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Gambling, Saving, and Lumpy Liquidity Needs[†]

By Sylvan Herskowitz*

I present evidence that unmet liquidity needs for indivisible, "lumpy," expenditures increase demand for betting as a second-best method of liquidity generation in the presence of financial constraints. With a sample of 1,708 sports bettors in Kampala, Uganda, I show that participants' targeted payouts are linked to anticipated expenditures, while winnings increase lumpy expenditures disproportionately. I show that a randomized savings treatment decreases demand for betting. And I use two lab-in-the-field experiments to show that unmet liquidity needs and saving ability are important mechanisms. These results cannot be explained by betting as a purely normal good. (*JEL* C93, D81, G51, L83, O12, O16)

Gambling has been popular for millennia (Schwartz 2013). Today, it is a global industry with revenues estimated at nearly half a trillion dollars.[1] Over the past decade, sports betting has emerged as one of the fastest growing forms of gambling, itself frequently valued over a hundred billion dollars.[2] While the world's largest markets have historically been in major developed countries such as the United Kingdom, Japan, Australia, and China, new technologies have enabled international companies to enter previously untouched markets, with growth fastest across the developing world and, in particular, throughout Africa.[3] While many view gambling as a valuable source of entertainment and tax revenues, critics raise concerns about potential harms from gambling, including increased crime, indebtedness, and

* Markets, Trade, and Institutions Division, International Food Policy Research Institute (email: s.herskowitz@cgiar.org). Benjamin Olken was coeditor for this article. I am deeply grateful to Jeremy Magruder and Elisabeth Sadoulet. I would also like to thank Michael Anderson, Pierre Bachas, Patrick Baylis, Peter Berck, Lauren Bergquist, Josh Blonz, Fiona Burlig, Alain de Janvry, Aluma Dembo, Seth Garz, Tarek Ghani, Marieke Kleemans, Ken Lee, David Levine, Ethan Ligon, Aprajit Mahajan, Craig McIntosh, Ted Miguel, Leo Simon, Chris Udry, Liam Wren-Lewis, and Bruno Yawe for their feedback and contributions. I would also like to thank Antoine Guilhin, Jackline Namubiru, Amon Natukwatsa, and Innovations for Poverty Action for excellent work implementing the study. This project would not have been possible without generous funding support from a Doctoral Dissertation Research Grant from the National Science Foundation (NSF 1530852), the Center for Effective Global Action's East Africa Social Science Translation Collaborative, the Rocca Center at UC Berkeley, the Agricultural and Applied Economics Association, and the Institute for Money, Technology, and Financial Inclusion at UC Irvine. The project had IRB approval from the University of California's Institutional Review Board: 2014-03-6147. The original study design was registered at the Social Science Registry: AEARCTR-0001025. All errors are my own. The most recent version and online appendix can be found at www.sylvanherskowitz.com/betting.html.

[†] Go to https://doi.org/10.1257/app.20180177 to visit the article page for additional materials and author disclosure statement(s) or to comment in the online discussion forum.

[1] https://www.statista.com/statistics/253416/global-gambling-market-gross-win/

[2] http://www.statista.com/topics/1740/sports-betting/
http://www.bbc.com/sport/0/football/24354124

[3] For background on global betting expansion, see industry reports from H2 Gambling Capital (2015), PricewaterhouseCoopers (2014), and Morss (2009).

addiction.[4] Understanding the underlying causes of betting demand is important for determining both whether and how gambling-targeted regulation or interventions should be enacted.

The broad and persistent popularity of gambles with negative expected returns has presented a long-standing puzzle for economists. The existing literature points to a wide range of explanations, including misperception or misunderstanding of odds (Bordalo, Gennaioli, and Shleifer 2012; Barberis 2013), addiction (Becker and Murphy 1988), and simply fun (Conlisk 1993). These prevailing explanations contribute to an image of gambling as either an indulgence or a symptom of errors of reasoning or understanding. However, seminal work by Friedman and Savage (1948) posited a source of rational demand for gambles resulting from nonconcavities in peoples' indirect utility curves. Nonconcavities can result from underlying demand for indivisible, "lumpy," expenditures and accompanying liquidity needs (Kwang 1965), while access to credit and ability to save provide alternatives that can reduce this source of appeal (Bailey, Olson, and Wonnacott 1980). However, existing efforts to test these relationships empirically are limited. This paper provides evidence that unmet liquidity needs and financial constraints can increase demand for gambles as a second-best method of liquidity generation.

Sports betting has exploded in popularity throughout Uganda over the past 15 years. A recent report estimated that 37 percent of adult males in the capital, Kampala, had placed bets in the past year.[5] Additionally, credit is expensive, and constraints on saving can be severe for much of this population.[6] Sports bettors in Kampala therefore present an ideal population and setting to test whether betting demand is heightened by unmet liquidity needs. The study included 1,708 sports bettors in Kampala; 957 men were included in a 2-month study with 5 biweekly visits, creating a high-frequency panel of reported betting behaviors, earnings, and expenditures. This group was supplemented with 751 additional participants in a condensed, single-visit study. The analysis includes evidence from reported expenditures and betting behavior, a randomized field experiment, and two lab-in-the-field experiments in support of the theory that unmet liquidity needs and financial constraints contribute to demand for betting.

First, I show that higher anticipated lumpy expenditures are associated with higher targeted payouts on respondents' betting tickets. Additionally, winnings significantly increase both the size and likelihood of large lumpy expenditures, but do not affect non-lumpy expenditures significantly. These responses are stronger for respondents with low saving ability, consistent with closer linkages between betting behavior and unmet liquidity needs among those with constrained alternatives.

Next, I test whether improving one's ability to save reduces betting demand. One month before the endline, randomly selected participants were offered a wooden saving box to assist them in saving. After receiving the saving box, these recipients

[4] See Grote and Matheson (2013), Bruce (2013), and Ariyabuddhiphongs (2011) for recent reviews of the literature.

[5] See Ahaibwe et al. (2016) for a report on the pervasiveness of gambling and sports betting in Uganda.

[6] See Dupas et al. (2016) for discussion of challenges to saving in Uganda. See also African Development Bank (2011) and Beck and Cull (2014) for background on high costs and limited availability of credit.

had 0.18 standard deviations lower betting demand in an index of reported betting expenditures and elicited betting demand.

I then use two lab-in-the-field experiments to isolate the role of betting as a method of liquidity generation, the key feature distinguishing it from other normal goods. In the first experiment, interviewers asked selected respondents a set of questions related to a previously identified and desired expense, designed to increase its salience. Respondents who were randomly selected to receive this prime before being offered a choice of cash or betting tickets were 16 percent more likely to demand the maximum number of tickets, an effect again driven by people with low saving ability. In the second experiment, respondents were guided through a brief budgeting exercise assisting them in making realistic assessments of their weekly saving potential. Randomly selected participants did this activity before the betting ticket offer, while others did it afterward. Respondents who did the exercise before the offer and improved their self-assessed ability to save reduced their likelihood of demanding the maximum number of tickets by 44 percent. If betting were purely a normal good, salience of liquidity needs or new information about one's ability to save would have been unlikely to cause these observed responses.

Together, the paper's results tell a consistent story: betting behavior is linked to participants' liquidity needs, and demand is amplified by constraints to one of its primary alternatives. Given negative expected returns, this is a costly way of generating liquidity. This work suggests that improving financial services for vulnerable populations may be an effective strategy for reducing these losses. While the interventions used in this study appeared to reduce betting demand, more enduring changes in behavior are likely to require more ambitious policies and interventions. The impacts of financial services on betting and risk-taking behavior more broadly are topics deserving further study.

This paper contributes to at least two broad areas of economic research. First, while studies have long observed that poorer, marginalized populations often have high levels of betting participation and intensity, empirical explanations for this tendency are thin.[7] Theoretical work on the linkages between demand for gambles, unmet liquidity needs, and financial constraints can potentially speak to these patterns, but existing empirical work showing these causal relationships is limited and presents mixed evidence. Snowberg and Wolfers (2010) examine American horse betting and find that misperceptions of odds explain more of the well-established long shot bias than demand for high payouts. Focusing on usage of winnings, Imbens, Rubin, and Sacerdote (2001) show that American lottery winners purchase large durable goods following wins. And Crossley, Low, and Smith (2016) present similar evidence in the United Kingdom while also showing that credit-constrained lottery participants use inheritances to make lumpy expenditures, suggesting that lottery participants face binding liquidity constraints. While these latter two papers are consistent with financial constraints affecting gambling demand, they are unable to show that this ex post behavior is a driver of ex ante demand. In addition, the choice of setting is itself a contribution to the gambling literature, where almost all

[7] See Welte et al. (2008) and Lang and Omori (2009) for examples of this in developed country settings; Ariyabuddhiphongs (2011) acknowledges these patterns in a broader review of the literature.

existing work is set in developed countries.[8] Linkages between liquidity needs and betting demand are likely to be particularly important in developing country settings (and among disadvantaged populations more broadly) where gambling is growing fastest and financial constraints are often severe.

Second, this paper links to a number of themes in the development literature. Existing work has shown that financial demands and constraints facing the poor can lead to unexpected, second-best financial management strategies (Collins et al. 2009, Banerjee and Duflo 2007). Many features of betting in this context resemble another unconventional saving method often seen in developing countries: rotating savings groups.[9] Recurrent payments or deposits are made to a third party in pursuit of a lump sum of liquidity, for savings groups, when it is one's turn, or for betting, when you win. However, for betting, expected returns are negative and payout is uncertain, payment frequency and size are flexible, and there is no need for coordination or trust with other participants (aside from the betting companies). Recent work by Casaburi and Macchiavello (2019) showed another manifestation of second-best liquidity generation strategies resulting from saving constraints, whereby Kenyan dairy farmers sacrifice a portion of their income in return for *less* frequent payments. In this paper, I contribute to the broader literature on savings and the impact of saving constraints.[10] Recent work has also shown disproportionately high valuations of lottery-linked incentives (relative to flat payments) in both developing and developed country settings, with a particular focus on lottery-linked savings products.[11] Notably, Dizon and Lybbert (forthcoming) and Cole, Iverson, and Tufano (2017) both show that these products are particularly appealing for populations facing other financial constraints, consistent with the causal findings of this paper.

Finally, Banerjee and Duflo (2007) documented high household expenditure levels on seemingly nonessential goods and products among the poor, such as alcohol, TVs, and traditional ceremonies. The broader literature on temptation goods is summarized by Banerjee and Mullainathan (2010), who offer declining temptation in income as a contributing factor to high expenditure levels among the poor. However, there may be other rational explanations as well. Alcohol may offer relief from physical pain. Participation in expensive community ceremonies may also serve as payment into informal insurance schemes. And TVs may simply be the highest return value for entertainment where entertainment is scarce. This paper provides evidence that the potential to relieve liquidity constraints can provide a rational basis contributing to high betting expenditures among the financially marginalized.

[8] Ariyabuddhiphongs (2011) conducted a comprehensive review of over 100 gambling studies and found only three based in developing countries (his review preceded the work on lottery-linked savings cited above). I was able to find only one additional paper testing causes of gambling in Africa, from Abel, Cole, and Zia (2015), that focuses on experiential learning about compound probabilities in South Africa.

[9] See Anderson and Baland (2002) for an overview of rotating savings and credit associations (roscas) and Anderson, Baland, and Moene (2009) for an example of potential costs and risks.

[10] This work was recently summarized by Karlan, Ratan, and Zinman (2014), with major contributions on the effects of saving constraints on financial investments and resiliency to shocks from Dupas and Robinson (2013a), Brune et al. (2016), and Dupas and Robinson (2013b).

[11] Kearney et al. (2011) review the literature on lottery-linked savings in the United States. See additional examples in developing countries from Gertler et al. (2018) and Brune (2015).

The paper proceeds as follows. Section I provides further background on sports betting and details on the experimental design and data collection. Section II presents descriptive evidence of demand for betting and financial constraints in the sample. Section III details the empirical results. Section IV concludes.

I. Background

A. *Conceptual Framework*

Demand for large, indivisible, "lumpy" expenditures where payment must be completed in a single transaction creates need for liquidity. Considerable attention has traditionally focused on access to credit and saving as ways to finance these purchases, but betting could provide a third alternative.

Betting is a bundled good. It includes direct enjoyment from the activity of betting. This could include excitement from the thrill of wagering and winning money or come from complementarities to supporting and following different teams. But it also serves as a financial asset with the possibility of monetary payout. This second feature distinguishes betting from other normal goods and makes it a potential source of liquidity. Betting therefore presents an alternative to more conventional liquidity generation strategies. People facing high costs of credit or impediments to saving may find the financial payouts from betting especially enticing. Similarly, improvements in one's ability to save (or to access affordable credit) may reduce the relative appeal of betting as a source of liquidity.

Because of these dual features, testing the effect of saving ability on demand for betting is an empirical challenge. A reduction in betting following an improvement in ability to save could result from either mechanism (or both). Improved ability to save may simply reduce all expenditures, with betting response similar to other normal goods. Or improved saving ability could undermine the appeal of betting as an alternative way to get liquidity. This paper aims to provide evidence, in particular, on the latter mechanism. A more complete treatment of this conceptual model is included in online Appendix C.

B. *Gambling and Sports Betting*

People have long sought opportunities to place wagers and win money. Gambling dice have been found dating back to 1300 BC, while today's range of opportunities and options for gambles covers casinos, lotteries, and betting on a nearly limitless range of events. The modern gambling industry has immense global reach and scale, with billions of people participating each year (Schwartz 2013). Gross gambling yield is estimated at nearly half a trillion dollars, an estimate that does not even include unofficial or illegal gambling, the scale of which may be even bigger.[12] Growth has been accelerating over the last ten years and is expected to continue.[13]

[12] https://www.statista.com/statistics/253416/global-gambling-market-gross-win/

[13] A recent report to the European Gaming and Betting Association (Foley-Train 2014) estimated that regulated gambling markets in Europe grew 19 percent between 2007 and 2012 and projected an additional 20 percent by

These high levels of revenues are mirrored by high incidence and intensity of participation in many parts of the world (H2 Gambling Capital 2015). Within countries, higher intensity of participation is frequently found in poorer and more marginalized populations, raising concern about loss of potentially scarce household resources (Welte et al. 2008, Lang and Omori 2009). Additionally, the American Psychiatric Association recently categorized gambling as a potential source of addiction (American Psychiatric Association 2013), while recent studies have found rates of problem gambling between 0.5 and 5 percent of the adult population in countries across Europe, Asia, Oceania, and North America (Calado and Griffiths 2016).

Despite these concerns, expansion of the industry has continued. Adaptation of online betting technology in the form of internet-linked, vendor-operated betting consoles and betting shops has broadened access to new betting products with higher payoffs and a wider range of betting options than previously available. These advances have enabled investors to enter into previously unprofitable markets while leveraging internationally calibrated odds, with growth fastest in many developing countries within Africa (Morss 2009, PricewaterhouseCoopers 2014). Scarcity of reliable data makes it difficult to know the exact size of the sports betting industry across the continent, but news coverage makes it clear that international companies are rapidly entering and expanding into African markets.[14] While regulation varies widely by country, new tax revenue streams provide strong incentives for local governments to permit continued growth of the industry.

In Uganda, sports betting is a legal, large, and rapidly expanding industry. As in most of the world, different forms of gambling have long existed in Uganda, but this format and ensuing explosion in popularity are new. The arrival and expansion of international betting companies began less than 15 years ago, but as of June 2015, there were 23 licensed companies operating in Uganda, with over 1,000 betting outlets spanning the country (Ahaibwe et al. 2016). These shops overflow with customers during peak hours.[15] A 2016 policy report from the Economic Policy Research Center (EPRC) at Makerere University recently conducted a representative survey of Kampala residents and found that 37 percent of men between 18 and 40 had bet during the last year, wagering an average of 12 percent of their income. Similar to demographic trends elsewhere, men in the lowest income quintile spend the largest share of their earnings on betting, with survey responses suggesting that betting primarily displaces household expenditures and investments. This rapid expansion and high level of betting intensity have received increasing attention and concern from local media and political figures voicing increasing concern about the social effects

2016. In the United States, monetized fantasy sports became a multibillion dollar industry led by companies like Fan Duel and Draft Kings before regulations in 2016 curbed their expansion. See http://fortune.com/2015/04/06/draftkings-and-fanduel-close-in-on-massive-new-investments/. A supreme court decision in 2018 recently legalized sports betting and may lead to another boom in popularity and participation in the United States.

[14] Recent media articles from Ghana, Nigeria, Senegal, Malawi, Sierra Leone, Tanzania, Liberia, Zimbabwe, and Kenya all observe a sharp rise in sports betting in their respective countries. Click on the country name for a linked article. In Kenya, the next wave of expansion and innovation is already taking place, with mobile betting technologies allegedly serving as a meaningful driver in the expansion of M-Pesa, Kenya's mobile money platform. See www.techweez.com/2016/05/10/m-pesa-sports-betting/ and www.bloomberg.com/news/articles/2016-05-09/vodafone-mobile-money-volumes-boosted-by-sports-betting-in-kenya

[15] http://www.monitor.co.ug/Business/Prosper/The-price-of-betting-on-Ugandans/-/688616/2107602/-/k7i4bh/-/index.html

of sports betting, including loss of scarce household resources, dissaving, domestic violence, addiction, and suicide.[16,17]

Betting in Uganda follows the same format spreading throughout the continent and widely available online. First, a bettor chooses which matches to include on his ticket from a list of available options, typically featuring over 100 games. He then predicts an outcome for each match, such as "Sevilla FC defeats Manchester United." Predicting less likely outcomes or adding additional games to a ticket is rewarded with a higher possible payout.[18] If every predicted outcome on the ticket occurs, it can be redeemed for its targeted amount. If any single outcome is incorrect, the ticket is worth nothing. Even by local standards, the minimum cost of placing a bet is relatively low, at just US$0.18 per ticket. While bettors can target extremely large payouts if they choose, companies often cap the maximum payout at around US$2,000, and most bettors target amounts much lower.

For most participants, the cost, payouts, and odds of betting relative to their incomes are similar to American scratch tickets. While the payouts and expected return to a betting ticket depend on a number of factors, I estimate that a "typical" ticket with mean attributes from the data targeting US$55, a bet of US$0.35, and including 7–8 predictions has roughly a 0.35 percent chance of winning and an expected value of US$0.19 (55 percent of its cost). Additional details on the structure of betting are contained in online Appendix B.

C. *Experimental Design and Data Collection*

Field work for the project was conducted over 11 months between September 2015 and July 2016, involving three phases of data collection and 1,708 participants. The "full study" was conducted in two waves. A total of 453 participants were included in Wave 1, between October and December of 2015. Wave 2 was conducted between April and June 2016, following similar protocols with a second group of 504 participants. The final phase of data collection was a "condensed," single-visit study, conducted in July 2016 with 751 additional respondents.[19]

The study targeted men 18–40 years old and self-employed in small microenterprises or services, with weekly incomes below US$50.[20] Each phase of data collection began with a listing exercise in selected parishes around Kampala. Listing was intended to establish broader betting incidence in this population and

[16] See www.allafrica.com/stories/201603150296.html, www.monitor.co.ug/Business/Prosper/The-price-of-betting-on-Ugandans/-/688616/2107602/-/k7i4bh/-/index.html, and www.monitor.co.ug/News/National/Soccer-fan-kills-self-over-Arsenal-s-loss-to-Monaco/-/688334/2639990/-/dn6tkoz/-/index.html.

[17] In January 2019, President Museveni echoed these concerns and announced that operating licenses would no longer be granted to foreign-owned betting companies. Whether this declaration marks a policy shift toward tighter regulation of betting or simply a shift in ownership and associated rents from the industry remains to be seen. See www.theconversation.com/ugandas-ban-on-sports-betting-was-the-right-thing-to-do-110728.

[18] Payout offerings are based off of internationally calibrated and continuously updated betting odds. It is therefore unrealistic to expect a bettor in Uganda to have enough information to be able to identify profitable bets and opportunities that have not already been arbitraged out of the market.

[19] The full size of this condensed study was 1,293. However, 542 participants were assigned randomly to a different treatment group testing hypotheses unrelated to those in this paper, about psychological "hot states" and betting demand. They are excluded from all analyses in this paper.

[20] Piloting and existing assessments in Uganda both suggested high incidence and intensity of betting along with unmet liquidity needs in this population (Ahaibwe et al. 2016, Ssengooba and Yawe 2014).

to identify suitable study participants who constituted a range of "typical" bettors and not just those who were most extreme.[21] Respondents were identified at their place of work and asked a short set of screening questions to determine whether they met the targeting criteria. Online Appendix Table A.2 summarizes the listing data. As expected, betting incidence was high. Of 5,522 people included in the listings, 32 percent reported betting in most weeks. A randomized selection of respondents were then invited to participate among those who bet regularly. The full study was launched immediately afterward. Additional details on field protocols are included in online Appendix D.

Full study participants were interviewed in person five times, once every two weeks. In addition, brief phone check-ins were conducted on weeks between visits. Surveys captured a wide range of respondents' backgrounds, including household composition, education, savings and credit experience, and risk and time preferences. For these topics, expected to be stable over the study period, questions were asked at only one of the in-person interviews. For responses expected to show greater variation, such as household expenditures, savings, earnings, betting expenditures, and winnings, recurrent modules were asked in each in-person interview. Phone check-ins were restricted to the most important recurrent variables: earnings and betting participation.

During the third in-person visit, four weeks before the final visit, members of the research team gave wooden saving boxes to randomly selected respondents in the full study. A priming experiment was conducted in conjunction with a betting ticket offer (detailed below) during the final visit for all participants in the full study as well as the baseline for those in Wave 2 and at the end of the condensed study. A time line of data collection and interventions for participants in the full study is illustrated in Figure 1. Additional randomized treatments unrelated to the hypotheses in this paper were also conducted during the study.[22]

The condensed study was designed to build on and extend the priming experiment with a randomized budgeting exercise. It was conducted over three weeks following the conclusion of the full study in July 2016. Recruitment followed the same eligibility criteria. With only a single visit, these respondents were not included in the saving box experiment. All treatments, for all study groups, were randomized and included as controls in all estimating regressions. Further details on the treatments are provided in Section III.

To capture demand for betting that was not reliant on self-reported behavior, field team members collected a revealed-preference measure of betting demand. This was conducted in the final in-person visit for all participants in the full study, during the baseline for participants in Wave 2, and at the end of the condensed study. Respondents were offered the choice between prefilled betting tickets and

[21] In Wave 1, parishes were randomly chosen from the full set of parishes in Kampala with commercial centers where the target population could be found. In Wave 2, parishes closer to the city center were targeted due to logistical challenges and budget constraints.

[22] The second round contained a randomized offer of a wallet with which respondents were encouraged to budget for betting. The fourth round contained a randomized information treatment whereby selected respondents were given an accounting of their betting expenses and winnings. The endline also included a randomized short video prime of football highlights. Finally, in the first wave, selected respondents were initially intended to receive help setting up formal saving accounts; however, this was abandoned almost immediately due to logistical challenges.

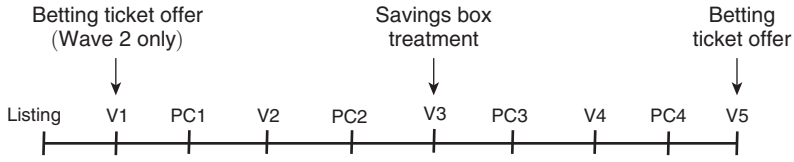

Figure 1. Full Study Timeline

Notes: The figure above illustrates the study timeline for the 957 participants in the full study. V indicates in-person visits, while PC indicates phone check-ins. The number associated with each indicates if it is the first, second, third, etc. visit or check-in. There was one week scheduled between each visit so that the final visit, V5, took place eight weeks after the first visit, V1. In-person visits included full-length interviews of approximately 35–50 minutes, with respondents including full betting, earning, and expenditure modules. Phone check-ins were five minutes in duration, only asking about overall betting and earnings in the past week.

The full study was conducted in two waves. Wave 1 was conducted with 453 participants in October–December 2015, while Wave 2 included 504 participants from April to June 2016. Lumpy good priming experiments were conducted in conjunction with the betting ticket offers. Other treatments were conducted in V2 (budgeting of betting expenditures) and V4 (feedback on betting performance) that were not linked to the liquidity generation hypotheses motivating this paper.

a designated amount of cash. Prefilling the tickets was done partially for logistical reasons but also because removing the selection of matches reduces the fun of a typical betting ticket and thus focuses its value on the financial gamble and potential for generating liquidity, the component of betting demand that motivates the study. Respondents were told the amount spent on the ticket as well as the approximate size of the payout should it win but were not permitted to see its actual predictions.[23] The cash value offered was set below the ticket price, preventing respondents from using the money to purchase new tickets themselves, but similar to its expected value. The cost of the tickets was 1,000 Ugandan shillings (approximately US$0.35), the most common ticket cost, and purchased from well-established betting companies familiar to all respondents. Respondents were then asked how many units of cash or tickets they would like to choose. Participants in the full study could select up to four, whereas participants in the condensed study were limited to two.[24]

This outcome is coded in three ways in the analysis. In the full sample, I use the count of tickets. When combining the full and condensed samples, I switch to the share of tickets offered, since these groups were offered different numbers of tickets. I also use a binary indicator for demanding the maximum number of tickets motivated by heavy censoring at the maximum. Forty-six percent of participants selected the full amount of tickets offered. Respondents' unconstrained demand from this exercise is not observed and therefore unknowable; however, the distribution from

[23] Preventing respondents from reviewing the actual predictions was done to make sure that disagreement over a given prediction did not reduce their valuation of the ticket to zero.

[24] There were two differences between the ticket offers in the full and condensed study. First, during the full study, participants were given the additional choice of whether they wanted tickets that targeted low, medium, or high payouts. In the condensed study, payout size was always medium. Second, the amount of money offered instead of a betting ticket was held fixed during the full study but was varied experimentally during the condensed study. All analyses control for these factors. Online Appendix Table A.1 shows a positive and significant relationship between this measure of betting demand and respondents' reported levels of betting.

reported betting expenditures suggests a long right tail so that the maximal coding emphasizes important variation on the right side of the distribution.[25]

II. Descriptive Evidence

A. *Background Characteristics*

Seventy-nine percent of respondents said that their primary reason for betting was to get money (fun was cited by just 15 percent). While cheap talk responses deserve skepticism, respondents' stated motives also merit serious consideration. Descriptive statistics from the survey add credence to these claims and provide context on the background and constraints shaping respondents' betting, saving, and expenditure decisions.

Table 1 shows statistics on participants' background, including income, betting expenditures, education, available liquidity, saving ability, and winning targets.[26] Respondents had personal earnings around US$30 per week and household income per capita of US$16–$20 per week, suggesting that most participants live at or below the poverty line. They also spend a lot on betting, with an interquartile range between 5 and 15 percent of weekly earnings. With expected losses of 45 percent, this corresponds with income losses of roughly 2 to 7 percent of weekly income. For higher-intensity bettors, expected losses may be considerably higher. While the study's sampling strategy was not designed to be representative of a broader population, these reported levels of betting are in line with the representative sample of Kampala men in the EPRC report.

Panel B provides motivation for why saving and betting could constitute competing ways to generate liquidity for currently unattainable purchases. "Available liquidity" is respondents' answers to the question, "What is the biggest expense you could make without needing to borrow?" The majority of participants could not afford an expense above the size of their normal weekly income without borrowing. Respondents claim that they have the potential to save between 25–35 percent of their weekly earnings without stretching their finances unduly. Meanwhile, the reported distribution of betting payout targets is roughly double peoples' available liquidity. These targets are suggestive of desire for expenditures that are currently unattainable but should be achievable within a few months of saving.

The data further suggest that respondents face considerable barriers to affordable credit. Less than 50 percent thought they would be able to get a bank loan if they wanted one. Even if they could, interest rates are high, 20–25 percent on a 6-month loan. In addition, 85 percent of respondents reported having a nonbusiness expenditure that they were eager to make in the coming months, expenditures which are

[25] For reported betting expenditures, censoring the top 46 percent would reduce the measured mean of betting expenditures to just 40 percent of the uncensored mean.

[26] Weekly income was calculated as mean reported income for panel respondents, while it was reported as "normal" weekly earnings for participants in the condensed study. Summary statistics, split by panel and condensed sample, are shown in online Appendix Table A.3. While the groups are broadly similar, differences are not a point of primary concern. Treatment randomizations were conducted within each study phase so that differences do not threaten identification.

Table 1—Summary Statistics: Household and Financial Background

	Mean	p25	p50	p75
Panel A. Household Background				
Weekly income (US$)	32.19	19.74	28.57	40.68
Betting expenditures (US$)	3.44	1.36	2.19	4.14
Percent of income spent on betting	12.28	4.65	8.49	15.16
Live alone	0.31	—	—	—
Household size (>1)	3.88	3.00	4.00	5.00
Percent contribution of household finances	71.41	50.00	75.00	100.00
Weekly household income per capita (US$)	20.85	8.65	16.10	28.57
Age	26.92	23.00	26.00	30.00
Primary	0.84	—	—	—
Junior secondary (O level)	0.45	—	—	—
Senior secondary (A level)	0.18	—	—	—
Panel B. Financial Background				
Available liquidity (US$)	97.02	11.43	28.57	85.71
Available liquidity/mean income	2.86	0.37	0.93	2.71
Saving potential (US$)	9.47	3.43	7.14	14.29
Saving potential/weekly income	0.35	0.13	0.26	0.46
Win target (US$)	360.97	22.86	57.14	171.43
Win target/mean income	16.71	0.75	2.00	6.67
Win target/liquidity available	32.82	0.60	2.00	10.00

Notes: All raw expenditure values shown in US$. Household income is only calculated for 97 percent in full and 92 percent in condensed study of respondents who contributed to household expenses. Weekly income is calculated as mean weekly income for each respondent. Contribution to household finances is only calculated for respondents who do not live alone.

not typically covered by bank loans, and only 48 percent thought they would be able to get a bank loan. Informal moneylenders are available in these communities but were viewed highly unfavorably due to even higher interest rates and risks of severe penalty or punishment in the case of default.[27]

B. *Saving Ability*

The link between saving ability and demand for betting is central to this paper. There are many different factors affecting peoples' ability to save. In response, there are many different ways the surveys aimed to capture these abilities. Beyond just setting money aside for saving, survey responses gave an indication of further challenges respondents face. Approximately 30 percent felt pressure to spend money, 55 percent feared theft at home, and 33 percent carried existing debt (see online Appendix Table A.4). I therefore create an index of saving ability using as much of this data as possible.

The index is created with four different components. First, I use the measure of ex ante saving potential reported as the share of income that could be allocated to saving. Second, I use the ex post measure of accrued saving reflected in the question

[27] While local moneylenders do not restrict how borrowers use their loans and have low barriers to borrowing, they typically charge 50 percent interest on a 6-month loan, equivalent to 33 percent expected losses. While still slightly better than betting, after factoring in the possibility of default, penalties, and risk of losing collateral, the expected losses from moneylender credit are likely comparable to betting.

about available liquidity relative to mean income. Third, as a measure of freedom from pressure on finances, I use the negative log of household size.[28] And finally, I construct a "saving experience index" from a set of binary questions related to security of savings and available saving technologies.[29] In creating an overall "saving ability index," I normalize each of these subindices, sum them together, and renormalize. People with "low saving ability" in the analysis refers to respondents with a saving ability index below the median in their phase of the study, while "high saving ability" refers to those above the median.

C. *Liquidity Needs and Sources*

Finally, a primary assumption of this paper is that bettors have lumpy expenditures they would like to make but cannot afford currently. Lumpy expenditures were defined as indivisible expenditures that require payment in full at the time of purchase and could include any type of good or service. In the full study, interviewers asked respondents about three categories of potential desired lumpy expenditures: business investments, household expenditures, and personal expenditures. Enumerators explained that these lumpy expenditures should be realistically attainable to avoid purely aspirational targets. Panel A of Table 2 shows the responses. The majority of respondents could readily identify an expense for all three categories, and only 5.8 percent were unable to identify any desired expenditures.

During the condensed study, after identifying a desired large expenditure, interviewers asked respondents about likely sources of liquidity for this purchase, shown in panel B. These responses are also split between high- and low-ability savers. Although both groups saw saving as a similarly likely source of liquidity (97 percent and 95.6 percent respectively), low-ability savers were substantially and significantly more likely to report betting as a likely source of liquidity (30.8 percent versus 19.5 percent) and less likely to report credit as a likely alternative (21.8 percent versus 27.5 percent). These responses suggest that betting is widely viewed as a plausible source of liquidity for large purchases (cited more highly than all sources of credit combined), particularly among those with a limited ability to save.

[28] Additional household members could also contribute to household finances and relieve financial obligations. However, in this sample, 84 percent of respondents living with others are heads of their households. On average, respondents report to be contributing 81 percent of their household's finances (71 percent for people not living alone). I therefore assume that additional household members are associated with greater financial pressure that outweighs shared obligations.

[29] The saving experience index has six components (weighted equally). The respondent (i) has a saving account, (ii) has ever participated in a rosca, (iii) has mobile money, (iv) has a piggy bank or lockbox, (v) feels free from family or other sources of pressure on his finances, and (vi) has never had money stolen from home and feels that money stored at home is safe from theft. Condensed study participants were not asked about lockboxes and piggy banks, and so their scores have a maximum of five. The saving experience index is the normalized sum of these measures.

Table 2—Lumpy Expenditures and Source of Liquidity

Panel A. Most frequently referenced desired lumpy expenditures by category

Good	Business	Household	Personal
#1	Working capital, 19%	Furniture, 17%	Clothes, 31%
#2	Improve work site, 13%	Entertainment, 17%	Phone, 11%
#3	Motorcycle, 13%	Build/repair, 9%	Vehicle, 4%
#4	Tools,12%	Appliance, 5%	Entertainment, 4%
#5	New venture, 2%	School fees, 5%	Jewelry, 3%
Other	10%	20%	9%
None	33%	27%	38%
Price	$285.6	$114.3	$42.8
Price/mean income	12.9	4.1	1.8

Panel B. Likely sources of liquidity for desired expenditure

	Overall mean	High Saving Ability	Low Saving Ability	*p*-value difference
Saving	96.3%	97.0%	95.6%	0.338
Betting	25.2%	19.5%	30.8%	0.000
Credit family or friend	13.7%	15.9%	11.4%	0.078
Credit bank or loan	10.7%	11.0%	10.4%	0.781
Credit moneylender	2.1%	2.5%	1.6%	0.425
Any credit source	24.6%	27.5%	21.8%	0.075

Notes: Panel A shows responses to the question "Is there a large expenditure that you are hoping to make in the next few months?" Respondents were asked to name something in each of the three categories. Interviewers were instructed to ensure that the item or expense named was in fact nondivisible (working capital would mean a bulk purchase), and they were additionally instructed to make sure that these expenditures were realistic and not simply something respondents would like to have as a dream. #1 refers to the most frequently referenced type of expenditure for the given category. #2 is the second most referenced, and so on. The full set of lumpy expenditures was only asked for participants in the full study. Panel B shows responses to the follow-up question conducted during the condensed study, typically following the identification of a business expense. The first column shows the overall mean from all respondents. The second and third columns show these mean responses split by high-ability and low-ability savers, respectively, as categorized by being above or below the median savings index. The fourth column provides the *p*-value from a *t*-test of the difference between high- and low-ability savers.

III. Results

A. *Lumpy Expenditures, Payout Targets, and Usage of Winnings*

At each in-person visit during the full study, participants were asked about upcoming large, lumpy expenditures that they were intent to make. The format of betting in Uganda allows participants to choose their potential payout (see Section IB), and respondents were asked to report the amounts they targeted. If betting motivation derives, even in part, from liquidity needs, we may expect a correspondence between anticipated expenses and targeted payouts. Leveraging the panel nature of the data, I estimate the following equation:

$$PayoutTarget_{i,t} = \beta_0 + \beta_1 ExpTarget_{i,t-1} + \beta_2 NoExp_{i,t-1} + \lambda X_{i,t} + \gamma_i + \delta_t + \psi_s + \epsilon_{i,t}.$$

The variable $PayoutTarget_{i,t}$ is the reported median payout targeted by individual i on his tickets in time period t; $ExpTarget_{i,t-1}$ is the size of the desired lumpy expenditure identified by the respondent two weeks earlier; $NoExp_{i,t-1}$ is an indicator equal to one if a respondent did not report any anticipated expenditures at that time; $X_{i,t}$

Table 3—Payout Targets and Desired Expenditures

	Prop (1)	IHST (2)	Prop (3)	IHST (4)	Prop (5)	IHST (6)
Expenditure target price (ETP)	0.0678	0.0771	0.0218	0.0378	0.0149	−0.0009
	(0.0249)	(0.0225)	(0.0223)	(0.0225)	(0.0295)	(0.0305)
ETP × low saving ability					0.0224	0.0757
					(0.0452)	(0.0445)
log(mean income)	−1.8427	0.1275				
	(0.3186)	(0.0508)				
Mean Y	3.529	3.574	3.529	3.574	3.529	3.574
p-value: $\beta_1 + \beta_2 = 0$	—	—	—	—	0.278	0.022
Individual fixed effects	No	No	Yes	Yes	Yes	Yes
Observations	3,602	3,602	3,602	3,602	3,602	3,602
R^2	0.0875	0.6494	0.5278	0.8222	0.5342	0.8239

Notes: Columns 1 and 2 are results from regression of $MedPayoutTarget_{i,t} = \beta_0 + \beta_1 TargetExpPrice_{i,t-1} + NoExpTarget_{i,t-1} + \lambda X_{i,t} + \delta_t + \epsilon_{i,t}$. Dependent variable is the reported median amount targeted in betting tickets purchased the preceding week. Expenditure target price was the anticipated lumpy expenditure mentioned during the previous interview. Weekly income and a dummy for no current purchasing target are also included as controls. Columns 3 and 4 replace individual time-invariant covariates with individual fixed effects. Columns 1, 3, and 5 with heading "Prop," scale expenditure target and payout target by individual's mean income. Columns 2, 4, and 6 apply the IHST conversion to these two raw variables. Standard errors are clustered at the individual level.

are time-varying individual controls including weekly earnings; γ_i, δ_t, and ψ_s are individual, time, and survey round fixed effects; and $\epsilon_{i,t}$ is the error term. Standard errors are clustered at the individual level.[30]

While this empirical setup cannot establish causality, these correlations highlight important patterns in the data and suggest deeper linkages between desired expenditures and payout targets unexplained in the preferred specification by income, flexible time trends, or individual-level, time-invariant factors. Table 3 shows these results. First, columns 1 and 2 exclude individual fixed effects. Both the linear form of the target price (scaled by mean income) or the inverse hyperbolic sine transformation (IHST) of its value show that payout targets rise significantly with anticipated expenditures. Adding individual fixed effects in columns 3 and 4, the magnitude and significance of these correlations are reduced, with both 95 percent confidence intervals covering 0, but remain positive ($p = 0.09$ in column 4). Columns 5 and 6 explore heterogeneity by saving ability. Point estimates are larger for those with low saving ability and significantly different from zero in column 6 ($p = 0.02$), providing suggestive evidence that anticipated expenditures may be linked to choice of betting targets among bettors with low saving ability.[31]

Next, I explore whether winnings affect lumpy expenditures. Over 60 percent of respondents reported to have won at least 1 ticket over the course of the study. For

[30] I estimate this model and the others in this paper with high-dimensional fixed effects using the approach described by Correia (2016).

[31] Respondents also reported top payout targets each week. However, the data suggest that top payouts are aspirational and unlikely linked to anticipated expenditures. The median payouts, scaled by mean income, had median values equal to 1.4 times their mean income and a mean of 4.4, comparable to expenditure targets with a median of 2.8 and mean of 6.3. By contrast, top targets had a median of 6 and mean of 20.2. Online Appendix Table A.6 shows results for top payout targets. Cross-sectionally, there is still a significant positive correlation, though this disappears with individual fixed effects.

weeks with positive winnings, median winning value was equal to 71 percent of weekly income. Empirically, estimating the effect of these winnings on expenditures is a challenge because winnings are not randomly assigned: different types of people bet with different frequency and target different payouts, affecting both their likelihood and amount of winnings. To make progress on this, I implement a selection on observables approach, controlling for the amount and types of bets that respondents made each week.[32] This is done by characterizing every individual's betting portfolio by its moments, based off reported number of tickets, average payoff targets, and betting expenditures collected during the in-person visits.[33] Accounting for those betting profiles allows me to control for expected winnings and focus on responses to winnings unexplained by the volume and targets of their bets.

If people who win more are systematically different from those who do not, their behavior may be different in other ways as well, leading to spurious empirical patterns in the data. Appendix Table A.7 examines "balance" by looking at whether higher reported winnings and residualized winnings (controlling for betting profiles and higher-order terms) predict baseline characteristics.[34] Accounting for betting profiles reduces imbalance by baseline characteristics, although 4 of 15 coefficients remain marginally significant at the 10 percent level, slightly greater than expected by chance.[35] The use of individual fixed effects mitigates concerns about cross-sectional misreporting, ensuring that results are driven by within-individual variation of winnings and expenditures, although ultimately the possibility of time-varying factors that influence both reported winnings and expenditures cannot be excluded entirely. Acknowledging this limitation, I implement a selection on observables approach with the following estimating equation:

$$Y_{i,t} = \beta_0 + \beta_1 Winnings_{i,t} + \sum_{m=1}^{4}\sum_{b=1}^{3} BetMoments_{i,m,t}^{b} + \lambda X_{i,t} + \gamma_i + \delta_t + \psi_s + \epsilon_{i,t}.$$

Here, $Y_{i,t}$ is an expenditure outcome measure for individual i reported in period t; $Winnings_{i,t}$ is the amount of winnings reported for that week; $BetMoments_{i,m,t}^{b}$ are the moments (mean, variance, skewness, and kurtosis) and higher-order terms (linear, quadratic, and cubic) characterizing the respondent's reported betting profile in that week; γ_i, δ_i, and ψ_s are individual, time, and survey round fixed effects. Winnings

[32] Anderson (2017) uses a similar approach while showing the impact of college sports success on fundraising ability. Conditional on bookmaker spreads, he argues that winning is uncorrelated with potential outcomes.

[33] Betting profiles are calculated for weeks of in-person visits where information on targeted payouts was collected. I approximate bookmakers' assessment of the likelihood that a bet will win and characterize the distribution of potential betting realizations for each bettor in each time period by their moments (mean, variance, skewness, and kurtosis). For robustness, I also implement a nonparametric approach using quartiles of positive per-ticket expenditures, number of tickets, and payout targets, creating, along with a bin for people who did not bet that week, 65 $(4 \times 4 \times 4 + 1)$ nonparametric betting profile bins. Additional details about the structure of betting in Uganda are contained in online Appendix B1. Online Appendix B3 provides details on the conversion of reported bets into the moments of a betting portfolio.

[34] Column 1 shows that reported winnings correlate (frequently significantly) with a number of baseline characteristics. Adding minimal betting controls (betting expenditures and number of tickets) makes imbalance worth. However, both parametric and nonparametric controls improve balance, with the parametric version performing slightly better. In addition to less significant baseline characteristics, 11 out of 15 estimated coefficients decrease in magnitude, also suggesting that imbalance may be less severe with the betting controls. Positive winnings are winsorized at the top 5 percent of individual-week observations.

[35] Further robustness checks are provided that directly control for different dynamic expenditure patterns across these dimensions of imbalance to ensure that they are not driving results.

TABLE 4—WINNINGS AND EXPENDITURES

	Expenditures				Other flows		Biggest exp size	
	Total exps (1)	Biggest exp (2)	Other exps (3)	Share (4)	Net saving (5)	Net transfer (6)	0.5× mean inc (7)	1 × mean inc (8)
Panel A								
Winnings	0.043	0.045	−0.003	0.013	0.077	0.015	0.037	0.028
	(0.047)	(0.026)	(0.029)	(0.005)	(0.044)	(0.011)	(0.015)	(0.018)
Mean Y	2.458	0.773	1.685	0.298	0.399	0.008	0.575	0.256
Observations	4,635	4,635	4,635	4,635	4,635	4,635	4,635	4,635
Number of individuals	945	945	945	945	945	945	945	945
R^2	0.648	0.508	0.665	0.397	0.385	0.356	0.450	0.453
Panel B								
Winnings	−0.034	0.005	−0.039	0.003	0.022	0.023	0.007	−0.003
	(0.070)	(0.041)	(0.041)	(0.008)	(0.070)	(0.016)	(0.018)	(0.027)
Winnings × LSA	0.165	0.092	0.073	0.023	0.107	−0.019	0.063	0.073
	(0.095)	(0.051)	(0.060)	(0.011)	(0.086)	(0.023)	(0.031)	(0.036)
Mean Y	2.458	0.773	1.685	0.298	0.399	0.008	0.575	0.256
p-value: $\beta_1 + \beta_2 = 0$	0.042	0.001	0.442	0.000	0.010	0.787	0.005	0.004
Observations	4,635	4,635	4,635	4,635	4,635	4,635	4,635	4,635
Number of individuals	945	945	945	945	945	945	945	945
R^2	0.651	0.513	0.668	0.403	0.397	0.364	0.457	0.461

Notes: Columns 1, 2, 3, 5, and 6 scale dependent variable by mean income. "Biggest exp" is the biggest reported lumpy expenditure where the good or service purchased was indivisible and required payment in full at the time of purchase. Columns 7 and 8 are binary indicators for whether the biggest expenditure in that week was above 0.5 or 1 × mean income for that respondent, respectively. Winnings and expenditures are all winsorized at the top 5 percent (as well as bottom 5 percent for net transfers and savings) to avoid outsized influence of outliers. LSA = low saving ability. All regressions control for betting expenditures, number of tickets, tickets squared, parametric betting profiles, and weekly income and use individual, week, and survey round fixed effects. Standard errors are clustered at the individual level. For results in panel B, all covariates and fixed effects are interacted with low saving ability.

and expenditures are both winsorized at the top 5 percent of reported values.[36] Standard errors are clustered at the individual level.

Table 4 presents these results. Expenditure outcomes are listed at the top of each column. Column 1 uses the total value of reported expenditures in that period as the dependent variable. Column 2 switches to the value of the respondent's biggest lumpy expenditure. Column 3 uses the value of all other expenditures. Column 4 looks at the share of expenditures spent on the lumpy expenditure. Columns 5 and 6 look at other financial flows in the form of net savings and transfers. Except for the share, these expenditure categories are all scaled by respondent's mean weekly income to avoid overweighting the behaviors of wealthier respondents.

Panel A shows expenditure responses to winnings in the full sample. Notably, biggest expenditure value increases ($p = 0.08$) as does its share of total expenditures ($p < 0.01$). There are no perceptible effects on other expenditures, although net savings increase, suggesting that all winnings may not be spent immediately. Panel B examines heterogeneity by saving ability. Effects on biggest expenditures value and share are significantly larger for those with low saving ability. Column 4

[36] This is done to avoid empirical patterns driven by a long right tail in reported win totals. Results are robust to alternative winsorization thresholds and shown in the online Appendix. Additionally, respondents with the top 1 percent of rate of return on betting were trimmed from the sample, removing a handful of respondents whose level of winnings raise suspicion of exaggeration and unreliable data.

of panel B shows that additional winnings equal to one's mean income increase the big expenditure share by just under 9 percent for people with low saving ability, more than 7 times the increase for people with high saving ability.

The relatively small magnitudes of the estimates across all categories of consumption suggest that the effect of winnings is not fully captured in the data. While this may raise concerns about the completeness or accuracy of the reported data, the broad patterns and heterogeneity are consistent with winnings having a particular impact on lumpy expenditures, especially among those with low saving ability.[37]

Columns 7 and 8 of Table 4 adopt an alternative approach, looking at the effect of winnings on the *likelihood* of making large lumpy expenditures. This has the added benefit of reducing the influence of outliers in the dependent variable on the estimates. To do this, the outcome variable is converted into an indicator for whether the respondent made a purchase above a given threshold that week. Columns 7 and 8 show that winnings increase the likelihood of making a lumpy expenditure that is at least half the value of his mean income or above his mean income, respectively. Again, these effects are especially strong for respondents with low saving ability. The results in column 8 of panel B suggest that winnings equal to one's mean income increase the likelihood that a low-ability saver makes a lumpy purchase equal to or greater than his mean income by 7 percentage points from an overall incidence rate of 25.6 percent in the data, with no discernible effect for high-ability savers.[38,39]

Expanding on this approach, Figure 2 shows these regression results over a range of thresholds for both lumpy and divisible expenditures. The panels show thresholds up to twice mean income for lumpy expenditures and up to four times mean income for divisible expenditures, consistent with lumpy expenditures roughly half as large as other expenditures on average in the data. These ranges were chosen where outcomes had sufficient variation to have power to detect effects and where win sizes in the range observed in the data could plausibly affect their attainment.[40] In the figure, the *x*-axes show the threshold for the biggest lumpy expenditure in that time

[37] This could be the result of a number of factors. First, while winsorization is implemented to improve data quality and mitigate the effect of outliers, it may also eliminate meaningful variation in the data. Online Appendix Table A.10 repeats the analysis without winsorizing and shows similar patterns but stronger responses in the data. The point estimates in columns 1, 5, and 6 now account for nearly 50 percent of reported winnings, corroborating this possibility. A second factor may be that recalled winnings are imprecise and introduce attenuation bias, pulling estimates toward zero. Third, respondents may be exaggerating wins or misattributing real wins to the most recent week, thus overcharacterizing the shocks to their weekly expenditures. Conversely, they may forget some of their expenditures. Or they may be holding on to winnings, intending to spend them soon, and thus not reporting them as savings at the time of the interview.

[38] Online Appendix Tables A.8 and A.9 show that results are broadly similar when using nonparametric betting profiles or no betting controls. Online Appendix Tables A.10, A.11, and A.12 show results with raw data or winsorizing the top 1 percent or 10 percent of outcomes, respectively. While magnitudes shift with different levels of winsorization, all show qualitatively similar results.

[39] Online Appendix Table A.7 revealed that four baseline characteristics were imbalanced with winnings: age, household size, O level completion, and delta discounting. For additional robustness, I repeat analysis of the impact of winnings on expenditures for the three main outcomes, big expenditure value, big expenditure share, and big expenditures above mean income, in online Appendix Tables A.13, A.14, and A.15, respectively. However, I allow for differential time trends by interacting the week of interview fixed effects with whether respondents are above or below the median of these measures (except O level, which is interacted directly since it is already binary). Results are virtually unchanged for both main and heterogeneous effects.

[40] Similarly, the incidence of a big lumpy expenditure twice a respondent's mean income is 7.5 percent, while it is 5.8 percent for nonlumpy expenditures 4 times respondents' income.

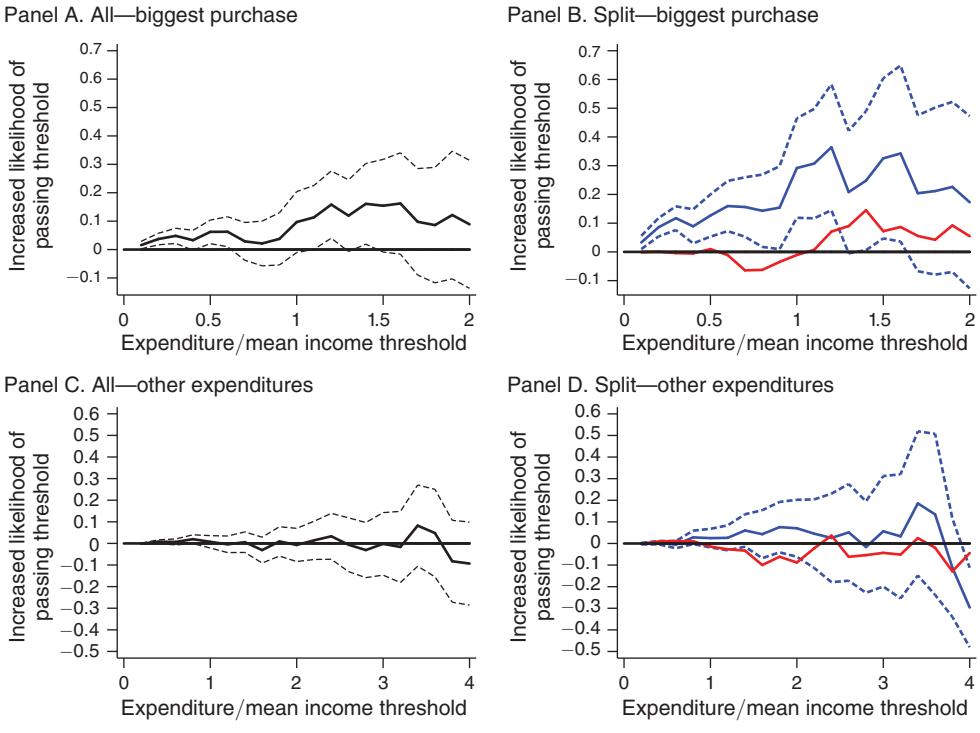

FIGURE 2. EFFECT OF WINNINGS ON PURCHASE THRESHOLDS—SCALED TO MEAN INCIDENCE

Notes: Each panel shows the coefficient estimates from a set of regressions of expenditure thresholds on winnings, using the parametric betting profile controls. The outcome variable is an indicator for having made a large expenditure above a threshold (indicated on the *x*-axis) in that time period relative to that individual's mean income. The magnitude of the estimate on winnings is captured on the *y*-axis and scaled by its baseline incidence. I include time, survey round, and individual fixed effects in all regressions. Standard errors are clustered at the individual level. Panels A and C are the estimates for all respondents together with the 90 percent confidence interval represented by the dashed lines around the estimates. Panels B and D split the sample by saving ability. Low saving ability is in blue in both subfigures, with 90 percent confidence intervals shown by the dotted lines for people with low saving ability. Point estimates for high-ability savers are in red. Panels A and B show results for the effect of winnings on peoples' likelihood of biggest expenditures being above different thresholds in that time period, whereas panels C and D look at effects of winnings on all other expenditures.

period, while the *y*-axes show the estimated coefficient on the win amount, scaled by the mean incidence for the relevant sample. It can be interpreted as the proportion increase in likelihood of making a purchase above a given threshold from winnings equal to one's mean income. Panel B splits the sample between high-ability savers, in red, and low-ability savers, in blue; the 90 percent confidence interval (dotted) is shown for the latter. Panels C and D repeat this exercise looking instead at nonlumpy expenditures.

For nearly all thresholds, additional winnings have a positive and significant effect on likelihood of lumpy purchases for low-ability savers, always larger than for high-ability savers, for whom the effect is never distinguishable from zero. Though slightly higher for low-ability savers, effects of winnings on nonlumpy expenditures are significantly smaller in magnitude than on lumpy expenditures

and rarely significantly different from zero.[41] Online Appendix Figure A.4 repeats this analysis, showing the raw regression coefficients. Online Appendix Table A.16 shows these results in regression form.

Regardless of specification, the results show that additional winnings impact both the size and likelihood of making large lumpy expenditures in a way that they do not impact others. This effect is consistently present and significantly stronger for those with low saving ability. Although the analysis cannot entirely exclude the possibility of other within-individual, time-varying factors affecting both reported winnings and expenditures, these patterns of heterogeneity would be surprising reflections of either reporting bias or misreporting. Ultimately, if individuals anticipate their own future consumption when deciding whether or not to bet, this analysis provides evidence that anticipated lumpy expenditures may contribute to betting demand.

B. *Commitment-Savings Treatment*

The previous section showed associations between saving ability and both betting payout targets and usage of winnings, but they are not able to show that improvements in saving ability can *cause* a reduction in betting demand. To test this, randomly selected participants were chosen to receive a soft commitment-savings device in the form of a wooden savings box. These boxes are nailed closed and have a small slit in the top so that money can be deposited easily but not retrieved without breaking it open. This basic technology contains features common to many saving products: a component of ex ante commitment to save and a reduction in exposure to spending pressure and temptation. These boxes can be found in Ugandan markets and were familiar to the study participants. At the end of the third visit, field team members gave randomly selected respondents a saving box and assisted them in writing down their saving target on the outside.

In Wave 1, 25 percent of participants were selected to receive the boxes, whereas 50 percent of participants in Wave 2 were selected.[42] Panels A and B of online Appendix Table A.19 show balance consistent with random assignment by wave.[43] I estimate the effect of the saving box treatment using a difference-in-difference estimation strategy with the following equation:

$$Y_{i,t} = \beta_0 + \beta_1 SaveBox_{i,t} + \lambda X_{i,t} + \gamma_i + \delta_t + \epsilon_{i,t}.$$

Here, $Y_{i,t}$ is an outcome measure of betting behavior for individual i at time t, $SaveBox_{i,t}$ is an indicator of whether an individual had been offered the saving box

[41] Online Appendix Tables A.17 and A.18 show results from a set of seemingly unrelated estimation tests to test for differences across outcome type (lumpy and nonlumpy expenditures) as well as across thresholds.

[42] In Wave 1, another 25 percent were selected to receive assistance setting up formal bank accounts. The tight time line of the study and logistical challenges led to this intervention being abandoned before respondents were able to open bank accounts. Assignment to this group is controlled for in the analysis.

[43] Despite random assignment, the endline lumpy good prime was administered to a slightly larger portion of participants in the saving box treatment group. To address this potentially confounding correlation, all analyses control for the effect of the endline lumpy good prime, and additional robustness checks are conducted to ensure that observed effects are not driven by an interaction between treatments. Ultimately, the effects of these treatments are in opposite directions. Therefore, the positive correlation works against finding measurable effects for either result.

TABLE 5—SAVINGS BOX TREATMENT

	Reported		Elicited		
	Number (1)	US$ (2)	Max (0/1) (3)	Number (0–4) (4)	Index (5)
Panel A					
Savings box	−0.0967	−0.0445	−0.1393	−0.3142	−0.1768
	(0.1833)	(0.1596)	(0.0550)	(0.1739)	(0.0870)
Adjusted R^2	0.4973	0.4311	0.2562	0.2819	0.5299
Panel B					
Savings box	−0.1400	−0.0916	−0.1590	−0.4454	−0.2551
	(0.2395)	(0.2066)	(0.0835)	(0.2604)	(0.1271)
Save box × low saving ability	0.1179	0.1088	0.0161	0.2073	0.1407
	(0.3676)	(0.3201)	(0.1131)	(0.3536)	(0.1806)
p-value: $\beta_1 + \beta_2 = 0$	0.9369	0.9440	0.0617	0.3198	0.3734
Adjusted R^2	0.4971	0.4309	0.2544	0.2776	0.5269
Panel C					
Savings box	0.3570	0.4146	−0.0666	−0.0789	0.0024
	(0.2760)	(0.2456)	(0.0894)	(0.2891)	(0.1392)
Save box × no box (at baseline)	−0.7080	−0.7048	−0.1200	−0.3952	−0.2963
	(0.3643)	(0.3215)	(0.1135)	(0.3621)	(0.1792)
p-value: $\beta_1 + \beta_2 = 0$	0.1401	0.1621	0.0080	0.0301	0.0095
Adjusted R^2	0.4980	0.4303	0.2613	0.2857	0.5310
Mean dependent variable	4.7595	2.8360	0.4655	2.5304	−0.0026
Observations	8,319	8,319	986	986	986
Other treatments	Yes	Yes	Yes	Yes	Yes

Notes: Estimated effects of the savings box with a difference-in-difference estimation. Reported measures of betting are from survey responses. Elicited measures are from the incentivized betting ticket offer. Index is the standardized sum of the standardized measures. All panels control income and other treatments as well as individual, week, and survey round fixed effects. Panel B assesses heterogeneity by low saving ability as indicated by being below the median on the saving ability index. Panel C analyzes heterogeneity by having neither a lockbox or piggy bank at baseline. Panels B and C interact all controls and fixed effects (except for individual fixed effects) by that dimension of heterogeneity.

at that time, $X_{i,t}$ are individual, time-varying covariates, γ_i and δ_t represent individual and time fixed effects, respectively, and $\epsilon_{i,t}$ is the error term. Standard errors are clustered at the individual level.

At the endline, one month after the savings boxes were distributed, interviewers asked participants if they had used a savings box at any time in the preceding month. The effect of treatment status on take-up is shown in online Appendix Table A.20. On average, people in the treatment group were 53 percentage points more likely to report using a saving box compared to a control group mean of 16 percent. Take-up rates were similar for low- and high-ability savers (both 53 percent) and similar but slightly higher for those who did versus those who did not have a lockbox or piggy bank at the time of the baseline (56 percent and 50 percent, respectively).

Table 5 shows the effect of the saving box on both reported and elicited measures of betting demand. Columns 1 and 2 look at the number of tickets and value of weekly betting expenditures. Columns 3 and 4 use two different formations of betting demand from the betting ticket offer: a binary indicator for demanding the

maximum and the number of tickets demanded. Column 5 constructs a standardized betting index from both the reported and elicited betting measures.[44]

Panel A shows negative point estimates for the reported betting measures, but the results are not statistically significant.[45] The elicited measures have larger magnitudes and better precision, showing statistically significant reductions with both the max and number codings.[46] The index suggests a 0.18 standard deviation reduction in betting demand.

Panel B looks at heterogeneity by saving ability. Perhaps surprisingly, effects are weaker for those with low saving ability. An intervention designed to improve saving ability may have, reasonably, been expected to have stronger effects on those with low baseline ability. However, the index used to make this distinction also captures characteristics likely to impede one's ability to use a saving box effectively, such as limited saving potential or high levels of pressure from family members. Panel C shows that the effects are concentrated among those who at baseline did not already have a similar technology (piggy bank or lockbox). This group shows a 0.3 standard deviation reduction in the betting index from treatment ($p < 0.01$), while those who already had access to similar technology show no effects.[47] While this does not elucidate mechanisms, it adds credence that those with greater potential to benefit from the treatment are driving the results.

Because baseline-elicited measures of betting demand were only captured for participants in Wave 2, only Wave 2 participants are included in the difference-in-difference estimates of those measures as well as the index. Additionally, Wave 2 participants had some baseline imbalance in these measures, whereby those in the treatment group had slightly higher initial betting demand in the elicited measure than those in the control group.[48] While difference-in-difference estimation appropriately adjusts for these baseline differences, reductions in betting could be exaggerated if there is regression to the mean. Online Appendix Table A.22 repeats the analysis using only posttreatment observations of respondents in Wave 1 (without the baseline measures). Estimates are very similar, with a 0.17 standard deviation reduction on the betting index for the full sample and 0.24 standard deviation reduction for respondents without a saving box at baseline, though some statistical significance is lost due to smaller sample size. Finally, online Appendix Table A.23 shows robustness of the saving box effect on elicited measures to interaction effects with the lumpy expenditure prime.

[44] The elicited measures were only captured at baseline and endline. Therefore, to make an aggregate index, I take individual pre- and posttreatment period averages for number of tickets and amount spent. I standardize each of these four components and create the index by restandardizing their sum.

[45] Online Appendix Figure A.5 shows cumulative distribution functions of betting expenditures and tickets before and after treatment by treatment group and confirms small reductions from the saving box treatment.

[46] Another factor that may lead to stronger effects on elicited rather than reported betting is that having prefilled the matches on the tickets in the betting ticket offer, a lot of the fun of betting has been removed. Therefore, the remaining value of these tickets is predominantly their potential monetary value and access to liquidity, the part of betting demand most likely to be undercut by improved ability to save.

[47] Online Appendix Table A.24 shows heterogeneity by the components of the aggregate saving ability index as well as the saving experiences index subcomponents. Across all of these dimensions, the effects are strongest among participants who did not have a lockbox or piggy bank.

[48] Respondents assigned to the treatment group demanded 0.3 more tickets at baseline than those in the control group, with a sample mean of 2.8 tickets, statistically significant at the 5 percent level. The difference in the maximum ticket measure was not statistically significant.

As discussed in Section IA, improved saving ability can lead to a reduction in betting through two channels: reduction in all current expenditures for future consumption and reduced relative appeal of betting as a liquidity generation strategy. While the saving box treatment shows evidence of a reduction in betting expenditures, the bundled nature of these two mechanisms along with the noisiness of expenditure data inhibit isolation of the role of the latter.[49] This limitation motivates two lab-in-the-field experiments designed to provide additional evidence on the importance of lumpy expenditures, liquidity constraints, and saving ability on betting demand.

C. *Prime on Lumpy Expenditures*

To make progress demonstrating the importance of liquidity needs as a mechanism, I use a lab-in-the-field experiment to show that increasing the salience of a desired lumpy expenditure increases demand for betting. During the baseline of the full study, interviewers asked respondents to identify a large expenditure they wanted to make in the next few months. During the condensed study, these questions were asked at the beginning of the survey. For randomly selected respondents, interviewers went through a dialogue referring to these desired expenditures just before the betting ticket offer at the end of the interview. The dialogue asked, "Earlier, you mentioned that you wanted to buy ____. How much would it cost? How much more money do you think you would need in order to be able to make that expense? Do you know where you would go to purchase it?"[50] These questions were designed to increase the salience of this expenditure before measuring betting demand. Right after these primes, respondents were offered the choice between betting tickets and cash. Respondents in the control group were asked these same questions immediately *after* the betting ticket offer.

Increased salience of a desired lumpy expenditure should increase demand for bets motivated by need for liquidity. Conversely, demand for betting based on consumption and enjoyment may fall following the prime if respondents consider the opportunity cost of putting the cash into saving toward the expenditure. These predictions push demand in opposite directions, making it an empirical question which effect dominates. I estimate the effect of the prime using the following equation:

$$B_i = \beta_0 + \beta_1 \, LumpyPrime_i + \lambda X_i + \epsilon_i.$$

[49] Further analysis gives some suggestive evidence that on-hand liquidity was lower and accrued savings higher among saving box recipients who had not had similar technologies at baseline. However, the estimates are too noisy to draw conclusions. Additionally, while the saving boxes reduced betting expenditures, point estimates are suggestive of reductions in other spending as well. With both of these outcomes measured noisily, it is not possible to draw conclusions about their relative responses to treatment or to say if the saving box affected betting expenditures disproportionately. This analysis is shown in online Appendix Table A.21.

[50] For respondents in the full study, the enumerators first checked to see whether the large expenditure had already been made and, if so, whether respondents needed to make that expense again (as in the case of rent or school fees). These answers were controlled for in the analysis. If a respondent said that he already had the money necessary to make the purchase readily available to him, he was dropped from the analysis.

The variable B_i is an indicator for whether the maximum number of tickets was demanded, $LumpyPrime_i$ is equal to one for those in the treatment group receiving the prime before the ticket offer and equal to zero for those in the control group, and X_i is a set of covariates for individual i. Regressions also include the week of the offer, the amount of cash offered, and treatment status for the other components of the study. Robust standard errors adjust for heteroskedasticity in the error term. This analysis includes respondents from both waves of the full study conducted at both endline and baseline for Wave 2 as well as participants in the condensed study sample (excluding those randomly assigned to the budgeting exercise treatment group discussed below).[51] Randomization balance is shown in panel C of online Appendix Table A.19.[52]

Table 6 shows the impact of the prime on betting demand. The preferred specification, in column 2, shows that the prime led to a 6.7 percentage point (16 percent) increase in the likelihood of demanding the maximum number of tickets ($p < 0.01$). Columns 3 and 4 test whether the effect of the prime varies by saving ability. Column 3 uses the continuous saving ability index, while column 4 tests for differences between high- and low-ability savers. Both results suggest that those with worse ability to save increase demand for betting in response to the prime more than those with better saving ability. Column 4 shows that those with low saving ability increase their likelihood of demanding the maximum number of tickets by 11 percentage points, 4 times more than those with high saving ability.[53]

Adding credence to these results, those who reported that betting was a likely source of liquidity for a desired expenditure also responded significantly more to the prime than those who did not (only asked in the condensed study; see online Appendix Table A.28). Alternatively, increased salience of a desired expenditure could make people less patient and more inclined to bet in the hope of getting liquidity more quickly. I test for whether people with different measures of baseline patience are more or less responsive to the prime but do not see significant differences in their responses (see online Appendix Table A.29).

Overall, these results show that increased salience of lumpy expenditures raises betting demand, consistent with liquidity needs amplifying betting behavior. Stronger responses by people with low saving ability corroborate this further while exhibiting parallel heterogeneity to usage of winnings shown in Section IIIA.

[51] Respondents in the budgeting exercise treatment group are excluded from the analysis to ensure that effects and heterogeneity of this nested treatment do not get misattributed to the lumpy expenditure prime.

[52] None of the 22 variables show imbalance, an unusual degree of balance following randomization. This is because the 510 participants from Wave 2 were given the priming experiment twice, once in the treatment group and once as controls. This created more balance across observable characteristics than would occur if each individual were allocated randomly to only one or the other treatment status.

[53] Online Appendix Table A.25 shows results using the continuous outcome of proportion of tickets demanded. Although magnitudes are smaller, they remain significant and suggest stronger effects for respondents with lower saving ability. Tests for differential responses by the full set of saving ability measures are included in online Appendix Tables A.26 and A.27.

TABLE 6—EFFECT OF LUMPY PRIME ON DEMAND OF MAXIMUM TICKETS OFFERED

	(1)	(2)	(3)	(4)
Lumpy good prime	0.0667	0.0665	0.0670	0.0213
	(0.0235)	(0.0234)	(0.0234)	(0.0332)
Prime × saving index			−0.0559	
			(0.0239)	
Prime × low saving ability				0.0914
				(0.0467)
Low saving ability				−0.0549
				(0.0426)
Saving index		−0.0016	0.0266	−0.0051
		(0.0119)	(0.0167)	(0.0184)
Mean dependent variable	0.4542	0.4542	0.4542	0.4542
Mean *Y*-control	0.4220	0.4220	0.4220	0.4220
p-value: $\beta_1 + \beta_2 = 0$	—	—	—	0.0006
Full set of covariates	No	Yes	Yes	Yes
Price of ticket fixed effects	Yes	Yes	Yes	Yes
Other treatments	Yes	Yes	Yes	Yes
Observations	1,801	1,801	1,801	1,801
Adjusted R^2	0.0164	0.0237	0.0263	0.0247

Notes: Results are from regression of $B_i = \beta_0 + \beta_1 LumpyPrime_i + \lambda X_i + \epsilon_i$. Dependent variable is an indicator for demanding the maximum number of tickets in the betting ticket offer (four in the full study sample and two in mini study sample). *LumpyPrime* is an indicator for going through the lumpy prime dialogue prior to the ticket offer. All regressions control for status of other treatments in the study and the amount of cash offered instead of tickets. Columns 2–4 also control for the price of the desired expenditure as well as whether it was purchased since the baseline for respondents in the full study. Saving index is a continuous standardized measure of saving ability. Low saving ability indicates respondents with saving ability indices below the median. Ability-robust standard errors are used to adjust for heteroskedasticity in the error term.

D. *Budgeting Exercise for Savings*

The final result uses a second lab-in-the-field experiment to identify the effect of changes in perceived saving ability on betting demand. So long as updates are credible, changing perceived ability to save should also affect the relative appeal of saving to betting.

To do this, interviewers guided respondents in the condensed study through a brief budgeting exercise. Early in the survey, interviewers asked all respondents how much they felt they could save per week (without straining their finances excessively). They were also asked about typical weekly earnings and essential expenditures on food, transportation, and rent. At the end of the survey (roughly 45–60 minutes later), respondents were guided through a budgeting exercise. Respondents were told, "Earlier in this interview you said that you earn ___ UGX in a typical week. You also said you normally spend ___ on food, ___ on transportation, and ___ on rent. This leaves you with ___ UGX per week. How much money do you think you could realistically save per week?" Tablets used for data collection automatically calculated and filled in the blanks based on their earlier responses. Respondents were unconstrained in their answers to this final question and were free to ignore this information. This was recorded as respondents' budgeted or

"assisted" saving potential.[54] Interviewers did not make any reference to the respondents' initial, "naïve" estimate from the beginning of the interview.

While all respondents went through this dialogue, randomization determined the order of modules at the end of the survey. The budgeting exercise was nested within the lumpy prime from the previous section so that respondents in the condensed study were randomly assigned to one of three possible module sequences:

(i) Prime and Budget: Lumpy expenditure dialogue → Budgeting exercise → Betting offer

(ii) Prime Only: Lumpy expenditure dialogue → Betting offer → Budgeting exercise

(iii) Control: Betting offer → Lumpy expenditure dialogue → Budgeting exercise.

The first group, who went through the budgeting dialogue just before the betting ticket offer, and therefore whose updates may affect their elicited betting demand, are considered the budgeting exercise treatment group.[55] Panel D of online Appendix Table A.19 shows balance by treatment.[56]

The expected effect of this treatment depends on whether those who did the exercise before the betting ticket offer update their perceived saving potential positively or negatively. People with positive updates may respond by valuing betting relatively less as a mode of liquidity generation and reduce betting demand. Conversely, negative updates may reveal that saving is more challenging than previously believed and lead to increases in betting demand. By having both a naïve and budgeted estimate of saving potential for everyone in the sample, I can assess the impact of receiving this update on betting demand for those in the treatment group while controlling for the appropriate counterfactual of someone who would have gotten the same update (but did the exercise after measuring betting demand).

Following the exercise, 48 percent of respondents decreased their estimated saving potential, 27 percent did not change their estimate, and 25 percent increased their estimate relative to their naïve estimate. The median raw positive update was US$4.25, and the median proportionate update was 10 percent of income. The

[54] After the respondent gave an answer, the enumerator said, "At that rate of saving, it would take you ___ weeks/months to have enough money to make your desired expense." The effect of time updates are estimated noisily and do not show statistical significance. If anything, more patient respondents react to learning that they need more time to save by demanding more tickets than less patient borrowers. Again, this suggests that feasibility of saving may be more important or salient to bettors than patience. Results are shown in online Appendix Table A.30.

[55] This approach is valid if the betting ticket offer did not affect peoples' responses in the budgeting exercise, which could create systematically different updates by treatment status and lead to invalid control group comparisons. Online Appendix Table A.31 shows that the betting ticket offer did not significantly affect the raw update size; update size relative to income; or likelihood of a positive, negative, or zero update.

[56] Baseline proportionate saving potential is significantly different across treatment despite randomization. That some imbalance emerges is to be expected, having checked across 20 variables. What matters most for this result is that saving updates are balanced across treatment status. There are no statistical differences by raw saving potential, raw saving update amount, and proportionate update amount. Baseline saving potential is included in all regressions to account for this baseline imbalance.

median raw negative update was US$4.85. The median negative proportionate update was 17 percent of income. Online Appendix Figure A.6 shows the distribution of update sizes. I estimate the following equation:

$$B_i = \beta_0 + \beta_1 LumpyPrime_i + \beta_2 Budget_i + \beta_3 \big(Budget \times Update\big)_i + \beta_4 Update_i + \lambda X_i + \epsilon_i.$$

Here, B_i is an elicited measure of betting demand from the betting ticket offer for individual i; $LumpyPrime_i$ indicates whether the individual received the lumpy prime before the ticket offer; $Budget_i$ is an indicator for being assigned to the budgeting treatment group; β_2 is the effect of the budgeting activity on betting demand, independent of the update; $Update_i$ is the difference between the respondent's new, budgeted estimate of saving ability and his original, naïve estimate, positive if the new estimate is greater than the original; β_3 is therefore the coefficient of interest, measuring the effect of the content of the update; β_4 controls for potential update content independent of treatment status; $Update_i$ is coded using both raw and scaled updates as well as binary indicators for positive or negative updates; and X_i is a set of covariates for individual i.[57] Robust standard errors are used to adjust for heteroskedasticity in the error term.

Table 7 shows results using the maximum ticket outcome. Column 1 shows that the budgeting exercise had a negative but insignificant average effect on demand for betting tickets. Columns 2 and 3 show that more positive updates, revealed by the budgeting exercise, lead to lower betting demand, regardless of whether the update is calculated in raw currency or scaled by income. Column 3 suggests that participants who learn that they could save an additional 10 percent of income, the median-sized positive update, reduce the likelihood that they demand the maximum number of tickets by 5 percentage points, or approximately 11.5 percent.

Recent work in behavioral economics has begun to explore whether people update behaviors and beliefs differently depending on whether new information reflects positively or negatively on them. Evidence up to now has been mixed, with some work finding evidence of this asymmetry (Eil and Rao 2011, Mobius et al. 2011) and other work finding symmetry over short time horizons (Zimmerman 2020). Column 4 splits the effect by positive or negative updates with binary positive or negative indicators and no update as the omitted category. The positive update causes a 26.6 percentage point reduction in the likelihood of demanding the maximum number of betting tickets. The effect for the negative update is indistinguishable from zero and significantly different from the inverse of the positive update ($p = 0.02$), rejecting symmetry in response to updates on opposite sides of zero. Columns 5 and 6 further explore this asymmetry with a linear relationship between the update amount and betting demand, again split at zero. These specifications both

[57] All specifications include controls for the amount of cash offered, whether the respondent lives with others, education levels, scores on a math test, measures of risk aversion, hypothetical demand for gambles, and time preferences. Results are similar using minimal covariates shown in online Appendix Table A.32 or switching to the number of tickets demanded in online Appendix Table A.33.

Table 7—Effect of Budgeting Exercise on Demanding the Maximum Number of Tickets Offered

	(1)	(2)	(3)	(4)	(5)	(6)
Lumpy good prime	0.081	0.078	0.079	0.080	0.078	0.080
	(0.042)	(0.042)	(0.042)	(0.043)	(0.043)	(0.043)
Budgeting exercise (BE)	−0.024	−0.046	−0.056	0.073	−0.030	−0.025
	(0.045)	(0.045)	(0.046)	(0.082)	(0.055)	(0.057)
BE × update		−0.016	−0.518			
		(0.006)	(0.224)			
Update		0.002	0.037			
		(0.003)	(0.116)			
BE × (update > 0)				−0.266		
				(0.106)		
BE × (update < 0)				−0.050		
				(0.099)		
Update > 0				0.085		
				(0.060)		
Update < 0				0.031		
				(0.053)		
BE × positive update amount					−0.022	−1.013
					(0.010)	(0.521)
BE × negative update amount					0.012	0.346
					(0.009)	(0.304)
Positive update amount					0.004	0.184
					(0.004)	(0.217)
Negative update amount					−0.001	0.018
					(0.005)	(0.143)
Form of update	—	US$	Prop	—	US$	Prop
Observations	683	683	683	683	683	683
Mean dependent variable	0.4129	0.4129	0.4129	0.4129	0.4129	0.4129
Control group mean	0.3689	0.3689	0.3689	0.3689	0.3689	0.3689
p-value of positive = −1 × negative update				0.0180	0.5465	0.3221
R^2	0.1441	0.1511	0.1505	0.1534	0.1514	0.1517
Adjusted R^2	0.1169	0.1214	0.1208	0.1212	0.1191	0.1194

Notes: Results from regression of $B_i = \beta_0 + \beta_1 LumpyPrime_i + \beta_2 Budget_i + \beta_3 (Budget \times Update)_i + \beta_4 Update_i + \lambda X_i + \epsilon_i$. Dependent variable is an indicator for demanding the maximum number of tickets in the betting ticket offer. $LumpyPrime_i$ is an indicator for doing the lumpy prime dialogue before the betting ticket offer. $Budget_i$ is an indicator for doing the budgeting exercise before the betting ticket offer. $Update_i$ is the assisted estimate of the amount that an individual can save from the budgeting exercise minus the naïve estimate. Form of update indicates whether updates resulting from the budgeting exercise are estimated in that column as dollars or are scaled by the respondent's mean income. Robust standard errors are used to adjust for heteroskedasticity in the error term.

show significant decreases in betting for positive updates. Negative updates have positive point estimates with (absolute) magnitudes just 30–50 percent as big as the positive updates but are noisily estimated, and symmetry cannot be rejected.

Figure 3 shows the nonparametric LOWESS regression of the saving update, scaled by weekly income, on demand for the maximum number of tickets in order to relax an assumption of linearity in the impact of updates imposed in the regressions. A linear model with a spline at zero is included for reference. These nonparametric estimates suggest that there is no clear effect of the budgeting exercise on people learning negative information about their saving potential, whereas positive information decreases demand for betting tickets with bigger effects for larger update

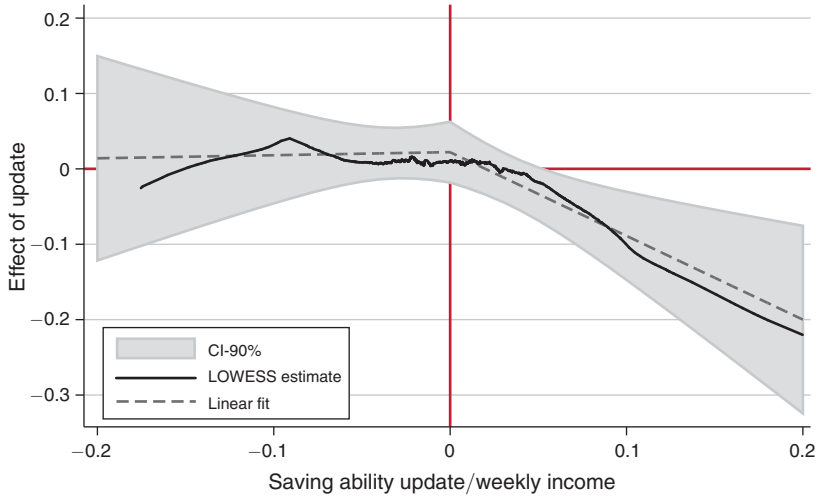

FIGURE 3. EFFECT OF SAVINGS ABILITY UPDATE ON MAX TICKET DEMAND–LOWESS

Notes: This figure shows the nonparametric LOWESS estimate of the effect of different saving ability updates from the budgeting exercise on betting demand. The update is the difference between the newly estimated amount an individual can save minus their original naïve estimate, scaled relative to mean income. The median negative update was −0.15, and the median positive update was 0.1. The *y*-axis is the likelihood of demanding the maximum number of betting tickets offered during the revealed preference measure of betting demand following the budgeting activity for people in the treatment group. The background is a linear regression with a linear spline at zero and its associated 90 percent confidence interval. Top and bottom 1 percent of the raw updates and residualized updates are trimmed for readabilty.

sizes. Overall, these results provide some further evidence, albeit sensitive to specification, in support of asymmetric updating.

Attributing the effect of the saving box treatment to a change in the relative appeal of saving and betting as competing methods of liquidity generation was confounded by other factors. In particular, I could not rule out that the effect was coming from crowding out all current expenditures on normal goods. However, an update revealing that a person has *more* disposable income available for saving does not face the same challenges. Learning that you have more available liquidity should *increase* demand for bets if it is exclusively a consumption good. These results show the opposite. The reduction in betting demand for people receiving positive saving updates suggests that improved perception of the feasibility of saving as a liquidity generation strategy undercuts that source of appeal for betting.

E. *External Validity and Interpretation*

This section has presented a broad set of empirical findings linking demand for betting to unmet liquidity needs and saving ability. However, the lessons we learn depend on the generalizability of the findings, which may be affected by a number of considerations and concerns related to the sample and design of the study that deserve further comment.

First, the sample was chosen to target a population known to have high incidence of betting with plausible unmet liquidity needs. Young men working in

microenterprises or services fit these criteria.[58] Within this group, the aim was to find and recruit "typical" bettors and not cherry-pick extreme participants. As a result, this sample is not representative of young men in Kampala, let alone the rest of the world. Young men working in microenterprises may have greater liquidity needs than those who do not have to accumulate their own working capital. However, their desired expenditures, reported in Section II, go beyond business needs and are nearly universal: furniture, clothes, school fees, and home repairs. Working in cash businesses, saving challenges could also be different for this population if earnings are exposed to higher levels of temptation or social pressure. But conversely, and in contrast to working for a wage or in formal employment, variability and unpredictability of profits from informal work may insulate them from oversight or pressures to spend at home. Variability could additionally impact natural access to lumps of liquidity as well as willingness to take on debt. All of these characteristics may influence liquidity needs and demand for betting and can be found in other populations all over the world. Understanding linkages between the structure and form of income and demand for gambles, or more general willingness to take on risk, is an important area for future research.

Second, many parts of this study rely on self-reported data. This raises two distinct issues. While not unique to this study, consumption recall is notoriously noisy, which can both attenuate estimates and widen confidence intervals in the analysis. Second, reported data may be vulnerable to experimenter demand effects. Recent work by de Quidt, Haushofer, and Roth (2018) suggests that these effects are minimal in most cases. Still, their possibility cannot be ruled out. Both of these concerns motivated inclusion of the betting ticket offer in the study so that an incentive-compatible measure of the primary outcome could be elicited from respondents directly. Ultimately, the patterns of heterogeneity shown throughout the analysis, consistent with the motivating hypotheses, would be a surprising pattern of induced biases to instead result from experimenter demand effects. Still, future research would benefit from the availability of administrative data on both betting behavior and household expenditures to mitigate these concerns.

Third, a challenging question is what portion of betting demand is actually explained by unmet liquidity needs. Fun, addiction, and misunderstanding are all likely to contribute as well. Confounding things further is that these factors likely complement and interact with one another. This complementarity is what motivated the randomized components of the study: to create exogenous variation in one hypothesized mechanism and gauge peoples' response. Still, to make some progress on this from another angle, I linked the soccer schedules of the major leagues and competitions followed in Uganda to the data from the period of the study. If fun is a central factor driving betting demand, that is likely linked, at least in part, to whether you follow, know about, and can possibly watch the teams you bet on. Following two different methods, I can only explain about 35 percent of the variation in betting

[58] Interviews conducted at a stable place of work had the added benefits of easier identification during listing, easier tracking for follow-ups, and creating a buffer from respondents' families, whose presence may have biased responses in home-based interviews.

expenditures with the schedule.[59] This does not rule out other avenues for fun or addiction to affect betting demand, but the majority of reported betting expenditures cannot be explained by the matches available for people to bet on.

A second approach is to think about what conditions would be required for betting in pursuit of liquidity to be rational, without any addiction, fun, or misunderstanding. In online Appendix D, I model demand for betting as a pure liquidity generation strategy for a desired lumpy expenditure (removing value from consumption) and compare it to the return that would come from pursuing a saving strategy. Even for people who are perfectly patient, weighting the future equal to the present, if the rate of return on saving falls below that from betting, betting will be a strictly preferred liquidity generation strategy. Many factors such as lack of safe storage options, challenges of self-control, external pressure to spend, inflation, and transaction costs may all push down peoples' return to saving and make betting more appealing whether they are in Uganda or anywhere else in the world. If people also overestimate the rate of return of, gain enjoyment from, or develop addictions to betting, this will raise incidence and intensity of betting even further as an alternative to saving in pursuit of liquidity.

IV. Conclusion

Using a sample of more than 1,708 sports bettors in Kampala, Uganda, I present a set of empirical results suggesting that unmet liquidity needs and saving constraints can affect demand for bets with a negative expected return. I show that bettors appear to select payoffs linked to anticipated large expenditures and use winnings disproportionately on large, lumpy expenditures. I then use a randomized experiment to show that a simple commitment-saving device lowers betting demand. Next, I use two lab-in-the-field experiments to isolate mechanisms. A prime increasing the salience of a desired lumpy expenditure increases elicited demand for betting tickets. And finally, a budgeting exercise reduces demand for betting among those who receive positive updates on their perceived ability to save. Together, these results tell a consistent story: liquidity needs, betting behavior, and saving ability, as an alternative strategy of liquidity generation, are all linked.

The findings in this paper contribute to a broader literature on the causes of gambling as well as literatures on the financial management strategies of the poor and the impacts of saving constraints. While the choice of setting and sample in Uganda was done with the intention of testing these linkages, the behavior of the participants documented in this paper is relevant to populations outside of Uganda as well.

Even the relatively simple interventions tested in this study affected betting demand, illustrating a plausible mechanism and avenue of intervention. More ambitious interventions and programs, such as lowering the cost of secure saving or expanding access to affordable credit, may have stronger effects. Broadly, if

[59] From the soccer schedules, I calculate the number of major league games that occurred in the preceding week for each day of the study. In one approach, I model betting expenditures on the number of games, income, income squared, and time fixed effects and can only explain 35 percent of variation. In a separate approach, I take the bottom quartile of game volume and compare average expenditures to those in the top quartile. Expenditures during low-game-volume weeks are about 35 percent lower than those in high-intensity weeks.

policymakers are interested in reducing demand for gambling motivated by unmet liquidity needs, marginalized populations need better financial services and alternative ways to access liquidity to avoid exposure to the high costs and potential risks associated with gambling.

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