 2 sixes. People are then told that the chance of winning the lottery is equivalent to rolling all 6s with nine dice. Our analysis is exploiting two stages of randomization. First, we randomly assign half of our sample of 840 individuals from rural South Africa to receive the gambling debias intervention. Within this treatment group, the number of rolls it takes people to get two 6s can be interpreted as randomly assigned treatment intensity. The effects we observe over one year after the intervention are stark. Treated people who, by chance, needed few dice rolls to get two 6s, are about 35% more likely to participate in a gamble we offer after the treatment or play the lottery in the following year. By contrast, the group that needed many rolls is about 20% less likely than the control group to gamble. In addition, there is suggestive evidence that the debiasing not only reduced the attractiveness of gambling in general, but also affected the sensitivity to changing winning odds. However, we did not find that the debiasing treatment led to behavior changes in other domains than gambling.

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 & Milt 1985, McMillen 1996). Despite its prevalence, however, gambling is fairly costly. In the US for example, gambling crowds out almost 2% of household consumption (Kearney 2005). Further, it can lead to negative externalities within households. For example, if a household does not share a common utility function, spending

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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 & 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.
money on gambling may come at the expense of other household expenditures such as children’s 
education and health.

Why do people gamble so much especially if it is so costly? The prevalence of gambling poses a 
challenge to the classical theory of decision-making under risk and uncertainty. Under the assumption 
of decreasing marginal utility, rational decision makers are risk-averse and should thus not engage in 
gambles which typically have a negative expected payoff (Tversky and Wakker, 1995). One explanation 
for gambling that is consistent with a utility maximization framework is that some people correctly 
compute winning probabilities but get entertainment utility out of the act of gambling which may offsets 
the negative expected utility of the lottery (Kearney 2005). However, there is ample evidence that 
numeric and cognitive abilities are extremely low among the poor, especially in developing countries, 
and assigning them the computational skills needed to discern probabilities is likely an unrealistic 
assumption.

A different set of explanations for why people gamble delve outside the predictions of neo-classical 
theory. Importantly, research in behavioral economics shows that individuals often exhibit cognitive 
biases that lead to misjudgment, in particular over-estimation of small probabilities (Kahneman and 
Tversky, 1979). As a result, people are often observed to be risk seeking in dealing with improbable 
gains such as winning in the lottery (Tversky and Kahneman 1992, Wu and Gonzales 1996).

A second deviation from classical decision theory uncovered by behavioral economists is that preferences 
for risk are not stable. Instead, reasoning under uncertainty is influenced by heuristics that rely on 
psychological cues such as ease of retrieval, constructing scenarios, or similarities (Jones, Jones and 
Frisch 1995). While these heuristics are often helpful rules of thumb for decision-making with imperfect 
information, they can also lead to systematic misjudgments (Plous 1993). One example particularly 
relevant for assessing winning probabilities of gambling is the availability heuristic: people’s 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 1973). While 
availability is generally a useful cue for assessing probabilities as more frequent events are usually 
called 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). The 
gambling industry is a striking example where providers take ample advantage of the availability 
heuristic. Advertisements of lotteries often display jackpot winners, casinos typically have bells that 
ring if somebody wins a major prize, and betting houses strategically place slot machines next to each 
other in big groups so that gamblers hear the sound of others winning (Clothfelter and Cook 1989).2 
As such, the availability heuristic tends to loom large in reinforcing gambling.

In this paper, we address the misjudgment of winning odds and availability heuristic in a sample of 
South African households who are exposed to the popular national lottery. We take an innovative 
approach to de-biasing – instead of conveying simple instructional messages, we adopt experiential 
learning as our de-biasing tool. Specifically, we play a simple dice game with treated households where 
participants are asked to roll a six-sided die until they get a six. Upon success, they are asked to roll 
two dice until they get two sixes. For most players in our sample, it became painfully obvious that the 
ods of rolling 2 straight sixes was much more difficult than rolling 1 six. We then revealed to them 
that their chance of winning the South African national lottery jackpot was equivalent to them rolling 
ine dice with all nine showing up sixes. This simple game was effective because the experience of 
rolling one die versus two dice conveyed the concept of probability without having subjects sit through

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2 Three advertisement schemes are particularly common the lottery industry in the U.S. (Clothfelter et al 1999): (i) 
advertising the size of the jackpot, (ii) emphasizing the fun and excitement of playing, and (iii) promoting awareness 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.”
math camp. It also provided them a useful benchmark to assess the likelihood (or lack of chance) in being able to simultaneously roll nine sixes on nine dice, having just experienced the difficulty of rolling just two sixes. Moreover, it became clear to those who had difficulty rolling two sixes that rolling nine straight sixes would be virtually impossible.

More generally, experiential learning methods have the potential to be more effective than standard lectures for several reasons. First, experiential debiasing techniques can be more effective as they tend to be simpler and more intuitive and thus do not tax cognitive resources like memory or attention (Bell, Raiffa and Tversky, 1988). Second, experiential learning designs can be more novel and thus more memorable while still building on preexisting knowledge. For example, our debiasing intervention combined the familiar activity of rolling dices with the novel concept of linking it to varying winning probabilities. Third, experiential learning can leverage cognitive biases to induce desired behavioral changes, a strategy referred to as ‘counter-biasing’ (Jolls and Sunstein 2006). For example, in our intervention the dice rolling experience may have become the basis of a new availability heuristic.

The de-biasing game described above was implemented on a set of 840 individuals with 50% of the sample randomly selected to receive the de-biasing treatment following a household survey on financial access. The remaining 50% also played a game on an unrelated topic. Further, the study design featured two stages of randomization. While 50% of our sample was randomly selected to play the debiasing game, within these 50%, the number of rolls it took to get two sixes varied randomly among the players. Hence, there was random variation in the intensity of treatment – the longer it took for two sixes to show up, the clearer it became to the player that their chance of winning was very low.

We measure gambling outcomes through surveys and lottery offerings that elicit preferences for lotteries as well as lottery purchasing behavior. Outcomes were elicited immediately at baseline, at a 6 month interval (mid-line), and then a final survey one year later. We aggregate gambling outcome measures across these three survey rounds to a standardized index (following Kling, Liebman and Katz 2007). Our findings are quite stark. We find substantial variation in outcomes based on treatment intensity. People who took more than the median number of rolls to obtain two sixes (high intensity) gambled 40% less in a lottery offered after the debiasing intervention and were 35% less likely to have played the lottery after one year compared to the control group. Conversely, the low treatment intensity group (below median number of rolls) gambled 29% more in a lottery offered immediately after the intervention and was 45% more likely to have played the lottery. These results are statistically significant at the 5% level. What is more, only the high treatment intensity showed a higher sensitivity to probabilities in a lottery offered after six month where we randomly assigned winning odds. However, these effects cannot be estimated precisely enough to be statistically significant.

These results provide strong evidence that our debiasing method was effective in changing people’s understanding of small probabilities and their gambling behavior. Findings on the increased sensitivity towards probabilities in the high intensity treatment group further provide suggestive support for the theory that our intervention affected participants’ sensitivity to varying winning odds and not only reduce the entertainment value/utility that people derive from gambling.

In an attempt to compare different debiasing methods, we designed a second treatment that aimed to change the prevalent use of buying things via hire purchase agreement. A flipchart and toy money were used to visualize the high share of fees and compound interest rate payments relative to paying the cash price. Different goods were then presented that one could buy if one would either use different sources of credit or savings to buy the item. We find that this intervention had little impact on the attitude of people towards hire-purchase, nor did it reduce the use of hire purchase in the year after the intervention.

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3In the analysis, we also exploit the reverse feature of this design. That is, if by chance the players rolled two sixes right away or in a few number of tries, then their biases may be reinforced.
While the two debiasing methods are not directly comparable as they aimed to change different outcomes, these findings confirm earlier debiasing studies showing that the effectiveness of experiential learning depends on both the particular setting and intervention design. However, more research is needed to identify what factors determine the success of debiasing.

The rest of this paper is structured as follows. Section 2 discusses the theoretical motivation and framework that guides the empirical strategy. Section 3 discusses the study background, sample, debiasing treatments and outcome measures. Section 4 introduces the empirical strategy and Section 5 reports findings. Section 6 discusses results and concludes.

2 Theoretical Motivation and Framework

2.1 Debiasing through Experiential Learning

The effectiveness of teaching basic concepts of financial literacy, such as concepts of compound interest and expected values, are limited by people’s poor numeric skills and arithmetic intuition. Evaluations of financial literacy trainings have found no or only modest effects (Carpena, Cole and Zia 2011 for a review).

While teaching rules of thumb may not be useful and even counterproductive for the complex decisions required in modern financial markets (Willis 2008), Drexler, Fisher, and Shoar (2011) find that in the Dominican Republic, financial education was only effective in changing behavior when it focused on a few simple rules of thumb. However, the use of rules of thumbs may be limited and ineffective in changing habits affected by cognitive biases such as gambling. It is unlikely that rules of thumb like ‘don’t gamble’ would effectively change behavior.

Insights from behavioral economics have helped in the field to design interventions that address cognitive biases rather than focusing on knowledge transmission. One of the main insights of this literature is that a wide range of factors such as framing or contextual information affects people’s assessment of probabilities. Consequently, it is unlikely that there is “one way to perfect intuitive judgment” (Griffin and Buehler 1999, p.75). Rather than finding a general method to improve decision making, Heath, Larrick and Klayman (1998) conclude that different interventions may be effective in different circumstances.

In the field of financial decision making, simply telling people about their cognitive bias has not proven to be effective. Instead, debiasing interventions have tried three types of methods: (i) repeat interaction with immediate unambiguous feedback, (ii) consider the opposite, and (iii) counter-biasing (Willis 2008, Jolls and Sunstein 2006).\(^4\)

The first method of immediately providing feedback on an action has been used successfully in the lab to address overconfidence (Lichtenstein and Fischhoff 1980). However, getting feedback on financial decision making in a classroom setting has not proven to be effective (Prabhu and Tellis 2000). Applications of this method in the form of educational financial games have led to some improvement in financial knowledge. However, this did not translate into improvements in financial decision making (Mandell 2006).

\(^4\)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). 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 second method may be implemented by asking participants to list alternative financial decisions. In theory, participants place increasing weight on these alternatives as they become more mentally available. However, the few studies that 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 in fact induce desired behavior. If people overestimate the chance of winning in the lottery, this method may take advantage of the availability bias and present vivid cases of pathological gamblers who lost their possession to gambling (Jolls and Sunstein 2006).

Our debiasing interventions, discussed in detail below, build on the first two of these methods. Rolling dice provides the participants with immediate feedback on probabilities of winning in a lottery (presented by getting a certain number of sixes). The hire purchase debiasing method incorporates aspects of the ‘consider the opposite’ principle by telling participants the amount of money they would save and which other goods they could buy with these savings. In contrast to some of the earlier studies, this intervention not only provides participants with alternatives but also with information on the means to achieve these (save).

2.2 Framework

A decade after introducing the concept of heuristics and cognitive biases, Kahneman and Tversky (1982) pointed out 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% has 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%. The concluded that the “psychophysics of chance induce overweighting of sure things and of improbable events, relative to events of moderate probability” (Kahneman and Tversky 1982). They introduced the concept of a probability weighting function that translates objective probabilities $p$ into weights $\pi(p)$ used in decision making.

Figure 1 shows the shape of the weighting function that corresponds to Kahneman and Tversky’s observations. Decision weights lower than objective probability values near $p=1$ corresponds to people’s tendency to be risk averse in dealing with unlikely losses. By contrast, decisions weights higher than actual probability values near $p=0$ reflect that people are often risk seeking in dealing with improbable gains such as winning in the lottery. Several empirical studies confirmed the inverted S-shape of the probability weighting function (Camerer and Ho 1994, Tversky and Kahneman 1992, Wu and Gonzales 1996).

Gonzales and Wu (1999) note that there are two distinct features that describe 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. A flatter slope than 45% degree line means that people are too insensitive to a change in probability. The extreme form of a step function corresponds to the case in which people lump probabilities into categories in which they perceive events to be equally likely (Piaget and Inhelder 2013). Conversely, the steeper the curvature of the weighting functions the more are people sensitive to changing probabilities. A rational individual has a weighting function equal to the objective probability function with constant unit probability change along the probability scale as depicted by the 45% line. The observed inverse-S-shape of the probability function implies diminishing sensitivity to probabilities further away from the two reference points uncertainty ($p=0$) and certainty ($p=1$).

Available evidence suggests that experts often have relatively linear weighting functions in their specific area of expertise. Thaler and Ziemba (1988) find that decisions of experienced racetrack betters are
sensitive to small differences in probabilities. By comparison, inexperienced betters disproportionately bet on long-shot horses. Likewise, Fox, Rogers and Tversky (1996) show that the median option trader in their sample shows equal sensitivity throughout the probability interval. However, it is unclear if discriminability varies intra-personally, i.e. whether the option trader also has a linear probability weighting function when he bets at the race track (Gonzales and Wu 1999).

The level of the weighting function, referred to as attractiveness, can be interpreted as the interpersonal inclination of people to take risk and bet on chance events (Gonzales and Wu 1999). There may also be intra-personal difference of chance domains: holding winning odds constants, people may prefer betting on sporting events compared to outcomes of political elections (Heath and Tversky 1991).[5]

In summary, the concepts of attractiveness and discriminability, which characterize the weighting function, are two independent psychological properties. This distinction helps to understand different mechanisms through which debiasing interventions may reduce people’s inclinations to gamble. First, interventions may shift down the weighting function and thus lowering the attractiveness of any lottery regardless of the winning odds. This may be the effect of an intervention emphasizing the potential adverse effects of gambling such as the risk of addiction.

Secondly, interventions could focus on making people more sensitive to understand winning odds. This may ‘straighten’ the weighting function and bring it closer to the 45 degree line at which decision weights correspond to the objective probability distribution. Decision weights at the lower end of the probability scale are reduced. The largest reduction in gambling should thus be observed in forms of gambling with very small winning probabilities such as the lottery. By contrast, we should theoretically observe an increase in the use of forms of gambling with winning odds in the midrange of the probability scale.

Both reducing the attractiveness and increasing discriminability would induce people to attach a lower decision weight to small probabilities and thus reduce gambling. However, these two concepts are con-

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[5] 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.
Table 1: Test of Odds Discriminability

<table>
<thead>
<tr>
<th>Winning Odds</th>
<th>Control</th>
<th>Treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low ($p_l$)</td>
<td>$a$</td>
<td>$c$</td>
</tr>
<tr>
<td>High ($p_h$)</td>
<td>$b$</td>
<td>$d$</td>
</tr>
</tbody>
</table>

consistent with different economic frameworks. Lowering the attractiveness of lotteries can be interpreted as reducing the utility that people get from any gamble. Even a decision maker who fully understands winning odds of lotteries may thus be affected by this kind of intervention. Since these actors already have a straight weighting function, increasing the discriminability should only affect gambling in a prospect theory framework.

We test if our intervention affects both attractiveness and discriminability of gambling by randomly assigning different winning odds to lotteries offered to people in the control and treatment group. Half of the people in each group are offered a lottery with a low winning probability $p_l$ and half are offered a lottery with a higher winning chance $p_h$. The difference in the share of people in the control group provides information on the shape of the weighting function at baseline. The smaller the difference between cell $a$ and $b$, the flatter the weighting function in the domain $[p_l, p_h]$ (Table 1). The difference in change between cells $[a, b]$ and $[c, d]$ after the intervention shows how the debiasing treatment affected the weighting function. A similar reduction from $a$ to $c$ and $b$ to $d$ would reflect that the change in gambling was mainly driven by a reduction in the attractiveness of gambling. By contrast, a larger difference in $d - c$ relative to $b - a$ would indicate a greater sensitivity to probability. This test of discriminability corresponds to a difference-in-difference strategy.

3 Study Design

3.1 Background

Gambling: Since the legalization of gambling in South Africa in 1996, the gambling industry has grown substantially with gross gaming revenues more than doubling between 2001 and 2009, to R18.13 billion (Nzimande et al. 2010). A 2003 study finds that 43% of players earn less than R2 000 (about $250) a month and spend on average R84 per month on playing lotto. The authors conclude that ‘the lower-income levels in society [were] making big sacrifices to play’ (Smith 2003, p.3 cited in van Wyk 2010).

Sharp and Dellis (2010) argue that easy access to gambling opportunities through the internet and the recent lifting of gambling restrictions in many countries has the potential to put especially adolescents at risk. In South Africa, gambling among teens is increasingly being perceived as a significant problem. While school-based interventions try to reduce high-risk behavior, these curricula solely focus on sexual behavior (Sharp and Dellis 2010).

Detailed data on the gambling behavior of 5,500 South Africans was collected in 2001 by the National Urban Prevalence Study of Gambling Behavior (NUPSGB). Results show that gambling was most common among black people: about 55% report that they gamble at least occasionally and 24% report

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6 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).

7 Adolescents are particularly at risk because they have a reduced capacity for effective decision-making (Millstein, 2003) and are especially vulnerable to the effect of emotions (Slovic, 2003).
to play the lottery regularly. Recent data collected in the Eastern Cape in 2009 shows that playing the lottery is by far the most common form of gambling: 49% of respondents had tried it at least once; active gamblers play an average of 3.5 times per month (TNS 2009). Results from a survey of adults in KwaZulu-Natal show that gambling was common, and with the exception of the national lottery mainly informal and unlicensed (Hofmeyer, Dellis, Kincaid and Ross 2010).

When asked why they gamble, 85% of respondents mention the chance of winning big money. Gambling does not seem to have a social stigma in South Africa: 69% report that either some or all forms of gambling is ok.

Hire Purchase: 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. The prevalence of hire purchase and similar arrangements may have contributed to the 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 people with lower income levels often have a poor understanding of both the overall cost of purchasing goods through HP and the general concept of (compound) interest rates.

3.2 Study Sample

This study was part of a broader program that delivered financial literacy training to people in rural and peri-urban areas. Participants were organized in burial societies and women borrowing groups. 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 was drawn from 27 women borrowing groups and 45 burial societies. Some baseline characteristics of the sample are reported in Table 1. As the majority of burial society member are female, our sample consists of almost 90% women. Our simple is also significantly 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%). Since our sample was drawn from a more rural, older, and disproportionately female population, gambling prevalence rates are below those reported in other gambling studies from South Africa. At the time of the baseline survey, 15% of the sample report that they have gambled.

Between July and November 2011, a survey team visited the villages to conduct a baseline survey that collected data on a wide range of data including demographic characteristics, financial knowledge and behavior, and gambling practices. At the end of the baseline, a handheld device randomly assigned participants to receive one of two debiasing treatments described in more detail next.

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8 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 form of gambling (Rogers 1998).

9 The Financial Diary Project finds that 24% of the sample households were classified as over-indebted (Collins, Murdoch, Rutherford, and Ruthven 2009).

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

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

12 Clusters include Flagstaff, Bizana, Mount Frere, Matatiele, Queenstown, Mthatha, Butterworth, East London, Port Elizabeth, Underberg, Empangeni, Mtubatuba, and Port Shepstone.
3.3 Debiasing Treatment

Gambling: Even if people overestimate the odds of winning the lottery, they generally know that these odds are low. However, they may 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 the everyday experiences of probabilities (Smith and Walker, 1992).

Instead of trying to convey the meaning of miniscule probabilities arithmetically, our debiasing intervention uses an interactive, experiential method. We demonstrate the probability of winning the jackpot in a lottery through a simple dice game that field workers played with respondents in individual meetings. We first let participants roll one die until they get a ‘6’. Then we add another die and let them roll until they get two ‘6’ s. We stop the dice rolling at this point but continue with telling participant the equivalence of number of dice and the odds of winning different prizes in the lottery. The chance of having four right numbers, e.g., is equivalent to rolling all sixes with five dice and the odds of winning the jackpot is smaller than getting all sixes with nine dice. This debiasing treatment takes about 10 minutes. Importantly, we note the number of rolls it took the participants to receive two sixes.

Hire Purchase: A poor understanding of (compound) interest rates is likely to be one of the reasons for the prevalence of hire purchase agreements. We are trying to address this behavior by visually showing that finding alternative cheaper loan courses (e.g., microloans) allows the purchase of 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 microloan interest rates.

Participants first calculate the overall payment of hire purchase and microloan agreements both for 12 and 36 months. Toy money is used to visualize the amount of interest and fee payments relative to the original loan amount for purchases with varying length (see Figure 6 in Appendix). Participants compute the savings of using the microloan and saving strategy and are finally presented with different durable goods like cell phones or microwaves that one may buy with this saving.

3.4 Gambling Outcome measures

In order to test the robustness of results and explore whether potential effects of the debiasing treatment would persist over time, we collected three independent gambling indicators immediately after the treatment, after six months, and after one year.

i) Immediate outcome: Following the survey, participants receive 10 Rand (~$1.00) and are offered to use part of this money in the following game. First, they are shown a non-transparent bag with 50 balls of which five balls are red. Participants are then offered to pay 1 Rand each round to draw a ball. If they draw a red ball they receive 5 Rand in return. On average, participants played 0.8 rounds. 57% of people decided not to gamble.

ii) Midline outcome: About six months after the debiasing treatment, participants were contacted via cell phone to collect an intermediate gambling outcome. Surveyors said they were part of a research project at the University of Cape Town to study how people make decisions with money. They offered people to participate in the research that would allow them to win money.

Participants were given offered the choice of a lottery in which they could win R250 or to receive R15 for certain (delivered via 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 a particular date three month ago. The winning odds were randomly assigned within each
group and gambling treatment (high vs. low intensity) strata: half participants would win if they picked all six numbers correctly and half would win with at least four correct numbers. Overall, 26.6% of the participating sample chose to play the lottery, 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 the gambling behavior of participants in the last six months. Information was also collected on a range of financial behaviors and attitudes.

4 Empirical Strategy

4.1 Identification

In the spirit of Crepon, Duflo, Gurgand, Rathelot and Zamora (2013), this study uses an innovative two-stage randomization strategy. In the first stage, participants are randomly assigned to receive either the gambling or compound interest debias treatment. In the second stage, the number of rolls it takes people in the gambling debias group to get two sixes can be regarded as a random assignment of the treatment intensity. Participants who, by chance, get two sixes on the third roll receive a less intense debiasing treatment than participants who need thirty rolls. We will take advantage of this random variation in treatment intensity in our analysis.

There are three critical identification assumptions in our two-staged randomization strategy: i) the stable unit treatment value assumption (SUTVA, Rubin 1974), ii) characteristics of people across control and treatment groups are balanced, and iii) there is no non-random attrition in the follow-up surveys.

SUTVA: To address concerns about potential Hawthorne effects and to maximize statistical power, each study participant received either the gambling or hire purchase debiasing treatment. The interventions were designed so that the hire purchase treatment would not affect gambling behavior and vice versa. Each treatment group can thus serve as the counterfactual for the behavior it is not addressing. A violation of the SUTVA assumption, i.e. if learning about compound interest would affect gambling or better understanding small probabilities changes the use of hire purchase, would likely lead to a downward bias of our results.\footnote{One potential mechanism that may lead to a violation of the SUTVA assumption is that if the hire purchase debiasing intervention was effective reducing these purchasing agreements in the control group, they may have more money to spend on gambling. While this is theoretical plausible, this is of less concern of a concern in our study since we not observe a change in behavior in the control group.}

In addition, participants may talk about their particular intervention with people 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 out these violations of the SUTVA condition, our results should be interpreted as a lower bound of the true effect.

Group Balance

First Stage: Next we will test if the random assignment at the two stages resulted in groups that are balanced along a range of observable characteristics. The left panel in Table 2 reports the sample means and p-value of a test of equal means between the gambling debiasing group (T) and compound interest participants who serve as a control group (C). Of the 15 baseline characteristics tested, only one difference in means is (marginally) significant.

Second Stage: Figure 4 (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 6s. 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 distribution heaps 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 2 reports a balance test of the second stage randomization. The first two columns report average baseline characteristics of the low intensity (<median rolls) and high intensity (>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 is 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 is statistically significant (results not reported).

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 have 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: Not capturing outcome data of people that were part of the initial sample is problematic.
for two reasons. First, it reduces the precision with which we can estimate impacts. Second, and more concerning, attrition biases our estimates if characteristics of attriters are correlated to both the random assignment and the outcome of interest.

Attrition was not an issue for the immediate outcome measure since it was captured after the baseline survey and treatment was administered. For the midline 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 3, Columns (1-4)) show that both the probability of reaching people and participants’ decision to participate in the survey are not statistically significant. As an additional test, we find that the decision to participate in the midline survey is not significantly correlated with the gambling decision in the immediate outcome measure. This supports the claim that attrition does not bias results.

Table 3: Linear Probability Model: Attrition Analysis

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>reached (mid)</td>
<td>reached (mid)</td>
<td>particip (mid)</td>
<td>particip (mid)</td>
<td>Attrit (end)</td>
<td>Attrit (end)</td>
</tr>
<tr>
<td>Gambling debias</td>
<td>-0.002</td>
<td>-0.014</td>
<td>-0.014</td>
<td>-0.014</td>
<td>-0.014</td>
</tr>
<tr>
<td>(0.034)</td>
<td>(0.034)</td>
<td>(0.034)</td>
<td>(0.032)</td>
<td>(0.032)</td>
<td>(0.032)</td>
</tr>
<tr>
<td>&gt;median rolls</td>
<td>-0.016</td>
<td>-0.056</td>
<td>-0.040</td>
<td>-0.040</td>
<td>-0.040</td>
</tr>
<tr>
<td>(0.041)</td>
<td>(0.041)</td>
<td>(0.037)</td>
<td>(0.037)</td>
<td>(0.037)</td>
<td>(0.037)</td>
</tr>
<tr>
<td>&lt;median rolls</td>
<td>0.016</td>
<td>0.039</td>
<td>0.018</td>
<td>0.018</td>
<td>0.018</td>
</tr>
<tr>
<td>(0.044)</td>
<td>(0.044)</td>
<td>(0.040)</td>
<td>(0.040)</td>
<td>(0.040)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>N</td>
<td>832</td>
<td>832</td>
<td>829</td>
<td>829</td>
<td>841</td>
</tr>
</tbody>
</table>

Standard errors in parentheses. * p < 0.10 , ** p < 0.05 , *** p < 0.01

Columns refer to whether participants were reached in the midline 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.

Overall attrition in the endline is at 30.4%. This relatively high attrition rate is relatively high because some of the data was lost due to a PDA syncing problem that occurred at the data procession stage in the field. This reduces the precision with which we can estimate outcome measures collected at the endline. However, Table 2 show that the attrition rates do not vary significantly between treatment and control group (Column 5) or between the treatment intensity groups (Column 6).

4.2 Estimation

Given that these assumptions are met, the average treatment effect is identified and can be estimated by comparing average outcomes across treatment and control groups. We will estimate results using regression analyses.

Main specification: Our main regression estimation specification is as follows:

\[ y_i = \alpha_0 + \beta_1 T_{low} + \beta_2 T_{high} + \gamma X_i + e_i \] (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

---

14While attrition does not seem to be significant, it is noteworthy that the midline decision coefficient for the high intensity treatment group is negative. Under the reasonable assumption that those more averse to gambling are more likely to reject the offer to participate in the game, the high intensity treatment group would be on average more critical of gambling which would make it less that we find the treatment to be effective in reducing gambling.
\( \beta_1 \) and \( \beta_2 \) estimate the average effect of being in the low and high intensity treatment group compared to the control group. We will also report results from an F-Test that tests whether estimates of \( \beta_1 \) and \( \beta_2 \) are equal.

\( X_i \) 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. Most reported results control for these covariates to increase the precision of treatment estimates. Regressions are estimated using robust standard errors \( e_i \). Results from this analysis are reported in Section 5.1.

Odds sensitivity: As discussed in Section 2.2, we may observe a reduction in gambling because people get less utility from playing any lottery or because they are more sensitive to the small winning chances of a lottery. To distinguish between these two mechanisms, we will estimate the following specification:

\[
y_i = \alpha_0 + \beta_1 T_{low} + \beta_2 T_{high} + \eta_{odds} + \delta_1 T_{low} \ast odds + \delta_2 T_{high} \ast odds + \gamma X_i + e_i \tag{2}
\]

The variable \( odds \) refers to the randomly assigned better winning odds in the midline outcome. Estimates of \( \delta_1 \) (\( \delta_2 \)) show how the odds sensitivity of the low (high) intensity treatment group compared to the control group. A test of equal coefficients (\( \delta_1 = \delta_2 \)) tests if the treatment intensity had an effect on the odds sensitivity of participants. Results from the odds sensitivity analysis are reported in Section 5.2.

## 5 Results

### 5.1 Gambling behavior

As discussed in Section 3.4, we collected three independent gambling outcome measures at different points in time. The immediate outcome measure collected after the debiasing treatment measures the number of rounds participants decide to gamble. The Intermediate outcome measures the decision to participate in a low winning odds gamble half a year after the debiasing treatment. The endline outcome captures whether participants played the lottery in the last six months. To take advantage of the fact that we have outcome variables for individuals at three points in time and increase statistical power of our study, we follow Kling, Liebman, and Katz (2007) and create an index of gambling outcomes.

We first present results graphically in Figure 2. The four panels show the mean and 95% confidence interval for the low treatment intensity and high treatment intensity groups across the three outcomes and index. The red line presents the mean outcome for the control group. A consistent picture emerges from these panels: for each of the outcome measures, the high intensity treatment group gambles less than the control group whereas the low intensity group seems to gamble more. To increase the precision of estimates and ensure that these effects are not due to differences in observable covariates, we next report results from regression specification (1).

Table 4 reports coefficients of the low (below median rolls) and high intensity treatment dummies. Unsurprisingly, the coefficients remain almost unchanged when we include control variables. These results confirm the previous conclusion that people in the high intensity treatment group are less likely and participants receiving the low intensity treatment are more likely to gamble. Coefficients are large.

---

\( ^{15} \) Results reported restrict the midline sample to those offered the low probability lottery. Results do not change substantially and results remain significant when we include people offered the lottery with better winning odds.

\( ^{16} \) The index is created by adding values for the two indicator outcomes (midline, endline) and a standardized measure of the number of rounds played (immediate).
Figure 2: Gambling Debias Effects (by treatment intensity)

Gambling Index

Immediate Outcome

65% Confidence Intervals; Sample: 429 gambling-debias participants
Lottery Gambling Index measures average standardized lottery decision across three follow-up surveys
Red line: Control Group mean

Midline Outcome

Endline Outcome

65% Confidence Intervals; Sample: 199 gambling-debias participants
Lottery Decision for people offered a lottery with low winning odds, endline
Red line: Control Group mean

95% Confidence Intervals; Sample: 298 gambling-debias participants
Lottery played in last 6 months, endline
Red line: Control Group mean
<table>
<thead>
<tr>
<th>Lottery Index</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Above median rolls</td>
<td>-0.110**</td>
<td>-0.104*</td>
</tr>
<tr>
<td>(0.055)</td>
<td>(0.054)</td>
<td></td>
</tr>
<tr>
<td>Below median rolls</td>
<td>0.170**</td>
<td>0.155*</td>
</tr>
<tr>
<td>(0.085)</td>
<td>(0.083)</td>
<td></td>
</tr>
<tr>
<td>financial education</td>
<td>0.078</td>
<td>0.078</td>
</tr>
<tr>
<td>(0.055)</td>
<td>(0.055)</td>
<td></td>
</tr>
</tbody>
</table>

Control Variables
- N: 831
- Y: 825
- R-squared: 0.014
- 0.059

Control Mean
- 0.483
- 0.484

$\beta_1 = \beta_2$ (p-value)
- 0.001
- 0.002

Notes: Standard errors in parentheses.
- * $p < 0.10$
- ** $p < 0.05$
- *** $p < 0.01$

Column 1-2 report treatment effects on an index of the standardized three gambling outcome measures. For disaggregated results see Table 6 in the Appendix. Control variables include age, education, gender, marital status, previous gambling behavior, financial education, and a range of asset and income measures.

in magnitude – ranging from 20% to 40% of the control mean in most specifications. Interestingly, across all specifications, the absolute magnitude of the low intensity treatment effect is higher than that of the high intensity treatment.

While effects are economically significant, estimates for the intermediate and endline outcome are not statistically significant at conventional levels. This may be the result of the limited sample size for these outcomes measures. However, across all specifications we can reject that the low and high intensity treatment coefficient are equal at statistically significant levels. P-values from a test of equal coefficients are reported in the last row.

Results from the gambling index measure estimated with control variables (Column 2), which is our preferred specification, suggest that the high intensity group reduces gambling by 20% while the low intensity treatment group increases gambling by about 30% compared to the control group. These estimates are statistically significant.

Figure 5 shows the relationship between the treatment intensity and the gambling index using non-parametrically. Fitting a local polynomial function using a Epanechnikov kernel confirms the negative relationship between the number of rolls and gambling behavior.

These estimates mainly present the effect of the debiasing treatment on gambling on the extensive margin, i.e. whether an individual decides to gamble or not. With data from the endline survey, we can also explore whether we find an effect on the intensive margin, i.e. whether people spend a different amount when they gamble. A comparison of means shows that both the control and low treatment intensity group spend on average 15 Rand when they play the lottery, whereas the gamblers in the high intensity group spend on average 7.3 Rand (results not reported). However, these results should be interpreted with caution given the small number of people surveyed in the endline that reported to have gambled in the past 6 months (N=61). In addition, the effect on the extensive margin changed the composition of gamblers between the different groups.
5.2 Gambling Odds Sensitivity

As discussed in Section 2.2, the observed reduction in gambling behavior may be the result of a reduction in utility from playing any form of lottery and/or of a greater sensitivity towards winning probabilities. This section tries to shed some light on this question. First we represent graphical results graphically. Figure 3 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 will choose the lottery over a certain airtime amount for the low intensity (left panel) and high intensity (right panel) treatment group.

Surprisingly, the probability of people choosing the lottery almost does not change (and even slightly decreases) when we improve the winning odds for the low intensity group (left panel). By comparison, in the high intensity treatment group, the probability of choosing the lottery doubles from less than 15% to 30% when the winning odds improve.

The control group also responds to a change in probabilities, although less so than the high-intensity treatment group. Improving the winning odds increases the likelihood that they choose the lottery from 18% to 29%. These findings suggest that low intensity treatment reduced the odds sensitivity of participants, whereas the high intensity treatment made participants somewhat more sensitive to winning odds.

Table 5 reports results from a regression analysis. Column 1 shows that when we pool winning probabilities, higher winning odds are associated with a higher probability of choosing the lottery. The low intensity group is more likely and high intensity group is less likely to choose the gamble compared to the control group. However, these estimates are not significant at conventional levels. The p-value of a test of equal coefficients between the two treatment groups is 0.15 providing some evidence that the treatment intensity led to opposite effects.

The specification in Column 2 includes interaction terms between the treatment groups and the better odds dummy. The coefficients on these interaction terms confirm that the low intensity group is less sensitive and the high intensity group is 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=0.2). Likewise, the difference in response to improving winning probabilities ($\beta_2=\delta_2$) is only marginally significant for high intensity treatment effects (p-value: 0.167) despite an almost doubling in the share of people choosing the lottery (Figure 3).
Table 5: Odds Sensitivity (Midline Outcome)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1=Better Odds</td>
<td>0.087*</td>
<td>0.113*</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Above median rolls</td>
<td>0.052</td>
<td>0.122</td>
</tr>
<tr>
<td></td>
<td>(0.059)</td>
<td>(0.085)</td>
</tr>
<tr>
<td>Below median rolls</td>
<td>-0.045</td>
<td>-0.059</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Better Odds x below median</td>
<td>-0.138</td>
<td>(0.117)</td>
</tr>
<tr>
<td>Better Odds x above median</td>
<td>0.031</td>
<td>(0.107)</td>
</tr>
<tr>
<td>Financial education</td>
<td>0.039</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>(0.046)</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Control Variables</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.064</td>
<td>0.069</td>
</tr>
<tr>
<td>N</td>
<td>381</td>
<td>381</td>
</tr>
<tr>
<td>Control Mean</td>
<td>0.236</td>
<td>0.236</td>
</tr>
<tr>
<td>( \beta_1 = \beta_2 )</td>
<td>0.151</td>
<td>0.045</td>
</tr>
<tr>
<td>( \beta_1 = \delta_1 ) (&lt;median)</td>
<td>0.559</td>
<td></td>
</tr>
<tr>
<td>( \beta_2 = \delta_2 ) (&gt;median)</td>
<td>0.167</td>
<td></td>
</tr>
<tr>
<td>( \delta_1 = \delta_2 ) (equal Interaction)</td>
<td>0.204</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Standard errors are reported in parentheses.
* \( p < 0.10 \), ** \( p < 0.05 \), *** \( p < 0.01 \)

The table shows results of regression specification (2):
\[ y_i = \alpha_0 + \beta_1 T_{low} + \beta_2 T_{high} + \gamma_{oddsg} + \delta_1 T_{low} * odds_{g} + \delta_2 T_{high} * odds_{g} + \gamma X_i + \epsilon_i \]

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.

In sum, these results provide suggestive evidence that at the change in gambling behavior can at least partly be explained by a change in sensitivity to winning odds.

### 5.3 Hire Purchase Results

In this section we briefly summarize the effect of the hire purchase debiasing. Table in the Appendix 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 between treatment and endline as well as the length of any agreements.

Overall, we find little evidence that the hire purchase debiasing was effective. Treatment participants are less likely to agree that HP is convenient. However, they are also less likely to agree that HP should only be used for necessary purchases. This pattern suggests that respondents want to please the surveyor rather than a true change in attitude. Likewise, we observe only very modest changes in HP knowledge. The treatment group is 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 group were less likely to accept it or entered a shorter HP contract (Column 8-9).

6 Discussion and Concluding Remarks

The goal of this study was to investigate whether interactive, experiential debiasing methods that do not assume that participants have formal mathematical knowledge, can be effective in changing poor financial behavior such as using hire purchase or gambling.

Results of the gambling debias treatment across all outcomes and specifications show a consistent pattern: participants that need many rolls to get the two 6s are less likely to gamble and more sensitive to a change in winning odds compared to the control group while the opposite is true for people that got the two 6s on fewer rolls. One explanation for the behavior of the low treatment intensity group is that the central message of the debiasing treatment that getting additional sixes becomes exponentially more difficult with each additional die got lost ‘by chance’.

However, given that most of the previous studies in the debiasing literature have found modest results, it may seem somewhat surprising that a simple experiential debiasing treatment that did not take longer than ten minutes led to these large treatment effects. In what follows, we will discuss several explanations for why our intervention had significant effects. More research is needed to give a more definite answer on the effectiveness of different design features.

Although we tried to follow some of the debiasing principles used in previous studies (see Section 3), our specific treatment may have been more effective 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 debiasing technique may have been successful because it combines both novel and familiar elements: while participants are generally familiar with the concept of rolling dice, they are likely to be unfamiliar with the link 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.

Second, 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. A preliminary analysis of heterogeneous treatment effects suggests that the high intensity treatment was particularly effective for participants with low initial levels of math ability (results not reported). 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, Raiffa, and Tversky, 1988). Future research should replicate this and similar interventions to test if findings translate to different target populations and settings.

Third, we may observe large effects because the treatment has 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. 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

17 Finding of earlier research showing that emotional events are particularly effective in creating cognitive biases (Nisbet 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.
to predictions of a Bayesian model. Kahneman (1998) dubbed this phenomenon the ‘power of the particular’. 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 (Slavic and Lichtenstein 1971). Consequently, people are overconfident in evidence generated by small samples.

Our results support conclusions in earlier studies pointing out that debiasing strategies have the ‘potential to backfire’ (Willis 2008, p.36). In our study, the perverse effects observed in the low intensity treatment group provide in some sense indirect support for the effectiveness of our technique. However, to reduce the risk of these perverse effects similar studies should have fewer misleading chance events. In our treatment this could be achieved by simply adding a third die.

A natural next question is whether the debiasing not only affected gambling also led to other changes in other behaviors. The literature has discussed the tradeoff in choosing the range of contexts that the cognitive fix should aim to address (Heath et al. 1998, Lichtenstein and Fischoff 1977). Domain-specific repairs that are tailored for a specific context have the advantage that individuals can identify applicable situations more easily. Domain-general repairs that convey more general abstract concepts, by contrast, have the potential to affect behaviors across different domains. It is a priori unclear whether participants apply lessons learned in our gambling debias intervention narrowly to playing the lottery or whether a better understanding of probabilities affected saving behavior or the demand for insurance. A preliminary analysis of endline data suggests that we do not see any effects of the gambling debias treatment on these and other financial behavior measures. Our treatment seems to have effectively changed one important behavior, gambling, but did not affect behaviors in other domains.

References


### Appendix

**Table 6: Gambling Outcomes**

<table>
<thead>
<tr>
<th></th>
<th>Immediate Outcome</th>
<th>Intermediate Outcome</th>
<th>Endline Outcome</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>&gt;median rolls</strong></td>
<td>-0.146</td>
<td>-0.123</td>
<td>-0.028</td>
</tr>
<tr>
<td></td>
<td>(0.095)</td>
<td>(0.091)</td>
<td>(0.065)</td>
</tr>
<tr>
<td><strong>&lt;median rolls</strong></td>
<td>0.241*</td>
<td>0.230*</td>
<td>0.119</td>
</tr>
<tr>
<td></td>
<td>(0.132)</td>
<td>(0.131)</td>
<td>(0.079)</td>
</tr>
<tr>
<td><strong>financial education</strong></td>
<td>0.015</td>
<td>-0.042**</td>
<td>(0.060)</td>
</tr>
</tbody>
</table>

Control Variables

<table>
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<tr>
<th></th>
<th>N</th>
<th>Y</th>
<th>N</th>
<th>Y</th>
<th>N</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-squared</td>
<td>0.011</td>
<td>0.044</td>
<td>0.019</td>
<td>0.063</td>
<td>0.006</td>
<td>0.104</td>
</tr>
<tr>
<td>N</td>
<td>813</td>
<td>813</td>
<td>193</td>
<td>192</td>
<td>585</td>
<td>583</td>
</tr>
<tr>
<td>Control Mean</td>
<td>0.775</td>
<td>0.775</td>
<td>0.176</td>
<td>0.176</td>
<td>0.074</td>
<td>0.074</td>
</tr>
<tr>
<td>$\beta_1 = \beta_2$ (p-value)</td>
<td>0.004</td>
<td>0.007</td>
<td>0.093</td>
<td>0.055</td>
<td>0.071</td>
<td>0.067</td>
</tr>
</tbody>
</table>

Notes: Standard errors in parentheses. * $p < 0.10$ , ** $p < 0.05$ , *** $p < 0.01$  

The dependent variable in Column 3-4 is the number of rounds played in the gamble offered after the baseline. Column 5-6 reports effects on the decision to choose the lottery. The sample is restricted to people who are offered the low winning odds lottery. Column 7-8 measures the effect on having played the lottery in the last 6 months by the time of the endline survey. Column 1-2 report the effect on an index of the standardized three outcome measures. Control variable include age, education, gender, marital status, previous gambling behavior, financial education, and a range of asset and income measures.
### Table 7: Hire Purchase Outcomes

<table>
<thead>
<tr>
<th>HP Attitudes</th>
<th>HP Knowledge</th>
<th>HP Behavior</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>convenient</td>
<td>necessary</td>
<td>helpful</td>
</tr>
<tr>
<td>HP debias</td>
<td>-0.066*</td>
<td>-0.087**</td>
</tr>
<tr>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>financial educ</td>
<td>-0.068*</td>
<td>-0.064</td>
</tr>
<tr>
<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>used HP (basel.)</td>
<td>0.003</td>
<td>-0.005</td>
</tr>
<tr>
<td>(0.04)</td>
<td>(0.05)</td>
<td>(0.04)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Control Variables</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-squared</td>
<td>0.039</td>
<td>0.018</td>
<td>0.036</td>
<td>0.025</td>
<td>0.037</td>
<td>0.054</td>
<td>0.037</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>578</td>
<td>578</td>
<td>578</td>
<td>578</td>
<td>578</td>
<td>578</td>
<td>578</td>
<td>578</td>
</tr>
<tr>
<td>Control Mean</td>
<td>0.33</td>
<td>0.48</td>
<td>0.31</td>
<td>0.32</td>
<td>0.69</td>
<td>0.62</td>
<td>0.61</td>
<td>0.86</td>
</tr>
</tbody>
</table>

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 questions measure the effect on accepting HP agreements conditional on receiving a HP offer (Column 8) and the length of the agreement measured in months.

### Figure 4: Treatment Intensity Distribution

![Treatment Intensity Distribution](image-url)

N=409, 6 observations with more than 25 rolls excluded (Max: 50)
The histogram reports the number of rolls it took people in the debiasing group to get two 6s
Spikes at 15, 20, and 25 are the result of different stopping rules interviewers used
Figure 5: Nonparametric Regression

Nonparametric Regression: Gambling Index and Treatment Intensity

Local nonparametric regression using the Epanechnikov kernel. 95% Confidence Interval.
Table 1: Hire Purchasing Debiasing Material

<table>
<thead>
<tr>
<th>LOAN AMOUNT</th>
<th>INTEREST</th>
<th>FEES</th>
</tr>
</thead>
<tbody>
<tr>
<td>R2000</td>
<td>R 400</td>
<td>R 1200</td>
</tr>
</tbody>
</table>

If you borrow R2 000 for 12 months, how much do you pay in interest and fees?

Total to be repaid = R2 600