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What Drives Demand for State-Run Lotteries? Evidence and Welfare Implications

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We use natural experiments embedded in state-run lotteries and a new nationally representative survey to provide reduced-form and structural estimates of risk preferences and behavioural biases in lottery demand, and to explore the implications for optimal lottery design. We find that sales respond more to the expected value of the jackpot than to price but are unresponsive to variation in the second prize—a pattern that is consistent with probability weighting but is inconsistent with standard parameterizations. In the survey, we find that lottery spending decreases modestly with income and is strongly associated with measures of innumeracy, poor statistical reasoning, and other proxies for behavioural bias, which also decline with income. Regression predictions suggest that Americans would spend 43% less on lotteries if they were unbiased, while the remaining lottery demand is due to other factors such as anticipatory utility or entertainment value. We use these empirical moments to estimate a model of socially optimal lottery design. In the model, current multi-state lottery designs increase welfare but may harm heavy spenders.

Key words: Behavioural public economics, Behavioural welfare analysis, Probability weighting, Lotteries

JEL codes: D12, D61, D91, H21, H42, H71

"[A lottery] preys upon the hard earnings of the poor; it plunders the ignorant and simple."

–U.S. Supreme Court, in Phalen v. Virginia (1850)

The editor in charge of this paper was Katrine Løken.

"In our stressful world, the ability to dream is well worth the price of a lottery ticket ... The lottery is simply a form of entertainment that happens to benefit your state."
– National Association of State and Provincial Lotteries (2021b)

"Since this regressive, addictive, partially hidden tax is here to stay, might a little improvement still be conceivable? ... Here's a modest suggestion: States should consider reducing their skim of the wagers."

– Purdue University president and former Indiana governor Mitch Daniels (2019)

1. INTRODUCTION

People have long debated whether states should run lotteries. Opponents argue that lotteries are a regressive tax on people who are bad at math. Proponents argue that lotteries are a win-win, generating both consumer surplus and government revenues. If states do run lotteries, there are further debates, such as the optimal "implicit tax"—the share of revenues that is allocated to the government instead of returned to prize winners. Economists are divided: a recent survey of the University of Chicago IGM experts panel found that 23% of leading economists believe that state-run lotteries increase social welfare, 28% disagree, and 45% were uncertain or had no opinion.[1]

These debates matter. Americans spent a remarkable \$679 per household (or \$87 billion in total) on lottery tickets in 2019, generating \$25 billion in state government revenues. This was more than the revenue raised by federal estate or tobacco taxes, and just less than the revenue raised by the federal gas tax (Internal Revenue Service, 2021). Americans spend more on lottery tickets than they do on cigarettes, and more than they do on music, sports tickets, movie tickets, books, and video games combined (Isidore, 2015).

Embedded within these debates is a series of core (behavioural) economics questions. How does people's demand for lotteries vary with their prize structure, and what does this imply about underlying risk preferences? How much of lottery consumption is driven by innumeracy or other behavioural biases, as opposed to entertainment and other normatively respectable preferences? Do lower-income people spend more on lotteries, and is this good (because it reflects consumer surplus for people with higher marginal utility) or bad (because it reflects exploitation of behavioural biases)? How should states design lotteries to maximize welfare, accounting for consumer surplus, possible behavioural biases, concerns about regressivity, and the value of public funds?

We address these questions with new data on how people respond to variation in prizes and sales, and a new nationally representative survey linking lottery expenditures to household income and proxies for behavioural biases such as incorrect perceptions of lottery returns, overoptimism, or self-control problems. We complement the reduced-form results from these data by calibrating a structural model of lottery demand, including nonlinear probability weights (as in, *e.g.* Kahneman and Tversky, 1979; Prelec, 1998). Finally, we illustrate the policy relevance of our empirical estimates by considering state-run lotteries in an optimal taxation model, and deriving implications for welfare and optimal design.

Section 3 lays out our conceptual framework. We begin with a positive model of lottery demand in which consumers apply flexible decision weights to potential outcomes, and we show that demand elasticities with respect to prizes and prices of lottery tickets identify these weights.

1. See www.igmchicago.org/surveys/state-run-lotteries.

These decision weights may be driven by behavioural biases, normative preferences, or a combination thereof. We then present an optimal policy model for studying the welfare effects of different lottery designs. This model can be applied to goods other than lotteries, and it generalizes the "optimal sin tax" model of Allcott *et al.* (2019) to settings where the government can also regulate or directly control a good's attributes—for example, cigarette nicotine content or lightbulb energy efficiency. In the model, the policymaker has multiple instruments that determine the implicit tax on lotteries, including raising the price, reducing the jackpot or other prizes, and reducing the prize probabilities. Optimal policy takes into account how these instruments can both *counteract* bias (the usual corrective taxation logic) and *affect* bias—for example, if a change in the jackpot win probability affects the misperception of that probability.

The model of positive lottery demand motivates the empirical analysis in Section 4, where we estimate the aggregate semi-elasticities of demand with respect to prizes and price by exploiting natural experiments built into the two large multi-state lotteries, Mega Millions and Powerball. When nobody wins the jackpot, the jackpot prize money is "rolled over" to the next drawing. Since the winning numbers are randomly selected, rollovers are random conditional on ticket sales, generating conditionally random variation in the jackpot over time. In California, lower prizes also roll over if they are not won, and winning the second prize is unlikely enough that it rolls over regularly. We identify the effect of ticket prices on demand from event studies of when Mega Millions and Powerball separately increased their prices from \$1 to \$2.

The semi-elasticities of demand with respect to the jackpot expected value, second prize expected value, and price are about 1.7, statistically zero, and −0.5, respectively. Strikingly, this means that ticket sales increase over three times as much if the jackpot expected value increases by \$1 than if the price decreases by \$1. This is the opposite of what would be expected for risk-averse consumers, and it is not explained by substitution across games or time. This pattern is qualitatively consistent with the long literature on probability weighting.[2] Quantitatively, however, the jackpot elasticity is so large relative to the second prize elasticity that our estimates cannot be fit by three standard functional forms from the literature (Goldstein and Einhorn, 1987; Tversky and Kahneman, 1992; Prelec, 1998). We show that these estimated elasticities are instead consistent with the neo-additive specification formalized by Chateauneuf *et al.* (2007).

We complement the quasi-experimental analysis with a new nationally representative survey to inform two complementary questions. First, how much of the apparent probability weighting is due to behavioural biases versus normative preferences like wishful thinking or the joy of playing? Second, does demand for lotteries vary by income? We carried out the survey on the AmeriSpeak panel, a high-quality probability-based sample that includes households that might not participate in cheaper opt-in surveys.

We find that the spending distribution is highly skewed, generating some imprecision in the estimated means, but point estimates suggest that lottery spending declines moderately with income: people with household income under \$50,000 spend 29% more on the lottery than people with household income above \$100,000. Measures of perceived self-control problems, financial illiteracy, statistical mistakes (such as the Gambler's Fallacy, non-belief in the Law of Large Numbers, and difficulty calculating expected values), and incorrect beliefs about expected returns from lottery play are highly statistically significantly associated with more lottery spending. This holds both unconditionally and after controlling for demographics, risk aversion, and questions measuring how much people enjoy playing the lottery. Interestingly, not all of these relationships suggest that bias increases consumption: while in reality 60% of lottery revenues

2. See, for example, Kahneman and Tversky (1979), Tversky and Kahneman (1992), Prelec (1998), Gonzalez and Wu (1999), Wakker (2010), Filiz-Ozbay *et al.* (2015) and Bernheim and Sprenger (2020).

are returned to winners, the average person believes that the expected returns are only 29%, a misperception that presumably decreases demand. We measure and correct for imperfect test-retest reliability by resampling the same survey respondents 1 year later, building on other resampling designs such as those of Beauchamp *et al.* (2017), Gillen *et al.* (2019), Chapman *et al.* (2023), and Stango and Zinman (2023).

Motivated by our model, we use these results to estimate the quantity of lottery demand that is driven by behavioural biases. Regression predictions suggest that Americans would spend 43% less on lotteries if they had perfect self-control, had the financial literacy and statistical ability of the highest-scoring people in our sample, and had correct beliefs about expected returns. Lower-income people score lower on financial literacy and statistical ability, so the point estimates suggest that a larger share of their spending is attributable to bias. Although we control for a rich array of demographics and preference measures, a key caveat is that these regression predictions are not the causal effects of behavioural biases. With that important caveat, these results are consistent with concerns that behavioural biases play a role in lottery spending.

These reduced-form results allow us to calibrate our structural model of lottery demand. The structural estimates imply that the weight people attach to the jackpot is 221 times as large as the objective probability of winning the jackpot. We estimate that on average, 29% of the difference between the decision weight and the probability is driven by bias, although there is significant heterogeneity. The bias share ranges from 32% for heavy-spending high-income consumers to 17% for middle- and high-income consumers who buy lottery tickets only occasionally.

Using our structural model to simulate the implications of alternative lottery designs, we find that the optimal implicit tax rate on lotteries is slightly lower than current Mega Millions and Powerball designs. In our model, actual consumer surplus is much smaller than consumers' perceived surplus at our baseline behavioural bias estimates, but the current Mega Millions and Powerball designs increase welfare and deliver close to maximal welfare levels. A key channel for these gains comes through the effect on revenues: lotteries raise public funds while also generating (much smaller) consumer surplus for lottery purchasers. These results hinge on the magnitude of behavioural bias. For example, if we alternatively assume zero bias, then low-income heavy spenders derive the most surplus. If bias is more than about twice as large as our baseline estimate, lotteries would reduce overall welfare. This highlights the importance of our survey evidence but also underscores the need for future work.

Our main contribution to the literature is the new empirical results on decision-making under risk and key parameters relevant for lottery design, including elasticities and the relationship between lottery consumption, income, and proxies for behavioural bias. Our article is also the first to formalize and empirically implement a framework for studying optimal lottery policy with behavioural bias and redistributive concerns.

We build on six distinguished literatures. The first is a reduced-form empirical literature on state-run lotteries; see Clotfelter and Cook (1989, 1990), Kearney (2005a), and Grote and Matheson (2011) for overviews. This includes papers studying how lottery spending varies by income and other demographics.[3] While lotteries have changed substantially in the past two decades, to our knowledge our AmeriSpeak survey is the first to measure individual-level lottery spending using a nationwide probability sample since Clotfelter *et al.* (1999).[4] This literature also includes papers studying aggregate demand patterns and substitution across games.[5] We extend that work

3. See, for example, Clotfelter and Cook (1987), Clotfelter *et al.* (1999), Farrell and Walker (1999), Price and Novak (1999, 2000), and Oster (2004).

4. Lottery spending is "drastically underreported" in the Consumer Expenditure Survey (Kearney, 2005b).

5. See, for example, Clotfelter and Cook (1989), Cook and Clotfelter (1993), Farrell *et al.* (1999), Farrell *et al.* (2000), Kearney (2005b), Grote and Matheson (2006), Guryan and Kearney (2010), and Knight and Schiff (2012). We

by (i) using instrumental variables to address simultaneity bias in the relationship between jackpots and sales, (ii) using new data to estimate the elasticity with respect to the second prize, which we find to be very different than the jackpot elasticity, and (iii) exploiting recent Mega Millions and Powerball price changes to estimate the price elasticity of demand for those games. Both (ii) and (iii) are necessary for structural estimates of the probability weighting function.

The second literature we build on is the work in structural behavioural economics (DellaVigna *et al.*, 2012, 2017, 2022), particularly in its application to field and natural experiments.[6] The third literature we build on studies behavioural biases that might affect gambling and lottery demand in the field.[7] These papers are quite different from ours: they typically study one or two biases in isolation and are designed to reject null hypotheses of "standard" behaviour, whereas we attempt to estimate a comprehensive measure of many different biases in units of dollars, which is the required object for quantitative policy evaluation. The fourth literature studies the use of lotteries to encourage beneficial behaviours such as saving money (Kearney *et al.*, 2011), charitable giving (Landry *et al.*, 2006; Lange *et al.*, 2007a, 2007b), and healthy behaviours (Haisley *et al.*, 2012). These are distinct from the state-run lotteries that we study because the objective of these lotteries is behaviour change, rather than striking an optimal balance between raising revenue and increasing consumer surplus through entertainment, while mitigating overconsumption. The fifth literature is the work in *behavioural public economics,* studying other settings where behavioural biases affect optimal policy design.[8] The sixth literature studies how survey measures of bias predict behaviour.[9]

Sections 2–7 present the background, conceptual framework, quasi-experimental evidence on lottery demand, survey evidence on lottery expenditures and behavioural biases, model calibration, and welfare analysis, respectively.

2. BACKGROUND ON LOTTERIES IN THE UNITED STATES

From 1995 to 2019, real lottery spending grew from \$540 per household (\$53 billion in total) to \$679 per household (\$87 billion in total); see Supplementary Appendix Figure A1(a) (U.S. Census Bureau, 2019b, 2020; U.S. Bureau of Labor Statistics, 2020). There are two major types of lottery games: instant (or "scratch-off") games and draw games, where players choose numbers and win if their numbers match those selected in the next drawing. The largest draw games are two multi-state lotteries, Mega Millions and Powerball. From 1995 to 2019, instant games grew from 38% to 65% of sales, Mega Millions and Powerball grew from 3% to 9%, and all other games dropped from 59% to 26%.

calculate that these papers' estimates of the effects of jackpots on ticket sales range from 33 to 250% of our estimate, with an average of 114% of our estimate. See details in Supplementary Appendix Table A8.

6. See, also Conlin *et al.* (2007), Giaccherini *et al.* (2020), Laibson *et al.* (2023), and Strulov-Shlain (2022). See DellaVigna (2018) for a review.

7. Studies outside of laboratory settings include Clotfelter and Cook (1993), Guryan and Kearney (2008), Haisley *et al.* (2008), Post *et al.* (2008), Snowberg and Wolfers (2010), Suetens *et al.* (2016), and Amano and Simonov (2023). A separate large literature, *e.g.* Kahneman and Tversky (1979) and subsequent work, studies related biases in laboratory settings.

8. See, *e.g.* Bernheim and Rangel (2004, 2009), Mullainathan *et al.* (2012), Allcott *et al.* (2014), Allcott and Taubinsky (2015), Baicker *et al.* (2015), Bernheim *et al.* (2015), Handel and Kolstad (2015), Spinnewijn (2017), Taubinsky and Rees-Jones (2018), Allcott *et al.* (2019), Handel *et al.* (2019), Farhi and Gabaix (2020), Goldin and Reck (2020), Rees-Jones and Taubinsky (2020), Ambuehl *et al.* (2022), and Beshears *et al.* (2023); see Bernheim and Taubinsky (2018) for a review.

9. See, *e.g.* Chabris *et al.* (2008), Meier and Sprenger (2010), Beauchamp *et al.* (2017), Gillen *et al.* (2019), Chapman *et al.* (2023), and Stango and Zinman (2023).

Of the $87 billion in 2019 sales, 60% was returned in prizes, 10% was overhead (6.5% commissions and 3.9% administrative costs), and the remaining 29% represented state government proceeds; see Supplementary Appendix Figure A1(b) (U.S. Census Bureau, 2019b; North American Association of State and Provincial Lotteries, 2021a). This 29% implicit tax has decreased from 34% since 1995, a trend that is associated with the growing market share of instant games, which return a larger share to winners.[10] Lottery prizes are taxed as income, so an additional share of prize money returns to governments through the income tax.

Our aggregate demand estimation focuses on Mega Millions and Powerball from June 2010 through February 2020. In Mega Millions, players select five numbers from 1 to 70 and one Mega Ball number from 1 to 25; this is the "5/70 + 1/25 format." Powerball uses a 5/69 + 1/26 format. Players win the jackpot if their numbers match all six balls selected in the next semi-weekly drawing; players can also win lower prizes from $2 to $1,000,000 by choosing one or more numbers correctly. Table 1 presents ticket price and prize information for the formats in place during our sample period. For both games, tickets now cost $2, and the jackpot odds are about 1/300,000,000. The ratios of ticket expected value to price are 0.28 and 0.32, so accounting for 10% overhead gives implicit tax rates of 62% and 58%, respectively.

Jackpot amounts are determined on a parimutuel basis: the jackpot prize pool depends on ticket sales, and the jackpot is split equally among all winners. Jackpot winners can choose to receive 30 annual instalments that increase by 5% per year or the discounted present value of that annuity at current interest rates; most choose the latter. Before each drawing, Mega Millions and Powerball advertise an "estimated jackpot," which is the undiscounted value of the annuity based on projected ticket sales. If no one wins the jackpot, the jackpot prize pool is rolled over to the next drawing. If someone wins the jackpot, the next drawing's jackpot returns to a reset value, which was a $40 million annuity for both Mega Millions and Powerball at the end of our sample in February 2020.[11]

In most states, the lower prize amounts are fixed. However, the California Supreme Court ruled in 1996 that the California State Lottery Act allows parimutuel games where players play against other players, but not games where players play against the house. As a result, both Mega Millions and Powerball have California-specific parimutuel prize pools for each lower prize that roll over to the next draw if they are not won. The second prize odds are about 1/12,000,000 for both games, so there are many drawings when no one wins the second prize and it thus rolls over. The third and lower prizes have high enough odds that they generally do not roll over.

Powerball began in 1992 with 15 states, and Mega Millions began in 2002 with 9 other states. Both games replaced earlier multi-state games with different names, and both have gradually added states over time. After a cross-selling agreement was reached, individual states began to offer both games in 2010. By June 2010, 42 states had joined Mega Millions and 41 had joined Powerball. From September 2014 through the end of our sample, both games were available through all 45 state lotteries and the D.C. and U.S. Virgin Islands lotteries.[12]

Mega Millions and Powerball have both adjusted their pricing and formats multiple times since 2010, as shown in Table 1. There are five key trends. First, both games increased prices from $1 to $2. Second, the jackpot odds have been reduced, increasing the frequency of rollovers:

10. See Clotfelter (2024) for further discussion of this trend.

11. In March 2020, lottery sales dropped substantially due to the coronavirus pandemic, and both games temporarily lowered their reset value to a $20 million annuity at the beginning of April. We say "current design" to refer to the design in place just before the pandemic.

12. Alabama, Alaska, Hawaii, Nevada, and Utah do not have state lotteries. The Puerto Rico lottery only offers Powerball.

TABLE 1
Mega Millions and Powerball prices and prize structures

	Mega Millions			Powerball		
Start date	22 June 2005	19 October 2013	28 October 2017	7 January 2009	15 January 2012	7 October 2015
Ticket price	$1	$1	$2	$1	$2	$2
Format	5/56 + 1/46	5/75 + 1/15	5/70 + 1/25	5/59 + 1/39	5/59 + 1/35	5/69 + 1/26
Jackpot (average)	$34 million	$57 million	$102 million	$39 million	$66 million	$101 million
Reset value	$7 million	$9 million	$24 million	$12 million	$24 million	$24 million
Probability	1/175,711,536	1/258,890,850	1/302,575,350	1/195,249,054	1/175,223,510	1/292,201,338
Expected value	$0.18	$0.20	$0.31	$0.18	$0.34	$0.31
Second prize	$250,000	$1 million	$1 million	$200,000	$1 million	$1 million
Probability	1/3,904,701	1/18,492,204	1/12,607,306	1/5,138,133	1/5,153,633	1/11,688,054
Expected value	$0.064	$0.054	$0.079	$0.039	$0.19	$0.086
Third prize	$10,000	$5,000	$10,000	$10,000	$10,000	$50,000
Probability	1/689,065	1/739,688	1/931,001	1/723,145	1/648,976	1/913,129
Expected value	$0.015	$0.0068	$0.011	$0.014	$0.015	$0.055
Fourth prize	$150	$500	$500	$100	$100	$100
Probability	1/15,313	1/52,835	1/38,792	1/19,030	1/19,088	1/36,525
Expected value	$0.0098	$0.0095	$0.013	$0.0053	$0.0052	$0.0027
Fifth prize	$150	$50	$200	$100	$100	$100
Probability	1/13,781	1/10,720	1/14,547	1/13,644	1/12,245	1/14,494
Expected value	$0.011	$0.0047	$0.014	$0.0073	$0.0082	$0.0069
Sixth prize	$7	$5	$10	$7	$7	$7
Probability	1/306	1/766	1/606	1/359	1/360	1/580
Expected value	$0.023	$0.0065	$0.016	$0.019	$0.019	$0.012
Seventh prize	$10	$5	$10	$7	$7	$7
Probability	1/844	1/473	1/693	1/787	1/706	1/701
Expected value	$0.012	$0.011	$0.014	$0.0089	$0.0099	$0.01
Eighth prize	$3	$2	$4	$4	$4	$4
Probability	1/141	1/56	1/89	1/123	1/111	1/92
Expected value	$0.021	$0.035	$0.045	$0.032	$0.036	$0.043
Ninth prize	$2	$1	$2	$3	$4	$4
Probability	1/75	1/21	1/37	1/62	1/55	1/38
Expected value	$0.027	$0.047	$0.055	$0.049	$0.072	$0.10
Probability, any prize	1/40	1/15	1/24	1/35	1/32	1/25
Lower prize expected value	$0.18	$0.17	$0.25	$0.17	$0.36	$0.32
Total expected value	$0.36	$0.38	$0.55	$0.36	$0.70	$0.63

Notes: This table reports the prizes, win probabilities, and expected values corresponding to each prize level and the overall ticket for all Mega Millions and Powerball formats used since 2010. All jackpot prize amounts are discounted to their approximate present values as described in Section 4.1, resulting in lower reset values than the advertised annuity amounts. The non-jackpot prize amounts are the fixed prizes offered in states other than California. The expected value is computed simply as the win probability multiplied by the advertised prize (or average prize discounted by a constant factor to account for prize-splitting, in the case of the jackpot).

the jackpot was won every 7.4 drawings in 2010–2011 but only every 15.4 drawings in 2018–2019. Third, the prize structure is being hollowed out: there is less expected value in the middle prizes and more in the jackpot and lowest prizes. Fourth, as a result of the previous two trends, average jackpots have grown: the average jackpot was $37 million in 2010–11 and $103 million in 2018–19. Fifth, the ratio of expected value to price is decreasing, *i.e.* winners receive a smaller share of the revenues. This pushes against the overall trend of lower implicit taxes described above.

3. CONCEPTUAL FRAMEWORK

In this section we present a simple model to formalize the concepts that guide our empirical analysis. We first present a positive model of lottery demand, and we show how key parameters are identified from prize and price elasticities. We estimate these elasticities from historical sales data in Section 4. We then incorporate a general specification of behavioural biases, which includes probability misperceptions, present focus, and misforecasted happiness. We end by characterizing optimal price and lottery structure as a function of behavioural biases, elasticities, and society's preference for inequality reduction.

3.1. *A positive model of lottery demand*

In the tradition of Kahneman and Tversky (1979) and Tversky and Kahneman (1992), we model individuals as maximizing their utility by aggregating across different outcomes with outcome-specific "decision weights" that may differ from objective probabilities. Differences could be due to salience or focusing effects (Bordalo *et al.*, 2013; Kőszegi and Szeidl, 2013; Bushong *et al.*, 2021), advertising effects, incorrect beliefs about objective probabilities, and non-standard preferences. Although some papers building on this literature use the phrase "probability weights" (*e.g.* Prelec, 1998) we use the more general phrase "decision weights" to emphasize that the psychological weight applied to a potential outcome may depend on factors other than that outcome's objective probability.

Individuals choose whether to buy a lottery ticket $x_t \in \{0, 1\}$ on each of many choice occasions indexed by t. We disaggregate demand into a series of binary decisions on different choice occasions because decision weighting most plausibly applies at the level of each individual ticket, rather than at the level of an aggregate portfolio. This is consistent with the evidence on narrow bracketing (Tversky and Kahneman, 1981; Rabin and Weizsacker, 2009), particularly as it applies to lottery tickets (Haisley *et al.*, 2008). This is also consistent with our empirical results that there is no substitution between different types of lotteries. To simplify exposition in the body of the article, we assume that there is a single choice occasion. The more general case with multiple choice occasions is characterized in Supplementary Appendix C.

To integrate our model of lottery demand into a broader policy model with redistributive taxation and the associated distortions, we assume individuals also choose labour supply, and thus earnings z, which are subject to a nonlinear income tax $T(z)$. Lottery tickets are purchased, at price p, out of net-of-tax income, the rest of which is spent on numeraire consumption c whose price is normalized to one. We define $\boldsymbol{a}$ as a vector of lottery attributes, including the K prizes $\boldsymbol{w} = (w_1, \ldots, w_K)$ and corresponding probabilities $\boldsymbol{\pi} = (\pi_1, \ldots, \pi_K)$, as well as other possible attributes such as advertising.

Individuals have heterogeneous types θ capturing income-earning ability, preferences, and behavioural biases. On each choice occasion, individuals receive a lottery taste shock ε drawn from a continuous distribution. We think of ε as representing the transaction cost of buying a lottery ticket. We let $F(\theta, \varepsilon)$ denote the joint distribution over types and taste shocks, and we let F_θ denote the marginal distribution over θ, and $F_{\varepsilon|\theta}$ the conditional distribution of ε. We define $u(\boldsymbol{a}; \theta, \varepsilon)$ as the perceived subutility from purchasing a lottery ticket—described in detail below—and we define $\psi(z; \theta)$ as the labour disutility of generating earnings z. Individuals maximize total "perceived utility"

$$U = G(c + x \cdot u(\boldsymbol{a}; \theta, \varepsilon) - \psi(z; \theta)), \tag{1}$$

subject to their budget constraint $z - T(z) = c + px$, where G is twice-differentiable and concave. The more general model in Supplementary Appendix C relaxes the quasilinearity assumption. Empirically, we find income effects on lottery consumption to be small, and in our welfare simulations we find that these effects have a negligible impact on our results.[13]

We assume that the subutility from a lottery ticket takes the form

$$u(\boldsymbol{a};\theta,\varepsilon)=\sum_k \Phi_k(\theta)m\left(w_k;\theta\right)-\varepsilon, \tag{2}$$

where $m(w_k;\theta)$ is the incremental utility from gaining w_k more post-tax income, normalized by the individual's marginal utility of consumption. Formally, if $\mathcal{U}(W)$ is the utility function over continuation wealth W and y denotes the agent's (net) continuation wealth absent any prize, then $m(w)=\frac{\mathcal{U}(y+w)-\mathcal{U}(y)}{\mathcal{U}'(y)}$. Consequently, concavity of $\mathcal{U}$ implies that $m'(w)=\mathcal{U}'(y+w)/\mathcal{U}'(y)\leq 1$. The decision weight corresponding to outcome k is Φ_k, so that $\Phi_k(\theta)\equiv\pi_k$ corresponds to expected utility preferences. Because we normalize m by the local marginal utility of consumption, $\sum_k \Phi_k(\theta)m(w_k;\theta)$ can be interpreted as the certainty equivalent of the lottery, absent transaction costs.

This utility specification nests many modifications of expected utility theory proposed in the literature on prospect theory and cumulative prospect theory.[14] In this class of models, the weight applied to a particular outcome is invariant to the outcome's payoff, so payoff variation can be used to identify weights, as we describe in the next subsection. Although a decision weight Φ_k may depend on the objective probability π_k, as in models of probability weighting, it may also depend on other factors, such as advertising, game frequency, or even other prize levels and their probabilities.

Type θ's demand function is the average across many binary purchase decisions of type-θ individuals with different taste shocks ε:

$$s(p,\boldsymbol{a};\theta)=\Pr\left(u(\boldsymbol{a};\theta,\varepsilon)>p\right) \tag{3}$$

$$=F_{\varepsilon\,|\,\theta}\left[\sum_k \Phi_k(\theta)m\left(w_k;\theta\right)-p\right]. \tag{4}$$

We define $\bar{s}(p,\boldsymbol{a}):=\int s(p,\boldsymbol{a};\theta)dF_\theta(\theta)$ as population-level aggregate demand. When no ambiguity arises, we sometimes suppress arguments in the demand functions.

3.2. *Using elasticities to identify decision weights*

With minor abuse of notation, we sometimes write $s(z)$ and other statistics as functions of z, to denote consumption of s among all z-earners, and so forth. We define $\zeta_p(z):=\frac{d\ln s(z)}{dp}$ as the semi-elasticity of demand with respect to ticket price, and we define $\zeta_a(z):=\frac{d\ln s(z)}{da}$ as the semi-elasticity of demand with respect to attribute a. We define $\bar{\zeta}_p$ and $\bar{\zeta}_a$ as population-wide semi-elasticities. When there is no ambiguity, we use ζ_k to denote the semi-elasticity with

13. Quasilinearity also implies that changes to the lottery structure or price do not affect labour supply. The more general model in the Supplementary Appendix allows for such distortionary effects but shows that they are negligible if income effects on lottery consumption are negligible.

14. See, *e.g.* Kahneman and Tversky (1979), Prelec (1998), Gonzalez and Wu (1999), Wakker (2010), Filiz-Ozbay *et al.* (2015), and Bernheim and Sprenger (2020).

respect to the expected value of the kth prize, $\pi_k w_k$. Consistent with our empirical analysis, this semi-elasticity is defined with respect to variation in the prize w_k, not in the probability π_k.[15]

Our model implies the following relationship between decision weights Φ_k and the semi-elasticities:

$$\frac{\zeta_k}{|\zeta_p|} = \frac{\Phi_k}{\pi_k} m'(w_k). \tag{5}$$

To see this, note that changing the ticket price by $-dp < 0$ induces an increase in lottery purchases equal to $ds = |\zeta_p| s \cdot dp$. The increase in the expected value of prize k that would generate the same change in demand, denoted $dx_k = \pi_k dw_k$, satisfies $dp = \frac{\Phi_k}{\pi_k} m'(w_k) dx_k$. The change in demand generated by this prize increase is $ds = \zeta_k s \cdot dx_k$. Therefore, $|\zeta_p| s \frac{\Phi_k}{\pi_k} m'(w_k) \cdot dx_k = \zeta_k s \cdot dx_k$, which simplifies to equation (5). This logic generalizes the simple principle that if m is concave and decision weights equal objective probabilities, then people must be less responsive to a \$1 change in the expected value of a prize than they are to a \$1 change in the price. That is, a prize semi-elasticity ζ_k that is higher than $|\zeta_p|$ is inconsistent with the standard assumptions of $\Phi_k = \pi_k$ and concave utility over wealth.

Comparing prize semi-elasticities to each other also provides insight into the decision weights. A corollary of (5) is that

$$\frac{\zeta_k}{\zeta_{k'}} = \frac{\Phi_k}{\pi_k} \cdot \frac{\pi_{k'}}{\Phi_{k'}} \cdot \frac{m'(w_k)}{m'(w_{k'})}. \tag{6}$$

Letting $w_k > w_{k'}$, note that if utility from wealth is (weakly) concave, so that $\frac{m'(w_k)}{m'(w_{k'})} \leq 1$, then if decision weights are equal to objective probabilities, we should observe $\zeta_k \leq \zeta_{k'}$.[16] Thus, $\zeta_k > \zeta_{k'}$ is evidence that decision weights do not equal objective probabilities, and in particular that people attach a relatively much larger decision weight to the larger prize than to the smaller prize.

If $m(w_k)$ is specified, semi-elasticities with respect to price and prizes can be used to recover the decision weights Φ_k. This observation motivates our reduced-form analysis in Section 4, where we estimate aggregate demand semi-elasticities with respect to price, jackpot, and second prize. These estimates can also be used to calibrate the structural model of lottery demand in Section 6.

3.3. *Behavioural biases and welfare*

The function u can reflect a variety of possible motives for playing the lottery, including both normatively relevant preferences and behavioural biases. For example, it can include any entertainment derived from playing the lottery (Conlisk, 1993; Kearney, 2005b), or anticipatory utility from thinking about a chance of winning (*e.g.* Loewenstein, 1987; Caplin and Leahy, 2001; Brunnermeier and Parker, 2005; Gottlieb, 2014). If the entertainment utility individuals receive from playing is bounded away from zero, as long as the likelihood of winning is positive, individuals will behave as if they overweight small probabilities. We also allow for perceptual distortions, such as over- or under-estimating the likelihood of winning or imperfect processing of small probabilities (Woodford, 2012; Steiner and Stewart, 2016). Biases induced by salience

15. Thus, this semi-elasticity is $1/\pi_k$ multiplied by the semi-elasticity with respect to the prize w_k. The $1/\pi_k$ factor is a normalization that improves exposition by ensuring that all of our estimated elasticities are of similar orders of magnitude.

16. Note that $m''(w) = \mathcal{U}''(y+w)/\mathcal{U}'(y)$, and thus $m(w)$ is concave in w if $\mathcal{U}$ is concave in wealth.

or focusing effects (Bordalo *et al.*, 2013; Kőszegi and Szeidl, 2013; Bushong *et al.*, 2021) could affect demand as well.

To formalize the possibility of mistakes, we draw a distinction between perceived utility, which individuals maximize, and "normative utility," which enters the planner's objective function:

$$V = G(c + x \cdot v(\boldsymbol{a}; \theta, \varepsilon) - \psi(z; \theta)). \tag{7}$$

We define $s^V(p, \boldsymbol{a}; \theta) := \Pr(v(\boldsymbol{a}; \theta, \varepsilon) > p)$ as the type-θ demand function that would obtain if individuals maximized normative utility. We assume that v is also additively separable in ε.

Bias is the difference between the perceived utility and normative utility from consuming a lottery ticket: $\gamma(\boldsymbol{a}; \theta) := u(\boldsymbol{a}; \theta, \varepsilon) - v(\boldsymbol{a}; \theta, \varepsilon)$.[17] This representation of bias mirrors Allcott *et al.* (2019, henceforth "ALT"), where γ is equivalent to the price decrease that would lead consumers maximizing V to purchase as many lottery tickets as consumers maximizing U, *i.e.* $s^V(p - \gamma, \boldsymbol{a}; \theta) = s(p, \boldsymbol{a}, \theta)$.

Examples: Consider a simple lottery that offers a single large prize of amount w with probability π, so that $\boldsymbol{a} = \{w, \pi\}$, and consider demand from a given type of agent (with index θ suppressed for simplicity). Further suppose that the perceived subutility from a lottery ticket is $u(\boldsymbol{a}; \varepsilon) = (1 + \phi)\pi m(w) - \varepsilon$, where $m(w)$ is the utility gain from winning a prize of size w, and $(1 + \phi)\pi$ is the decision weight that the individual applies to that utility. If $\phi = 0$, the individual is an expected utility maximizer. We now provide examples of the types of biases that can be accommodated by this framework. These examples also illustrate how our decision weights capture psychological motivations other than just misperception or overweighting of certain probabilities.

3.3.1. Misperceived probability of winning. Suppose the individual has expected utility preferences but misperceives the probability of winning as $\tilde{\pi} \neq \pi$. Then normative utility from lottery consumption is $v(\boldsymbol{a}; \varepsilon) = \pi m(w) - \varepsilon$, perceived utility is $u(\boldsymbol{a}; \varepsilon) = \tilde{\pi} m(w) - \varepsilon$, and bias is $\gamma(\boldsymbol{a}) = u(\boldsymbol{a}; \varepsilon) - v(\boldsymbol{a}; \varepsilon) = (\tilde{\pi} - \pi)m(w)$.

3.3.2. Present focus (and addiction). Suppose that $\phi^V \pi m(w)$ is the immediate hedonic gain from anticipatory utility and joy of playing. Suppose further that individuals are quasi-hyperbolic discounters who discount all consumption other than the immediate utility $\phi^V \pi m(w)$ by a factor $\beta < 1$. Finally, suppose that normative utility corresponds to long-run preferences that set $\beta = 1$. Then, normative and perceived utility can be written, respectively, as $v(\boldsymbol{a}; \varepsilon) = (1 + \phi^V)\pi m(w) - \varepsilon$ and $u(\boldsymbol{a}; \varepsilon) = (1 + \phi^V/\beta)\pi m(w) - \varepsilon$. Bias is then $\gamma(\boldsymbol{a}) = (1/\beta - 1)\phi^V \pi m(w)$.

Our framework can also accommodate the interaction between present focus and addiction, as studied by, *e.g.* Gruber and Kőszegi (2001) in the context of smoking. Suppose that buying a lottery ticket today imposes expected costs of $d\pi m(w)$ on one's future self because prior experience with gambling makes it more painful not to gamble, and possibly also makes future gambling less enjoyable. If these expected costs are down-weighted by present focus β (but additional anticipatory utility $\phi^V \pi m$ is not), then $u(\boldsymbol{a}; \varepsilon) = (1 + \phi^V)\pi m(w) - \beta d\pi m(w) - \varepsilon$, $v(\boldsymbol{a}; \varepsilon) = (1 + \phi^V)\pi m(w) - d\pi m(w) - \varepsilon$, and $\gamma(\boldsymbol{a}) = (1 - \beta)d\pi m(w)$.

17. Note that γ is not a function of ε because both u and v are additively separable in ε.

3.3.3. Misforecasted happiness. Suppose individuals overestimate the happiness they would gain from winning the prize w by a factor of b. Then $u(\boldsymbol{a};\varepsilon)=(1+\phi^V+b)\pi m(w)-\varepsilon$, while $v(\boldsymbol{a};\varepsilon)=(1+\phi^V)\pi m(w)-\varepsilon$, and thus $\gamma(\boldsymbol{a})=\pi bm(w)$.

3.4. *Optimal lottery policy*

Turning to the question of optimal policy, we assume the government seeks to maximize normative utility, aggregated across individuals using type-specific Pareto weights $\mu(\theta,\varepsilon)$:

$$\int_{\theta,\varepsilon}\mu(\theta,\varepsilon)V(c,s,\boldsymbol{a},z;\theta,\varepsilon)dF(\theta,\varepsilon), \tag{8}$$

subject to individuals' maximization of their perceived utility U, and to the government's budget constraint,

$$\int_{\theta}(ps(\theta)+T(z(\theta)))dF_{\theta}(\theta)-C(\boldsymbol{a},\bar{s})\geq R, \tag{9}$$

where $C(\boldsymbol{a},\bar{s})$ is the cost to the government of selling $\bar{s}$ tickets with attributes $\boldsymbol{a}$ that includes the expected prize payout plus administration, marketing, and any other costs. We refer to the percent markup above average cost, $\frac{p\bar{s}-C(\boldsymbol{a},\bar{s})}{p\bar{s}}$, as the "implicit tax rate." Supplementary Appendix C (Proposition C1) derives general optimality conditions that hold for an arbitrarily dynamic model with any number of choice occasions, without requiring additive separability in ε, and allowing for income effects.

We let λ denote the marginal value of public funds (*i.e.* the multiplier on the government budget constraint in equation (9) at the optimum), and we define $g(\theta,\varepsilon):=\mu(\theta,\varepsilon)U_c'/\lambda$ to denote the Pareto-weighted marginal utility from consumption for type (θ,ε). Following Saez (2002a) and others, we assume that this "social marginal welfare weight" $g(\theta,\varepsilon)$ is equal for all individuals with a given level of earnings (and thus, all who have a common type θ) and declining with income under the optimal tax system. We thus use $g(z)$ to denote social marginal welfare weights as a function of income.

We now characterize optimality conditions for ticket prices and attributes. We define $\kappa(\theta)$ to be the average willingness-to-pay (WTP) among θ-types for a marginal increase in attribute a. This statistic can be computed from empirically measurable semi-elasticities in response to variation in p and a, as $\kappa(\theta)=-\zeta_a(\theta)/\zeta_p(\theta)\cdot s(\theta)$. We define the average WTP among z-earners as $\kappa(z):=\mathbb{E}[\kappa(\theta)\mid z(\theta)=z]$, and the average WTP across all consumers as $\bar{\kappa}:=\mathbb{E}[\kappa(\theta)]$.

We define $\gamma_p(z):=\frac{\mathbb{E}[\gamma(\theta)\frac{ds(\theta)}{dp}\mid z(\theta)=z]}{\mathbb{E}[\frac{ds(\theta)}{dp}\mid z(\theta)=z]}$ and $\bar{\gamma}_p:=\frac{\mathbb{E}[\gamma(\theta)\frac{ds(\theta)}{dp}]}{\mathbb{E}[\frac{ds(\theta)}{dp}]}$ to be the average bias among z-earners and across all individuals, respectively, who are marginal to a price change. We define $\gamma_a(z)$ and $\bar{\gamma}_a$ analogously over individuals marginal to a change in attribute a.

Because bias can depend on the attribute a, individuals' perceived utility from a change in a may be biased. The bias in z-earners' valuation of a marginal increase in a is $\rho(z):=\mathbb{E}[\frac{d}{da}\gamma(a;\theta)\cdot s(\theta)\mid z(\theta)=z]$. We define $\bar{\rho}:=\mathbb{E}[\rho(z)]$ as the population average. By definition, $\bar{\kappa}-\bar{\rho}$ is the average impact on normative utility of increasing a, measured in dollars.

Finally, because our framework includes redistributive motives, the welfare effects of a change in consumption depend on whose consumption is changed. All else equal, the welfare change is more positive when more of the benefits of correcting bias accrue to low-income individuals. Because we assume that social marginal welfare weights depend only on income, these statistics depend on the concentration of bias correction across incomes z, rather than of types θ, and we define $s(z)$ as the lottery demand aggregated across all z-earners. To capture these redistributive concerns, we define $\sigma_p := Cov[g(z), \frac{\gamma_p(z)}{\bar{\gamma}_p} \frac{\zeta_p(z)s(z)}{\bar{\zeta}_p\bar{s}}]$, which we call the "progressivity of bias correction" from a price change. We define an analogous statistic for an attribute change: $\sigma_a := Cov[g(z), \frac{\gamma_a(z)}{\bar{\gamma}_a} \frac{\zeta_a(z)s(z)}{\bar{\zeta}_a\bar{s}}]$. These statistics quantify the extent to which the benefits of bias correction accrue to low-income individuals, per unit change in $\bar{s}$.

Our optimal policy conditions can be stated in terms of intuitive mark-up formulas.

Proposition 1. *If p and a are interior optima, then*

$$\overbrace{p - \frac{\partial C}{\partial \bar{s}}}^{\text{Mark-up above MC}} = \overbrace{\bar{\gamma}_p(1+\sigma_p)}^{\text{Bias correction}} - \frac{\overbrace{Cov\left[s(z), g(z)\right]}^{\substack{\text{Regressivity of} \\ \text{increasing } p}}}{|\bar{\zeta}_p|\bar{s}} \tag{10}$$

$$\overbrace{p - \frac{\partial C}{\partial \bar{s}}}^{\text{Mark-up above MC}} = \overbrace{\bar{\gamma}_a(1+\sigma_a)}^{\text{Bias correction}} - \frac{\overbrace{\bar{\kappa} - \bar{\rho} - \frac{\partial C}{\partial a}}^{\substack{\text{Mechanical effect on} \\ \text{consumer surplus} \\ \text{and revenues}}} + \overbrace{Cov[\kappa(z) - \rho(z), g(z)]}^{\substack{\text{Regressivity of} \\ \text{increasing } a}}}{\bar{\zeta}_a\bar{s}} \tag{11}$$

This result is a special case of Proposition C1 in Supplementary Appendix C, which derives these optimal policy conditions in a more general setting with income effects and many purchase occasions.

For intuition, notice first that equation (10) is a special case of equation (11) if we think of price p as an attribute. Because we assume that people do not misperceive prices, $\rho(z) \equiv 0$. Moreover, $\kappa(z) = s(z)$, as the mechanical effect on consumer surplus of lowering the price by dp is simply $dps(z)$. Finally, $\frac{\partial C}{\partial p} = \bar{s}$, as the mechanical revenue effect of lowering price by dp is simply a decrease $dp\bar{s}$ in revenue. Thus, $\bar{\kappa} - \bar{\rho} - \frac{\partial C}{\partial a} = 0$ when $a = p$, and equation (11) reduces to equation (10).

Equation (11) is a generalization of Ramsey-style optimal commodity tax formulas. The wedge $p - \frac{\partial C}{\partial \bar{s}}$ is analogous to a per-unit tax on a lottery ticket. This "tax" must equal the difference between two terms. The first term, $\bar{\gamma}_a(1+\sigma_a)$, is a Pigouvian correction that corresponds to the social marginal benefits of decreasing lottery consumption. This term is increasing in σ_a, the progressivity of bias correction. The second term is the mechanical effect on consumer welfare net of revenues; it consists of two parts. The first part, $\bar{\kappa} - \bar{\rho} - \frac{\partial C}{\partial a}$, is the direct effect on consumer surplus net of revenues. The second part is the extent to which the effects on consumer surplus are distributed in a regressive or progressive way. In the case of a price change, this is simply the extent to which lower-income individuals buy more lottery tickets and are thus more impacted by the price change. In the case of an attribute change more generally, this is the extent to which lower-income individuals have a higher (normative) WTP for this attribute change.

To provide further intuition for the above conditions, Supplementary Appendix B.1 presents several special cases of Proposition 1, including (i) no bias and homogeneous preferences, (ii) no bias and heterogeneous preferences, (iii) homogeneous bias and preferences, and (iv) the revenue-maximizing lottery structure.

Although we use the above model for our empirical analysis, we note two natural extensions to it here. The first involves income effects on lottery consumption, which are considered in the more general model of Supplementary Appendix C. That extension creates a link to the celebrated theorem in Atkinson and Stiglitz (1976), as we elaborate in Supplementary Appendix C.

Second, note that our baseline model assumes no substitution, motivated by our empirical result in Section 4 that there is limited substitution between state-run lottery games, and by Kearney's (2005b) result that the introduction of state-run lotteries has no detectable effect on non-state-sponsored gambling.[18] If such substitution is present, one must account for the degree of bias over substitute goods to which spending is diverted. Building on ALT's formulas, a diversion ratio r to other (non-state-run) gambling subject to the same bias implies that $\bar{\gamma}$ should be replaced by $(1-r)\bar{\gamma}$ in Proposition 1.

3.5. *From theory to measurement*

Our model and theoretical results motivate the following main empirical analyses. The first is estimating semi-elasticities of lottery demand with respect to ticket price and prizes. Section 3.2 shows that these identify decision weights, and Section 3.4 shows that these elasticities are a key input in the optimal design formulas. We obtain these from the quasi-experimental analysis in Section 4.

The second is estimating the variation of lottery expenditures by income. Section 3.4 shows that this is a key input into the regressivity component of the optimal price and attribute formulas. We obtain this from our survey, which we analyse in Section 5. The third is a measure of bias, which we also obtain from the survey.

The theory also motivates several secondary analyses, also performed in Sections 4 and 5. One is substitution between lotteries. This can affect optimal attribute formulas, as we summarize at the end of Section 3.4. The other is the causal effect of additional income on lottery demand. This is fleshed out in Supplementary Appendix C.

4. AGGREGATE LOTTERY DEMAND

This section presents estimates of the aggregate semi-elasticities of demand $\bar{\zeta}_a$ and $\bar{\zeta}_p$ for the two major multi-state lotteries, Mega Millions and Powerball.

4.1. *Data: lottery prizes and aggregate sales*

Our primary analyses use draw-level sales and prize data for Mega Millions and Powerball from June 2010 through February 2020. We scraped jackpot and sales data from the website LottoReport.com (Nettles, 2024), and we scraped California second prize amounts from the California Lottery website. Jackpots are advertised jackpot amounts, and ticket sales exclude the Just the Jackpot, Power Play, and Megaplier add-ons.

Table 2 presents descriptive statistics. There are 2,035 observations: two draws per week for almost 10 years, for both Mega Millions and Powerball. The California sample is slightly smaller, because California did not join Powerball until April 2013.

To study substitution across games, we purchased data on lottery sales by game, state, and week from La Fleur's (2021), a standard data provider. We construct a balanced panel of instant

18. Interestingly, the introduction of new state-run lotteries did affect cross-border demand for existing state-run lotteries (Knight and Schiff, 2012).

TABLE 2
Descriptive statistics: Mega Millions and Powerball sales and prize data

	Obs.	Mean	Std. dev.	Min	Max
Jackpot ($millions)	2,035	68.8	68.1	7.1	946.3
California 2nd prize pool ($000s)	1,705	948.2	1, 034.6	82.7	7, 660.3
Nationwide ticket sales (millions)	2,035	23.0	30.6	8.8	651.9
California ticket sales (millions)	1,705	3.3	5.1	0.9	120.2

Notes: This table presents descriptive statistics for draw-level Mega Millions and Powerball sales and prize data from June 2010 through February 2020. Jackpot amounts and sales data are from LottoReport.com; California second prize amounts are from https://www.calottery.com/draw-games/. Jackpots are advertised jackpot amounts, and ticket sales exclude the Just the Jackpot, Power Play, and Megaplier add-ons.

games plus the 85 other games for which we have complete data from June 2010 through February 2020 in the 41 states that had Mega Millions and Powerball over that period, representing 61% of total lottery sales reported in the Census of Governments over the sample period.

Because prize amounts are typically round numbers in nominal dollars, we use nominal dollars throughout the article except for Supplementary Appendix Figure A1. When there are multiple winners of the jackpot or any prize in California, the prize is split equally among all winners. To account for prize-splitting, we use our LottoReport sales data to approximate the average factor by which each prize is reduced in expectation by prize-splitting and apply that factor to prize amounts when computing expected values. The factors applied to jackpots and California second prizes are 0.91 and 0.71, respectively.[19] We also discount all jackpots to their present value using a conversion factor of 0.59. We compute this conversion factor as the ratio between (i) the stock of cash required to purchase bonds that yield enough interest in each period to pay out the jackpot annuity as scheduled and (ii) the total annuity value of the jackpot.[20]

4.2. *Prize elasticities*

4.2.1. Estimation strategy. We identify the jackpot elasticity off of jackpot variation generated by randomness in whether someone won the jackpot in the previous draw, and we identify the second prize elasticity off of analogous variation in California second prizes. As an example, Figure 1 illustrates the identifying variation for Powerball in 2014. Over that year, the jackpot varied between $24 million and $237 million in present value. The odds of winning the jackpot were about 1/200,000,000 in 2014, so the expected value of the jackpot varied from roughly $0.15 to $1.25. The California second prize varied from $183,000 to $7.7 million, and the second prize odds were about 1/5,000,000, so the second prize expected value varied from roughly $0.03 to $1.00. This illustrates that the California second prize expected value can be material (and even larger than the jackpot), although the jackpot expected value is about 3.3 times larger on average during our sample.

The figure also plots California ticket sales against the right axis. Sales and jackpots move together, and sales rise especially sharply when jackpots are unusually high. However, sales do not seem to respond to second prize variation.

19. Supplementary Appendix Figure A2 compares jackpot and California second prize expected values, accounting for prize-splitting under the assumption that players select numbers randomly, to simple approximations of the expected values—the product of the prize level and win probability—for Powerball in 2014.

20. We use the average 30-year Treasury yield curve rate (U.S. Treasury Department, 2021) as the interest rate in our calculations. We also set the number of annual payments to 30 and require payments to increase by 5% each year, reflecting the most common annuity structure.

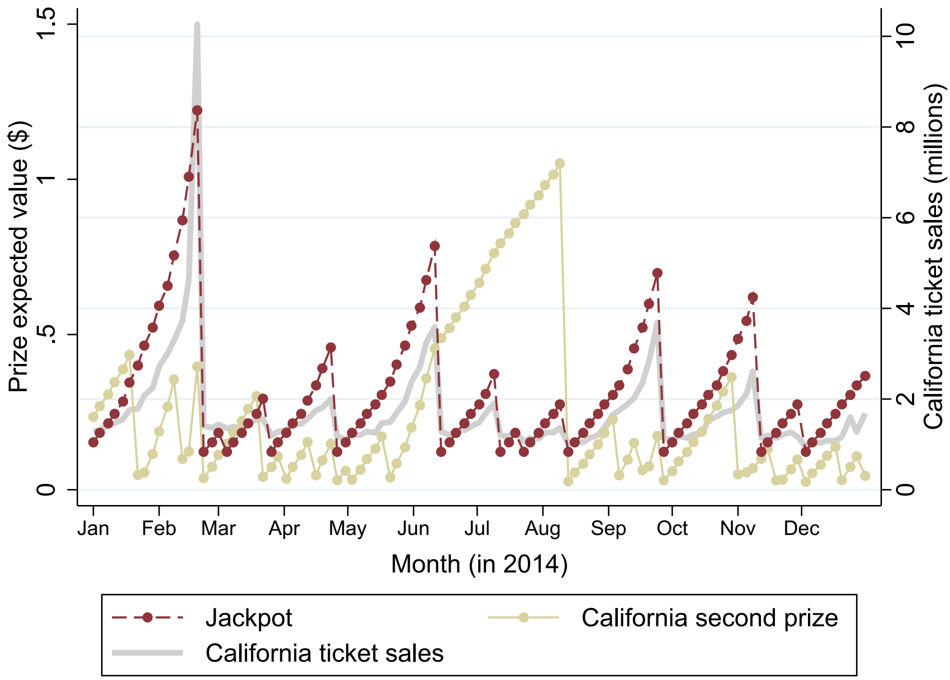

FIGURE 1

Powerball prizes and ticket sales in 2014

Notes: This figure presents the expected values of the jackpot and California second prize as well as California ticket sales for each Powerball drawing in 2014.

While the evolution of prize amounts is partially random, there are two reasons why we do not simply regress sales on prize amounts. First, the draw t advertised jackpot is directly determined by forecasted ticket sales for draw t, potentially generating simultaneity bias. Second, due to rollovers, the draw t prize pool is also directly affected by previous draws' sales, which may be correlated with draw t demand if demand shocks are serially correlated.

To isolate the random variation in prize amounts in game j, we instrument for prize k's expected value $\pi_{kjt}w_{kjt}$ with a forecast $\pi_{kjt}Z_{kjt}$ based solely on whether or not the prize rolled over from the previous period.[21] Following Borusyak and Hull (2023), we address serially correlated demand shocks by including a control $\bar{Z}_{kjt}$ for the forecast of the prize prior to the realization of the rollover outcome.[22] We also add a vector of fixed effects collectively denoted ξ_{jt}: game-format fixed effects to soak up any changes in demand caused by changes in lower prize amounts and probabilities, game-regional coverage fixed effects to soak up changes in

21. Define r_{kjt} as an indicator for whether prize k rolled over from $t-1$ into t. A rollover from $t-1$ is less likely when $t-1$ ticket sales $\bar{s}_{j,t-1}$ are higher, but the realization of r_{kjt} is random conditional on $\bar{s}_{j,t-1}$. Let $\iota_{kjf(t)}$ denote the observed average percent increase in prize k in game j conditional on a rollover when format f, a function of the time of the draw t, is in effect, and let $\underline{w}_{kjf(t)}$ denote prize k's reset value in game j. The *prize forecast* is

$$Z_{kjt} = r_{kjt} \cdot \left(1+\iota_{kjf(t)}\right) \cdot w_{kj,t-1} + \left(1-r_{kjt}\right) \cdot \underline{w}_{kjf(t)} \tag{12}$$

22. Borusyak and Hull (2023) formally show that including this control yields consistent estimates. This *pre-rollover prize forecast* is

$$\bar{Z}_{kjt} = (1-\pi_{kjt-1})^{\bar{s}_{j,t-1}} \cdot \left(1+\iota_{kjf(t)}\right) \cdot w_{kj,t-1} + \left(1-(1-\pi_{kjt-1})^{\bar{s}_{j,t-1}}\right) \cdot \underline{w}_{kjf(t)} \tag{13}$$

demand when new states join, game-quarter of sample indicators to soak up changes in demand over time, and game-weekend fixed effects to soak up higher demand for Friday and Saturday draws. We do not include time fixed effects that are common across both games, because this could introduce bias if consumers substitute across games.

Our estimating equation is

$$\ln \bar{s}_{jt} = \bar{\zeta}_1 \pi_{1jt} w_{1jt} + \bar{\beta}_1 \pi_{1jt} \bar{Z}_{1jt} \left(+ \bar{\zeta}_2 \pi_{2jt} w_{2jt} + \bar{\beta}_2 \pi_{2jt} \bar{Z}_{2jt} \right) + \xi_{jt} + \epsilon_{jt}. \quad (14)$$

The second prize elasticity term in parentheses is included only in our California-specific estimates. We instrument for $\bar{\zeta}_1 \pi_{1jt} w_{1jt}$ (and $\bar{\zeta}_2 \pi_{2jt} w_{2jt}$) with the jackpot forecast $\pi_{1jt} Z_{1jt}$ (and the second prize forecast $\pi_{2jt} Z_{2jt}$).

4.2.2. Estimation results. Figure 2 presents binned scatter plots of the variation that identifies the prize semi-elasticities $\bar{\zeta}_1$ and $\bar{\zeta}_2$, conditional on the controls in equation (14). Figure 2(a) shows that national ticket sales are highly responsive to the jackpot expected value fitted values $\widehat{\pi_{1jt} w_{1jt}}$ from the first stage of equation (14). The relationship is very close to linear, and the slope is slightly less than 2.0, meaning that a \$0.10 increase in the jackpot expected value increases sales by nearly 20 log points. However, Figure 2(b) shows that California ticket sales are not responsive to the California second prize expected value first-stage fitted values.

Table 3 presents estimates of equation (14). The first stages are very strong; see Supplementary Appendix Table A1. In all estimates in this section, we use Newey-West standard errors with up to ten lags. Our standard errors do not change much if we allow more or fewer Newey-West lags or cluster standard errors at the intersection of game and month, quarter, or half year.

Panel (a) presents estimates of the jackpot elasticity $\bar{\zeta}_1$ using the nationwide sales data, while Panel (b) presents estimates of the jackpot and second prize elasticities $\bar{\zeta}_1$ and $\bar{\zeta}_2$ using California sales only. In both panels, Column 1 presents the OLS estimates without a $\pi \bar{Z}$ pre-rollover prize forecast control, and Column 2 presents our IV estimates with that control.

The OLS estimates are slightly larger, consistent with slight simultaneity bias. The estimates match the binned scatter plots in Figure 2. In both panels of Table 3, the jackpot semi-elasticity is around 1.7 to 1.8. In Panel (b), the second prize semi-elasticity is statistically indistinguishable from zero, and the 95% confidence intervals in Column 2 exclude values larger than about 0.19.

As shown in equation (6) in Section 3.2, the large difference between these two elasticities implies that decision weights do not equal objective probabilities, and that the decision weight on the jackpot is relatively much larger than the decision weight on the smaller prize. A probability weighting function with this form could arise for several reasons. First, individuals might underappreciate differences between the (small) second prize probability and the (very small) jackpot probability. Second, individuals could derive larger anticipatory utility from larger prizes, and anticipatory utility might be insensitive to probabilities. Third, because the second prize expected value doesn't vary much (its standard deviation is only one-third of the jackpot's), individuals might be inattentive to the second prize, as in Gabaix (2014) and related theories of focusing and salience (Bordalo *et al.*, 2013; Kőszegi and Szeidl, 2013; Bushong *et al.*, 2021); these theories

Thus, after controlling for $\bar{Z}_{kjt}$, we identify only off of conditionally random variation in the prize forecast Z_{kjt} delivered by randomness in whether the prize rolled over.

This prediction assumes that players randomly select the numbers on their tickets. Supplementary Appendix Figure A3 shows that the frequency of rollovers predicted under this assumption is close to the observed frequency of rollovers; the mean predicted and observed likelihood of a jackpot rollover are 0.91 and 0.90, respectively, while both the predicted and observed likelihood of a California second prize rollover are 0.72.

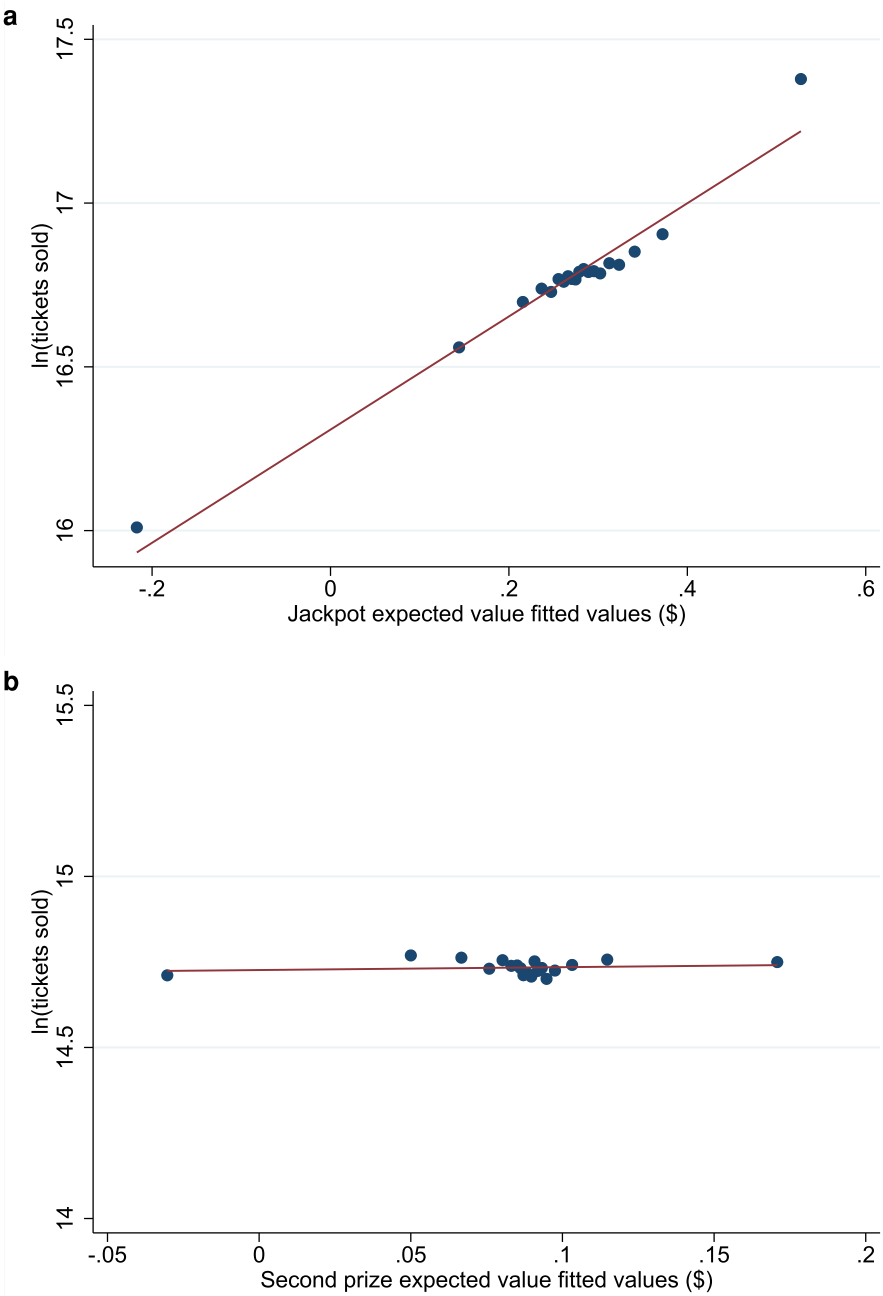

FIGURE 2

Responsiveness of ticket sales to jackpot and California second prize: (a) national sales versus jackpot expected value first-stage fitted values and (b) California sales versus second prize expected value first-stage fitted values

Notes: Panel (a) presents a binned scatter plot of the natural log of national sales against the jackpot expected value fitted values from the first stage of equation (14), residual of the controls in that equation. Panel (b) presents a binned scatter plot of the natural log of California sales against the California second prize expected value fitted values from the first stage of equation (14), residual of the jackpot expected value first-stage fitted values and the other controls in that equation. The sample includes all Mega Millions and Powerball drawings from June 2010 through February 2020.

TABLE 3
Prize semi-elasticity estimates

	(1) OLS	(2) IV
(a) **Jackpot semi-elasticity: national sales**		
Jackpot expected value ($)	1.8648***	1.7277***
	(0.0576)	(0.0619)
Observations	2,035	2,035
(b) **Jackpot and second prize semi-elasticities: California sales only**		
Jackpot expected value ($)	2.0154***	1.8466***
	(0.0776)	(0.0852)
2nd prize expected value ($)	−0.0202	0.0837
	(0.0590)	(0.0554)
Observations	1,705	1,701

Notes: This table presents estimates of equation (14), a regression of the natural log of sales on prize expected values, controlling for game-format, game-regional coverage, game-quarter of sample, and game-weekend fixed effects. The IV regressions instrument for prize expected values with a forecast based on the previous period prize amount and an indicator for whether the prize was won in the previous period and additionally control for the expectation of the forecast prior to the realization of the rollover outcome. Panel (a) uses nationwide sales, while Panel (b) uses California sales only. The samples include all Mega Millions and Powerball drawings from June 2010 to February 2020; the sample in Panel (b) is smaller because California did not join Powerball until April 2013. Newey-West standard errors allowing up to ten lags are in parentheses. ***: statistically significant with 99% confidence.

have more recently been suggested as attentional microfoundations for the probability weighting function (Bordalo *et al.*, 2012; Dertwinkel-Kalt and Koster, 2020; Bordalo *et al.*, 2022). Fourth, high jackpots generate extra media attention that may temporarily increase sales. Fifth, while jackpot amounts are covered in the media and heavily promoted on billboards and in online ads, the estimated second prize for the next draw must be inferred from results of the previous drawing.[23] Of course, the second prize might not be promoted precisely because individuals would be unresponsive.

Substitution. As described in Clotfelter and Cook (1990), Grote and Matheson (2011), and the literature cited therein, it is ambiguous whether draw games such as Mega Millions and Powerball are substitutes or complements for other lottery games. While their similarity suggests that they might be substitutes, the attention to high jackpots could also spill over to other games. Furthermore, high jackpots bring additional consumers into lottery outlets, where they can immediately buy other games. It could also be that high jackpots primarily bring in new consumers who wouldn't otherwise buy lottery tickets.

Supplementary Appendix D.1 shows that Mega Millions or Powerball jackpots have tightly estimated zero effects on sales of other games. Our confidence intervals from Supplementary Appendix Table A2 rule out diversion ratios of more than about 4% to the other multi-state game, major state-level draw games, instant games, and other state-level games. This limited substitution is consistent with our "narrow bracketing" model assumption under which people consider each lottery in isolation rather than forming a utility-maximizing portfolio from a combination of different lotteries.

Short-run versus long-run responses. As in many other studies, we have a well-identified short-run elasticity, but our policy analysis requires a long-run elasticity. To address this concern,

23. People can estimate the California games' upcoming second prize amounts by using each game's webpage to look up the previous second prize pool and whether the prize was won, and then adding a guess about the increase in the prize pool from the upcoming draw's sales.

Supplementary Appendix D.2 shows that the jackpot elasticity is very similar when we aggregate over time and that lagged jackpot amounts have positive but relatively small effects on current sales. While not dispositive, this is consistent with the idea that the long-run elasticity is not much different from the short-run elasticity.

4.3. *Price elasticity*

4.3.1. Estimation strategy. We identify the price semi-elasticity $\bar{\zeta}_p$ from the change in ticket sales when Mega Millions and Powerball raised their prices from \$1 to \$2. To use these event studies, we must also consider the simultaneous format changes described in Table 1. Both games substantially increased their jackpot amounts and expected values. However, as shown in Table 1, the expected return (*i.e.* expected value per dollar spent) from all lower prizes did not change very much. Because of this limited change, and because we saw insignificant elasticity with respect to second prize variation in Table 3, we assume that the lower prize changes did not affect demand.

Define W_{jt} as an indicator for the 12-month period around game j's price change, six months before and six months after, and W^{+}_{jt} as an indicator for the 12-month period that follows. Our estimating equation modifies equation (14) into an event study estimator that identifies the change in sales within a 12-month event window around the price change:

$$\ln \bar{s}_{jt} = \bar{\zeta}_p p_{jt} W_{jt} + \beta_1 W_{jt} + \beta_2 p_{jt} W^{+}_{jt} + \beta_3 \pi_{1jt} w_{1jt} + \xi_j + \epsilon_{jt}, \tag{15}$$

where ξ_j is now simply an event fixed effect. The jackpot expected value $\pi_{1jt} w_{1jt}$ control increases precision and controls for the simultaneous format change. To identify the coefficients on the controls with the most relevant data, we limit the regression sample to the 36-month period around the price change. To maintain a consistent sample as states join Mega Millions or Powerball, we construct separate national sales series for each 36-month period that only include sales from the states that participated for the full 36-month period.

4.3.2. Estimation results. The red lines with circular markers in Figure 3 present ticket sales residual of the jackpot expected value, *i.e.* $\ln \bar{s}_{jt} - \hat{\beta}_2 \pi_{1jt} w_{1jt}$, in the 36-month event study window for the game whose price changed. Figure 3(a) presents the Powerball price change in January 2012, while Figure 3(b) presents the Mega Millions price change in November 2017. We recentre so that the average residual equals zero before the price change when the jackpot is within \$10 million of the reset value. In both event studies, sales drop by about 50 log points immediately after the price increase.

The other lines on Figure 3 present ticket sales for the other multi-state game, major state draw games, and all other games, respectively. To reduce noise, the other multi-state game $-j$'s sales are residual of that game's jackpot expected value control $\hat{\beta}_2 \pi_{1-jt} w_{1-jt}$. Some long-run trends become visible over the full 36-month period: both Mega Millions and Powerball sales gradually decline after the other game's price increases, and other game sales (mostly instant games) gradually increase. However, the effect on own-game sales is much larger and more immediate than these gradual trends for other games, suggesting that the other games' trends are unrelated to the price change.

Table 4 presents estimates of equation (15). Column 1 presents our primary estimates pooling the two event studies, while Columns 2 and 3 consider each event study separately. Consistent with Figure 3, the estimates suggest that the price changes decreased demand by 44 to 59 log points.

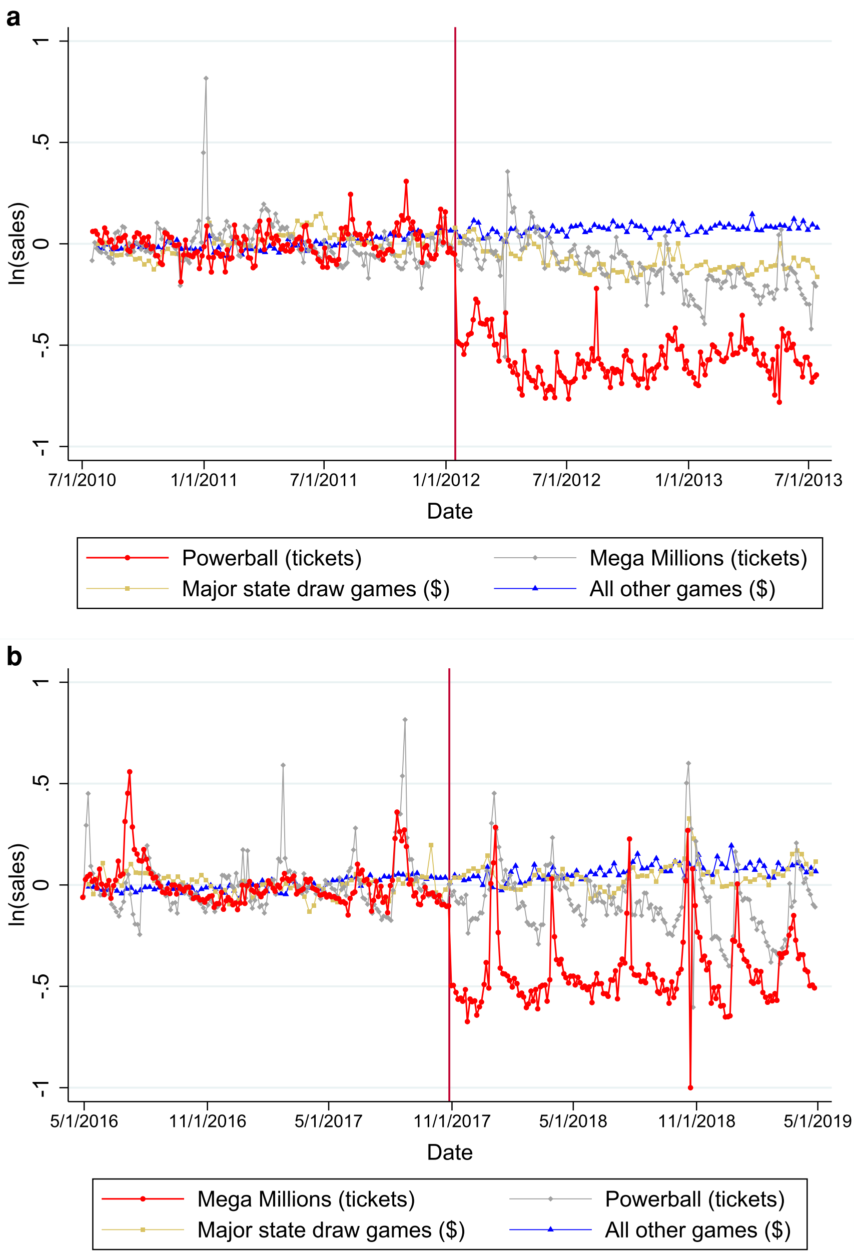

FIGURE 3

Price change event studies: (a) Powerball and (b) Mega Millions

Notes: These figures present the natural log of Powerball and Mega Millions ticket sales (residual of jackpot expected values and weekend fixed effects from Columns 2 and 3 of Table 4, respectively) and the natural log of other games' sales in dollars (residual of week fixed effects) before and after price increases, which are indicated by the vertical lines. The levels of Mega Millions and Powerball sales are adjusted so that the average natural log of sales is zero before the price change when jackpots are within \$10 million of the reset value, while the levels of other games' sales are adjusted so that the average natural log of sales is zero before the price change. In Panel (a), the Powerball ticket price increased from \$1 to \$2 on 15 January 2012. In Panel (b), the Mega Millions ticket price increased from \$1 to \$2 on 28 October 2017. One value in Panel (b) from a Mega Millions drawing with a record jackpot is winsorized at −1.

TABLE 4
Price semi-elasticity

	(1) Pooled	(2) Powerball	(3) Mega Millions	(4) Pooled	(5) Powerball	(6) Mega Millions
Price × 12-month window	−0.5150***	−0.5935***	−0.4408***	−0.5163***	−0.5448***	−0.5049***
	(0.0412)	(0.0536)	(0.0528)	(0.0461)	(0.0523)	(0.0604)
Jackpot expected value ($)	1.8516***	1.9379***	1.8071***			
	(0.0861)	(0.0469)	(0.1274)			
Jackpot ($millions)				0.0064***	0.0098***	0.0056***
				(0.0007)	(0.0002)	(0.0005)
Observations	625	312	313	625	312	313

Notes: This table presents estimates of equation (15), a regression of the natural log of sales on (i) ticket price interacted with an indicator for the 12-month window—six months before and six months after—around a price change event, (ii) the 12-month window indicator, and (iii) ticket price interacted with an indicator for the 12-month period following the 12-month window around the price change event, controlling for game-weekend fixed effects and either the jackpot expected value or the jackpot amount. Columns 1 and 4 pool the data from both the Powerball and Mega Millions price changes and also include a price-change event fixed effect, while Columns 2, 3, 5, and 6 consider each price change in isolation. We use Newey-West standard errors with up to 10 lags. ***: statistically significant with 99% confidence.

While we model demand as a function of the jackpot expected value, it could be that people pay attention only to the jackpot amount and not the probability (Cook and Clotfelter, 1993). From Table 1, we can calculate that the Mega Millions jackpot probability decreased by 14% when the price increased, while the Powerball jackpot probability increased by 12%. If demand responds to the jackpot amount instead of the expected value, our price elasticity estimates would be biased, although in opposite directions for the two games. Column 4 shows that the pooled estimate changes little when we control for the jackpot amount. Columns 5 and 6 show that the estimates from each event are almost identical (and thus close to the pooled estimate) under this alternative control.

Substitution. Consistent with the graphical evidence in Figure 3, Supplementary Appendix Table A4 shows statistically zero substitution to other games after Mega Millions and Powerball increase prices. However, the estimates are not precise enough to rule out economically significant diversion ratios.

Placebo tests. As shown in Table 1, there were also two format changes during our sample period that did not involve price changes. We can use these as placebo tests: if our price elasticity estimates are unbiased, these format changes should not affect demand other than through their impact on the jackpot. Supplementary Appendix Table A7 presents estimates of equation (15) for these two other format changes, where we substitute p_{jt} for a post-format change indicator variable and again limit to the 36 months around the format change. These format changes have statistically zero effect on demand after controlling for the jackpot level, and the confidence intervals suggest that any confounding effects are small relative to the price change coefficients in Table 4.[24]

Summary. Lottery purchases are (i) highly elastic to jackpot variation, (ii) unresponsive to variation in smaller prizes, and (iii) less responsive to a $1 price change than to a $1 jackpot

24. In both of these format changes, the jackpot probabilities decreased substantially—much more than the jackpot probabilities changed when the games increased prices. This means that controlling for jackpot level versus jackpot expected value matters more. Supplementary Appendix Table A7 shows that controlling for the jackpot expected value (instead of level) does not explain the demand increases after the format changes. This is consistent with a model in which individuals respond to the jackpot level but are not responsive to the jackpot probability.

expected value change. The third result suggests that jointly raising price and jackpot expected value increases demand, consistent with the trends toward larger jackpots and higher ticket prices. Taken together, these three results are consistent with a probability weighting function that weights the jackpot higher than its objective probability and places little weight on smaller prizes. In the next section, we consider the extent to which these lottery purchasing patterns might be driven by innumeracy, confusion, or other types of mistakes.

5. INDIVIDUAL-LEVEL DEMAND

5.1. *AmeriSpeak survey*

This section provides evidence on how lottery expenditures vary with income and proxies for behavioural biases. We use a new survey that we designed to measure lottery spending and proxies for preferences and biases potentially related to lottery purchases. The survey was fielded on AmeriSpeak, a high-quality survey panel managed by the National Opinion Research Corporation (NORC). Unlike internet panels that allow anyone to opt in, AmeriSpeak is a probability sample that includes only U.S. households that have been randomly selected (and heavily incentivized) to participate. This helps to reduce sample selection biases that can make surveys unrepresentative on unobserved characteristics. The average spending estimates in Section 5.2 are weighted for national representativeness on age, sex, race, education, geography, and other key characteristics using sample weights provided by NORC. The bias proxy regressions in Section 5.3 are left unweighted to maximize precision, although the results with sample weights are similar.

The survey was fielded in April 2020, and a follow-up survey was fielded in April 2021. 3,013 people completed the 2020 survey, of whom 2,879 passed basic data quality checks. Table 5 presents descriptive statistics.[25] Panel (a) presents panellist demographics, Panel (b) presents survey questions on spending and income effects, and Panel (c) presents questions that proxy for preferences and bias. Sample sizes differ on individual questions due to item nonresponse. Supplementary Appendix E.1 presents the text of the survey questions, which we summarize here.

5.1.1. Spending and income effects. *Monthly lottery spending* is the response to the question, "How many dollars did you spend in total on lottery tickets in an average month in 2019?" We asked panellists to "please include Mega Millions, Powerball, and other lotto/prize drawings, instant/scratch-off games, and any other lottery game offered by your state lottery." To ensure that large expenditures were correctly reported, any person who reported more than $500 monthly lottery spending was asked to explicitly confirm or update their response.

To measure income effects, the survey asked people to report the percent change in their household income and lottery spending in 2019 compared to 2018 (*income change* and *spending change*), as well as how much they think their lottery spending would change "if you got a raise and your income doubled" (*self-reported income effect*).

5.1.2. Preference proxies. We construct three proxies of preferences for playing the lottery. First, we proxy for risk aversion using two questions: "In general, how willing or unwilling are you to take risks?" and a second question measuring aversion to financial risks when saving or investing money. Our *risk aversion* preference proxy is the average of these two measures

25. Supplementary Appendix Table A10 presents descriptive statistics for the follow-up survey.

TABLE 5

Descriptive statistics: 2020 survey data

	Obs.	Mean	Std. dev.	Min	Max
(a) **Demographics**					
Household income ($000s)	2,879	72.12	53.08	5	250
Years of education	2,879	14.32	2.26	4	20
Age	2,879	48.82	16.79	18	91
1(Male)	2,879	0.50	0.50	0	1
1(White)	2,879	0.66	0.47	0	1
1(Black)	2,879	0.11	0.31	0	1
1(Hispanic)	2,879	0.16	0.36	0	1
Household size	2,879	3.04	1.62	1	6
1(Married)	2,879	0.53	0.50	0	1
1(Employed)	2,879	0.63	0.48	0	1
1(Urban)	2,879	0.83	0.37	0	1
1(Attend church)	2,879	0.36	0.48	0	1
Political ideology	2,878	3.83	1.59	1	7
(b) **Spending and income effects**					
Monthly lottery spending ($)	2,877	15.16	38.04	0	1,000
Income change (%)	2,871	0.17	18.52	−50	50
Spending change (%)	2,870	−5.46	19.17	−50	50
Self-reported income effect (%)	2,855	−1.41	16.28	−50	50
(c) **Proxies for preferences and biases**					
Unwillingness to take risks	2,879	−3.93	1.38	−7	−1
Financial risk aversion	2,879	3.05	0.82	1	4
Lottery seems fun	2,875	0.16	1.83	−3	3
Enjoy thinking about winning	2,871	0.81	1.93	−3	3
Self-control problems	2,875	−0.34	1.10	−3	3
Financial literacy	2,879	0.77	0.25	0	1
Financial numeracy	2,879	0.63	0.32	0	1
Gambler's fallacy	2,879	0.29	0.39	0	1
Non-belief in law of large numbers	2,879	0.42	0.18	0.00	0.93
Expected value miscalculation	2,879	0.69	0.37	0	1
Overoptimism	2,865	−0.01	0.51	−4.95	4.95
Expected returns	2,871	0.28	0.20	0.05	0.95
Predicted life satisfaction	2,850	2.34	4.76	−10	10

Notes: This table presents descriptive statistics for our 2020 AmeriSpeak survey. Panel (a) presents demographics, Panel (b) presents spending and income effects, and Panel (c) presents proxies for preferences and biases. Section 5.1 summarizes the coding of these variables.

after standardizing each to have a standard deviation equal to one. Second, our *lottery seems fun* preference proxy is the extent to which people agree or disagree that "For me, playing the lottery seems fun." Third, our *enjoy thinking about winning* preference proxy, which is intended to measure anticipatory utility, is the extent to which people agree or disagree that "I enjoy thinking about how life would be if I won the lottery."

We designed the survey questions to allow us to construct proxies for six biases that might be related to lottery purchases.

5.1.3. Self-control problems. Self-control problems might affect lottery purchases if the enjoyment of playing is in the present, while the cost of buying the ticket (reduced consumption of other goods) is incurred later. To measure perceived self-control problems, the survey said, "It can be hard to exercise self-control, and some people feel that there are things they do too much or too little—for example, exercise, save money, or eat junk food. Do you feel like you play the lottery too little, too much, or the right amount?" Our *self-control problems* bias proxy is the response to that question, on a seven-point scale from "far too little" (coded as −3) to "the right amount" (coded as 0) to "far too much" (coded as +3).

5.1.4. Financial illiteracy. Financial illiteracy and innumeracy might affect lottery purchases by making it harder to evaluate risky prospects and correctly perceive small probabilities. *Financial literacy* is the share of correct answers on five standard questions from Lusardi and Mitchell (2014), and *financial numeracy* is the share of correct answers on three numeracy questions from Banks and Oldfield (2007). Our *financial illiteracy* bias proxy is the share of incorrect answers across all eight questions.

5.1.5. Statistical mistakes. Poor statistical reasoning might similarly make it harder to evaluate risky prospects and correctly perceive small probabilities. The survey included three measures of statistical reasoning. First, we measured the Gambler's Fallacy (Jarvik, 1951; Tversky and Kahneman, 1971; Rabin, 2002) by eliciting beliefs about the probability that an unbiased coin lands heads after three different sequences of heads and tails. The true probability is of course 50%. *Gambler's Fallacy* is the share of answers that differ from 50%; Table 5 reports that people gave some other answer 29% of the time. Second, we measured non-belief in the Law of Large Numbers (Benjamin *et al.*, 2016, 2018) by asking the probability that out of 1000 coin flips, the number of heads would be between 481 and 519 (correct answer = 0.78), 450 and 550 (correct answer = 0.9986), and 400 and 600 (correct answer = 0.9999). *Non-belief in the Law of Large Numbers* is the average absolute deviation from the correct answer. Third, we asked people to calculate the expected value of four simple example lotteries. *Expected value miscalculation* is the share of answers that are incorrect. To construct our *statistical mistakes* bias proxy, we standardize each of these three measures to have a standard deviation equal to one in the 2020 sample, take the average, standardize the average to have a standard deviation equal to one in 2020, and recentre so that zero is the best score in 2020.

5.1.6. Overoptimism. Overoptimism could increase lottery purchases by increasing people's perception of the chance of winning. The survey said, "Imagine **you** could keep buying whatever lottery tickets you want, over and over for a very long time. For every $1,000 you spend, how much do you think you would win back in prizes, on average?" The survey also asked people to report how much "the **average** lottery player" would win back. *Overoptimism* is the difference between own and average person expected winnings per $1 spent.

5.1.7. Expected returns. Misunderstanding the expected returns for the average person might also affect lottery purchases. *Expected returns* is the response to the question, "Think about the total amount of money spent on lottery tickets nationwide. What percent do you think is given out in prizes?"

5.1.8. Predicted life satisfaction. As argued by Kahneman *et al.* (2006) and others, people may overestimate the effect of wealth on happiness, and such a bias would cause people to overestimate the utility gains from winning a lottery. Using random variation in lottery winnings conditional on winning some amount, Lindqvist *et al.* (2020) estimate that the effect of an additional $100,000 on life satisfaction (measured on a 0–10 scale) is 0.071 points. The survey told panellists about the Lindqvist *et al.* (2020) study design (but not the effect size), informed them that the sample average life satisfaction was 7.21 out of 10, and asked them to predict the effect of an additional $100,000 on life satisfaction. *Predicted life satisfaction* is the response to that question.

5.1.9. 2021 follow-up survey. We fielded the April 2021 follow-up survey to help address measurement error. NORC invited everyone who had completed the 2020 survey to participate. 2,186 people responded, representing a normal follow-up response rate for AmeriSpeak, of whom 2,124 passed our data quality checks. The 2021 survey asked the same preference and bias proxy questions as in 2020. It also re-elicited *monthly lottery spending* in 2019 for 104 people who reported outlying values in 2020; we use this to confirm or winsorize the outlying responses.[26]

5.2. *Lottery spending by income*

The lottery spending distribution is highly skewed: in our survey data, the top 10% of spenders account for 56% of spending, while over 40% of people report no spending at all; see Supplementary Appendix Figure A5. This skewness reduces the precision of our estimates and underscores the importance of our efforts to validate outlying self-reports of monthly spending. The average spending of $15 per month multiplied by 255 million American adults (U.S. Census Bureau, 2019a) gives $47 billion, which is smaller than the $87 billion total nationwide sales reported in Supplementary Figure A1(a). Clotfelter *et al.* (1999, Table 6) also found that survey responses understate total nationwide sales. This understatement and other forms of measurement error would bias our conclusions only if correlated with income or bias proxies. As a suggestive test, we find no evidence that income or bias proxies are correlated with the change in 2021 versus 2020 reports of *monthly lottery spending*; see Supplementary Appendix Table A13.

Figure 4 presents average monthly lottery spending by income. People with household income above $100,000 spend an average of $13 per month on the lottery, while people with household income under $50,000 spend an average of $17, or 29% more.[27] The cross-sectional income elasticity of lottery spending (from a regression of ln(1 + spending) on ln(income)) is −0.111. The share of people with non-zero spending also declines slightly with income; see Supplementary Appendix Figure A6. Clotfelter *et al.* (1999, Table 10) also found that lower-income households spend more on lotteries, although their point estimates suggest a steeper decline in spending by income as of 1998. Golosov *et al.* (2024) find that U.S. lottery winners have wage earnings, employment status, and age similar to the average tax filer, although lottery winners are more likely to be single.

Proposition C1 in Supplementary Appendix C distinguishes two reasons why lottery spending might vary with income: the causal effect of income and preference heterogeneity that is correlated with income. The survey offers two ways to measure causal income effects. First, regressing *spending change* on *income change* suggests a causal income elasticity of 0.194; see Supplementary Appendix Table A11 for formal regression results. This should be interpreted cautiously because changes in life circumstances correlated with income changes might also change lottery consumption preferences. Second, the average of *self-reported income effect* (the amount by which people thought their lottery spending would change if their income doubled) is −1.4%, suggesting a causal income elasticity of $d\ln s/d\ln z \approx -0.014/\ln(2/1) \approx -0.02$. This should be interpreted cautiously because the question was hypothetical.

26. Specifically, we resampled the 104 people who had reported spending more than $150 per month or more than 10% of their income on lottery tickets. If the 2021 report was within 50% of the 2020 report, we use the average. Otherwise, we use the minimum. We then regress this modified monthly spending on the 2020 report and use the prediction for the 25 out of the 104 people who did not take the 2021 survey.

27. If we do not winsorize outliers using the second elicitation in 2021, average monthly spending increases by about $9. However, our policy analyses use only the *differences* in spending across income groups, and those differences are not significantly affected by winsorization; see Supplementary Appendix Figure A7.

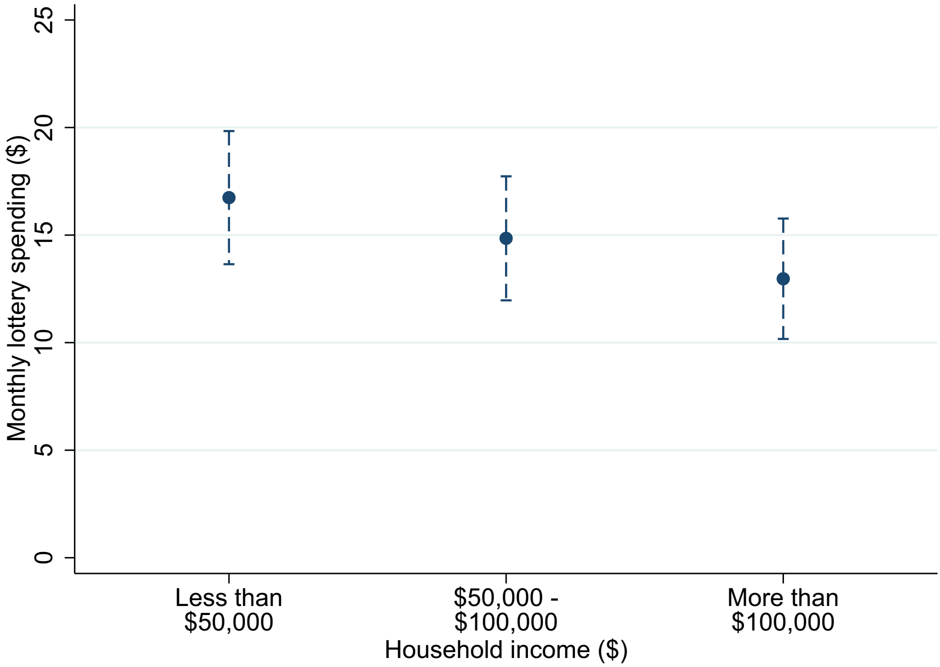

FIGURE 4
Lottery spending by income

Notes: This figure presents average monthly lottery spending within household income groups, with 95% confidence intervals, using data from our AmeriSpeak survey. Observations are weighted for national representativeness.

While the exact point estimates differ, both of these strategies are consistent in suggesting limited income effects, and they are both statistically less negative than the cross-sectional income elasticity of -0.111 illustrated in Figure 4.

5.3. *Association between bias proxies and lottery spending*

This section presents the relationships between bias proxies and lottery spending. Although we control for confounders such as measures of preferences, caution is warranted in interpreting these relationships as causal.

Define s_i as person i's monthly lottery spending, define b_{ik} as person i's value of bias proxy k, and define b_k^V as the benchmark value of b_k for an unbiased consumer who does not have self-control problems, has high financial literacy and statistical reasoning ability, is not overoptimistic, and has correct beliefs about expected returns and the effect of lottery winnings on life satisfaction. Define the standardized bias proxy $\tilde{b}_{ik} := \frac{b_{ik}-b_k^V}{SD(b_{ik})}$ as the difference between person i's proxy b_{ik} and the unbiased value b_k^V in 2020 standard deviation units, and define $\tilde{\boldsymbol{b}}_i$ as a vector of the six standardized bias proxies. All bias proxies are signed so that a more positive value should cause more lottery consumption. Finally, define $\boldsymbol{x}_i$ as a vector of controls, including the three preference proxies (*risk aversion*, *lottery seems fun*, and *enjoy thinking about winning*), the demographic characteristics presented in Panel (a) of Table 5, and state fixed effects.

5.3.1. Test-retest reliability. To summarize test-retest reliability, Figure 5 presents binned scatter plots of (unstandardized) bias proxies b_{ik} elicited in 2021 versus 2020. The area of each

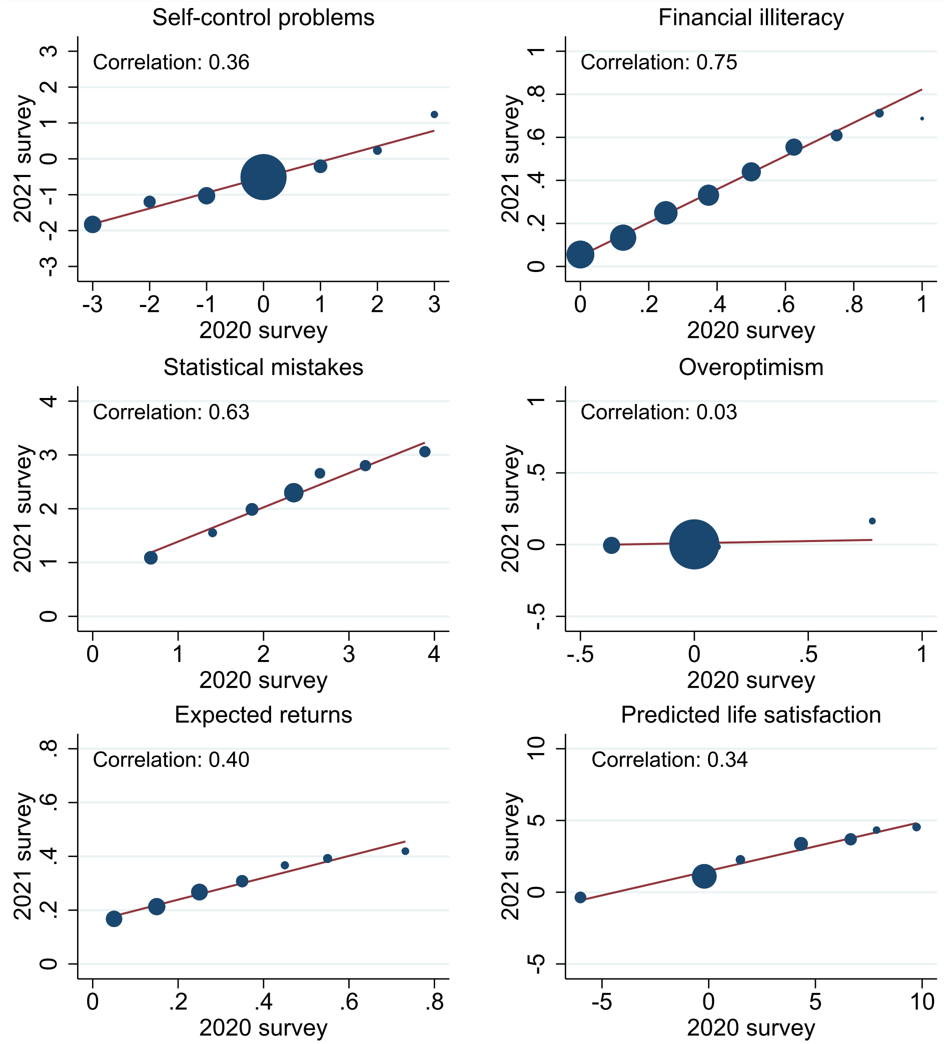

FIGURE 5
Test–retest reliability of bias proxies

Notes: This figure presents binned scatter plots of the 2020 versus 2021 elicitations of our six bias proxies, using data from our AmeriSpeak surveys.

circle is proportional to the share of observations in each bin. For *overoptimism*, the large mass at zero reflects the fact that 65% of people expect to win the same amount as the average lottery player, and there is close to zero correlation in relative optimism or pessimism across years. For the other five bias proxies, however, the correlations range from 0.34 to 0.75. For comparison, Stango and Zinman (2022, Table 3) find within-person rank correlations of 0.04 to 0.59 for bias proxies similar to ours in surveys separated by 3 years, and Chapman *et al.* (2023, Table 2) find correlations of 0.30 to 0.96 between "econographic" preference measures elicited twice on the same survey.

5.3.2. Descriptive correlations. Figure 6 presents binned scatter plots of (unstandardized) bias proxies b_{ik} against the natural log of 1 + *monthly lottery spending*, using the 2020 survey

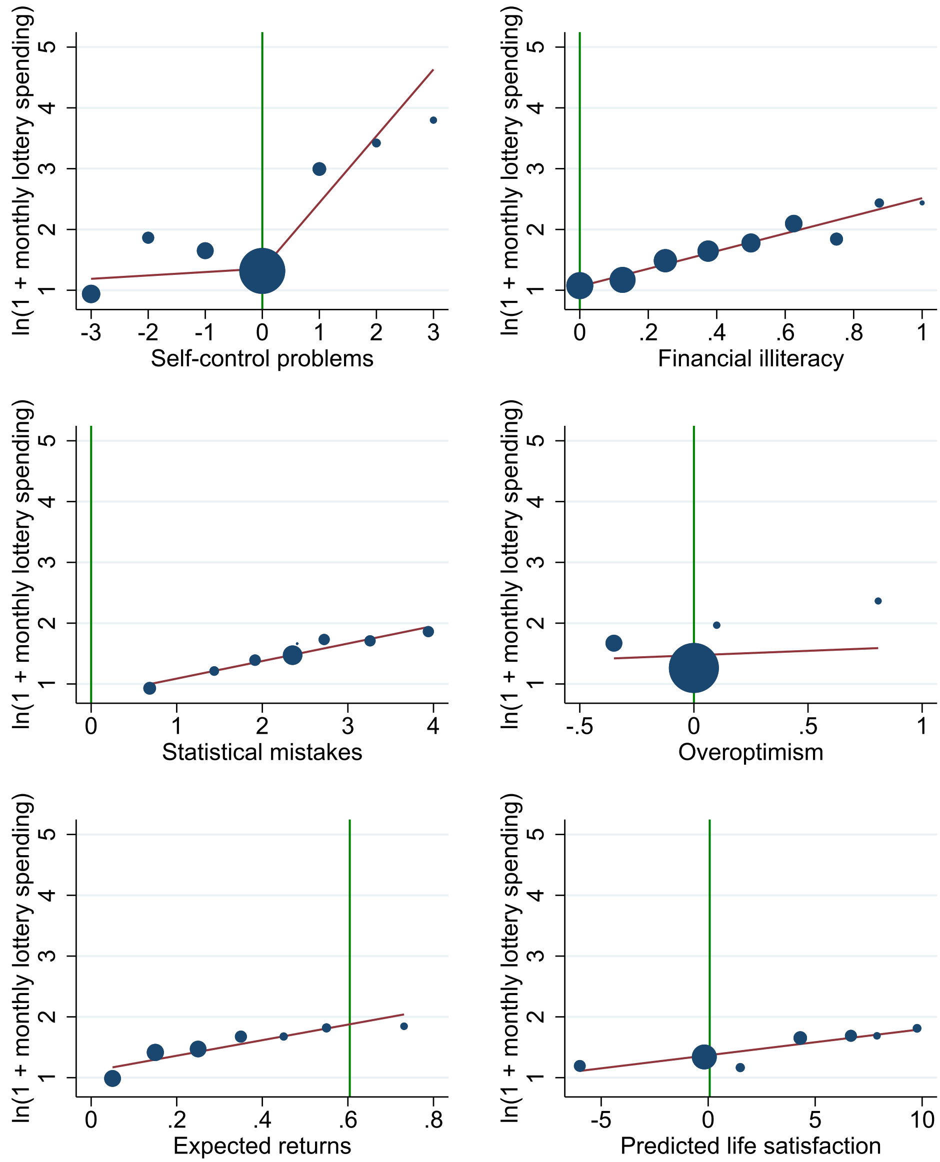

FIGURE 6
Relationship between lottery spending and bias proxies

Notes: This figure presents binned scatter plots of ln(1+*monthly lottery spending*) versus our six bias proxies, using data from our 2020 AmeriSpeak survey. The vertical line on each panel corresponds to the correct or "unbiased" value of the bias proxy.

data. We use natural logs because spending is skewed and it is natural to think of bias entering multiplicatively, as in the examples from Section 3.3, and we add 1 to spending to be able to include zero-spending observations. Our results in Table 6 below are similar when using spending levels or the inverse hyperbolic sine of spending. In each of the six panels, a vertical line indicates the unbiased benchmark b_k^V.

For *self-control problems*, the unbiased benchmark b_k^V is playing the lottery "the right amount" instead of "too little" or "too much." The relationship between lottery spending and

TABLE 6

Regressions of monthly lottery spending on bias proxies

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) ORIV
Self-control problems	0.281***	0.414***	0.293***	0.280***	0.279***	0.708***
	(0.029)	(0.033)	(0.031)	(0.030)	(0.035)	(0.143)
Financial illiteracy	0.123***	0.190***	0.142***	0.127***	0.137***	0.182*
	(0.032)	(0.034)	(0.030)	(0.032)	(0.040)	(0.099)
Statistical mistakes	0.101***	0.157***	0.133***	0.097***	0.096***	0.019
	(0.027)	(0.031)	(0.027)	(0.027)	(0.033)	(0.097)
Overoptimism	0.029	0.034	0.032	0.027		
	(0.023)	(0.029)	(0.024)	(0.024)		
Expected returns	0.068***	0.199***	0.098***	0.068***	0.051*	−0.025
	(0.024)	(0.028)	(0.025)	(0.024)	(0.029)	(0.079)
Predicted life satisfaction	0.006	0.153***	0.024	0.005	−0.009	−0.082
	(0.025)	(0.027)	(0.025)	(0.024)	(0.029)	(0.097)
Risk aversion	−0.012		−0.013	−0.009	−0.012	0.028
	(0.026)		(0.025)	(0.027)	(0.031)	(0.046)
Lottery seems fun	0.614***		0.604***	0.608***	0.606***	1.082***
	(0.029)		(0.029)	(0.029)	(0.033)	(0.085)
Enjoy thinking about winning	0.167***		0.171***	0.176***	0.175***	0.064
	(0.029)		(0.029)	(0.029)	(0.033)	(0.084)
ln(household income)	0.104***			0.104***	0.099**	0.096**
	(0.036)			(0.036)	(0.043)	(0.046)
ln(years of education)	−0.652***			−0.635***	−0.552***	−0.160
	(0.170)			(0.173)	(0.192)	(0.211)
1(Black)	0.560***			0.572***	0.533***	0.271**
	(0.095)			(0.093)	(0.115)	(0.121)
1(Hispanic)	0.387***			0.348***	0.441***	0.329***
	(0.080)			(0.075)	(0.097)	(0.103)
Other demographics	Yes	No	No	Yes	Yes	Yes
State fixed effects	Yes	No	No	No	Yes	Yes
R^2	0.41	0.16	0.36	0.39	0.40	0.57
Observations	2,810	2,810	2,810	2,810	2,072	4,144
Clusters	2,810	2,810	2,810	2,810	2,072	2,072

Notes: This table presents estimates of equation (16), a regression of ln(1+*monthly lottery spending*) on bias proxies, preference proxies, demographic controls, and state fixed effects using data from our AmeriSpeak surveys. "Other demographics" includes age, household size, political ideology, and indicators for male, other (non-white) race, married, employed, urban area, and attends religious services at least once a month. Columns 1–5 present OLS estimates. Column 6 presents Obviously Related Instrumental Variables estimates: we estimate equation (16) in a stacked dataset with the 2021 bias and preference proxies below the 2020 bias and preference proxies, instrumenting for the 2020 variables with their 2021 values and vice versa, while clustering standard errors by respondent. Robust standard errors are in parentheses. *, **, ***: statistically significant with 90, 95, and 99% confidence, respectively.

self-control problems is not as close to linear as with the other five bias proxies. To the left of zero, a stronger feeling that one plays the lottery "too little" is not clearly associated with spending. We thus recode negative values as 0 for the regressions and predictions described below. To the right of zero, a stronger feeling that one plays "too much" is positively associated with spending, suggesting that self-control problems might contribute to overconsumption. This contribution may be limited, however, because the circle sizes indicate that 71% of people report playing "the right amount," and more people report playing "too little" than "too much."

For *financial illiteracy* and *statistical mistakes*, we define the unbiased benchmarks b_k^V as the best scores in the sample. For *financial illiteracy*, this is answering all eight questions correctly, and *statistical mistakes* is constructed so that 0 is the best score in the sample. The best fit lines' upward slopes mean that people with higher financial illiteracy and more statistical mistakes spend more on lotteries. The figure suggests that this might contribute to overconsumption: many people score relatively poorly on these two scales, and people with the worst scores spend 100 log points more on the lottery than people with the best scores.

For *overoptimism*, we define the unbiased benchmark b_k^V as predicting no difference between one's own lottery winnings and the average person's lottery winnings. The figure suggests that overoptimism may not contribute much to overconsumption: there is little relationship between overoptimism and spending, and 65% of people reported the same expected earnings for themselves and the average player. The lack of relationship between *overoptimism* and spending is unsurprising given the low test-retest reliability.

For *expected returns*, the unbiased benchmark b_k^V is 60%: the true share of state lottery ticket sales that are given out as prizes, using data reported in Supplementary Appendix Figure A1(b). The best fit line's upward slope means that people who think the expected returns are higher spend more on lotteries. Most of the mass is to the left of b_k^V, and the average person believes that only 29% of lottery spending is returned to winners. This suggests that people might play *more* if they did not underestimate the expected returns.

Finally, the unbiased benchmark b_k^V for *predicted life satisfaction* is the actual effect from Lindqvist *et al.* (2020): an additional \$100,000 of lottery winnings increased life satisfaction by 0.071 points on the 0–10 scale. The slope of the best fit line suggests that predicting that additional winnings increase life satisfaction by 1 additional point on the 0–10 scale is associated with spending about 4.3 log points more on lottery tickets.

5.3.3. Regression estimates. To test whether these relationships survive controls for demographics and preferences, we estimate the following regression:

$$\ln(s_i + 1) = \boldsymbol{\tau}\tilde{\boldsymbol{b}}_i + \boldsymbol{\beta}\boldsymbol{x}_i + \epsilon_i. \tag{16}$$

Table 6 presents results. Column 1 presents the full model, Column 2 presents the regression without any controls, and Columns 3 and 4 progressively add controls. Column 1 shows that four of the unconditional relationships from Figure 6 survive controls: *self-control problems*, *financial illiteracy*, *statistical mistakes*, and *expected returns* are all strongly conditionally associated with lottery spending, while *overoptimism* and *predicted life satisfaction* are not. All the estimated $\hat{\tau}$ coefficients are positive.

Comparing Columns 2 and 3 shows that the preference proxies explain a large share of the variation in lottery spending, increasing the R^2 from 0.16 to 0.36. These controls also materially attenuate the $\boldsymbol{\tau}$ coefficients, which underscores the importance of having collected the preference control variables. Adding the demographic controls in Column 4 increases the R^2 slightly and has limited effects on the $\boldsymbol{\tau}$ coefficients.

Measurement error can attenuate the relationships in Columns 1–4. To address this, we use the Obviously Related Instrumental Variables (ORIV) approach of Gillen *et al.* (2019): we estimate equation (16) in a stacked dataset with the 2021 $\tilde{\boldsymbol{b}}_i$ and $\boldsymbol{x}_i$ below the 2020 $\tilde{\boldsymbol{b}}_i$ and $\boldsymbol{x}_i$, instrumenting for the 2020 variables with their 2021 values and vice versa, while clustering standard errors by i. The ORIV approach is more efficient than an unstacked IV approach that instruments the 2020 variables with their 2021 values *or* vice versa, and it avoids the ambiguity that arises if those two unstacked estimates are different.

We drop *overoptimism* because the low test–retest reliability causes a weak instruments problem. After that drop, the first stage regressions involve highly statistically significant relationships between the resampled values of the same variable and limited correlations with other variables; see Supplementary Appendix Table A12. The one exception is that *financial illiteracy* and *statistical mistakes* are moderately correlated.

Column 5 of Table 6 presents OLS estimates in the subsample that also responded in 2021; the coefficients change little relative to Column 1. Column 6 presents the ORIV estimates using the same sample as Column 5. The coefficient on *self-control problems* grows substantially, consistent with its lower test–retest reliability. The *financial illiteracy* coefficient also grows, while the coefficient on *statistical mistakes* becomes insignificant. The coefficients on *expected returns* and *predicted life satisfaction* also become statistically insignificant. Interestingly, the coefficient on education shrinks substantially and becomes statistically insignificant, meaning that after correcting for measurement error, our bias and preference proxies explain why higher-education people spend less on the lottery. Meanwhile, the Black and Hispanic indicators remain strongly positively associated with lottery spending, even after all other covariates are included.

5.3.4. Share of consumption attributable to bias. We can use the regression results to predict what lottery spending would be without systematic bias, *i.e.* if all individuals' bias proxies b_{ik} equalled the unbiased benchmarks b_k^V. Define $\hat{s}^V$ as predicted consumption with $\tilde{b}_{ik} = 0$. Equation (16) implies that $\ln(s_i + 1) - \ln(\hat{s}_i^V + 1) = \hat{\boldsymbol{\tau}} \tilde{\boldsymbol{b}}_i$, and thus $\hat{s}_i^V = \frac{s_i + 1}{\exp(\hat{\boldsymbol{\tau}} \tilde{\boldsymbol{b}}_i)} - 1$. We winsorize at $\hat{s}_i^V \geq 0$, and we fix $\hat{s}_i^V = 0$ for people with zero spending ($s_i = 0$). Using the OLS $\hat{\boldsymbol{\tau}}$ in Column 1 of Table 6, the share of consumption levels statistically attributable to bias is $\frac{\sum_i (s_i - \hat{s}_i^V)}{\sum_i s_i} \approx 43\%$.

We can also compute the share of consumption attributable to each individual bias k by constructing $\hat{s}_i^V$ with $\exp(\hat{\tau}_k \tilde{b}_{ik})$ instead of $\exp(\hat{\boldsymbol{\tau}} \tilde{\boldsymbol{b}}_i)$. Figure 7 presents estimates using the OLS $\hat{\tau}_k$. For *self-control problems*, *financial illiteracy*, and *statistical mistakes*, the average $\tilde{b}_{ik} > 0$ and $\hat{\tau}_k$ is positive, so Figure 7 correspondingly attributes increased lottery spending to these biases. The $\hat{\tau}_k$ coefficients for *overoptimism* and *predicted life satisfaction* are both very close to zero, so the figure attributes little spending to those biases. Since the average person underestimates expected lottery returns, the average $\tilde{b}_{ik} < 0$ for *expected returns*, and the figure attributes about a 10% spending reduction to this.

As we will show in Section 3.4, optimal policy depends on whether lower-income people are more or less biased. Figure 8 presents binned scatter plots of each bias proxy by income. *Self-control problems* is the only bias proxy that becomes more positive with income: higher-income people are more likely to report that they play the lottery "too much." *Financial illiteracy* declines strongly with income: people with household incomes under \$20,000 incorrectly answered 44% of our eight financial literacy and financial numeracy questions, while people with household incomes over \$100,000 incorrectly answered only 17%. Similarly, people with household incomes under \$20,000 scored about 0.7 standard deviations worse on our statistical mistakes questions than people with household incomes over \$100,000. *Overoptimism*, *expected returns*, and *predicted life satisfaction* differ little across income groups.

Using these differences in bias proxies by income, we construct the share of consumption attributable to bias separately for each income group. Figure 9 shows that this share declines moderately by income, from 46% for people with household incomes under \$50,000 to 40% for people with household incomes over \$100,000.

We can also adjust these two figures for measurement error by using the instrumental variables estimates from Column 6 of Table 6; see Supplementary Appendix Figures A8 and A9. Consistent with the results in Table 6, the shares of consumption attributable to *self-control problems* and *financial illiteracy* grow, while the shares attributable to the other variables attenuate. The estimates are less precise, but they continue to suggest that a larger share of consumption is attributable to bias for lower-income people. On average across all incomes, the share of consumption attributable to bias increases slightly to 47%.

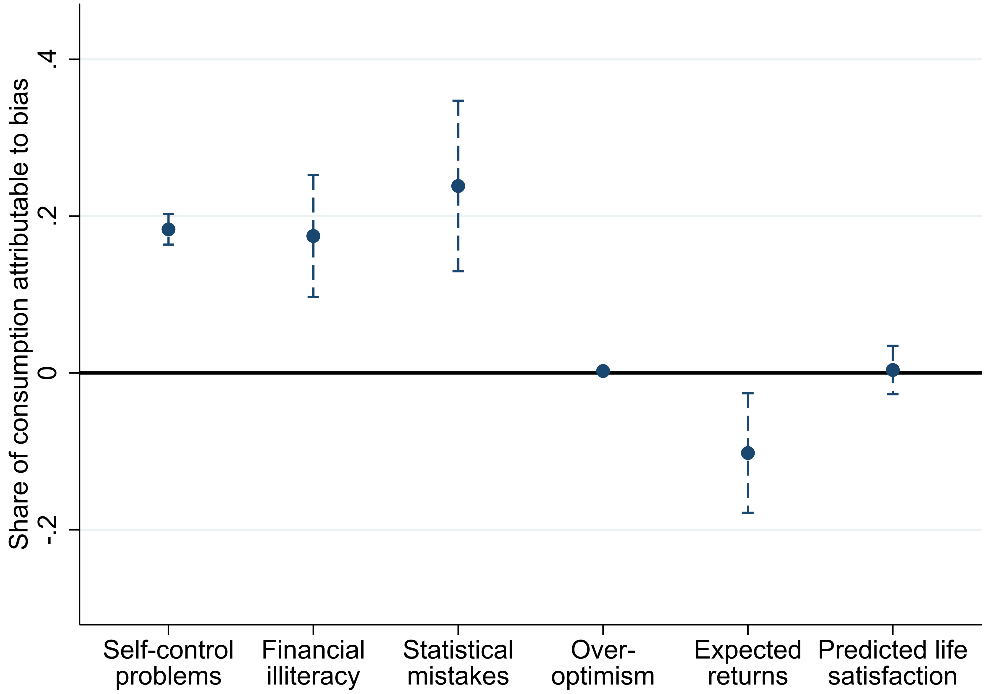

FIGURE 7
Share of lottery spending attributable to biases

Notes: This figure plots the share of lottery spending attributable to each of our six bias proxies, with 95% confidence intervals. Predicted unbiased consumption is $\hat{s}_{ik}^{V} = \frac{s_i+1}{\exp(\hat{\tau}_k \tilde{b}_{ik})} - 1$, where s_i is *monthly lottery spending*, $\hat{\tau}_k$ is the OLS estimate from Column 1 of Table 6, and $\tilde{b}_{ik} = \frac{b_{ik}-b_k^V}{SD(b_{ik})}$ is the difference between person i's proxy b_{ik} and the unbiased value b_k^V in standard deviation units. We winsorize at $\hat{s}_i^V \geq 0$, and we fix $\hat{s}_{ik}^V = 0$ if $s_i = 0$. The share of consumption attributable to each bias proxy is $\frac{\sum_i (s_i - \hat{s}_{ik}^V)}{\sum_i s_i}$.

6. STRUCTURAL MODEL

In this section, we impose additional structure on the model of lottery demand presented in Section 3 and calibrate the model using the reduced-form moments from Sections 4 and 5. In Section 7, we use this calibrated model for policy evaluation.

6.1. *Functional form assumptions*

6.1.1. Utility of prizes. We assume that $m(w_k;\theta)$ arises from a concave constant relative risk aversion (CRRA) utility function. This rules out the possibility that lottery demand is driven by convexity in the value function, as proposed by Friedman and Savage (1948). The theory that utility might be convex at high amounts of money is largely inconsistent with the bulk of the evidence, as reviewed in Supplementary Appendix F.4. Supplementary Appendix F.2 presents the formal derivation of m arising from continuation utility with a constant coefficient of relative risk aversion. Our baseline specification employs a CRRA parameter of 1, the central estimate from Chetty (2006), corresponding to logarithmic utility over continuation wealth. We consider modestly higher and lower values in our sensitivity analyses, and in Supplementary Appendix F.4 we summarize evidence that CRRA parameters more substantially different from 1 generate unrealistic implications for consumers' willingness to pay for lottery tickets.

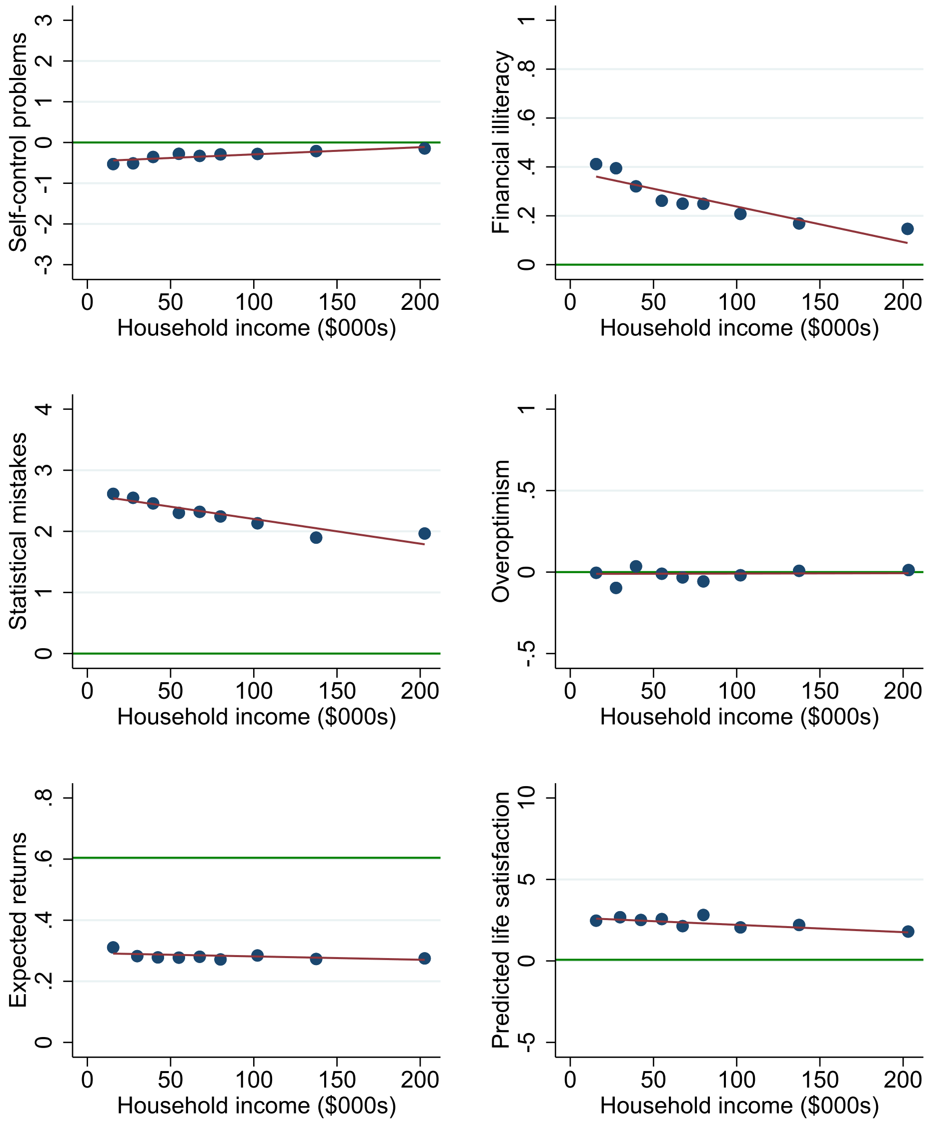

FIGURE 8
Relationship between income and bias proxies

Notes: This figure presents binned scatter plots of our six bias proxies by household income, using data from our 2020 AmeriSpeak survey. The horizontal line on each panel corresponds to the correct or "unbiased" value of the bias proxy.

6.1.2. Decision weights. As shown in Section 3.2, equation (5) implies a relationship between decision weights Φ_k and the semi-elasticity ratio $\zeta_k/|\zeta_p|$. Using this relationship and our specification of $m(w_{k;};\theta)$, we can compute the jackpot and second-prize decision weights Φ_1 and Φ_2.[28] Because we lack prize variation to identify semi-elasticities and thus decision

28. Because ζ_1 and ζ_2 are constant in the range of prizes we consider, there is no evidence that Φ_1 and Φ_2 depend on the size of their corresponding prizes in the range of prizes we consider.

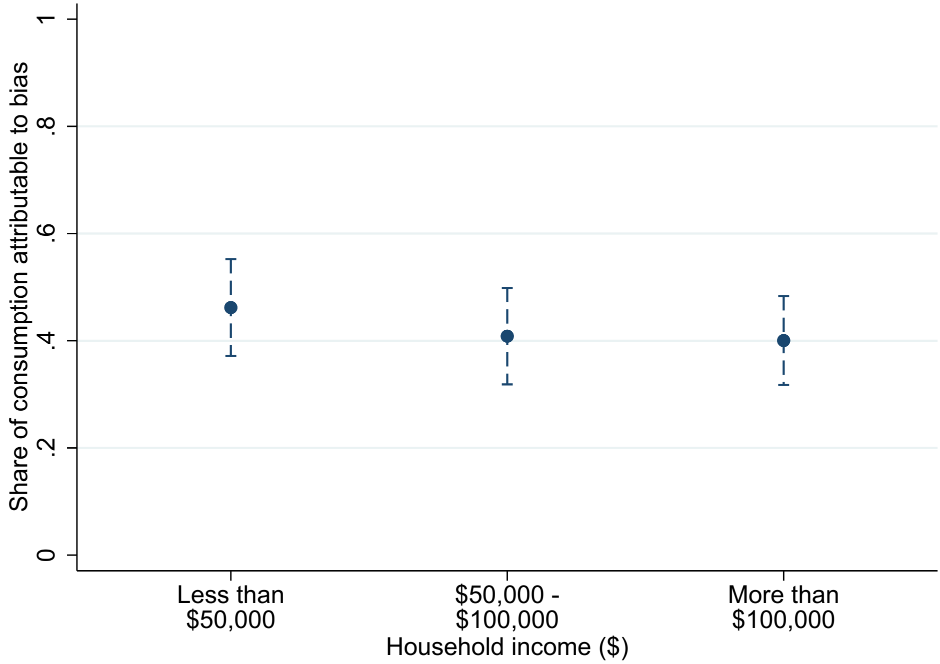

FIGURE 9
Share of lottery spending attributable to bias within income groups

Notes: This figure plots the share of lottery spending attributable to bias within household income groups, with 95% confidence intervals. Predicted unbiased consumption is $\hat{s}_i^V = \frac{s_i+1}{\exp(\hat{\boldsymbol{\tau}}\tilde{\boldsymbol{b}}_i)} - 1$, where s_i is *monthly lottery spending*, $\hat{\boldsymbol{\tau}}$ is the OLS estimate from Column 1 of Table 6, and $\tilde{b}_{ik} = \frac{b_{ik}-b_k^V}{SD(b_{ik})}$ is the difference between person i's proxy b_{ik} and the unbiased value b_k^V in standard deviation units. We winsorize at $\hat{s}_i^V \geq 0$, and we fix $\hat{s}_{ik}^V = 0$ if $s_i = 0$. The share of consumption attributable to bias is $\frac{\sum_i (s_i - \hat{s}_i^V)}{\sum_i s_i}$.

weights at lower prize levels, we must impose assumptions about their shape. We therefore consider a variety of standard parameterizations proposed previously in the literature on prospect theory and probability weighting (Goldstein and Einhorn, 1987; Tversky and Kahneman, 1992; Prelec, 1998; Chateauneuf *et al.*, 2007), although we do not literally interpret these weights as being functions (only) of probabilities. As we show in Supplementary Appendix F.1, with the exception of the "neo-additive" weights proposed by Chateauneuf *et al.* (2007), the standard parameterizations cannot simultaneously fit our estimates of Φ_1 and Φ_2, because these parameterizations imply that the ratio of second-prize to jackpot expected value semi-elasticities must be significantly larger than what we estimate, and in fact larger than 1. However, we show that the neo-additive decision-weight function axiomatized by Chateauneuf *et al.* (2007) matches our estimated semi-elasticities. We use the neo-additive form to specify the lower prize decision weights in our structural model. As we show below, our welfare results are not sensitive to this assumption: they remain very similar if we instead set lower prize decision weights equal to objective probabilities.

The intuition for the Chateauneuf *et al.* (2007) decision-weight function is that the best outcome (here, jackpot) and the worst outcome (here, winning nothing) receive the most attention, and thus particularly high decision weights. But because the weights on all outcomes must add up to one, all other outcomes receive less weight than their objective probabilities. For a given set of probabilities, this weighting function is discontinuous at the endpoints $\pi = 0$ and $\pi = 1$,

TABLE 7

Estimates of parameters in structural model

Representative agent model

	b_0	b_1	χ
	7.53×10^{-7}	0.35	0.29

Model with heterogeneity

	Below-median s			Above-median s		
	b_0	b_1	χ	b_0	b_1	χ
Low incomes	1.45×10^{-6}	0.45	0.19	1.45×10^{-6}	0.45	0.29
Middle incomes	7.27×10^{-7}	0.34	0.16	7.27×10^{-7}	0.34	0.28
High incomes	3.95×10^{-7}	0.29	0.17	3.95×10^{-7}	0.29	0.32

Notes: This table reports estimates of parameters for the structural models, both in the representative agent case (top panel), and in the heterogeneous agent case with three income levels and three levels of consumption (bottom panel; lottery non-consumers are not displayed). Parameters b_0 and b_1 are the intercept and slope parameters of the neo-additive probability weighting function. The parameter χ represents the share of the departure from expected utility weighting that is attributed to bias, as opposed to normative preferences. In the heterogeneous agent specification, semi-elasticities are assumed to be constant, resulting in homogeneous values of b_0 and b_1 conditional on income. See Section 6 for details.

and linear on the interval (0, 1), with intercept b_0 and slope b_1. However, the decision-weight function is cumulative, and the weights can change as the set of outcomes and associated probabilities changes. For example, simply splitting the jackpot into two (approximately) equal prizes will not alter the how the lottery is valued. See Supplementary Appendix F.1 for details.

6.1.3. Distribution of taste shocks. We assume that θ and ε are independently distributed. The distribution of ε is then inferred from our estimates of the semi-elasticities at various levels of lottery demand. In the utility specification from equation (4), demand is determined by the net-of-price certainty equivalent $\sum_k \Phi_k m(w_k) - p$, and we assume that the semi-elasticity of demand with respect to this certainty equivalent is constant over the range of net certainty equivalents generated by the variation in our data. Supplementary Appendix F.2 provides further details on this calibration.

6.1.4. Specification of bias. In Section 3.3, we showed how various biases, including misperceived probabilities and present focus, enter utility by multiplying $m(w)$. In line with those examples, we assume that a share $\chi(\theta)$ of the difference $\Phi_k(\theta) - \pi_k$ between the decision weight and the objective probability is due to bias, and the remaining share is due to normative factors such as anticipatory utility. Thus, normative utility is

$$v(\boldsymbol{a}; \theta, \varepsilon_t) = u(\boldsymbol{a}; \theta, \varepsilon_t) - \underbrace{\chi(\theta) \sum_k (\Phi_k(\theta) - \pi_k)\, m\,(w_k; \theta)}_{\gamma(\boldsymbol{a};\theta)}. \tag{17}$$

This specification allows us to recover the bias share $\chi(\theta)$ from the quantity effect of bias estimated in Section 5.3. Supplementary Appendix B.2 shows that each of the simple examples of biases in Section 3.3 is consistent with the functional form above.

6.1.5. Redistributive preferences. The welfare weights $g(z)$ in our optimal policy formulas entail normative judgments about the policymaker's degree of inequality aversion. We follow

TABLE 8
Optimal lottery tax and attributes under alternative assumptions

	Ticket price ($)	Average jackpot expected value ($)	Effective tax rate
1. Baseline	2.75	0.75	0.57
2. Completely unbiased	1.41	1.06	−0.05
3. 100% more biased	3.76	0.45	0.77
4. CRRA = 0.9	2.87	0.76	0.59
5. CRRA = 1.5	2.32	0.61	0.55
6. Weaker redistribution	2.72	0.76	0.56
7. Stronger redistribution	2.79	0.74	0.58
8. Lower value of $\bar{\zeta}_2 = 0$	2.74	0.75	0.57
9. Higher value of $\bar{\zeta}_2 = \bar{\zeta}_1$	2.76	0.83	0.54
10. All bias is on jackpot	2.75	0.76	0.57
11. Variable jackpot	2.67	0.59	0.56
12. Measurement error correction	2.92	0.71	0.61
13. Same bias share across incomes	2.77	0.75	0.58
14. Same bias share for everyone	2.19	0.89	0.40
15. Steeper decline across incomes	2.74	0.74	0.58
16. Finer top tail of consumption	2.77	0.75	0.58

Notes: This table reports key features of the optimal representative lottery according to our structural model. The first two columns report the jointly optimal price and jackpot expected value of a lottery ticket resembling a current Powerball ticket. The third column reports the optimal effective tax rate, calculated as the share of price that is a mark-up over marginal cost (net-of-tax total ticket expected value plus overhead). See Section 7 for details about the specifications considered in each row.

Saez (2002b) in setting these weights proportional to $c(\theta)^{-\nu}$, where $c(\theta)$ denotes consumption, which is drawn from our survey measure of pre-tax income using the pre- to post-tax income mapping from Piketty *et al.* (2018). Our baseline calibrations assume $\nu = 1$; we consider higher and lower values in the robustness results in Table 8. For numerical simplicity, we treat these weights as fixed (*i.e.* as arising from the Pareto weights $\mu(\theta, \varepsilon)$ rather than concavity in $G(\cdot)$) during our policy optimization.

6.2. *Calibration*

We summarize the intuition behind the calibration here; Supplementary Appendix F.2 presents details.

We calibrate the model assuming a single, representative lottery game with price, prizes, and probabilities set to match the current values for Powerball from Table 1. We assume that all prizes are reduced by 30% to account for income taxes.

The positive model of demand is fully characterized by the decision weight function parameters b_0 and b_1. We first calibrate a representative consumer model using our estimates of aggregate demand semi-elasticities from Section 4.

The bias share parameter χ is identified from the average counterfactual level of lottery spending if consumers were unbiased, based on the survey results in Section 5.3. We use equation (17) to compute the bias share χ that would generate this normative level of consumption. This analysis requires the strong assumption that the results from Section 5.3 identify the *causal* effect of bias, which could be violated if there are omitted variables correlated with both bias and lottery demand, or if our bias proxies do not cover all relevant biases.

We then allow for heterogeneity by exploiting the survey microdata on household income and lottery spending. We partition income into the three bins displayed in Figure 4: less than \$50,000, \$50,000 to \$100,000, and more than \$100,000. Within each income bin, we specify

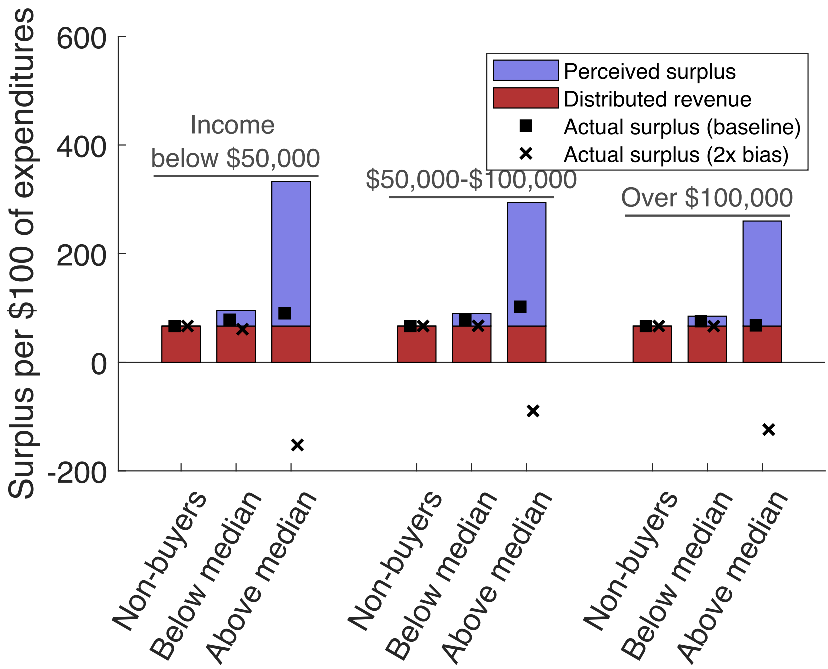

FIGURE 10
Estimated surplus from lotteries in the status quo

Notes: This figure plots the estimated surplus per capita that each consumer type derives from $100 of per-capita spending on the status quo representative lottery in our structural model, relative to a setting with no lottery. Income bins are partitioned into those who purchase no lottery tickets, those who purchase less than the median amount (conditional on purchasing), and those who purchase more than the median.

three types of individuals: those who consume zero lotteries, and among positive consumers, those with below- versus above-median consumption. We assume non-consumers continue to not purchase lottery tickets in all counterfactual scenarios. Among the remaining types, we draw the average level of lottery spending and counterfactual unbiased spending from our survey, and we assume our semi-elasticity estimates are homogeneous across types. This allows us to compute type-specific parameters.

Table 7 presents the estimated model parameters b_0, b_1, and χ in both the representative agent and heterogeneous calibrations. The probability weighting function intercept term b_0, though small in absolute terms, is large relative to the jackpot probability π_1, implying substantial overweighting of small probabilities. Approximately 29% of the wedge between decision weights and objective probabilities is attributable to bias, with above-median lottery consumers being the most biased in the heterogeneous specification.

7. IMPLICATIONS FOR WELFARE AND OPTIMAL LOTTERY DESIGN

We use the calibrated structural model to address two questions. First, what is the net welfare under the status quo lottery design? Second, what are the implications for optimal lottery attributes? We focus on the optimal attributes for which we observe variation in our empirical data: ticket price, and jackpot size.

Figure 10 plots the estimated surplus per capita that each consumer type derives from the status quo representative lottery. For ease of interpretation, these numbers are normalized by each \$100 of total lottery spending. Total perceived surplus is decomposed into lottery revenues, which we assume are distributed evenly across individuals, and perceived consumer surplus, reflecting consumers' WTP for lotteries. Behavioural biases reduce actual (normative) consumer surplus below perceived surplus, to the point that actual surplus may be negative. We plot actual surplus both for our baseline bias estimates and under the alternative assumption that the bias share $\chi(\theta)$ is 2 times as large. We find substantial heterogeneity in surplus conditional on income, with heavier consumers deriving far more perceived utility from lotteries, while also incurring larger bias costs. Total surplus is positive in our baseline specification, but it declines if we scale up bias in the model to be larger than in our estimates, and surplus is negative for the heaviest consumers in the "2x bias" specification. The threshold at which total surplus from the status quo becomes negative is 2.19 times our baseline bias estimates.

Figure 11 presents our baseline estimates of optimal ticket price and jackpot size. Both panels display plots of social welfare (relative to a counterfactual scenario with no lottery) across a range of prices (Figure 11a) and jackpots (Figure 11b). These figures report results for three different assumptions about bias. The dashed green lines report results under the assumption that all observed demand is fully normatively justified ($\chi(\theta) \equiv 0$). Unsurprisingly, lotteries generate substantial surplus in this case. The optimal "effective tax rate"—by which we mean the implicit tax rate (share of ticket price that is a markup over marginal cost) after reducing marginal cost to account for additional revenues recovered by a 30% income tax on lottery winnings—is lower than in the status quo because there is no corrective benefit from reducing consumption. In fact, redistributive considerations favour a small subsidy, because poorer consumers buy more lottery tickets. Relative to the current Powerball design, decreasing the price (Figure 11a) or increasing the jackpot (Figure 11b) would increase welfare in this case.

The solid blue lines in Figure 11 show the welfare gain from the lottery given our empirical estimates of bias. The lottery generates lower welfare gains, although welfare remains positive under the status quo price and jackpot. Holding prizes fixed, the status quo price is close to optimal, although the welfare effect of changing the price is small. Holding price fixed, the optimal jackpot is substantially higher than the status quo, reflecting the normative utility that consumers derive from larger jackpots. The dot-dashed red lines plot the welfare gains assuming that the bias share $\chi(\theta)$ is 2 times our empirical estimates. In this case, the welfare gain under the status quo lottery is barely positive, and the optimal policy is to set the price substantially higher (or the jackpot somewhat lower) in order to reduce lottery overconsumption.

In Supplementary Appendix G, we compute the optimal price and jackpot using the optimal policy conditions derived in Section 3.4, using the approximation that statistics like demand elasticities and money-metric bias are the same at the optimum as we estimate in our data. Reassuringly, those estimates are similar to the ones estimated in the structural model, suggesting that the welfare conclusions are not sensitive to the assumptions in either approach.

Finally, we use the structural model to jointly solve for the optimal *combination* of ticket price and jackpot size, and the resulting effective tax rate. Table 8 presents the results. Row 1 presents estimates under our baseline assumptions. The optimal price is \$2.75, the optimal jackpot expected value is \$0.75, and the optimal effective tax rate is 57%. This optimal effective tax rate is slightly lower than the current Mega Millions and Powerball effective rates, which are about 70%, assuming that prizes are subject to income taxes of 30%.[29] Our model's predicted optimal price and jackpot are both somewhat higher than in the status quo because our estimates suggest that substantial normative utility is derived from higher jackpots. Thus, a revenue-neutral perturbation that jointly raises jackpots and prices above status quo levels would increase consumer surplus.

29. The status quo effective taxes on instant games are somewhat lower.

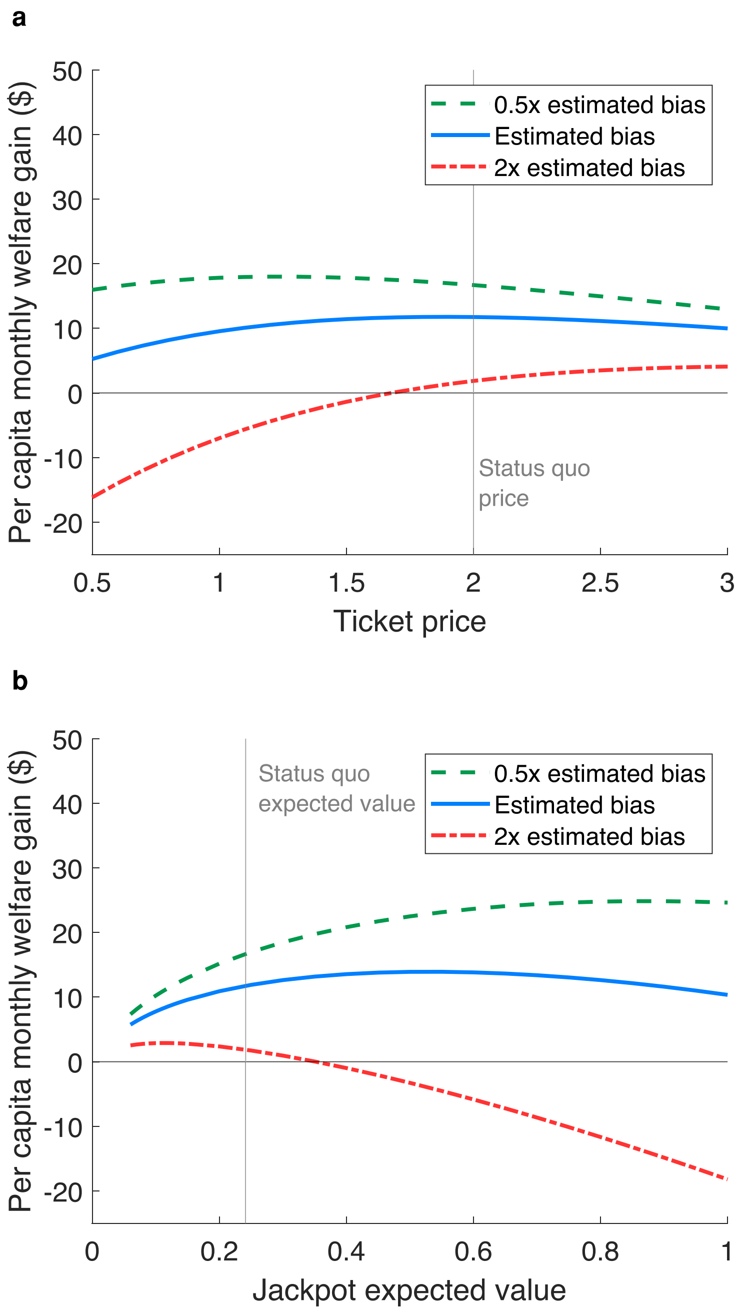

FIGURE 11

Effect of lottery attributes on social welfare (a) Variation in Ticket Price and (b) Variation in Jackpot Size

Notes: These figures plot the simulated social welfare gain from a representative lottery relative to no lottery, when varying ticket price (a) or jackpot size (b). The baseline representative lottery is based on a standard $2 Powerball ticket with a jackpot pool of $101 million. Prizes are reduced by 30% to account for income taxes.

The remaining rows present results under alternative assumptions. Rows 2 and 3 report the consequences of alternative bias assumptions. When consumers are completely unbiased (Row 2), the optimal effective tax rate is close to zero, and in fact is slightly negative due to regressivity concerns. When consumers are 2 times as biased as in the baseline (Row 3), the optimal effective tax rate increases. For sufficiently high levels of bias, welfare would be maximized by eliminating the lottery altogether.

Rows 4 and 5 consider alternative assumptions about the curvature of utility over wealth. Our baseline assumption was a CRRA parameter of 1 (Chetty, 2006), and we consider alternative values of 0.9 and 1.5. These values cover the CRRA range across which the model predicts reasonable willingness to pay for lottery tickets.[30]

Rows 6 and 7 consider weaker and stronger redistributive preferences, with welfare weights proportional to $c(\theta)^{-0.25}$ and $c(\theta)^{-4}$, rather than $c(\theta)^{-1}$ as in our baseline. Rows 8 and 9 consider alternative possibilities for the second prize semi-elasticity. Motivated by the fact that our baseline estimate for $\hat{\bar{\zeta}}_2$ in Table 3 is statistically indistinguishable from zero, row 8 assumes that $\bar{\zeta}_2 = 0$. To account for the possibility that our statistically insignificant estimate for $\hat{\bar{\zeta}}_2$ reflects inattention to *variation* in the California second prize, rather than a low weight on those prizes' expected value, Row 9 assumes a second-prize semi-elasticity of $\bar{\zeta}_2 = \bar{\zeta}_1$ as a conservative upper bound. Row 10 assumes $b_1 = 1$ for all consumers, implying that decision weights depart from expected utility maximization only for the jackpot and, correspondingly, only the jackpot decision weight is subject to bias. Row 11 examines the case where the jackpot varies over time, cycling over 10 values corresponding to the average value of each decile of Powerball jackpots in our data. In this case, jackpot size policy variation is performed by rescaling all values of the jackpot proportionally. Row 12 reports results when we estimate bias with the ORIV measurement error correction. The results in Rows 6–12 are all broadly similar to Row 1.

The remaining rows explore the role of differences in bias and consumption across the income distribution. Rows 13 and 14 report results when the bias share $\chi(\theta)$ is assumed to be the same at all incomes, while still varying across the three consumption groups (Row 13), or homogeneous across incomes and consumption groups (Row 14). Row 15 reports results when we assume a steeper decline in expenditures across income groups, assuming consumption in the bottom (top) income bin is the highest (lowest) level in the 95% confidence intervals of consumption in each bin. Finally, Row 16 explores sensitivity to breaking out the top decile of consumers in each income partition as a separate consumer type; results are basically identical to the baseline specification.

8. CONCLUSION

People have long debated whether state-run lotteries are a regressive "tax on people who are bad at math" or a win-win that generates both enjoyment and government revenues. In this article, we provide a novel set of empirical results that are relevant for optimal policy. We find that aggregate demand responds more to a $1 change in jackpot expected value than it does to

30. In our model, the CRRA parameter affects WTP for lottery tickets. With more curvature, the value function $m(w)$ is less sensitive to variation in the jackpot, requiring a higher decision weight Φ_1 to rationalize our empirical estimates of the jackpot EV semi-elasticity $\hat{\bar{\zeta}}_1$. In Supplementary Appendix F.4, we describe how CRRA values from 1 to 1.5 appear consistent with lottery purchasers' willingness to pay for a ticket, as measured in the short 200-subject supplementary survey described in Supplementary Appendix E.3. In contrast, CRRA values below 0.9 imply low WTP for the representative lottery ticket, to the point that if the jackpot declines to the Powerball jackpot reset value, demand falls to zero.

a $1 price change or to a $1 change in second prize expected value, a result consistent with a particular form of probability weighting. In our new nationally representative survey, lottery spending is correlated with proxies of behavioural bias such as innumeracy and poor statistical reasoning, and regression predictions suggest that Americans would spend 43% less on lotteries if they were unbiased.

Using these empirical moments, we calibrate a structural model of lottery demand to study welfare and optimal policy. Results suggest that current multi-state lotteries increase welfare overall, and—under our baseline bias estimates—across most consumer types. However, higher levels of bias would lead above-median spenders to receive the least—and possibly negative—surplus. This suggests that quantity restrictions such as monthly spending limits could increase welfare. The model's socially optimal implicit tax rate is slightly lower than the current Mega Millions and Powerball designs.

Our optimal policy and welfare results hinge on estimates of bias, which highlights the importance of our survey work but also motivates additional research in that area. In addition, our results have a limited ability to speak to the structural determinants of decision weights, and to the determinants of lottery demand for products beyond lotto-style games, such as scratch games or non-lottery gambling like the growing field of sports betting. More research is warranted in each of these areas, and we think of this article as a first step toward studying state-run lotteries through the lens of behavioural optimal taxation. Our theoretical and empirical techniques may also be more broadly useful for studying regulation of non-price attributes in the presence of behavioural bias.

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Supplementary Data

Supplementary data are available at *Review of Economic Studies* online.

Data availability statement

A subset of the data used to support the findings of this study has been deposited in the Zenodo repository: https://doi.org/10.5281/zenodo.10850867. The data available in the repository were collected by the authors primarily via surveys and scraping or are freely accessible online, and are available under a Creative Commons license. The remaining data are restricted and must be purchased from La Fleur's (https://lafleurs.com/).

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Online Appendix

What Drives Demand for State-Run Lotteries? Evidence and Welfare Implications

Benjamin B. Lockwood ⓡ Hunt Allcott ⓡ Dmitry Taubinsky ⓡ Afras Sial

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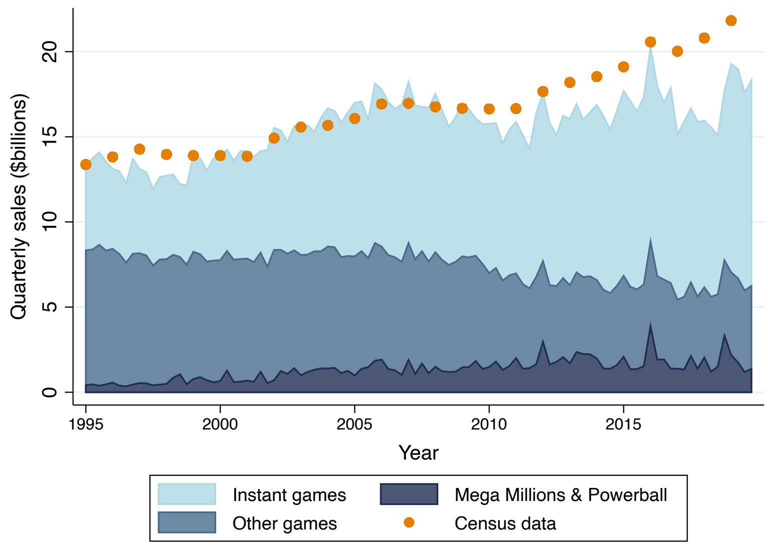
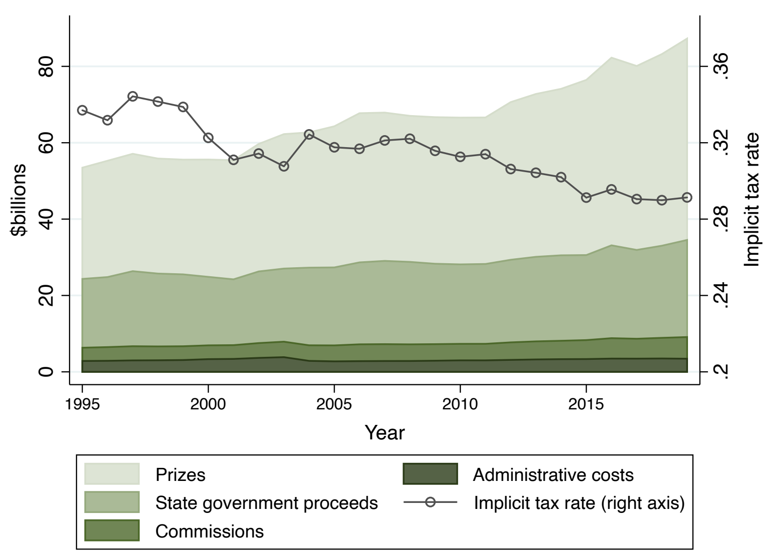
A Background Appendix

Figure A1: **Lottery Sales over Time**

(a) **Sales by Game Type**



(b) **Sales Allocation and Implicit Tax Rate**



Notes: Panel (a) of this figure presents total U.S. lottery sales by type of game, using data from La Fleur's. Census data are from the Census of Governments, inflated to account for the assumption that retailers receive 6.5 percent of sales as commissions, the midpoint of the typical range (North American Association of State and Provincial Lotteries 2021a). Panel (b) presents the allocation of the proceeds of U.S. lottery sales and the implicit lottery tax rate using data from the Census of Governments under the same commissions assumption. The implicit tax rate equals state government proceeds divided by total sales. Monetary amounts are in real 2019 dollars.

B Additional Theoretical Results

B.1 Special Cases of Proposition 1

To provide intuition for the implications of our formulas, we consider a number of special cases.

No bias, homogeneous preferences. When $\gamma(\theta) \equiv 0$ and $s(z)$, $\kappa(z)$ and $\rho(z)$ are constant across the population, Proposition 1 implies $p = C'_s(\boldsymbol{a}, \bar{s})$ and $\bar{\kappa} = C'_a(\boldsymbol{a}, \bar{s})$. In other words, the price is equal to the marginal cost of an additional lottery ticket, while a is set such that lottery buyers' surplus from an increase in a is equal to the marginal cost of increasing a.

To further build intuition, consider these implications when applied to a simple single-prize lottery like the one from Section 2.3 with only two attributes $\boldsymbol{a} = \{w, \pi\}$, where w= is the size of the single prize and π is the probability of winning. Assume that the only costs of the lottery are prize payouts and a constant administrative cost o per ticket, so that $C(\boldsymbol{a}, \bar{s}) = (\pi w + o)\bar{s}$. Then the condition for the optimal price requires $p = C'_s(\boldsymbol{a}, \bar{s}) = \pi w + o$, i.e., price should be equal to the expected value of the lottery ticket plus its administrative cost. Letting attribute a denote the prize size w, the optimal attribute condition requires that $\bar{\kappa} = C'_w(\boldsymbol{a}, \bar{s}) = \pi \bar{s}$. Assume as in Section 2.3 that individual utility is $u(\boldsymbol{a}; \varepsilon) = (1 + \phi)\pi m(w) - \varepsilon$, so that $\bar{\kappa} = \frac{\partial u(\boldsymbol{a};\varepsilon)}{\partial w} \cdot \bar{s} = (1 + \phi)\pi m'(w)\bar{s}$. Then the condition for the optimal prize attribute implies $1 = (1 + \phi)m'(w)$, which determines the optimal value of w. For example, if $m(x) = \ln(1 + x)$, then the optimal prize is $w = \max\{\phi, 0\}$, and thus $p = \pi \max\{\phi, 0\} + o$. This implies that $w > 0$ at the optimum if and only if $\phi > 0$, i.e., if entertainment utility leads individuals to value lotteries above their monetary expected value.

No bias, heterogeneous preferences. Retaining $\gamma(\theta) \equiv 0$ but allowing for heterogeneous preferences, so that s and κ vary across types, Proposition 1 implies the conditions $p - C'_s(\boldsymbol{a}, \bar{s}) = -\frac{Cov[s(z),g(z)]}{|\bar{\zeta}_p|\bar{s}}$ and $\bar{\kappa} = C'_a(\boldsymbol{a}, \bar{s}) + Cov[s(z), g(z)]\frac{\bar{\zeta}_a}{|\bar{\zeta}_p|} - Cov[\kappa(z), g(z)]$. The first condition is analogous to Diamond's (1975) "many-person Ramsey tax rule," which states that the tax is proportional to its degree of progressivity and is inversely proportional to the elasticity. The condition for $\bar{\kappa}$, which results from substituting (10) into (11), is new, and states that lottery buyers' surplus from a marginal increase in a must equal the marginal cost of increasing a plus the degree to which increasing a is more progressive than decreasing p.

Homogeneous bias and preferences. When $s(z)$, $\gamma(z)$, $\kappa(z)$ and $\rho(z)$ are homogeneous across the income distribution, Proposition 1 implies $p - C'_s(\boldsymbol{a}, \bar{s}) = \bar{\gamma}$ and $\bar{\kappa} = C'_a(\boldsymbol{a}, \bar{s}) + \bar{\rho}$. In this case, the price is set above a lottery ticket's marginal cost when $\bar{\gamma} > 0$, so as to discourage lottery consumption. Moreover, the optimal level of an attribute a is set such that $\bar{\kappa} > C'_a(\boldsymbol{a}, \bar{s})$ when individuals overvalue not just the absolute utility of the lottery ticket but also changes in a (i.e., $\bar{\rho} > 0$). This implies that the optimal choice of a is lower than what it would be when individuals correctly evaluate lottery tickets (under the reasonable assumption that $\bar{\kappa}(a)$ is decreasing in a due to the concavity of m). Thus, individuals are effectively taxed in two ways relative to the no-bias benchmark. First, the price is set to be higher than the marginal cost of a lottery ticket. Second, utility-increasing attributes of the lottery ticket (e.g., its prize levels) are set to be lower than what would be optimal in the absence of bias.

Returning to the simple single-prize lottery example considered above and in Section 2.3 where $u = (1+\phi)\pi m(w)$ and $v = (1+\phi^V)\pi m(w)$, we have $\bar{\kappa} = (1+\phi)\pi m'(w)\bar{s}$, $\bar{\rho} = (\phi - \phi^V)\pi m'(w)\bar{s}$, and $\gamma = (\phi - \phi^V)\pi m(a)$. At an interior optimum, we thus have the first-order conditions $p - \pi a = (\phi - \phi^V)\pi m(a)$ and $(1+\phi)m'(a) = 1 + (\phi - \phi^V)m'(a)$. Note that if ϕ^V is sufficiently low, it is optimal to choose $a = 0$.

Revenue-maximizing lottery structure. The revenue-maximizing lottery structure can be obtained from our calculations by ignoring the effects on consumer surplus. The revenue effects of changing a and p are $p\frac{d\bar{s}}{da} - \frac{d}{da}C(a, \bar{s}(a))$ and $p\frac{d\bar{s}}{dp} - \frac{d}{dp}C(a, \bar{s}(a))$, respectively. This leads to the conditions $p - C_s'(a, \bar{s}) = \frac{1}{|\bar{\zeta}_p|}$ and $\frac{C_a'(a,\bar{s})}{\bar{s}} = \frac{\bar{\zeta}_a}{|\bar{\zeta}_p|}$. The first condition is just the standard inverse elasticity rule for product pricing. The second condition states that the per-ticket marginal cost of increasing a has to equal the ratio of the semi-elasticities. The intuition for the second condition is that increasing a by da and increasing p by $dp = da\frac{C_a'(a,\bar{s})}{\bar{s}}$ has a zero direct effect on government revenue; thus, this perturbation cannot affect consumer demand if a and p are set optimally. For example, when a corresponds to expected payout of a lottery ticket, so that $C_s' = a$ and $C_a'/\bar{s} = 1$, the optimal choice of p and a must satisfy $p - a = 1/\left|\bar{\zeta}_p\right|$ and $\left|\bar{\zeta}_p\right| = \bar{\zeta}_a$.

B.2 Motivating the Parameterization of Bias in the Structural Model

In our structural model we assume that

$$v(\boldsymbol{a}; \theta, \varepsilon_t) = u(\boldsymbol{a}; \theta, \varepsilon_t) - \underbrace{\chi(\theta) \sum_k \left(\Phi_k(\theta) - \pi_k\right) m\left(w_k; \theta\right)}_{\gamma(\boldsymbol{a};\theta)}. \tag{18}$$

Here we illustrate how this parameterization of bias is consistent with the examples in Section 2.3 in the setting of a simple lottery with a single large prize.

Misperceived probability of winning. In this example, $u - v = (\tilde{\pi} - \pi)$, $\Phi_k = \tilde{\pi}$, and thus $\chi = 1$.

Present focus over joy-of-playing. In this example, $u - v = (1/\beta - 1)\phi^V \pi m(w)$, $\Phi_k = (1 + \phi^V/\beta)\pi$, and thus

$$\begin{aligned} \chi &= \frac{(1/\beta - 1)\phi^V \pi}{(1 + \phi^V/\beta)\pi - \pi} \\ &= \frac{(1/\beta - 1)\phi^V}{\phi^V/\beta} \\ &= 1 - \beta \end{aligned}$$

Present focus over addiction. In this example, $u - v = (1 - \beta)d\pi m(w)$, $\Phi_k = (1 + \phi^V - \beta d)\pi$, and thus

$$\chi = \frac{(1 - \beta)d}{\phi^V - \beta d}$$

which is constant in π and w as long as d and ϕ^V are also constant in π and w.

Misforecasted happiness. In this example, $u - v = b\pi m(w)$, $\Phi_k = (1 + \phi^V + b)\pi$, and thus

$$\chi = \frac{b}{b + \phi^V}$$

which is constant in π and w as long as b and ϕ^V are also constant in π and w.

C Theory Appendix: A More General Model and Generalizations of Proposition 1

C.1 A More General Model

We consider a more general model in which individuals first choose income z and then choose whether or not to buy lottery tickets on various occasions. Specifically, we assume that individuals choose their income in period $t = 0$, and then choose whether or not to buy a lottery ticket on choice occasions $t = 1, \ldots, t^*$. Individuals realize taste shocks ε_t at the beginning of each period determining their hassle costs (or other utility shocks) from purchasing a lottery ticket in each period. Individuals' utility given a vector of shocks $\boldsymbol{\varepsilon}$ and a vector $\boldsymbol{x} = (x_1, \ldots, x_{t^*}) \in \{0,1\}^{t^*}$ of lottery ticket purchase decisions is given by $U(x, c, z; \boldsymbol{a}, \theta, \boldsymbol{\varepsilon}) = G(n(c;\theta) + \sum_t u(x_t; \boldsymbol{a}, \theta, \varepsilon_t) - \psi(z;\theta))$, where $\boldsymbol{a}$ is a vector of attributes, with jth component a_j, and n is increasing and weakly concave in c. Without loss of generality, we can consider individuals' optimization problem as a static problem where the vector of shocks $\boldsymbol{\varepsilon}$ is realized in period 1 and individuals choose a consumption plan $\boldsymbol{X}$ for all t^* periods. Formally, $\boldsymbol{X}$ maps each period-t history $H_t = (\varepsilon_1, x_1, \ldots, \varepsilon_{t-1}, x_{t-1})$ of taste shocks and lottery decisions into a period t choice $x_t \in \{0,1\}$ of whether or not to buy the lottery.

Lottery demand is a random variable $\boldsymbol{s}_\theta(\boldsymbol{\varepsilon})$ that maps shocks $\boldsymbol{\varepsilon}$ to a total number of lottery tickets purchased. We let $\bar{s}_\theta$ denote expected lottery purchases. We assume that $\boldsymbol{\varepsilon}$ is smoothly distributed, so that $\bar{s}_\theta$ is smooth in p and a_j. For shorthand, we will sometimes write $\boldsymbol{u}(s;\boldsymbol{a},\theta,\boldsymbol{\varepsilon}) = \text{argmax}_{\boldsymbol{x}}\{\sum_t u(x_t;\boldsymbol{a},\theta,\varepsilon_t)|\sum_t x_t = s\}$; that is, $\boldsymbol{u}$ is utility obtained after a vector of shocks $\boldsymbol{\varepsilon}$ is realized and the person executes an optimal consumption plan given the constraint that s lottery tickets are purchased.

In contrast to the body of the paper, this functional form allows for exogenous shocks to income to change lottery consumption, but we still maintain the assumption of weak separability. The weak separability assumption could also be relaxed by following the approach of ALT, and replacing the (causal) income elasticity of lottery demand with the elasticity of lottery demand with respect to changes in earnings z, where appropriate.

We let $\kappa_j(p,\boldsymbol{a},z;\theta)$ denote the valuation of a marginal increase in the jth attribute of $\boldsymbol{a}$. We let $V(x,c,z;\boldsymbol{a},\theta,\boldsymbol{\varepsilon}) = G(n(c;\theta)+\sum_t v(x_t;\boldsymbol{a},\theta,\varepsilon_t)-\psi(z;\theta))$ denote normative utility. We define $\boldsymbol{v}(s;\boldsymbol{a},\theta,\boldsymbol{\varepsilon})$ analogous to $\boldsymbol{u}(s;\boldsymbol{a},\theta,\boldsymbol{\varepsilon})$.

We let $C(\boldsymbol{a},\bar{s})$ be the cost of supplying lottery tickets, with C'_j denoting the derivative with respect to the jth component a_j of $\boldsymbol{a}$, and C'_s denoting the derivative with respect to $\bar{s}$.

Note that we assume that the utility from gambling does not depend on the history of prior gambling decisions (i.e., no habit formation) for expositional simplicity. Our results, which apply the Envelope Theorem to the expected perceived utility function, do not require this form of stationarity.

C.2 Assumptions

We make the following assumptions:

Assumption 1. *Utility from numeraire consumption, $n(c)$, has bounded relative risk aversion: there is $r>0$ such that $|cn''(c)/n'(c)|<r$ for all c.*

Assumption 2. *Lottery expenditures are a small share of the total budget, so that terms of order $\frac{\bar{s}_\theta}{z(\theta)-T(z(\theta))-p\bar{s}_\theta}$ and $\frac{pVar[s_\theta(\varepsilon)]/\bar{s}_\theta}{z(\theta)-T(z(\theta))-p\bar{s}_\theta}$ are negligible.*

Assumption 3. *Constant social marginal welfare weights conditional on income at the optimum: $g(\theta,\boldsymbol{\varepsilon}) = g(\theta',\boldsymbol{\varepsilon})$ if $z(\theta)=z(\theta')$.*

Assumption 4. *U and V are smooth functions that are strictly concave in c, s, and z, and μ is differentiable with full support.*

Assumption 5. *The optimal income tax function $T(\cdot)$ is twice differentiable, and each consumer's choice of income z admits a unique global optimum, with the second-order condition holding strictly at the optimum.*

Assumption 6. *$\bar{s}_\theta$ and $\kappa_j(\theta)$ are orthogonal to the income elasticity ζ_z conditional on income.*

Assumptions 1 and 2 ensure unpredicted variation in an individual's lottery expenditures does not have consequential effects on her marginal utility from numeraire consumption, as is clarified in Lemma C1 and its proof. Assumption 2 also implies that the difference between compensated and uncompensated demand for lottery tickets is negligible (see ALT). The term $\frac{\bar{s}_\theta}{z(\theta)-T(z(\theta))-p\bar{s}_\theta}$ is negligible when lotteries are a small share of total expenditures. By the Central Limit Theorem, the term $\frac{pVar[s_\theta(\varepsilon)]/\bar{s}_\theta}{z(\theta)-T(z(\theta))-p\bar{s}_\theta}$ approaches zero when the number of choice occasions grows large while $\bar{s}_\theta$ stays constant. Thus, the second part of Assumption 2 mechanically holds when there are many choice occasions and $\bar{s}_\theta$ is assumed to not exceed a certain fixed share of expenditures.

Assumption 3 is analogous to Assumption 1 in Saez (2002a). Saez (2002a) argues this is a reasonable normative requirement even under heterogeneity "if we want to model a government that does not want to discriminate between different consumption patterns..." Therefore we sometimes write $g(z)$ to denote the welfare weight directly as a function of earnings.

Assumptions 4 and 5 ensure that the income distribution does not exhibit any atoms and consumers' labor supply and consumption decisions respond smoothly to perturbations of the tax system (Jacquet and Lehmann 2021).

C.3 Elasticity Concepts and Sufficient Statistics

All statistics are understood to be endogenous to the tax regime (t, T), though we suppress those arguments for notational simplicity. We begin by defining the elasticities related to sin good consumption.

Price and attribute elasticities

- $\zeta_p(\theta)$: the price semi-elasticity of demand for s from type θ, formally equal to $\left(\frac{d\bar{s}_\theta}{dp}\right)\frac{1}{\bar{s}_\theta}$
- $\zeta_{a_j}(\theta)$: the price semi-elasticity of demand for s from type θ, formally equal to $\left(\frac{d\bar{s}_\theta}{da_j}\right)\frac{1}{\bar{s}_\theta}$
- $\xi(\theta)$: the causal income elasticity of demand for s, equal to $\frac{d}{dz}\bar{s}_\theta\left(p, \boldsymbol{a}, z; \theta\right) \cdot \frac{z}{s}$.

Income Elasticities

We define labor supply responses to include any "circularities" due to the curvature of the income tax function, which is assumed to be differentiable. Thus, following Jacquet and Lehmann (2021), we define a tax function $\hat{T}$ which has been locally perturbed around the income level z_0 by raising the marginal tax rate by τ and reducing the tax level by ν:

$$\hat{T}(z; z_0, \tau, \nu) := T(z) + \tau(z - z_0) - \nu. \tag{19}$$

Let $z^*(\theta)$ denote a type θ's choice of earnings under the status quo income tax T, and let $\hat{z}(\theta; \tau, \nu)$ denote θ's choice of earnings under the perturbed income tax $\hat{T}(z; z^*(\theta), \tau, \nu)$. Then the compensated elasticity of taxable income is defined in terms of the response of $\hat{z}$ to τ, evaluated at $\tau = \nu = 0$:

$$\zeta_z^c(\theta) := \left(-\left.\frac{\partial \hat{z}(\theta; \tau, 0)}{\partial \tau}\right|_{\tau=0}\right)\frac{1 - T'(z^*(\theta))}{z^*(\theta)}. \tag{20}$$

The income effect is similarly defined in terms of the response of $\hat{z}$ to a tax credit ν (this statistic will be nonpositive if leisure is a non-inferior good):

$$\eta_z(\theta) := \left(\frac{\partial \hat{z}(\theta; 0, \nu)}{\partial \nu} \bigg|_{\nu=0} \right) \left(1 - T'(z^*(\theta))\right). \tag{21}$$

These definitions are comparable to those in Saez (2001), except that they include circularities and thus permit a representation of the optimal income tax in terms of the actual earnings density, rather than the "virtual density" employed in that paper.

Bias

We continue defining bias γ analogous to the definition in the body of the paper: it is the value of $\gamma(p, a, y; \theta, \varepsilon)$ that satisfies

$$u(1; \boldsymbol{a}, \theta, \varepsilon) - v(1; \boldsymbol{a}, \theta, \varepsilon) = n(y - p + \gamma; \theta) - n(y - p; \theta)$$

where y is disposable income. In other words, γ is the degree, in units of dollars, by which the individual overestimates the value of the lottery ticket.

We define

$$\begin{aligned}\gamma(z; \boldsymbol{a}, \theta) = \mathbb{E}[&\gamma(p, \boldsymbol{a}, z - T(z) - s_\theta(\boldsymbol{\varepsilon}); \theta, \varepsilon) \\ &|\boldsymbol{u}(s_\theta(\boldsymbol{\varepsilon}) + 1; \boldsymbol{a}, \theta, \boldsymbol{\varepsilon}) - \boldsymbol{u}(s_\theta(\boldsymbol{\varepsilon}); \boldsymbol{a}, \theta, \boldsymbol{\varepsilon}) = n(z - T(z) - p(s_\theta(\boldsymbol{\varepsilon}) + 1); \theta) \\ &- n(z - T(z) - s_\theta(\boldsymbol{\varepsilon}); \theta), z(\theta) = z]\end{aligned}$$

In other words, $\gamma(z)$ is the average bias of z-earners who are on the margin of purchasing an additional lottery ticket. The statistics $\bar{\gamma}$, σ_p and σ_{a_j} are constructed as in the body of the paper. By definition, the social welfare impact of inducing a marginal z-earner to purchase one fewer lottery ticket is $\gamma(z)g(z)$ plus any resulting fiscal externalities due to tax revenues.

We define ρ_j more generally as the difference $\rho_j = \kappa_j - \kappa_j^V$, where κ_j^V is the willingness to pay for a marginal change in a_j that would result if consumers chose according to normative preferences V.

Aggregation

With some abuse of notation, we write $s(z)$, $\gamma(z)$, $\kappa_j(z)$ and so forth to denote the averages among z-earners. We denote population averages of these statistics using "bar" notation. For example, average consumption of s is denoted $\bar{s}$. The cumulative density function of the income distribution is denoted $H(z)$, which we assume possesses a density function $h(z)$.

Income-effect Augmented Welfare Weights

We use $\hat{g}(z)$ to denote social marginal welfare weights augmented to reflect the welfare effects of the behavior change that occurs when individuals earning z are given additional income. These are given by

$$\hat{g}(z') = g(z') + \mathbb{E}\left[\eta_z(\theta)\frac{T'(z')}{1-T'(z')}|z(\theta) = z'\right] \\ + \mathbb{E}\left[(p - C_s' - g(\theta)\gamma(\theta)) + \frac{\xi(\theta)}{1-T'(z')}\frac{s}{z}\left(1 + \frac{\eta_z}{1-T'(z')}\right)\right]$$

Causal Income Effects and Preference Heterogeneity

Following ALT, we distinguish between two sources of cross-sectional variation in $s(z)$: income effects and (decision) preference heterogeneity. Let $\bar{s}'(z)$ denote the cross-sectional change in s with respect to income z at a particular point in the income distribution. This total derivative can be decomposed into two partial derivatives: the (causal) income effect, $s'_{inc}(z)$, and between-income preference heterogeneity $s'_{pref}(z)$. The causal income effect depends on the empirically estimable income elasticity of s: $s'_{inc}(z) = \mathbb{E}\left[\xi(\theta)/z \mid z(\theta) = z\right]$. Between-income preference heterogeneity is the residual: $s'_{pref}(z) = \bar{s}'(z) - s'_{inc}(z)$. The key sufficient statistic for preference heterogeneity, "cumulative between-income preference heterogeneity" is defined as:

$$s_{pref}(z) := \int_{x=z_{min}}^{z} s'_{pref}(x)dx$$
$$s_{inc}(z) := \int_{x=z_{min}}^{z} s'_{inc}(x)dx$$

The $s_{pref}(z)$ term quantifies the amount of lottery consumption at income z, relative to the lowest income level z_{min}, that can be attributed to preference heterogeneity rather than income effects.

Analogously, we define $\kappa_j'(z)$ to be the cross-sectional heterogeneity in the valuation of a marginal increase in a_j. We define $\kappa'_{j,inc}(z) := \mathbb{E}\left[\frac{\partial}{\partial z}\kappa_j(p, \boldsymbol{a}, z; \theta)|z(\theta) = z\right]$, and let $\kappa'_{j,pref}(z) = \kappa'_j(z) - \kappa'_{j,inc}(z)$ be the residual. We define

$$\kappa_{j,pref}(z) := \int_{x=z_{min}}^{z} \kappa'_{j,pref}(x)dx$$
$$\kappa_{j,inc}(z) := \int_{x=z_{min}}^{z} \kappa'_{j,inc}(x)dx.$$

C.4 Results and Derivations

Preliminary Lemmas

In contrast to standard optimal tax models, this model features discrete choice of a commodity, but we show that we can still establish an approximate Roy Identity under assumptions 1 and 2, and thus derive a simple expression for how changes in lottery attributes affect labor supply. This is the content of Lemma C1 below.

Lemma C1. *The change in earnings of type θ induced by a small change da_j is equal to the change in earnings that would be induced by imposing a type-specific $dT^\theta(z) = -da_j \cdot \kappa_j(p, \boldsymbol{a}, z; \theta)$. Under assumptions 1 and 2, the change in earnings of type θ induced by a small change dp in the price is equal to $dT^\theta(z) = dp \cdot \bar{s}(p, \boldsymbol{a}, z; \theta)$ up to negligible terms.*

Proof. The first statement follows from Lemma 1 of Saez (2002a). To prove the second statement, assume, without loss, that G is linear. The Envelope Theorem implies that a change dp in the price of the lottery has an expected utility impact of $\mathbb{E}_\varepsilon\left[n'(z - T(z) - ps_\theta(\varepsilon))s_\theta(\varepsilon)\right]dp$. Similarly, a change $dy = dp\bar{s}_\theta$ in after-tax income has an expected utility impact of $\mathbb{E}_\varepsilon\left[n'(z - T(z) - ps_\theta(\varepsilon))\right]\bar{s}_\theta dp$. Up to second order, the difference between these two terms is

$$
\begin{aligned}
|\mathbb{E}\left[n''(z - T(z) - \bar{s}_\theta)((s_\theta(\varepsilon))^2 - s_\theta(\varepsilon)\bar{s}_\theta)\right]dp| &= |n''(z - T(z) - \bar{s}_\theta)dp|Var[s_\theta] \\
&\leq rn'(z - T(z) - \bar{s}_\theta)\frac{pVar[s_\theta(\varepsilon)]/\bar{s}_\theta}{z(\theta) - T(z(\theta)) - p\bar{s}_\theta}|dp|
\end{aligned}
$$

Thus, for $dT^\theta(z) = dp \cdot \bar{s}(p, \boldsymbol{a}, z; \theta)$,

$$
\frac{dz(\theta)}{dp} / \frac{dz(\theta)}{dT^\theta} = 1 + O\left(\frac{pVar[s_\theta(\varepsilon)]/\bar{s}_\theta}{z(\theta) - T(z(\theta)) - p\bar{s}_\theta}\right)
$$

□

The next lemma will also prove useful in the derivations below.

Lemma C2. *Let $q(x)$ be any continuously differentiable function with $q(z_{min}) = 0$. Then*

$$
\int_{z=z_{min}}^{\infty}\int_{x=z}^{\infty}(1 - \hat{g}(x))h(x)dxq'(z)dz = \int_{z=z_{min}}^{\infty}q(z)(1 - \hat{g}(z))h(z)dz.
$$

Proof. This follows from integration by parts and the fact that $\int_{z=z_{min}}^{\infty}(1 - \hat{g}(z))h(z) = 0$ at the optimum. □

The Main Result

Proposition C1. *If p, $\boldsymbol{a}$, and T are set optimally, then*

$$\overbrace{p - \frac{\partial C}{\partial \bar{s}}}^{\textit{Mark-up above MC}} = \overbrace{\bar{\gamma}_p(1+\sigma_p)}^{\textit{Bias correction}} - \overbrace{\frac{Cov\left[s_{pref}(z), \hat{g}(z)\right]}{|\bar{\zeta}_p|\bar{s}}}^{\textit{Regressivity of increasing } p}$$

$$\overbrace{p - \frac{\partial C}{\partial \bar{s}}}^{\textit{Mark-up above MC}} = \overbrace{\bar{\gamma}_{a_j}(1+\sigma_{a_j})}^{\textit{Bias correction}} - \frac{\overbrace{\bar{\kappa}_j - \mathbb{E}[\rho_j(z)g(z)] - \frac{\partial C}{\partial a_j}}^{\textit{Mechanical effect on consumer surplus and revenues}} + \overbrace{Cov[\kappa_{j,pref}(z), \hat{g}(z)]}^{\textit{Regressivity of increasing } a_j}}{\bar{\zeta}_{a_j}\bar{s}}$$

for all a_j, with equality when $a_j > 0$.

If the income tax T is not necessarily optimal, but p and $\boldsymbol{a}$ are set optimally, then

$$p - C'_s = \bar{\gamma}(1+\sigma_p) - \frac{\mathbb{E}\left[s(z)(\hat{g}(z)-1)\right]}{|\bar{\zeta}_p|\bar{s}} - \frac{1}{|\bar{\zeta}_p|\bar{s}}\mathbb{E}\left[\frac{T'(z)}{1-T'(z)}\zeta_z(z)zs'_{inc}(z)\right]$$

$$p - \frac{\partial C}{\partial a_j} = \bar{\gamma}(1+\sigma_{a_j}) - \frac{\mathbb{E}\left[\kappa_j(z)\hat{g}(z) - \rho_j(z))g(z)\right] - \frac{\partial C}{\partial a_j}}{\bar{\zeta}_{a_j}\bar{s}} + \frac{1}{\bar{\zeta}_{a_j}\bar{s}}\mathbb{E}\left[\frac{T'(z)}{1-T'(z)}\zeta_z(z)z\kappa'_{j,inc}(z)\right]$$

The intuition behind the "regressivity" and "consumer surplus" terms comes from considering a joint reform where a change in p or a_j is accompanied by a corresponding change in the income tax T that leaves labor supply preserved. When there are no causal income effects, a change in p or a_j has no effect on labor supply, and thus no accompanying change in the income tax T is necessary; in this case, $s_{pref}(z) = s(z)$ and $\kappa_{j,pref}(z) = \kappa_j(z)$. When lotteries are a normal good, an increase in the price, for example, generates a higher tax burden on those choosing to earn more, and thus creates disincentives for higher labor supply equivalent to the change produced by an increase in the marginal income tax rate—this is formalized in Lemma 1. Thus, an increase in p must be accompanied by a decrease in the income tax, which leads the net tax burden of the reform to be proportional to $s_{pref}(z)$ rather than $s(z)$.

Proposition C1 generalizes the classic Atkinson and Stiglitz (1976) result in three ways. First, note that in the case of no correlated preference heterogeneity, $s_{pref} \equiv 0$, and thus the optimal price equals the marginal cost. This is analogous to the classic Atkinson and Stiglitz (1976) result that when consumption preferences are homogeneous, commodity taxes are not useful for redistribution in the presence of nonlinear income taxation. Second, our results allow us to establish an Atkinson-Stiglitz type result for optimal attribute regulation. In the absence of biases, and when $\kappa_{j,pref} \equiv 0$, meaning that preferences for the attribute are uncorrelated with earnings ability, the optimal attribute choice must satisfy $\bar{\kappa}_j = C'_j + (p - C'_s)\left|\bar{\zeta}_{a_j}\right|\bar{s}$. In other words, consumers' average marginal valuation of each attribute component must equal the marginal cost of increasing that attribute component. This again parallels the classic Atkinson and Stiglitz (1976) results, but extends to the case of attribute regulation. Third, while the case of $s_{pref} = 0$, and $\kappa_{j,pref} \equiv 0$ is a special case corresponding to the assumptions of Atkinson and Stiglitz (1976), our general result in Proposition C1 provides a characterization of optimal regulation under a much broader set of assumptions.

Proof. Consider first increasing the marginal tax rate between z^* and $z^* + dz$ by a small amount $d\tau$. Assumption 2 implies that the effects of small changes in z induced by this perturbation have negligible effects on the consumption s (this is a simple extension of the derivations in ALT of the proof of Proposition 1). Following the derivations of Saez (2001) or ALT, the optimal income tax T must thus satisfy

$$\frac{T'(z^*)}{1-T'(z^*)} \quad = \quad \frac{\int_{x=z^*}^{\infty}(1-\hat{g}(x))dH(x)}{\bar{\zeta}_z(z^*)z^*h(z^*)} \tag{22}$$

Consider now the effect of increasing the price p by dp. The total welfare effect, written in terms of the marginal value of public funds, can be decomposed into the following components:

- *Mechanical revenue effect*: the reform mechanically raises revenue from each consumer by $dp \cdot s(\theta)$, for a total of $dp\bar{s}$.
- *Mechanical welfare effect*: As in the proof of Lemma 1, the reform mechanically reduces each consumer's net income by $dp \cdot s_\theta(\varepsilon)$. To isolate the mechanical effect, we compute the loss in welfare as if this reduction all comes from composite consumption c. Under Assumption 2, and using the derivations in the proof of Lemma 1, we can write this $dp \cdot \bar{s}_\theta$ up to negligible higher-order terms. Thus the total mechanical welfare effect is $-dp\mathbb{E}\left[s(z)\hat{g}(z)\right]$
- *Revenue effects of substitution.* The reform changes costs by $C_s' \frac{d\bar{s}}{dp}dp$, and changes earnings by $p\frac{d\bar{s}}{dp}$. The net effect is thus $(p - C_s')\,\bar{\zeta}\bar{s}dp$
- *Bias-correcting effects of substitution:* the reform causes each consumer to decrease their s consumption by $dp \cdot \zeta(\theta)/p$. This generates a behavioral welfare effect equal to

$$-dp\mathbb{E}\left[g(z)\gamma(z)\zeta_p(z)s(z)\right] = -dp\bar{\gamma}_p(1+\sigma_p)\bar{\zeta}\bar{s}$$

- *Effect on earnings:* The reform causes a change in income tax revenue collected from type θ equal to $\frac{dz(\theta)}{dp}T'(z(\theta))$. Lemma 1 implies that $\frac{dz(\theta)}{dp} = -\zeta_z(\theta)\left(\frac{z(\theta)}{1-T'(z(\theta))}\right)\frac{\partial s(p,\boldsymbol{a},z;\theta)}{\partial z}$. By Assumption 6, this generates a total fiscal externality through the income tax equal to $-dp \cdot \mathbb{E}\left[\frac{T'(z)}{1-T'(z)}\zeta_z(z)zs_{inc}'(z)\right]$.
- *Indirect effects on sin good consumption:* The change in earnings affects consumption indirectly. However, relative to the other effects above, these effects are of order $\frac{\bar{s}_\theta}{z(\theta)-T(z(\theta))-p\bar{s}_\theta}$ and therefore negligible by Assumption 2 (formally, this is easily proven by extending the calculations of ALT in their proof of Proposition 1).

Combining these components, and taking into account that the income tax T is set optimally, the total welfare effect of the price change is equal to

$$\frac{dW}{dp} = \mathbb{E}\left[s(z)(1-\hat{g}(z))\right] + \left(p - C_s'\right)\bar{\zeta}_p\bar{s} - \bar{\gamma}(1+\sigma_p)\bar{\zeta}_p\bar{s} \tag{23}$$

$$- \mathbb{E}\left[\frac{T'(z)}{1-T'(z)}\zeta_z(z)zs_{inc}'(z)\right] \tag{24}$$

$$= \mathbb{E}\left[s(z)(1-\hat{g}(z))\right] + \left(p - C_s'\right)\bar{\zeta}_p\bar{s} - \bar{\gamma}_p(1+\sigma_p)\bar{\zeta}_p\bar{s}$$

$$- \int_{z=z_{min}}^{\infty}\int_{x=z}^{\infty}(1-\hat{g}(x))h(x)dx s_{inc}'(z)dz \tag{25}$$

$$= \mathbb{E}\left[s(z)(1-\hat{g}(z))\right] + \left(p - C_s'\right)\bar{\zeta}_p\bar{s} - \bar{\gamma}_p(1+\sigma_p)\bar{\zeta}_p\bar{s}$$

$$- \int_{z=z_{min}}^{\infty}(1-g(z))s_{inc}(z)h(z)dz \tag{26}$$

$$= -Cov\left[s_{pref}(z),\hat{g}(z)\right] + \left(p - C_s'\right)\bar{\zeta}_p\bar{s} - \bar{\gamma}_p(1+\sigma_p)\bar{\zeta}_p\bar{s}$$

In the computations above, expression (25) follows from (22), while expression (26) follows from Lemma C2. At the optimum, $\frac{dW}{dp} = 0$, which implies the first-order condition

$$p - C_s' = \bar{\gamma}_p(1+\sigma_p) - \frac{Cov\left[s_{pref}(z),\hat{g}(z)\right]}{|\bar{\zeta}_p|\bar{s}} \tag{27}$$

Next consider the effects of increasing a_j. The total welfare effect, written in terms of the marginal value of public funds, can be decomposed into the following components:

- *Mechanical welfare effect*: The reform mechanically changes consumers' perceived utility by $\kappa_j(\theta)$ dollars, and consumers' normative utility by $\kappa_j(\theta) - \rho_j(\theta)$ dollars. Thus the total mechanical welfare effect is $\mathbb{E}\left[(\kappa_j(z)-\rho_j(z))g(z)\right]da_j + \mathbb{E}\left[\kappa_j(z)(\hat{g}(z)-g(z))\right]da_j$, or $\mathbb{E}\left[\kappa_j(z)\hat{g}(z) - \rho_j(z)g(z)\right]da_j$
- *Revenue effects*. The reform changes costs by $C_j'da_j + C_p'\frac{d\bar{s}}{da_j}da_j$, and changes earnings by $p\frac{d\bar{s}}{da_j}$. The net effect is thus $(p - C_s')\bar{\zeta}_{a_j}\bar{s}da_j - C_j'da_j$
- *Bias-correcting effects of substitution:* The reform causes each consumer to decrease their s consumption by $dp \cdot \zeta_{a_j}(\theta)/p$. This generates a behavioral welfare effect equal to

$$-da_j\mathbb{E}\left[g(z)\bar{\gamma}(z)\zeta_{a_j}(z)s(z)\right] = -da_j\bar{\gamma}_{a_j}(1+\sigma_{a_j})\bar{\zeta}_{a_j}\bar{s}$$

- *Effect on earnings:* The reform causes a change in income tax revenue collected from type θ equal to $\frac{dz(\theta)}{da_j}T'(z(\theta))$. Lemma 1 implies that $\frac{dz(\theta)}{da_j} = \zeta_z(\theta)\left(\frac{z(\theta)}{1-T'(z(\theta))}\right)\frac{\partial k_j(p,\boldsymbol{a},z;\theta)}{\partial z}$. By Assumption 6, this generates a total fiscal externality through the income tax equal to $da_j \cdot \mathbb{E}\left[\frac{T'(z)}{1-T'(z)}\zeta_z(z)z\kappa_{j,inc}'(z)\right]$.

- *Indirect effects on sin good consumption:* The change in earnings affects consumption indirectly. However, relative to the other effects above, these effects are of order $\frac{\bar{s}_\theta}{z(\theta)-T(z(\theta))-p\bar{s}_\theta}$ and therefore negligible by Assumption 2 (formally, this is easily proven by extending the calculations of ALT in their proof of Proposition 1).

Combining these components, and taking into account that the income tax T is set optimally, the total welfare effect of the price change is equal to

$$\frac{dW}{da_j} = \mathbb{E}\left[\kappa_j(z)\hat{g}(z) - \rho_j(z)g(z)\right] + \left(p - C_s'\right)\bar{\zeta}_{a_j}\bar{s} - C_j' - \bar{\gamma}_{a_j}(1+\sigma_{a_j})\bar{\zeta}_{a_j}\bar{s} \tag{28}$$

$$+\mathbb{E}\left[\frac{T'(z)}{1-T'(z)}\zeta_z(z)z\kappa'_{j,inc}(z)\right] \tag{29}$$

$$= \mathbb{E}\left[\kappa_j(z)\hat{g}(z) - \rho_j(z)g(z)\right] + \left(p - C_s'\right)\bar{\zeta}_{a_j}\bar{s} - C_j' - \bar{\gamma}_{a_j}(1+\sigma_{a_j})\bar{\zeta}_{a_j}\bar{s}$$

$$+\int_{z=z_{min}}^{\infty}\int_{x=z}^{\infty}(1-\hat{g}(x))h(x)dx\kappa'_{j,inc}(z)dz$$

$$= \mathbb{E}\left[\kappa_j(z)\hat{g}(z) - \rho_j(z)g(z)\right] + \left(p - C_s'\right)\bar{\zeta}_{a_j}\bar{s} - C_j' - \bar{\gamma}_{a_j}(1+\sigma_{a_j})\bar{\zeta}_{a_j}\bar{s}$$

$$+\int_{z=z_{min}}^{\infty}(1-\hat{g}(z))\kappa_{j,inc}(z)h(z)dz$$

$$= \bar{\kappa}_j - \mathbb{E}[\rho_j(z)g(z)] + Cov[\kappa_{j,pref}(z),\hat{g}(z)] + \left(p - C_s'\right)\bar{\zeta}_{a_j}\bar{s} - C_j' - \bar{\gamma}_{a_j}(1+\sigma_{a_j})\bar{\zeta}_{a_j}\bar{s}$$

At the optimum $\frac{dW}{da_j} = 0$ if $a_j > 0$ and $\frac{dW}{da_j} < 0$ if $a_j = 0$, which implies the first-order condition

$$\bar{\kappa}_j - \mathbb{E}[\rho_j(z)g(z)] + Cov[\kappa_{j,pref}(z),\hat{g}(z)] \leq \bar{\gamma}_{a_j}(1+\sigma_p)\left|\bar{\zeta}_{a_j}\right|\bar{s} - \left(p - C_s'\right)\left|\bar{\zeta}_{a_j}\right| + C_j'.$$

with equality when $a_j > 0$. Rearranging gives the second condition in the Proposition.

Finally, note that the first-order conditions implied by (23)-(24) and (28)-(29) also allow us to characterize the optimal p and $\boldsymbol{a}$ even when the income tax is not optimal. □

D Aggregate Lottery Demand Appendix

Table A1: **First Stages for Prize Semi-Elasticity Estimates**

(a) **Jackpot Semi-Elasticity: Nationwide Data**

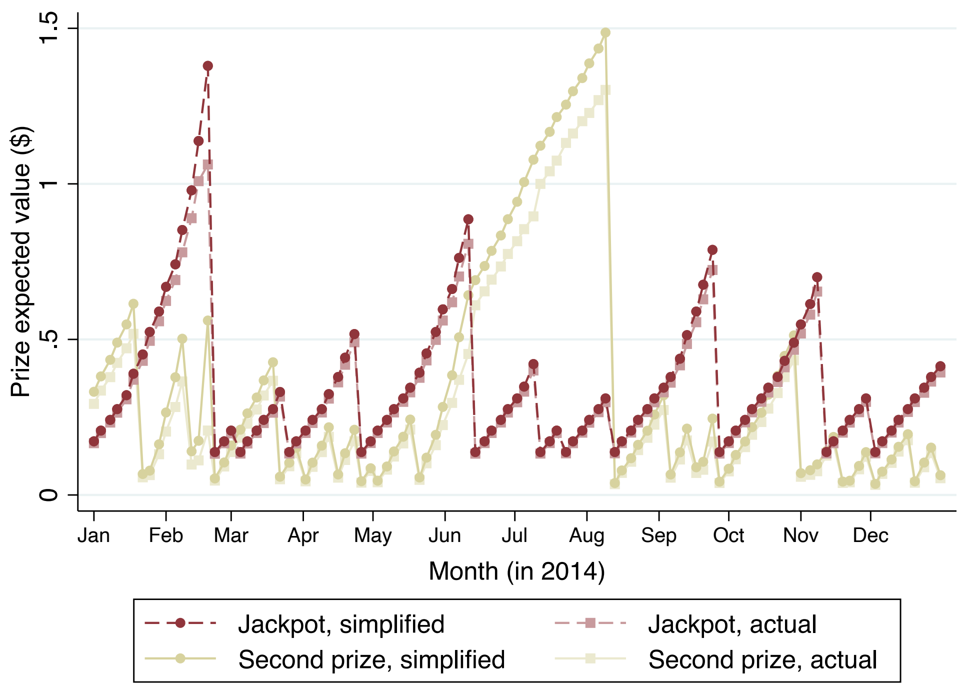
	(1) Jackpot EV ($)
Jackpot expected value forecast ($)	1.0884***
	(0.0466)
F-statistic	545
R^2	0.96
Observations	2,035

(b) **Jackpot and Second Prize Semi-Elasticities: California Data**

	(1) Jackpot EV ($)	(2) 2nd prize EV ($)
Jackpot expected value forecast ($)	1.0968***	0.1475***
	(0.0533)	(0.0339)
2nd prize expected value forecast ($)	-0.0162	1.0281***
	(0.0175)	(0.0300)
F-statistic	6,875	1,183
R^2	0.96	0.81
Observations	1,701	1,701

Notes: This table presents first stage estimates of equation (14). The first stages regress prize expected values on a forecast based on the previous period prize amount and an indicator for whether the prize was won in the previous period, controlling for the expectation of the forecast prior to the realization of the rollover outcome as well as game-format, game-regional coverage, game-quarter of sample, and game-weekend fixed effects. Panel (a) uses nationwide data, while Panel (b) uses California data only. The samples include all Mega Millions and Powerball drawings from June 2010 to February 2020; the sample in Panel (b) is smaller because California did not join Powerball until April 2013. Newey-West standard errors allowing up to ten lags are in parentheses. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

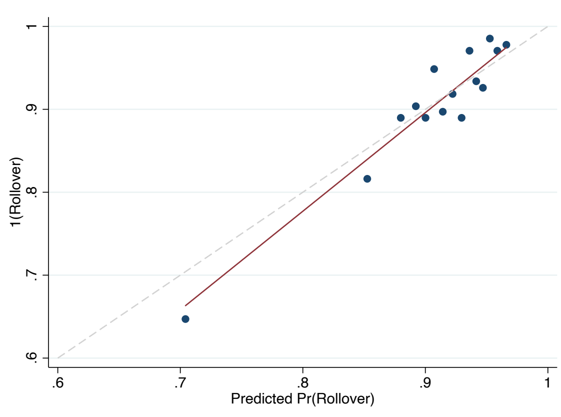
Figure A2: **Prize Expected Values Accounting for Prize Splitting**

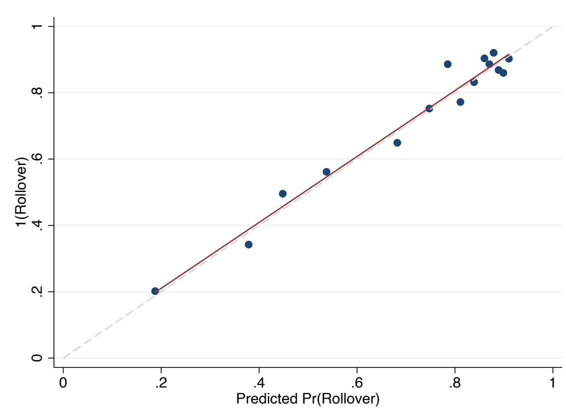


Notes: This figure presents "simplified" and "actual" expected values of the Powerball jackpot and California second prize for each drawing in 2014. The "simplified" expected value is the product of the win probability and prize amount. The "actual" expected value approximates the expected value accounting for the possibility of prize splitting among multiple winners, assuming players select ticket numbers randomly.

Figure A3: **Actual versus Predicted Jackpot and California Second Prize Rollovers**

(a) **Jackpot Rollovers** (b) **California Second Prize Rollovers**





Notes: This figure presents a binned scatter plot of the predicted probability of a rollover assuming that players select the numbers on their tickets randomly and an indicator for observed rollovers. A dashed 45-degree line is included for reference. Panel (a) uses nationwide jackpot data, while Panel (b) uses California second prize data only. The sample includes all Mega Millions and Powerball drawings from June 2010 through February 2020.

D.1 Substitution Across Games

D.1.1 Substitution in Response to Jackpot Variation

Our modeling considers only one good subject to behavioral bias. If changes in prices or attributes cause substitution to other goods subject to behavioral bias, optimal policy would have to account for this (Allcott, Lockwood, and Taubinsky 2019). To test for substitution between Mega Millions and Powerball, we re-estimate equation (14) with two changes. First, the dependent variable is in levels instead of logs, which allows us to easily construct a diversion ratio by dividing regression coefficients. Second, we add the jackpot for game $-j$. The regression is

$$\bar{s}_{jt} = \bar{\zeta}_j \pi_{1jt} w_{1,j,t} + \bar{\zeta}_c \pi_{1,-j,t} w_{1,-j,t} + \beta_j \pi_{1jt} \bar{Z}_{1,j,t} + \beta_c \pi_{1,-j,t} \bar{Z}_{1,-j,t} + \xi_{jt} + \epsilon_{jt}. \tag{30}$$

As before, we instrument for $\pi_{1jt} w_{1jt}$ and $\pi_{1,-j,t} w_{1,-j,t}$ with $\pi_{1jt} Z_{1jt}$ and $\pi_{1,-j,t} Z_{1,-j,t}$, and we control for $\pi_{1jt} \bar{Z}_{1jt}$ and $\pi_{1,-j,t} \bar{Z}_{1,-j,t}$ in order to isolate random variation in jackpot amounts. Mega Millions draws are on Tuesday and Friday, while Powerball draws are on Wednesday and Saturday. We define t by matching the Tuesday-Wednesday draws and Friday-Saturday draws for a given week.

Panel (a) of Appendix Table A2 presents OLS and IV estimates. Column 2 shows that when a game's jackpot expected value increases by \$1, that game's sales increase by 107.14 million tickets. However, the other game's ticket sales are statistically unaffected, and the 95 percent confidence intervals exclude effects larger than about 7.9 million tickets.

We can also estimate substitution to lottery games other than the multi-state games. To do that, we collapse the balanced panel of games in the La Fleur's data to the nationwide weekly level. Now let $\bar{s}_{jt}$ be sales in units of dollars, let $\pi_{1t} w_{1t}$ denote the average jackpot expected value across the four draws of Mega Millions and Powerball in week t. The regression is

$$\bar{s}_{jt} = \bar{\zeta}_c \pi_{1t} w_{1t} + \beta_c \pi_{1j,t} \bar{Z}_{1j,t} + \xi_{jt} + \epsilon_{jt}. \tag{31}$$

We instrument for $\pi_{1t} w_{1t}$ with a weekly version of the rollover instrument and only include the weekly version of the pre-rollover expectation of the instrument $\pi_{1j,t} \bar{Z}_{1j,t}$ in our IV regressions.[31] In these weekly data, ξ_{jt} represents quarter-of-sample fixed effects and 52 week-of-year fixed effects, which we have found to improve precision by soaking up seasonality.

Panel (b) of Appendix Table A2 presents the OLS estimates. The IV estimates are very similar; see Appendix Table A3. Each column considers sales of different games. Column 1 shows that when the average Mega Millions and Powerball jackpot expected values increase by \$1, their combined weekly ticket sales increase by \$500.36 million. Column 2 shows that sales of 13 major state-level draw games increase by \$1.79 million, suggesting statistically significant but economically small

[31] The weekly version of the instrument is the product of the jackpot win probability and the draw-level jackpot forecast, constructed as described in equation (12), averaged over weeks in the same way as the jackpot expected values.

complementarity.[32] Columns 3 and 4 show no statistically significant effects on instant games and on the combination of all games other than Mega Millions and Powerball. The 95 percent confidence interval in column 4 rules out that a $1 increase in the Mega Millions and Powerball jackpots increases sales of other games by more than $9.6 million or decreases sales by more than $11.9 million, implying economically very limited substitution. Appendix Figure A4 presents visual examples of these null effects for the 2014 data, paralleling Figure 1.

Table A2: **Cross-Game Substitution**

(a) **Mega Millions and Powerball**

	(1) OLS	(2) IV
Own game jackpot	108.32***	107.14***
expected value ($)	(14.62)	(16.76)
Other game jackpot	0.06	1.94
expected value ($)	(2.44)	(3.01)
Observations	2,035	2,035
Dependent variable mean	23.0	23.0

(b) **Different Game Types**

	(1) Mega Millions & Powerball	(2) Major state draw games	(3) Instant games	(4) Other state-level games
Jackpot expected value ($)	500.36***	1.79***	0.01	-1.16
	(74.03)	(0.32)	(4.99)	(5.47)
Observations	508	508	508	508
Dependent variable mean	108.2	12.4	509.5	669.2

Notes: Panel (a) of this table presents estimates of equation (30), a regression of the level of sales of a multi-state game on the prize expected values of both multi-state games, controlling for game-format, game-regional coverage, game-week, weekend, and quarter-of-sample fixed effects, using nationwide game-by-draw data. The IV regression instruments for prize expected values with a forecast based on the previous period prize amount and an indicator for whether the prize was won in the previous period and additionally controls for the expectations of the forecasts prior to the realization of rollover outcomes. Panel (b) presents estimates of equation (31), a regression of the aggregate level of sales of the lottery games indicated in each column on the week-average prize expected values of Mega Millions and Powerball, controlling for week and quarter-of-sample fixed effects, using a balanced panel of nationwide game-by-week data. Newey-West standard errors allowing up to ten lags are in parentheses. Sales are in millions of tickets in Panel (a) and millions of dollars in Panel (b). *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

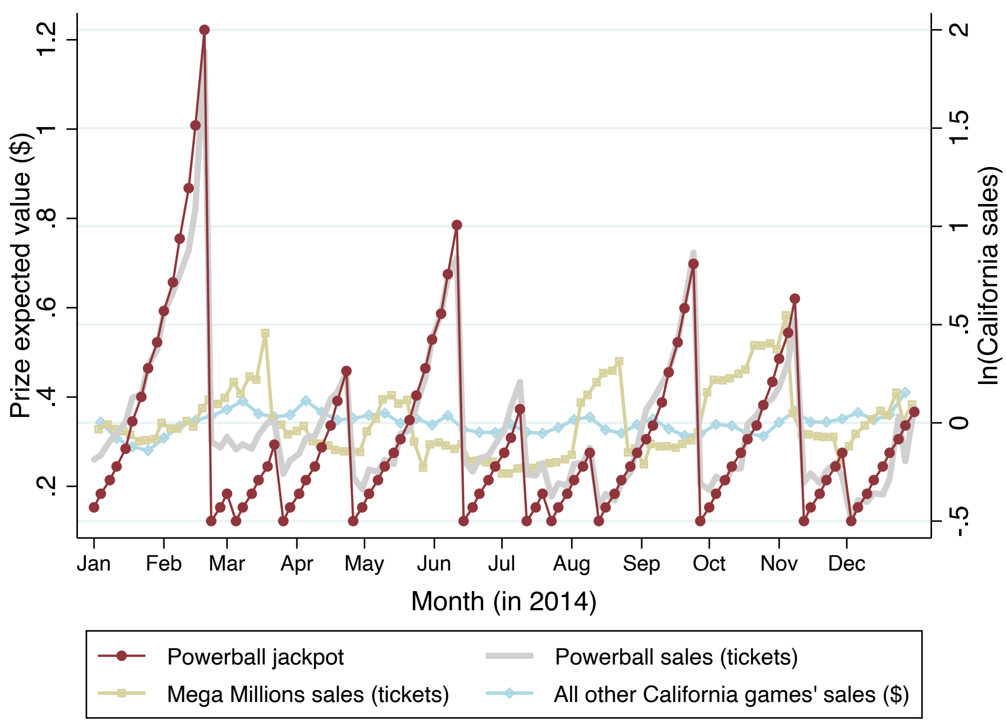
[32]We selected these 13 games because they were the most likely substitutes for Mega Millions and Powerball. We first selected the largest draw game in each state plus additional games where jackpot data were available, then limited to a balanced panel in states that were always Mega Millions and Powerball members. The 13 games are Lotto from Colorado, Lotto! from Connecticut, Lotto from Illinois, Megabucks Doubler from Massachusetts, Multi-Match from Maryland, Tri-State Megabucks Plus from Maine and New Hampshire, Gopher 5 from Minnesota, Lotto from New York, Classic Lotto and Rolling Cash 5 from Ohio, Megabucks from Oregon, Lotto Texas from Texas, and Lotto from Washington.

Table A3: **Cross-Game Substitution: IV**

	(1) Mega Millions & Powerball	(2) Major state draw games	(3) Instant games	(4) Other state-level games
Jackpot expected value ($)	470.69***	1.68***	-9.26	-13.96
	(106.77)	(0.49)	(13.01)	(14.51)
Observations	508	508	508	508
Dependent variable mean	108.2	12.4	509.5	669.2

Notes: This table presents estimates of equation (31), a regression of the aggregate level of sales in millions of dollars of the lottery games indicated in each column on the week-average prize expected values of Mega Millions and Powerball, using a balanced panel of nationwide game-by-week data. Week-average prize expected values are instrumented with week averages of a forecast based on the previous period prize amount and an indicator for whether the prize was won in the previous period. Controls for the week averages of the expectation of the forecast prior to the realization of each rollover outcomes as well as game-week and quarter-of-sample fixed effects are included. Newey-West standard errors allowing up to ten lags are in parentheses. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

Figure A4: **Powerball Prizes and Other Games Ticket Sales in 2014**



Notes: This figure presents the expected values of the Powerball jackpot, the natural log of Powerball and Mega Millions California ticket sales for each drawing in 2014, and the natural log of aggregate sales from a balanced panel of all other California game-by-week data. The levels of sales are adjusted so that the average natural log of sales is zero.

D.1.2 Substitution in Response to Price Variation

We can also test for substitution by estimating the effect of game j's price change on other games. To do this, we estimate an analogue to equation (15), except with the substitute game's sales level on the left-hand side, a control for the substitute game's jackpot expected value, and a vector of week-of-year and event fixed effects collectively denoted ξ_t:

$$\bar{s}_{-jt} = \bar{\zeta}_p p_{jt} W_{jt} + \beta_1 W_{jt} + \beta_2 p_{jt} W_{jt}^{+} \left(+\beta_2 \pi_{1-jt} w_{1-jt}\right) + \xi_t + \epsilon_{jt}. \tag{32}$$

The substitute game expected value control $\pi_{1-jt} w_{1-jt}$ is used only to study substitution to the other major multi-state game, not when we estimate substitution to other games in the La Fleur's data. Table A4 presents results.

Table A4: **Cross-Price Demand Responses**

	(1) Own-price response	(2) Other multi-state game	(3) Major state draw games	(4) All other games
Price × 12-month window	-21.15***	5.84	-0.03	7.82
	(3.55)	(6.62)	(0.37)	(6.46)
Jackpot expected value ($)	131.32***	167.38***		
	(14.94)	(40.55)		
Observations	312	312	312	312
Dependent variable mean	37.8	38.5	12.6	650.5

Notes: This table presents estimates of equation (32), a regression of the aggregate level of sales of the lottery games indicated in each column header on (i) the ticket price of a multi-state game interacted with an indicator for the 12-month window—six months before and six months after—around a price change event for that multi-state game, (ii) the 12-month window indicator, and (iii) the ticket price of the multi-state game interacted with an indicator for the 12-month period following the 12-month window around the price change event, controlling for week fixed effects and a price-change event fixed effect. Columns 1 and 2 also include controls for the week-average jackpot expected value of the game indicated in the column header. Each column pools data from a 36-month window around both the Powerball and Mega Millions price changes, using a balanced panel of nationwide game-by-week data. Newey-West standard errors allowing up to ten lags are in parentheses. Sales are in millions of tickets in columns 1–2 and millions of dollars in columns 3–4. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

D.2 Long-Run vs. Short-Run Elasticity

As in many other studies, we have a well-identified short-run elasticity, but our policy analysis requires a long-run elasticity. Consider two models in which these elasticities might differ. First, consumption might be substitutable or complementary over time, e.g. if previous purchases cause people to tire or get excited in the future. Second, consumers might have a desired average spending (e.g. $X per month) that they allocate across draws to maximize expected value. In the limiting case, demand might be fully inelastic to the average jackpot level but highly elastic to variation across draws.

To address these issues, we test for effects of lagged jackpot amounts and also aggregate over time. Define a "jackpot spell" as a group of draws beginning after a jackpot is won and continuing until the next win. The sawtooth pattern in Figures 1 and A4 illustrates that while the length of each jackpot spell varies, these spells are well-defined units of analysis that capture the variation we want to use. We collapse the data to the average $\ln \bar{s}_{jt}$ and average $\pi_{kjt} w_{kjt}$ over each of the 196 complete jackpot spells in our sample, which are 4.7 weeks long on average. Now using t to index jackpot spells, we estimate an analogue of equation (14) including lags indexed by l:

$$\ln \bar{s}_{jt} = \sum_{l=0}^{L} \bar{\zeta}_{1l} \pi_{1j,t-l} w_{1j,t-l} + \sum_{l=0}^{L} \beta_{1l} \pi_{1j,t-l} \bar{Z}_{1j,t-l} + \xi_{jt} + \epsilon_{jt}, \tag{33}$$

where the fixed effects ξ_{jt} are now game-format, game-regional coverage, and game-year of sample fixed effects based on the first draw in the spell. We instrument for $\pi_{1jt} w_{1jt}$ with a forecast of the spell midpoint jackpot expected value using the reset value $\underline{w}_{1jf(t)}$, the average percent increase $\iota_{1jf(t)}$, and the number of rollovers R_{jt} in the spell: $\left(1 + \iota_{1jf(t)}\right)^{R_{jt}/2} \cdot \pi_{1jt} \underline{w}_{1jf(t)}$. In our IV regressions, we control for the expectation of the spell midpoint jackpot expected value conditional on $\leq \bar{R}$ rollovers in the spell, where $\bar{R}$ is the observed number of rollovers in the spell, and assuming players randomly select the numbers on their tickets: $\left(1 + \iota_{1jf(t)}\right)^{\mathbb{E}[R_{jt}/2 | R_{jt} \leq \bar{R}]} \cdot \pi_{1jt} \underline{w}_{1jf(t)}$. The first stages are strong, and the jackpot expected value forecast instrument for lag $t - l$ strongly predicts the actual jackpot expected value for lag $t - l$ but not for other lags; see Appendix Table A6.

Table A5 presents results. Columns 1 and 2 present the OLS and IV estimates with no lags, while columns 3 and 4 add three lags. In case aggregating to jackpot spells is still not enough to identify a long-run elasticity, columns 5 and 6 present estimates after aggregating to groups of three jackpot spells. There are 64 complete three-spell groups in our sample, which are 15.2 weeks long on average.

The contemporaneous effects in columns 1, 2, 5, and 6 are comparable to the draw-level estimates from Table 3. The lag coefficients in columns 3 and 4 imply intertemporal complementarity: higher jackpots in recent prior spells cause higher demand now, with an effect that decays toward zero by the third lag. The OLS and IV estimates are similar, suggesting limited simultaneity bias.

Table A5: **Intertemporal Substitution**

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
Jackpot expected value, t (\$)	1.6699***	2.0158***	1.7178***	2.0001***	1.7928***	2.6474***
	(0.0797)	(0.1133)	(0.0943)	(0.1075)	(0.2589)	(0.4104)
Jackpot expected value, $t-1$ (\$)			0.2831***	0.7027***		
			(0.0697)	(0.1259)		
Jackpot expected value, $t-2$ (\$)			0.1624**	0.3870***		
			(0.0665)	(0.1480)		
Jackpot expected value, $t-3$ (\$)			0.0890**	0.0542		
			(0.0366)	(0.0745)		
R^2	0.87	0.89	0.88	0.92	0.74	0.81
Observations	193	191	187	185	61	61

Notes: This table presents estimates of equation (33), a regression of the average natural log of sales on contemporaneous and lagged average jackpot expected values, controlling for game-format, game-regional coverage, and game-year of sample fixed effects based on the first draw in the period of interest. In columns 1–4, we use nationwide game-by-jackpot spell data, where a jackpot spell is defined as a group of draws beginning after a jackpot is won and continuing until the next win. In columns 5–6, we use nationwide game-by-three-spell data, averaging across series of three jackpot spells. The sample includes all complete Mega Millions and Powerball jackpot spells from June 2010 to February 2020. Observation counts exclude singletons. Newey-West standard errors allowing up to ten lags are in parentheses. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

Table A6: **First Stages for Intertemporal Substitution Estimates**

	(1) Spell jackpot EV, t	(2) Spell jackpot EV, t	(3) Spell jackpot EV, $t-1$	(4) Spell jackpot EV, $t-2$	(5) Spell jackpot EV, $t-3$	(6) 3-spell jackpot EV, t
Jackpot expected value midpoint forecast, t (\$)	0.9462***	1.0234***	0.1431**	0.0450	-0.0627	1.6058***
	(0.0876)	(0.2586)	(0.0616)	(0.1087)	(0.1298)	(0.4377)
Jackpot expected value midpoint forecast, $t-1$ (\$)		0.1900*	1.0700***	0.1201	0.0499	
		(0.1059)	(0.2803)	(0.0839)	(0.0953)	
Jackpot expected value midpoint forecast, $t-2$ (\$)		0.0698	0.1052	1.1054***	0.1360	
		(0.0657)	(0.1218)	(0.2730)	(0.1030)	
Jackpot expected value midpoint forecast, $t-3$ (\$)		0.0501	0.0659	0.0693	1.1240***	
		(0.0814)	(0.0925)	(0.1229)	(0.2749)	
F-statistic	16.3	25.8	18.1	57.4	28.4	13.5
R^2	0.69	0.79	0.80	0.79	0.71	0.79
Observations	193	185	185	185	185	61

Notes: This table presents first stage estimates of equation (33). The first stages regress average jackpot expected values on forecasts of the midpoint of the jackpot expected value within a jackpot spell or averaged across a three-spell period based on the number of rollovers, expected reset value of the jackpot, and the average post-rollover percent jackpot increase for the game-format of the first draw in the period of interest. Controls for the approximate expectation of the expected value midpoint forecasts as well as game-format, game-regional coverage, and game-year of sample fixed effects based on the first draw in the period of interest are included. In columns 1–5, we use nationwide game-by-jackpot spell data, where a jackpot spell is defined as a group of draws beginning after a jackpot is won and continuing until the next win. In column 6, we use nationwide game-by-three-spell data, averaging across series of three jackpot spells. The sample includes all complete Mega Millions and Powerball jackpot spells from June 2010 to February 2020. Observation counts exclude singletons. Newey-West standard errors allowing up to ten lags are in parentheses. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

D.3 Format Change Appendix

Table A7: **Placebo Tests: Non-Price Format Change Event Studies**

	(1) Mega Millions	(2) Mega Millions	(3) Mega Millions	(4) Powerball	(5) Powerball	(6) Powerball
Post format change × 12-month window	0.3273*	0.1546***	-0.0226	0.3352	0.2944***	0.0516
	(0.1811)	(0.0500)	(0.0502)	(0.2466)	(0.0647)	(0.0757)
Jackpot expected value ($)		2.2981***			1.7557***	
		(0.1064)			(0.0760)	
Jackpot ($millions)			0.0088***			0.0061***
			(0.0003)			(0.0006)
Observations	313	313	313	313	313	313

Notes: This table presents estimates of a regression of the natural log of sales on (i) an indicator for a post-format change period interacted with an indicator for the 12-month window—six months before and six months after—around a game-format change event, (ii) the 12-month window indicator, and (iii) an indicator for the post-format change period interacted with an indicator for the 12-month period following the 12-month window around the format change event, controlling for weekend fixed effects in all columns, jackpot expected value in columns 2 and 5, and jackpot amounts in columns 3 and 6. In columns 1–3, the sample includes all Mega Millions draws in a 36-month window around the October 19, 2013 format change event. In columns 4–6, the sample includes all Powerball draws in a 36-month window around the October 7, 2015 format change event. We use Newey-West standard errors with up to ten lags. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

D.4 Jackpot Semi-Elasticity Estimates from Prior Studies

On the pages that follow, we compare lottery ticket demand responses to changes in jackpot expected values from a selection of prior studies to our jackpot semi-elasticity estimate in column 2 of Table 3a. We either convert these studies' estimates to a semi-elasticity or convert our estimates for comparability with their estimates. We calculate that their estimates range from 33 to 250 percent of our estimate, with an average of 114 percent of our estimate.

Table A8: **Comparisons with Jackpot Semi-Elasticities from the Literature**

	Type of estimate	Original estimate	Converted estimate	Conversion of our estimate	Conversion details	Ratio: $\frac{\text{Their estimate}}{\text{Our estimate}}$
Our estimate – Table 3	Jackpot EV semi-elasticity	1.73	–	–	From national sales data in column 2 of Table 3a; CA sales data in column 2 of Table 3a gives an estimate of 1.85.	1
Clotfelter and Cook (1989) – Table 6A.4	Payout rate semi-elasticity for lotto games	2.55	4.32	–	Assuming a price of $1 (not stated) and no variation in lower prizes, this would be equal to the jackpot EV semi-elasticity (though these assumptions may be too strong). Rescaled to present value approximation using our conversion factor of 0.59.	2.50
Clotfelter and Cook (1989) – Table 6A.5	Jackpot pool elasticity for lotto games	0.40	–	0.31	Need information about jackpots to convert; we can instead convert our estimate at our mean jackpot EV. In the oldest game-formats, nearest in time to this study, a 1% increase in jackpots ⇒ .18 cent increase in jackpot EV ⇒ (.18)/100·173% = .311% ⇒ 0.31 elasticity. (In the latest game-formats, a 1% increase in jackpots ⇒ .31 cent increase in jackpot EV ⇒ (.31)/100·173% = .536% increase in sales ⇒ 0.54 elasticity.)	1.29
Cook and Clotfelter (1993) – Reported in text	Jackpot pool elasticity for Massachusetts lotto (at means)	0.35	–	0.31	Need information about jackpots to convert; we can instead convert our estimate at our mean jackpot EV as described above.	1.13
Cook and Clotfelter (1993) – Table 4	Change in sales with respect to jackpot pool for Massachusetts lotto	0.347	1.156	–	Evaluated at the mean sales for the middle draw (#85). To convert from jackpot pool to EV, we use the win probability reported in Table 1 (for 4 years later) to obtain the change in sales/mean sales from ~$1 increase in EV.	0.67
Farrell, Morgenroth, and Walker (1999) – Table 2	Short-run "price" elasticity for UK Lotto, where price is one GBP minus the ticket EV (variation comes from the jackpot EV)	-1.04 on "price"	–	-1.11	Need more information about EVs to convert; we can instead convert our estimate at our mean ticket EV in the oldest game-formats, treating our jackpot semi-elasticity as the ticket EV semi-elasticity: a 1% increase in "price" (= $1 – ticket EV) ⇒ ∼.64 cents increase (assumed via a .64 cent decrease in the jackpot EV) ⇒ (.64)/100·173%·(-1) = ∼1.11% decrease in sales ⇒ -1.11 elasticity.	0.94
Farrell, Morgenroth, and Walker (1999) – Table 2	Long-run "price" elasticity for UK Lotto, where price is one GBP minus the ticket EV (variation comes from the jackpot EV)	-1.55 on "price"	–	-1.70	Need more information about EVs to convert; we can instead convert our long-run jackpot EV semi-elasticity of 2.65 in column 6 of Appendix Table A5 and do the same calculation as above: (.64)/100·265%·(-1) = ∼1.70 decrease in sales ⇒ -1.70 elasticity.	0.91

	Type of estimate	Original estimate	Converted estimate	Conversion of our estimate	Conversion details	Ratio: $\frac{\text{Their estimate}}{\text{Our estimate}}$
Farrell et al. (2000) – Table 1	Ticket EV semi-elasticity for UK lotto (variation comes from the jackpot EV)	0.654-0.857	0.965	–	Using the full information maximum likelihood elasticity estimate of 0.772. Figure 6 shows a mean EV of ∼GBP 0.5. Assuming an exchange rate of ∼1.6 (late 90s) and evaluating at the mean, holding other prizes' EV fixed. The prize does not appear to be annuitized so no present value conversion is needed.	0.56
Kearney (2005b) – Table 7	Ticket EV semi-elasticity for 91 lotto products	0.515	0.566	–	Rescaled to account for jackpot prize-splitting. Assuming all variation is due to jackpots (since product fixed effects are included).	0.33
Grote and Matheson (2006) – Table 2	Change in sales with respect to jackpot pool ($millions) for Colorado, New Jersey, and Ohio lottos	Approximately 54,000 to 238,000 on the jackpot, -1,700 to 11,600 on jackpot^2	–	–	Need information about the probability of winning to convert to jackpot EV semi-elasticity. We can compare to our pooled jackpot semi-elasticity in column 4 of Table 4 of .0064 (though we omit the direct comparison due to this not being our preferred estimate). Using the Ohio Saturday estimates at pre-multi-state game means: $1 million increase in jackpot ⇒ $(140{,}449 + 1{,}885(12.36^2 - 11.36^2))/3{,}817{,}820 = 4.8\%$ increase in sales, so a semi-elasticity of 0.048. This semi-elasticity is likely much higher due to the games having a higher win probability.	–
Guryan and Kearney (2010)	Semi-elasticity of store-level sales with respect to having sold a winning ticket	Not comparable because jackpot/EV are not independent variables in any of the regressions.				–
Knight and Schiff (2012) – Table 3	"Price" semi-elasticity for PB/MM, where price is one dollar minus the present value jackpot expected value net of taxes (essentially a rescaled jackpot semi-elasticity)	Approximately -2.3 on "price", -0.1 to -0.4 on the interaction with "inflow ratio" (a measure of concentration of population near borders)	3.29	–	Evaluated at the mean inflow ratio of 1.324, using the 50 km from the border specification. Assuming a top marginal tax rate of 35% and applying our jackpot discount factor for prize-splitting.	1.90
					Maximum ratio:	2.50
					Minimum ratio:	0.33
					Average ratio:	1.14

Notes: This table summarizes estimates of lottery ticket demand responses to changes in jackpots from a selection of prior studies. For each estimate, it lists the study it came from, the type of the estimate, the estimate, and either the estimate converted into a jackpot semi-elasticity or our estimate converted into the same type as the study's estimate. Conversion details are also provided, as well as the ratio between the study's estimate and our estimate. The last three rows of the table summarize these ratios, with the maximum, minimum, and average ratio.

E Survey Appendix

E.1 AmeriSpeak Survey Question Text

Variable	Question text
	Spending and income effects
Monthly lottery spending	How many dollars did you spend in total on lottery tickets in an average month in 2019?
Income change	How much income did you earn in 2019 compared to 2018? In 2019, I earned ... [Less than half as much, 25% to 50% less, 10% to 25% less, 5% to 10% less, 1% to 5% less, The exact same amount, 1% to 5% more, 5% to 10% more, 10% to 25% more, 25% to 50% more, Over 50% more]
Spending change	How much money did you spend in total on lottery tickets in 2019 compared to 2018? In 2019, I spent ... [Less than half as much, 25% to 50% less, 10% to 25% less, 5% to 10% less, 1% to 5% less, The exact same amount, 1% to 5% more, 5% to 10% more, 10% to 25% more, 25% to 50% more, Over 50% more]
Self-reported income effect	Imagine you got a raise and your income doubled. How do you think your lottery spending would change? I would spend ... [Less than half as much, 25% to 50% less, 10% to 25% less, 5% to 10% less, 1% to 5% less, The exact same amount, 1% to 5% more, 5% to 10% more, 10% to 25% more, 25% to 50% more, Over 50% more]
	Preferences
Unwillingness to take risks	In general, how willing or unwilling are you to take risks? [1 Very unwilling, 2, 3, 4, 5, 6, 7 Very willing]
Financial risk aversion	Which of the following statements comes closest to the amount of financial risk that you are willing to take when you save or make investments? [Substantial financial risks expecting to earn substantial returns, Above-average financial risks expecting to earn above-average returns, Average financial risks expecting to earn average returns, No financial risks]
Lottery seems fun	To what extent do you agree or disagree with the following statement: *For me, playing the lottery seems fun.* [-3 Strongly disagree, -2, -1, 0 Neutral, 1, 2, 3 Strongly agree]

Enjoy thinking about winning	To what extent do you agree or disagree with the following statement: *I enjoy thinking about how life would be if I won the lottery.* [-3 Strongly disagree, -2, -1, 0 Neutral, 1, 2, 3 Strongly agree]
	Bias proxies
Self-control problems	It can be hard to exercise self-control, and some people feel that there are things they do too much or too little – for example, exercise, save money, or eat junk food. Do you feel like you play the lottery too little, too much, or the right amount? [-3 Far too little, -2, -1, 0 The right amount, 1, 2, 3 Far too much]
Financial illiteracy	Normally, which asset displays the highest fluctuations over time? [Savings accounts, Bonds, Stocks]
	When an investor spreads her money among different assets, does the risk of losing money: [Increase, Decrease, Stay the same]
	A second hand car dealer is selling a car for $6,000. This is two-thirds of what it cost new. How much did the car cost new? [$_]
	If 5 people all have the winning numbers in the lottery and the prize is $2 million, how much will each of them get? [$_]
	Let's say you have $200 in a savings account. The account earns 10% interest per year. How much will you have in the account at the end of two years? [$_]
	Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow? [More than $102, Exactly $102, Less than $102]
	Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account? [More than today, Exactly the same as today, Less than today]
	Do you think that the following statement is true or false? "Buying a single company stock usually provides a safer return than a stock mutual fund." [True, False]

Statistical ability

For the next few questions, imagine flipping a coin that has a 50% chance of landing heads and a 50% chance of landing tails. Imagine that after eight flips, you observe the patterns described in the table below. What is the probability, in percent from 0-100, that the next flip is tails?
[tails-tails-tails-heads-tails-heads-heads-heads _%,
heads-heads-heads-heads-heads-heads-heads-heads _%,
heads-tails-heads-tails-tails-tails-tails-tails _%]

Now imagine starting over and flipping a coin 1000 times. What are the chances, in percent from 0-100, that the total number of heads will lie within the following ranges? [Between 481 and 519 heads _%, Between 450 and 550 heads _%, Between 400 and 600 heads _%]

Now we are going to ask you how much people might win from different lotteries. For each lottery described in the table below, please give us your best estimate of what percent (from 0-100) of the lottery revenues are returned to the winners. [Tickets cost $1, and 1 out of every 10 tickets wins $10. _%, Tickets cost $1, and 1 out of every 1,000 tickets wins $500. _%, Tickets cost $1, 1 out of every 400,000,000 tickets wins $200,000,000, **and** 1 out of every 1,000 tickets wins $100. _%, Tickets cost $1, and 1 out of every 300,000,000 tickets wins $200,000,000. _%]

Overoptimism

Imagine **you** could keep buying whatever lottery tickets you want, over and over for a very long time. For every $1000 you spend, how much do you think **you** would win back in prizes, on average? [$0 to $99, $100 to $199, $200 to $299, $300 to $399, $400 to $499, $500 to $599, $600 to $699, $700 to $799, $800 to $899, $900 to $999, $1000 to $1499, $1500 to $1999, $2000 to $5000, More than $5000]

Imagine that the **average** lottery player in the country could keep buying whatever lottery tickets they want, over and over for a very long time. For every $1000 they spend, how much do you think they would win back in prizes, on average? [$0 to $99, $100 to $199, $200 to $299, $300 to $399, $400 to $499, $500 to $599, $600 to $699, $700 to $799, $800 to $899, $900 to $999, $1000 to $1499, $1500 to $1999, $2000 to $5000, More than $5000]

Expected returns

Think about the total amount of money spent on lottery tickets nationwide. What percent do you think is given out in prizes? [0 - 9%, 10 - 19%, 20 - 29%, 30 - 39%, 40 - 49%, 50 - 59%, 60 - 69%, 70 - 79%, 80 - 89%, 90 - 100%]

Predicted life satisfaction	A recent study surveyed Swedish lottery winners. A typical person in the study had won between $100,000 and $800,000 in the lottery about 12 years before the survey. The study compared people who had won more vs. less money to determine the effect of additional lottery winnings. The survey asked the following question about life satisfaction: "Taking all things together in your life, how satisfied would you say that you are with your life these days?" People responded on a scale from 0 ("Extremely dissatisfied") to 10 ("Extremely satisfied"). The average response was 7.21 out of 10. Do you think lottery winnings increased life satisfaction, decreased life satisfaction, or had exactly zero effect? [Increased life satisfaction, Decreased life satisfaction, Had exactly zero effect] By **how much** do you think an additional $100,000 in lottery winnings [increased/decreased] average life satisfaction on the 0-10 scale?

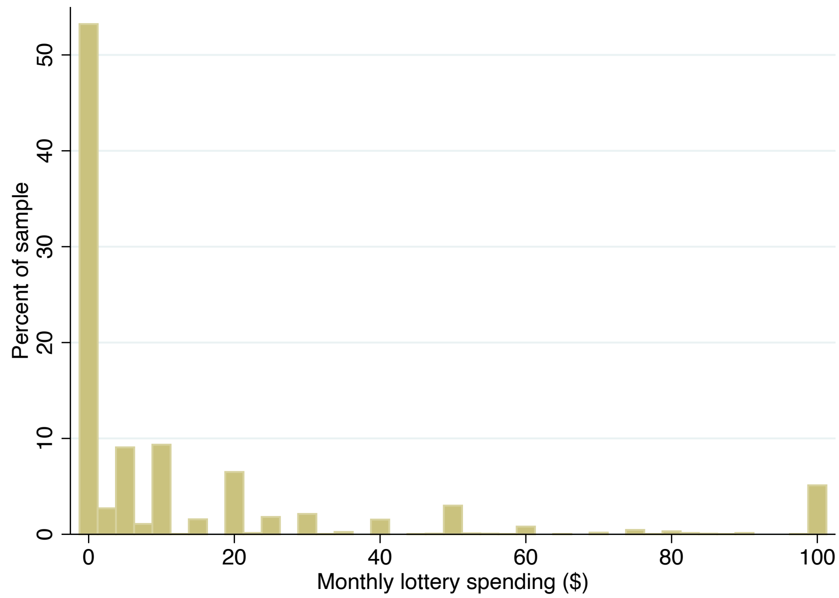
E.2 Additional Tables and Figures from AmeriSpeak Survey

Table A10: **Descriptive Statistics: 2021 Survey Data**

	Obs.	Mean	Std. dev.	Min	Max
Unwillingness to take risks	2,124	-3.96	1.37	-7	-1
Financial risk aversion	2,124	3.04	0.80	1	4
Lottery seems fun	2,124	-0.04	1.76	-3	3
Enjoy thinking about winning	2,122	0.71	1.86	-3	3
Self-control problems	2,124	-0.66	1.27	-3	3
Financial literacy	2,124	0.80	0.25	0	1
Financial numeracy	2,124	0.66	0.32	0	1
Gambler's Fallacy	2,124	0.27	0.39	0	1
Non-belief in Law of Large Numbers	2,124	0.39	0.17	0.00	0.93
Expected value miscalculation	2,124	0.66	0.38	0	1
Overoptimism	2,123	0.01	0.46	-4.95	4.65
Expected returns	2,123	0.27	0.20	0.05	0.95
Predicted life satisfaction	2,112	2.28	4.82	-10	10

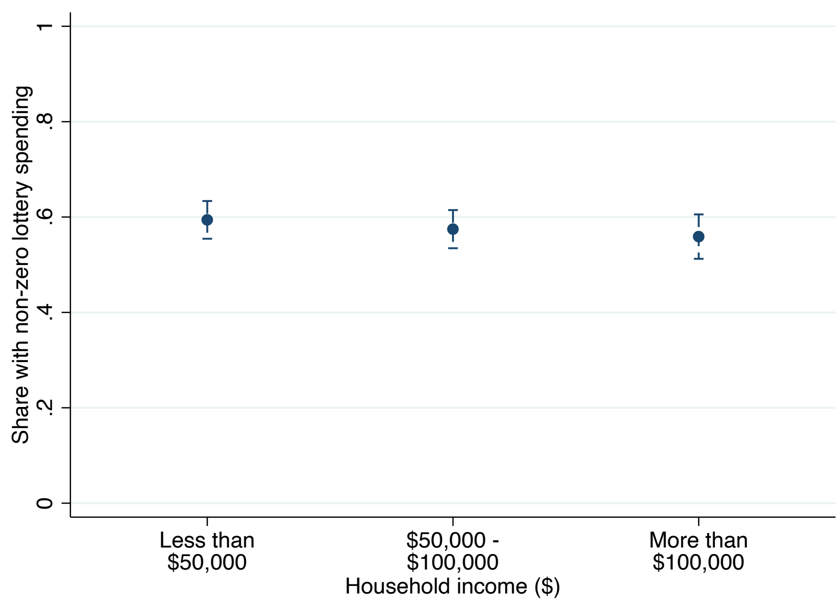
Notes: This table presents descriptive statistics for our 2021 AmeriSpeak survey, which resampled proxies for preferences and biases. Section 4.1 summarizes the coding of these variables.

Figure A5: **Distribution of Monthly Lottery Spending**



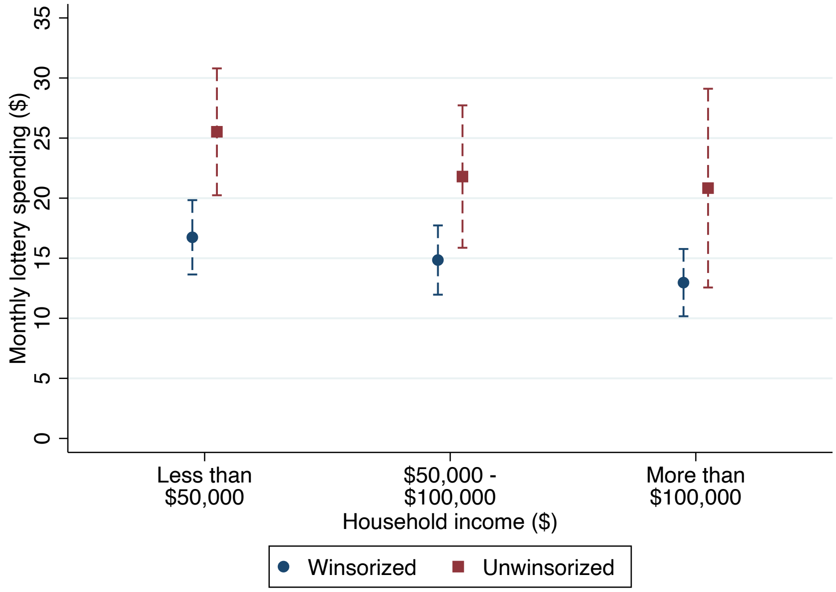
Notes: This figure presents a histogram of monthly lottery spending, using data from our AmeriSpeak survey. For this figure, spending is winsorized at $100 per month.

Figure A6: **Non-Zero Lottery Spending by Income**



Notes: This figure reports the share of people with non-zero monthly lottery spending in 2019 within household income groups, with 95 percent confidence intervals, using data from our AmeriSpeak survey. Observations are weighted for national representativeness.

Figure A7: **Lottery Spending by Income with and without Winsorization**



Notes: This figure presents average monthly lottery spending within household income groups, with 95 percent confidence intervals, using data from our 2020 AmeriSpeak survey. The winsorized values are the same as in Figure 4. The unwinsorized values are the original survey responses. Observations are weighted for national representativeness.

Table A11: **Causal and Cross-Sectional Income Effects**

	(1) Spending change	(2) Self-reported income effect	(3) ln(1 + monthly lottery spending)
Income change	0.194***		
	(0.025)		
ln(household income)			-0.111***
			(0.035)
Constant	-5.483***	-0.014***	1.911***
	(0.353)	(0.003)	(0.144)
Observations	2,862	2,855	2,877

Notes: Columns 1 and 2 report estimates of the causal elasticity of lottery spending with respect to income, using data from our AmeriSpeak survey. *Income change* and *spending change* refer to the self-reported percent change in household income and lottery spending in 2019 compared to 2018, respectively. *Self-reported income effect* is the answer to the question "Imagine you got a raise and your income doubled. How do you think your lottery spending would change?" in percent. Column 3 reports the cross-sectional elasticity of lottery spending with respect to income.

Table A12: **First-Stage Estimates for Preference and Bias Proxies**

	(1) Self-control problems	(2) Financial illiteracy	(3) Statistical mistakes	(4) Expected returns	(5) Predicted life satisfaction	(6) Risk aversion	(7) Lottery seems fun	(8) Enjoy thinking about winning
Self-control problems	0.353***	0.025**	0.008	0.022	-0.023	-0.002	0.008	0.003
	(0.058)	(0.010)	(0.013)	(0.015)	(0.017)	(0.010)	(0.013)	(0.012)
Financial illiteracy	0.064***	0.551***	0.248***	0.050***	-0.003	0.017	0.004	0.007
	(0.020)	(0.018)	(0.015)	(0.017)	(0.019)	(0.011)	(0.015)	(0.015)
Statistical mistakes	0.021	0.155***	0.439***	-0.017	0.026	0.008	0.036***	0.038***
	(0.018)	(0.011)	(0.019)	(0.016)	(0.017)	(0.010)	(0.013)	(0.013)
Expected returns	0.023	0.020**	-0.018	0.356***	0.011	0.012	0.036***	0.009
	(0.015)	(0.009)	(0.011)	(0.023)	(0.014)	(0.010)	(0.012)	(0.012)
Predicted life satisfaction	-0.016	0.005	0.019*	0.010	0.286***	-0.005	0.028**	0.054***
	(0.015)	(0.009)	(0.011)	(0.014)	(0.023)	(0.010)	(0.012)	(0.012)
Risk aversion	-0.027*	0.028***	0.011	0.002	-0.015	0.720***	-0.050***	0.009
	(0.014)	(0.008)	(0.011)	(0.015)	(0.015)	(0.014)	(0.011)	(0.011)
Lottery seems fun	0.028	0.004	0.021	0.071***	0.028	-0.034***	0.472***	0.115***
	(0.019)	(0.011)	(0.014)	(0.018)	(0.018)	(0.012)	(0.021)	(0.017)
Enjoy thinking about winning	0.017	0.005	0.025*	0.005	0.103***	0.022*	0.122***	0.491***
	(0.016)	(0.011)	(0.014)	(0.018)	(0.018)	(0.011)	(0.016)	(0.023)
ln(household income)	0.029	-0.059***	-0.031**	0.024	-0.011	-0.055***	-0.016	0.003
	(0.019)	(0.011)	(0.014)	(0.018)	(0.019)	(0.009)	(0.013)	(0.013)
ln(years of education)	-0.174**	-0.469***	-0.281***	-0.152*	-0.269***	-0.105**	-0.178***	-0.196***
	(0.083)	(0.047)	(0.070)	(0.087)	(0.092)	(0.041)	(0.062)	(0.061)
1(Black)	0.088	0.227***	0.161***	0.153***	0.102**	-0.050**	0.081**	0.043
	(0.054)	(0.028)	(0.033)	(0.046)	(0.050)	(0.021)	(0.033)	(0.029)
1(Hispanic)	0.055	0.190***	0.069**	0.088**	0.105**	-0.041**	0.024	0.022
	(0.038)	(0.025)	(0.028)	(0.037)	(0.043)	(0.019)	(0.028)	(0.028)
Other demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-statistic	50.4	506.9	299.0	225.0	132.7	2,570.9	363.9	312.2
R^2	0.22	0.82	0.91	0.77	0.30	0.60	0.38	0.40
Observations	4,144	4,144	4,144	4,144	4,144	4,144	4,144	4,144
Clusters	2,072	2,072	2,072	2,072	2,072	2,072	2,072	2,072

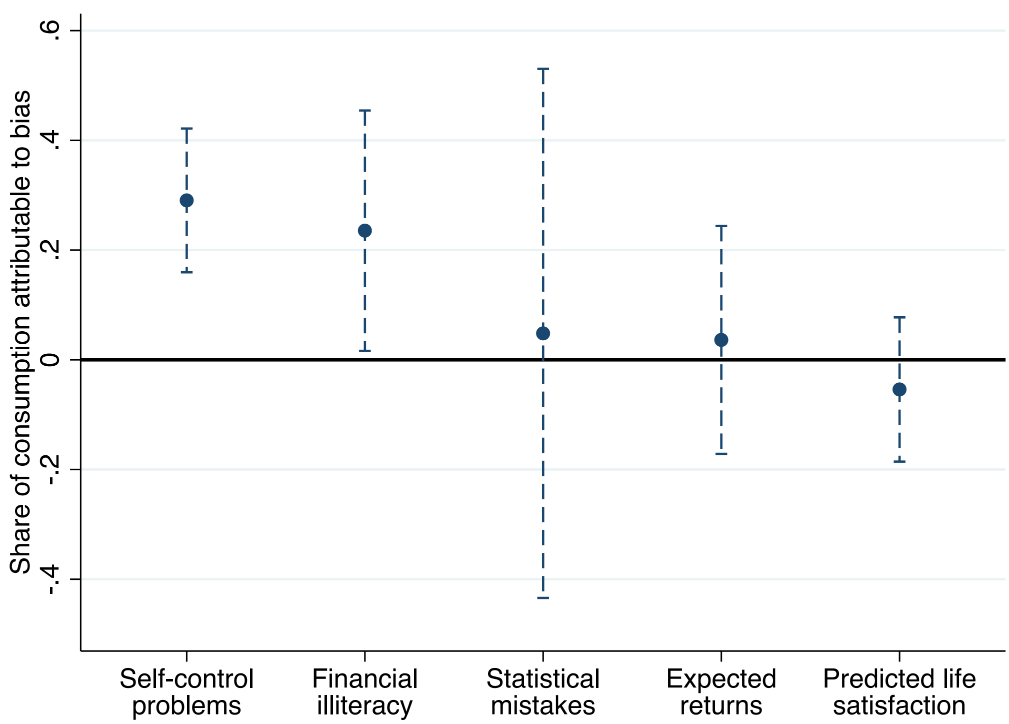
Notes: This table presents first stage estimates of the Obviously Related Instrumental Variables version of equation (16): regressions of 2020 and 2021 bias and preference proxies on 2021 and 2020 bias and preference proxies plus demographic controls and state fixed effects, using data from our AmeriSpeak surveys. “Other demographics” includes age, household size, political ideology, and indicators for male, Black, Hispanic, other (non-white) race, married, employed, urban area, and attends religious services at least once a month. Robust standard errors, clustered by respondent, are in parentheses. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

Table A13: **Association of Income and Bias Proxies with Differences in Reported Lottery Spending**

	(1) Household income ($000s)	(2) Self-control problems	(3) Financial illiteracy	(4) Statistical mistakes	(5) Over-optimism	(6) Expected returns	(7) Predicted life satisfaction
Δ monthly lottery spending	-0.000080	-0.000060	-0.000046	0.000001	0.000225	0.000430	0.000061
	(0.013641)	(0.000865)	(0.000303)	(0.000328)	(0.000290)	(0.000393)	(0.000268)
R^2	0.00	0.00	0.00	0.00	0.00	0.03	0.00
Observations	79	79	79	79	79	79	79

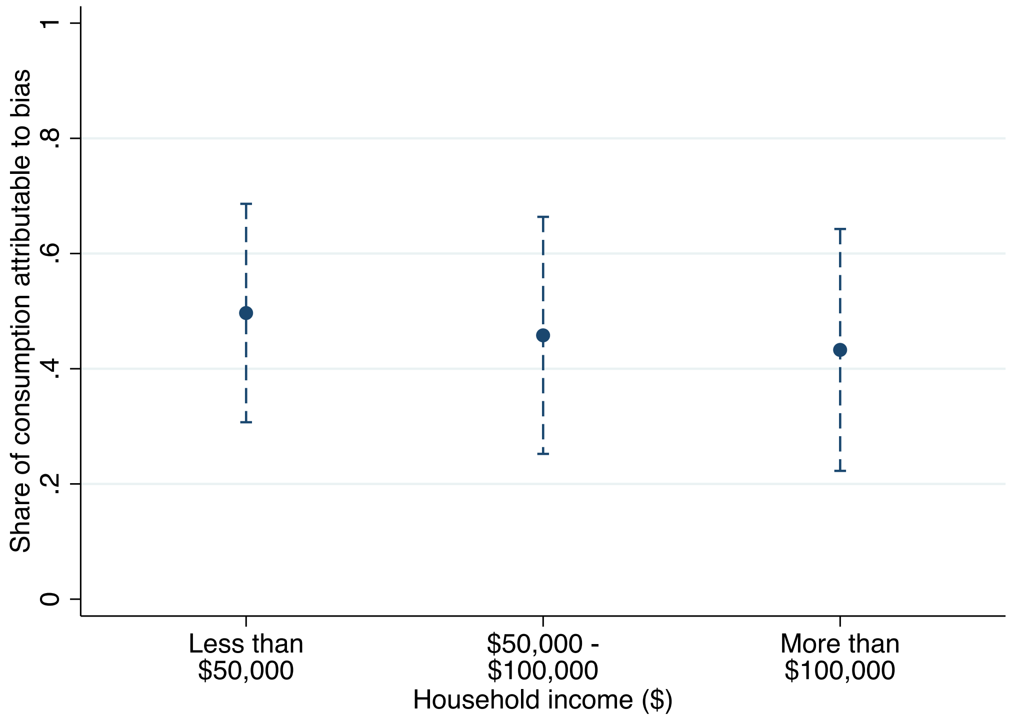
Notes: This table reports the associations of household income and bias proxies with the difference in 2019 *monthly lottery spending* reported on the 2020 vs. 2021 surveys. The sample includes all respondents from whom we re-elicited 2019 *monthly lottery spending* in the 2021 survey, which included only people who had reported spending more than $150 per month or more than 10 percent of their income on lottery tickets in our 2020 survey. Robust standard errors are in parentheses. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

Figure A8: **Share of Lottery Spending Attributable to Biases (Instrumental Variables Estimates)**



Notes: This figure plots the share of lottery spending attributable to each of our six bias proxies, with 95 percent confidence intervals. Predicted unbiased consumption is $\hat{s}^V_{ik} = \frac{s_i+1}{\exp(\hat{\tau}_k \tilde{b}_{ik})} - 1$, where s_i is *monthly lottery spending*, $\hat{\tau}_k$ is the IV estimate from column 6 of Table 6, and $\tilde{b}_{ik} = \frac{b_{ik}-b^V_k}{SD(b_{ik})}$ is the difference between person i's proxy b_{ik} and the unbiased value b^V_k in standard deviation units. We winsorize at $\hat{s}^V_i \geq 0$, and we fix $\hat{s}^V_{ik} = 0$ if $s_i = 0$. The share of consumption attributable to each bias proxy is $\frac{\sum_i (s_i - \hat{s}^V_{ik})}{\sum_i s_i}$.

Figure A9: **Share of Lottery Spending Attributable to Bias within Income Groups (Instrumental Variables Estimates)**



Notes: This figure plots the share of lottery spending attributable to bias within household income groups, with 95 percent confidence intervals. Predicted unbiased consumption is $\hat{s}_i^V = \frac{s_i+1}{\exp(\hat{\boldsymbol{\tau}}\tilde{\boldsymbol{b}}_i)} - 1$, where s_i is *monthly lottery spending*, $\hat{\boldsymbol{\tau}}$ is the IV estimate from column 6 of Table 6, and $\tilde{b}_{ik} = \frac{b_{ik}-b_k^V}{SD(b_{ik})}$ is the difference between person i's proxy b_{ik} and the unbiased value b_k^V in standard deviation units. We winsorize at $\hat{s}_i^V \geq 0$, and we fix $\hat{s}_{ik}^V = 0$ if $s_i = 0$. The share of consumption attributable to bias is $\frac{\sum_i \left(s_i - \hat{s}_i^V\right)}{\sum_i s_i}$.

E.3 Supplemental Survey

We administered a brief survey on the online platform Prolific in June 2021 with a final sample of 200 respondents. We restricted recruitment to respondents with (a) residency in the U.S., (b) at least 15 prior submissions on Prolific, and (c) a prior-submission approval rate of at least 95%. We did not allow respondents to take the survey on a mobile device to maintain the legibility of graphics in the survey. The average respondent took 2.8 minutes to complete the survey and was paid $1.50 for their participation.

The survey proceeded in the following steps. First, respondents consented to participate in the survey and entered their unique identifier used for anonymous compensation and communication on the platform. They then answered a set of four questions in which they expressed whether they would hypothetically prefer to receive a smaller certain dollar amount or a chance of receiving a larger dollar amount. Specifically, we asked whether they would prefer (i) $110 for sure or a 50% chance of $200, (ii) $210 for sure or a 50% chance of $400, (iii) $110 million for sure or a 50%

chance of \$200 million, and (iv) \$210 million or a 50% chance of \$400 million. The order in which the four questions were presented was randomized at the respondent level.

Next, we provided respondents with information about a Mega Millions drawing. We informed them that the cost of a Mega Millions ticket is \$2 and displayed a graphic stating that the next estimated jackpot was valued at \$252 million, with a cash option of \$153.9 million. We then displayed another graphic explaining how Mega Millions is played, the fixed lower prize amounts, and the odds of winning at each prize level as well as overall. We elicited respondents' hypothetical WTP for a ticket in the Mega Millions drawing we described.

Finally, we collected standard demographic information from respondents and asked whether they had purchased any lottery games with prize drawings (i.e., "any lottery game in which you pick numbers and win if you match the numbers from a drawing") in the past 12 months. The survey concluded with a request for feedback before redirecting respondents back to the Prolific platform. We excluded 20 respondents because of implausible WTP values of $\geq$ \$50 that seem more consistent with inattention. These high-WTP respondents were just as risk-averse in all of the binary gamble decisions as the subjects in our main sample, which is internally inconsistent behavior that is highly suggestive of these high-WTP responses being "noise."

F Details of Structural Estimation

F.1 Calibration of Lower-Prize Decision Weights and Comparison to Standard Probability Weighting Functions

As we discuss in Section 5.1, we can compute estimates of the jackpot and second-prize decision weights Φ_1 and Φ_2 without parametric assumptions on the shape of decision weights. Because we lack prize variation to identify semi-elasticities and thus decision weights at lower prize levels, we impose additional assumptions about their shape. In this appendix we therefore consider a variety of standard parameterizations proposed previously in the literature on prospect theory and probability weighting.

Because our elasticity estimates are measured at the population level, this calibration considers representative agent calibrations, and we therefore omit the dependence on type θ. We consider the four common probability weighting function parameterizations discussed in Wakker's (2010) textbook treatment (see Section 7.2: "Parametric Forms of Weighting Functions"), and Fehr-Duda and Epper (2012). These are applied cumulatively as proposed in Tversky and Kahneman (1992), so that the decision weight on the jackpot is $\mathcal{W}(\pi_1)$, the weight on the second prize is $\mathcal{W}(\pi_1 + \pi_2) - \mathcal{W}(\pi_1)$, and more generally,

$$\Phi_k = \mathcal{W}\left(\sum_{j=1}^{k} \pi_j\right) - \mathcal{W}\left(\sum_{j=1}^{k-1} \pi_j\right). \tag{34}$$

The four candidate parameterizations are:

- Tversky and Kahneman (1992):

$$\mathcal{W}(\pi) = \frac{\pi^b}{\left(\pi^b + (1-\pi)^b\right)^{1/b}} \tag{35}$$

- Goldstein and Einhorn (1987):

$$\mathcal{W}(\pi) = \frac{a\pi^b}{a\pi^b + (1-\pi)^b} \tag{36}$$

- Prelec (1998):

$$\mathcal{W}(\pi) = \left(\exp\left(-\left(-\ln(\pi)\right)^a\right)\right)^b \tag{37}$$

Finally, we consider the "neo-additive" form studied in Chateauneuf, Eichberger, and Grant (2007), which states that a non-degenerate lottery with at least two possible outcomes is evaluated as

$$\begin{aligned} &(1-\delta)\sum_k \pi_k m(w_k) \\ &+\delta\alpha \min\{m(w_k)\} \\ &+\delta(1-\alpha)\max\{m(w_k)\} \end{aligned} \tag{38}$$

where the second line captures additional weight placed on the worst outcome while the third line captures additional weight placed on the best outcome. In our application, the worst-case outcome is a payoff of zero, with $m(0) = 0$. When applied to a fixed set of probabilities with distinct outcomes, this neo-additive specification implies a particularly simple formulation for decision weights:

$$\Phi_k = \begin{cases} b_0 + b_1\pi_1 & \text{if } k = 1 \\ b_1\pi_k & \text{if } k > 1 \end{cases} \tag{39}$$

where $b_1 = 1 - \delta$ and $b_0 = \delta(1-\alpha)$ in terms of the parameterization in (38). The decision weights are endogenous to the prize rankings. For example, if the jackpot with initial probability of π_1 and size w_1 was split into two prizes, each occurring with probability $\pi_1/2$ and each of size w_1, then the formulation in (38) implies that the weight on the two prizes *combined* would stay at $b_0 + b_1\pi_1$. Similarly, if the jackpot is split into two prizes of probability $\pi_1/2$ each, but with sizes $w_1$and $w_1 - \varepsilon$, respectively, then then the formulation in (38) implies that the weight on the slightly larger prize of size w_1 would be $\delta(1-\alpha) + (1-\delta)\pi_1/2$ while the weight on the slightly smaller prize of size $w_1 - \varepsilon$ would be $(1-\delta)\pi_1/2$, so that the sum of the weights is still $\delta(1-\alpha) + (1-\delta)\pi_1 = b_0 + b_1\pi_1$.

Each of the first three specifications features a continuous "inverse S-shape" on the interval $[0, 1]$. Figure A10, Panel (a), illustrates this shape, plotting the Tversky and Kahneman (1992) and Prelec (1998) specifications for parameter values previously estimated in the literature, in solid blue and red.[33] (The other displayed parameterizations will be described below.) Panel (b) is constructed by zooming in on the bottom left corner of Panel (a), in order to display the behavior of these parameterizations across the very low probabilities relevant for top lottery prizes; the solid red and blue lines rise so steeply from zero that they are indistinguishable from the vertical axis.

To assess the ability of these functional forms to fit our empirical estimates, our starting point is equation (5) from the text:

$$\frac{\zeta_k}{|\zeta_p|} = \frac{\Phi_k}{\pi_k} m'(w_k). \tag{40}$$

We can use our semi-elasticity estimates and our specification of $m(\cdot)$ to compute the decision weights Φ_1 and Φ_2 non-parametrically; these correspond to points on the probability weighting function. For this calculation, we use values for π_k and w_k that correspond to a current Powerball ticket (net of income taxes), and we assume $m(\cdot)$ comes from a CRRA utility function, all as described in Section 5.1. Using our price semi-elasticity estimate from Section 3 of $\zeta_p = -0.5150$, and our prize semi-elasticity estimates of $\zeta_1 = 1.7277$ and $\zeta_2 = 0.0837$, which we divide by 1 minus the assumed income tax rate of 0.3 as described in Section 5.1, this calculation implies

$$\frac{\Phi_1}{\pi_1} = 311. \tag{41}$$

and

$$\frac{\Phi_2}{\pi_2} = 0.39. \tag{42}$$

Figure A10b plots the points on the probability weighting function $\mathcal{W}$ implied by these weights, $(\pi_1, \mathcal{W}(\pi_1))$ and $(\pi_2, \mathcal{W}(\pi_2))$.

As discussed in Section 3.2, our estimate of ζ_2 may be affected by the low salience of variation in the second prize in California, with the implication that if the second prize were as heavily advertised as the jackpot, the resulting ζ_2 would be higher. This concern rests on the observation that *variation* in the second prize (in California) lacks salience; there is no reason to suppose that the average *level* of the prize—which is stable across years—is similarly non-salient. Yet the low level of the second prize (relative to the jackpot) provides information about a natural upper bound for the elasticity ζ_2. Put simply: if the "full salience" semi-elasticity ζ_2 were in fact higher than the (observed) full salience jackpot semi-elasticity ζ_1, then lottery administrators could raise demand at zero cost by reallocating the prize pool away from the jackpot and toward the second prize, while holding the total ticket expected value constant. Yet despite frequent format revisions, we generally do not see adjustments in this direction; on the contrary, there is usually a relative reallocation toward a *higher* jackpot expected value relative to the second prize. We interpret this trend as suggestive evidence that the second prize semi-elasticity is weakly lower than the jackpot semi-

[33] The Tversky and Kahneman (1992, p. 312) specification (solid blue) plots the parameterization with $b = 0.61$, the preferred estimate in that paper. The Prelec (1998) specification (solid red) plots the parameterization at preferred values reported in Wakker (2010): "Ongoing empirical research suggests that the parameters $a = 0.65$ and $b = 1.0467$, giving intersection with the diagonal at 0.32, are good parameter choices for gains."

elasticity, and thus we plot an alternative value for $\mathcal{W}(\pi_2)$ in Panel (b) assuming, as a conservative upper bound, that $\zeta_2 = \zeta_1$.

We are interested in the features of probability weighting function parameterizations which can match the plotted points in Panel (b). The most straightforward case is the Tversky and Kahneman (1992) weighting function in equation (35): since this specification has only a single parameter b, there is a unique parameterization which passes through our estimated $\mathcal{W}(\pi_1)$; it is plotted as the dotted blue line. An immediate observation is that due to the steep slope of the dotted blue line across low probabilities, it predicts decision weights at π_2 that are far higher than even our upper bound estimate for $\mathcal{W}(\pi_2)$.

The red dot-dashed line shows how the failure of the Prelec (1998) class of functions is somewhat different. This two-parameter specification actually *can* be adjusted to pass through both our estimates of $\mathcal{W}(\pi_1)$ and $\mathcal{W}(\pi_2)$. (We use the upper bound in Panel (b); the specification passing through the lower point estimate is even more extreme.) Although this specification can technically fit both points, it results in an implausible weighting function beyond these two points. The extreme nature of this specification can be seen by returning to Panel (a), which also plots this specification, demonstrating that it places exceedingly low weights on almost the entire interval [0,1], before rising sharply at high probabilities to reach $\mathcal{W}(1) = 1$. Such a probability weighting function would imply that an agent would be unwilling to pay more than \$1 for a lottery ticket that pays out \$100 with a probability of 90%. This leads us to conclude that the Prelec (1998) specification cannot match our results under conventional parameterizations. The two-parameter Goldstein and Einhorn (1987) parameterization produces results very similar to the Prelec (1998) specification, and we thus omit it to minimize redundancy.

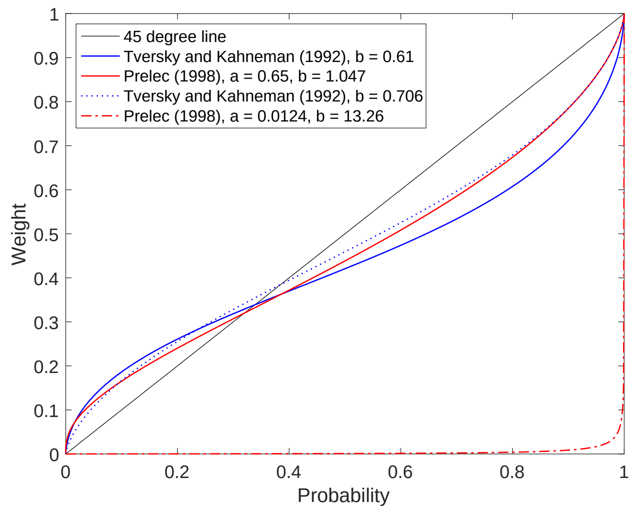
Other papers have found slightly different estimates of the three inverse S-shape functions than the ones reported plotted in Figure A10. See, e.g., also, Camerer and Ho (1994), Wu and Gonzalez (1996), Abdellaoui (2000), and Filiz-Ozbay et al. (2015). However, our arguments above show that none of these slightly different calibrations of the standard inverse S-shape functions can match our semi-elasticity estimates.

Finally, we consider the neo-additive parameterization. This weighting function simply corresponds to a straight line with a positive vertical intercept (at which the probability weighting function is discontinuous) passing through the estimated points for $\mathcal{W}(\pi_1)$ and $\mathcal{W}(\pi_2)$ in Panel (b). As such, it is readily apparent that this specification can easily match either set of points. Yet it is also apparent that although our estimate of $\mathcal{W}(\pi_1)$ provides a tight estimate of the vertical intercept parameter b_0, the uncertainty in our estimate of ζ_2 admits a wide range of potential values for the slope parameter b_1. As we show in our structural simulations, the key implications for optimal lottery design are insensitive to this slope parameter within this wide range of values.

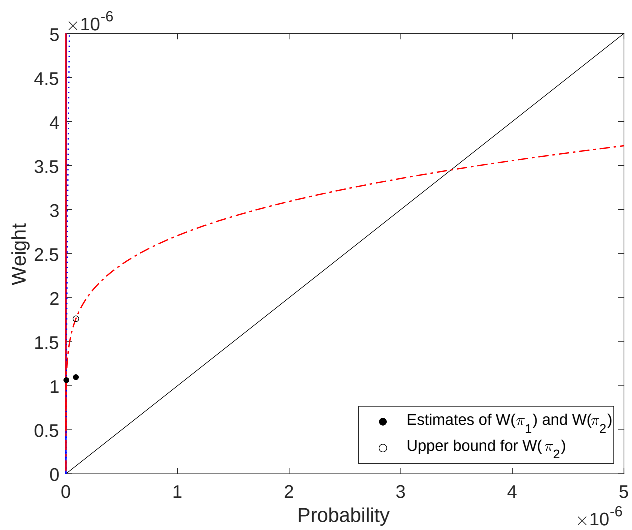
Under our assumption that a constant share $\chi(\theta)$ of the difference between the decision weight and objective probability is due to bias, i.e., $\Phi_k^V(\theta) = \pi_k + (1 - \chi(\theta))(\Phi_k - \pi_k)$, the normative weights Φ_k^V also turn out to have the simple neo-additive form expressed in equation (39) above, with $b_0^V(\theta) = (1-\chi(\theta))b_0(\theta)$ and $b_1^V(\theta) = 1 + (1-\chi(\theta))(b_1(\theta)-1)$.[34]

Figure A10: **Probability Weighting Function Parameterizations**

(a) **Plotted on the Interval [0,1]**



(b) **Plotted Over Small Probabilities**



Notes: These figures plot two common parameterizations of common probably weighting functions. The solid lines correspond to parameter values favored in the prospect theory literature. The dashed lines plot the parameterizations that match one or both of the probability weighting values consistent with our estimated demand elasticities. Panel (a) plots these functions across the full range of probabilities from 0 to 1, while Panel (b) "zooms in" on the bottom left corner of Panel (a), while displaying points motivated by the elasticity estimates from Section 3 (see text for details).

[34] Assuming instead that bias accounts for a constant share of the total decision weight $\Phi_k^V(\theta)$, rather than a constant share of the difference $\Phi_k^V(\theta) - \pi_k$, also produces neo-additive normative weights, with the same $b_0^V(\theta)$ but with $b_1^V(\theta) = (1-\chi(\theta)b_1(\theta)$. This specification produces essentially identical simulation results, which is unsurprising given that the results are not sensitive to assumptions about the bias share on lower prizes, as illustrated by the specification "All bias on jackpot" in Table 8.

F.2 Implementation of Structural Model

This appendix describes implementation details of the structural model described in Section 5. Equations are written as functions of individual types θ, in order to span the heterogeneous agent model.

Equation (4) in the text illustrates that once we have specified decision weights $\Phi_k(\theta)$ and the value function $m(w;\theta)$, the net-of-price certainty equivalent (in brackets) is a sufficient statistic for type θ's lottery demand. That is, any two lotteries with the same net-of-price certainty equivalent will generate the same demand. We will use this feature repeatedly, so it is useful to formally define this "net certainty equivalent":

$$NCE(L;\theta) = \sum_k \Phi_k(\theta) m\left(w_k;\theta\right) - p \tag{43}$$

In what follows, we calibrate the structural model above for a single representative lottery, which we then manipulate to find characteristics of the optimal representative lottery. To describe the model calibration, we proceed in two steps. In Step 1, we demonstrate how this model is exactly identified by the functional form assumptions in Section 5.1 and by estimates for the following type-specific parameters:

- $s(\theta)$: consumption of a representative lottery,
- $s^V(\theta)$: debiased consumption of that representative lottery,
- $\zeta_1(\theta)$, $\zeta_2(\theta)$: semi-elasticities of demand with respect to the expected value of the jackpot and the second prize, generated by (local) variation in the prizes w_1 and w_2 of the representative lottery,
- $\zeta_p(\theta)$: semi-elasticity of demand with respect to a price change in the representative lottery,
- $y(\theta)$: individual expected continuation wealth,
- $g(\theta)$: welfare weights.

In Step 2, we describe how we translate our empirical estimates into the necessary estimates of $\left\{s(\theta), s^V(\theta), \zeta_p(\theta), \zeta_1(\theta), \zeta_2(\theta), y(\theta), g(\theta)\right\}$ above, for each representative agent θ in a discretized grid of types Θ.

Step 1: Model Identification

Value function. We assume that agents have a concave utility function over continuation wealth W with a constant coefficient of relative risk aversion (CRRA) η:

$$\mathcal{U}(W) = \begin{cases} \ln(W) & \text{if } \eta = 1 \\ \frac{W^{1-\eta}-1}{1-\eta} & \text{if } \eta \neq 1 \end{cases} \tag{44}$$

See Appendix F.4 below for a discussion of this choice. Our value function $m(w;\theta)$ corresponds to the utility *gain* from winning a prize w, normalized by one's local marginal utility of wealth, so that the decision-weighted gain can be expressed in dollars. For an agent whose non-prize continuation wealth is $y(\theta)$, this value function can be written

$$m(w;\theta) = \frac{\mathcal{U}(y(\theta)+w) - \mathcal{U}(y(\theta))}{\mathcal{U}'(y(\theta))} \tag{45}$$

$$= \begin{cases} \frac{\ln(y(\theta)+w) - \ln y(\theta)}{y(\theta)^{-1}} & \text{if } \eta = 1 \\ \frac{\frac{1}{1-\eta}\left((y(\theta)+w)^{1-\eta} - y(\theta)^{1-\eta}\right)}{y(\theta)^{-\eta}} & \text{if } \eta \neq 1 \end{cases} \tag{46}$$

$$= \begin{cases} y(\theta) \ln\left(\frac{y(\theta)+w}{y(\theta)}\right) & \text{if } \eta = 1 \\ \frac{y(\theta)}{1-\eta}\left(\left(\frac{y(\theta)+w}{y(\theta)}\right)^{1-\eta} - 1\right) & \text{if } \eta \neq 1 \end{cases} \tag{47}$$

We can also compute the derivative, which proves useful for the calibrations below:

$$m'(w;\theta) = \frac{\mathcal{U}'(y(\theta)+w)}{\mathcal{U}'(y(\theta))} = \left(\frac{y(\theta)}{y(\theta)+w}\right)^{\eta}. \tag{48}$$

Decision weights. To identify decision weights, we can exploit the insight formalized in equation (5) from the text: decision weights imply a relationship between the relative responsiveness of demand to prices and prizes, quantified empirically by our estimates of ζ_p and ζ_k. Intuitively, if demand reacts more strongly to variation in the size of the jackpot expected value than to a change in ticket price (as we find), that is evidence of a high decision weight Φ_1 on the jackpot. Formally, substituting equation (39), with $k = 1$ and $k = 2$, into equation (5) gives two equations which identify the parameters of the neo-additive decision weighting function $b_0(\theta)$ and $b_1(\theta)$ from type-specific estimates of $\zeta_1(\theta)$, $\zeta_2(\theta)$, and $\zeta_p(\theta)$:

$$\frac{\zeta_1(\theta)}{|\zeta_p(\theta)|} = \frac{b_0(\theta) + b_1(\theta)\pi_1}{\pi_1} m'(w_1;\theta) \;\Rightarrow\; b_0(\theta) = \left(\frac{\zeta_1(\theta)}{|\zeta_p(\theta)|}\frac{1}{m'(w_1;\theta)} - b_1(\theta)\right)\pi_1 \tag{49}$$

$$\frac{\zeta_2(\theta)}{|\zeta_p(\theta)|} = \frac{b_1(\theta)\pi_2}{\pi_2} m'(w_2;\theta) \;\Rightarrow\; b_1(\theta) = \frac{\zeta_2(\theta)}{|\zeta_p(\theta)|}\frac{1}{m'(w_2;\theta)} \tag{50}$$

By first computing b_1 and then b_0, we can compute these parameters. Cumulatively applying these decision weights as in Chateauneuf, Eichberger, and Grant (2007), these parameters fully identify the certainty equivalent,

$$\sum_k \Phi_k(\theta) m\left(w_k;\theta\right) = b_0(\theta) m\left(w_1;\theta\right) + b_1(\theta)\sum_k \pi_k m\left(w_k;\theta\right), \tag{51}$$

and they thus fully specify the net certainty equivalent function in equation (43).

Preference shocks. Equations (3) and (4) imply that the preference shock distribution $F_{\varepsilon|\theta}$ is equivalent to specifying a $\mathbb{R} \rightarrow \mathbb{R}^+$ function mapping $NCE(L;\theta)$ to demand s, which we denote

$$S(NCE;\theta) = F_{\varepsilon|\theta}\left[NCE\right].$$

Rather than characterizing $F_{\varepsilon|\theta}$ directly, we directly characterize the function $S(NCE;\theta)$, which implicitly defines $F_{\varepsilon|\theta}$. Here we employ a simple structural assumption: that the semi-elasticity of demand is constant with respect to changes in NCE, and thus also in price. This assumption has two appealing features. First, it generates plausible patterns of demand across the range of variation in our data, in ways that other constant elasticity and semi-elasticity assumptions do not; see Figure A11 for plots of the structural predictions of both observed demand (thick lines) and latent debiased demand (thin lines) across variation in price and jackpot expected value for each type in our model. Second, this assumption implies that the hypothetical change in price required to induce a debiased consumer to purchase the observed (biased) quantity remains constant across changes in price and jackpot expected value. That hypothetical price change is equal to the money-metric bias γ—which plays an important role in our optimal policy formulas—and thus by using this specification for demand, we ensure that our results are not driven by changes in bias which are generated by structural functional form assumptions.

To compute demand for an arbitrary lottery L, we first compute the difference in net certainty equivalent from the status quo lottery L^0,

$$\Delta NCE(\theta) = NCE(L;\theta) - NCE(L^0;\theta). \tag{52}$$

We then compute demand as

$$S(NCE;\theta) = s(\theta) \cdot \exp\left(|\zeta_p(\theta)| \cdot \Delta NCE\right). \tag{53}$$

Bias. To calibrate bias, and thus *normative* (debiased) demand, we assume that a constant share χ of the difference $\Phi_k - \pi_k$, i.e., the difference between decision weights and expected utility maximization, is driven by behavioral biases. Therefore we compute the $\chi(\theta)$ for each agent that would rationalize a given debiased level of demand $\ln s^V(\theta)$. To do this, note that we can write the "debiased certainty equivalent" for lottery L as a function of the bias share $\chi(\theta)$:

$$NCE^V(L,\chi(\theta);\theta) := \sum_k \left(\pi_k + \left(\Phi_k(\theta) - \pi_k\right)\left(1 - \chi(\theta)\right)\right) m\left(w_k;\theta\right) - p$$

Using the estimate of debiased demand for the baseline lottery, $s^V(\theta)$, we thus compute the bias share $\chi(\theta)$ for each type that satisfies

$$s^V(\theta) = S(NCE^V(L^0, \chi(\theta))).$$

Having thus identified $\chi(\theta)$, we can then compute normative demand for an arbitrary lottery L as $S(NCE^V(L, \chi(\theta); \theta); \theta)$.

Welfare. To compute consumer surplus, and thus welfare, it suffices to show how welfare is computed for a given type; it is straightforward to aggregate across types by weighting these changes by the welfare weights $g(\theta)$. Here we can make use of the fact that surplus can be measured as the integral under the Hicksian demand curve, from the point where the quantity demanded is equal to zero. In this model, there are no income effects, and therefore the Hicksian demand curve is found simply by varying p in the demand curve we have already derived: $S(\sum_k \Phi_k(\theta) m(w_k; \theta) - p; \theta)$. Therefore we can compute surplus by integrating under this demand curve from the price at which demand is zero up to the actual price. And since NCE varies one-for-one with price, this is equivalent to integrating under S from the NCE at which demand is zero. Here we impose the assumption that quantity demanded falls to zero when $NCE = 0$, reflecting that we do not expect positive demand for a lottery that has a price of zero and prizes of zero. Then the integral under the Hicksian demand curve reflecting welfare from a given lottery L is identical to the integral $\int_{x=0}^{NCE(L;\theta)} S(x; \theta) dx$. This provides the perceived utility surplus, based on consumers' willingness to pay for lottery tickets. To compute normative utility, we subtract the bias costs $\chi(\theta) \sum_k (\Phi_k - \pi_k) m(w_k)$ from perceived utility.

Step 2: Estimation of Input Parameters

We now describe how we translate our reduced-form empirical results from Sections 3 and 4 into the parameters $s(\theta)$, $s^V(\theta)$, $\zeta_p(\theta)$, $\zeta_1(\theta)$, $\zeta_2(\theta)$, $y(\theta)$, and $g(\theta)$ which identify the model.

We assume a baseline CRRA parameter of $\eta = 1$, corresponding to log utility of continuation wealth.

To translate our empirical estimates into the context of this model with a single representative lottery game, we abstract from the diversity of games in the data and assume that our empirical estimates (of demand, elasticities, and the other statistics described below) align with those that would arise from a single lottery game with average attributes. Specifically, we specify a "representative lottery" with the features of a current Powerball lottery ticket described in Table 1, with a price of \$2 per ticket and a jackpot pool equal to the empirical average of \$101 million. To account for administration and overhead costs, which are typically between 5% and 15% of total lottery revenues in the U.S., we assume each lottery ticket has an additional cost of \$0.20 (see panel (b) of Appendix Figure A1).

To extend this approach to our heterogeneous agent specification, we then specify a discretized type space. This specification employs nine types, corresponding to the three income bins displayed in Figure 4, with three partitions of agents within each income bin. A share of agents purchase no lottery tickets (we assume these agents are expected utility maximizers, for whom $\Phi_k(\theta) = \pi_k$, implying that their demand is zero for any lottery with a price greater than expected value), while the remaining lottery purchasers are partitioned into two groups—above- and below-median consumers—at each income level. Population shares and type-specific averages are computed within each partition of the type space.

We calibrate type-specific estimates of $s(\theta)$, $s^V(\theta)$, $y(\theta)$, and $g(\theta)$ as follows. We draw our estimates of lottery consumption in the status quo, $s(\theta)$, directly from the reported expenditures in our survey, reported in Figure 4. To calibrate debiased consumption $s^V(\theta)$, we interpret the share of consumption attributable to bias (as estimated in Section 4.3) as the *causal* effect of bias. Thus for each individual, we reduce their reported level of consumption by their estimated quantity effect of bias to arrive at a debiased consumption, which we average within each partition of the type space to reach $s^V(\theta)$. To compute net continuation wealth $y(\theta)$, we compute the average reported income (according to our survey) within each partition of the type space. We then convert this into a measure of net (of tax) income $c(\theta)$ using the mapping between gross and net income from Piketty, Saez, and Zucman (2018). To arrive at continuation wealth, we multiple each type's net income by 20, to coarsely represent expected wealth accounting for future earnings for a representative worker. Following Saez (2002b), we set welfare weights proportional to $c(\theta)^{-\nu}$, with $\nu = 1$ in our baseline specifications, and with robustness checks for $\nu = 0.25$ and $\nu = 4$.

Our estimates of semi-elasticities with respect to price and the jackpot and second prizes, presented in Sections 3.2 and 3.3, rely on population data, and are not estimated separately across individuals. We assume these elasticities are homogeneous, with $\zeta_p(\theta) = \bar{\zeta}_p$ for each θ, etc. (It is straightforward to extend this model to data with heterogeneous elasticity estimates, as they would simply affect the values of $b_0(\theta)$ and $b_1(\theta)$ identified by equations (49) and (50) above.) We divide prize elasticities by one minus the assumed income tax rate of 30%, to convert these into elasticities with respect to the net-of-tax prize in the model.

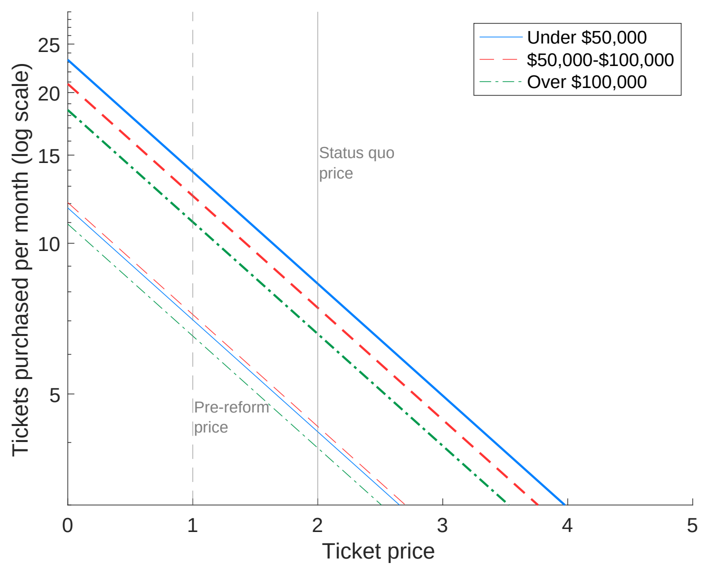
This completes the description of the structural model calibration. Figure A11 illustrates the behavior of the structural demand model, plotting average simulated monthly demand for lottery tickets in each income bin in response to variation in the price and the jackpot of the representative lottery. Thin lines plot the latent "debiased" demand from each type. Several identifying features of the model are apparent from these plots. The status quo price and jackpot expected value for the baseline representative lottery ticket are displayed as vertical lines, and the plotted demand curves intersect these status quo values at the quantities corresponding to the expenditure levels in each income bin from Figure 4. (Since the representative ticket price is \$2, these quantities are equal to half the level of dollar expenditures.)

The vertical axis of both plots is displayed with a log scale, so that a constant semi-elasticity of demand with respect to price appears as a constant slope in Panel (a). Our estimate of ζ_p therefore controls the slope of these demand curves, which is assumed to be constant across groups.

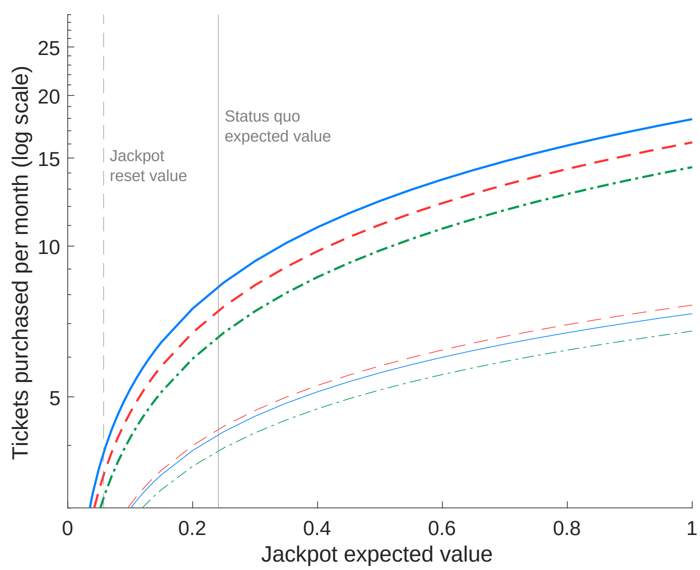
A ticket price of \$1 is shown with a dashed line—this depicts the discretely different price at which demand is measured prior to the Mega Millions and Powerball price changes described in Table 1. The model is calibrated so that the difference in demand at the price of \$1 vs. the status quo price of \$2 corresponds to our empirical estimate of ζ_p. Perceived surplus in the status quo can be understood as the integral under the demand curves in Panel (a) from the status quo price rightward, to the point where the net certainty equivalent falls to zero.

Figure A11: **Simulated Purchases and Expenditures by Income Bin**

(a) **Tickets Purchased varying Price**



(b) **Tickets Purchased varying Jackpot Size**



Notes: This figure plots the simulated average number of tickets purchased in each of three income bins from our structural model, across different values of the representative lottery ticket price and jackpot. Ticket purchases are plotted on a log scale, so that Panel (b) illustrates the structural assumption of a constant semi-elasticity of demand with respect to jackpot expected value across the range of jackpot values in our data. Latent demand that would obtain if consumers were counterfactually debiased is plotted with thin lines. (See the discussion in Section 5.1 and Appendix F.2 for additional details.)

F.3 The Role of Prize Splitting in the Structural Model

As we explain in Section 3.1, the possibility of prize splitting serves to dilute the effect of prize variation on the prize's expected value. In order to estimate the prize semi-elasticity with respect to the actual jackpot and second-prize expected value, we therefore reduce prizes (and thus inflate the estimated prize semi-elasticities) by a factor that accounts for the expected risk of splitting. Although this is the correct approach for computing semi-elasticities with respect to expected value, this raises the question of how best to handle the issue of prize splitting when calibrating our structural model.

To explore this question, suppose for simplicity that there is a probability κ that the jackpot w_1 is unsplit, and a residual probability $1-\kappa$ that it is shared equally with one other winner. Accounting for the possibility of splitting, the jackpot effectively represents two different potential prizes of sizes w_1 and $w_1/2$ with probabilities $\kappa\pi_1$ and $(1-\kappa)\pi_1$, respectively, and with associated decision weights $\Phi_{1,\text{unsplit}}$ and $\Phi_{1,\text{split}}$. Assuming that decision weights fit the neo-additive specification consistent with our empirical findings, we can write these decision weights in terms of the neo-additive parameters b_0 and b_1, so that the consumer's utility from the jackpot component of the lottery is

$$\Phi_{1,\text{unsplit}} m(w_1) + \Phi_{1,\text{split}} m(w_1/2) = (b_0 + b_1\kappa\pi) m(w_1) + b_1(1-\kappa)\pi m(w_1/2).$$

Differentiating this expression with respect to w_1 produces the effect on utility of a marginal change in the size of the jackpot:

$$\begin{aligned}\frac{d}{dw_1}\left[\Phi_{1,\text{unsplit}} m(w_1) + \Phi_{1,\text{split}} m(w_1/2)\right] &= b_0 m'(w_1) + b_1\pi_1\left(\kappa m'(w_1) + (1-\kappa)\frac{m'(w_1/2)}{2}\right)\\ &= \frac{1}{m'(w_1)}\left[b_0 + b_1\pi_1\left(\kappa + (1-\kappa)\frac{m'(w_1/2)}{2m'(w_1)}\right)\right]\end{aligned}$$

As we show in Appendix F.2, when consumers have logarithmic utility over continuation wealth, we have $m'(w) = \frac{y}{y+w}$, where y is non-prize continuation wealth. In this case, $\frac{m'(w_1/2)}{2m'(w_1)} = \frac{1}{2}\cdot\frac{y+w_1}{y+w_1/2}$, so when the prize w_1 is much larger than non-prize wealth, i.e., when $y/w_1 \approx 0$, this term is approximately equal to one, so the the above expression reduces to

$$\frac{d}{dw_1}\left[\Phi_{1,\text{unsplit}} m(w_1) + \Phi_{1,\text{split}} m(w_1/2)\right] \approx \frac{1}{m'(w_1)}\left[b_0 + b_1\pi_1\right].$$

This is the same effect on utility that we find if we ignore the possibility of prize splitting altogether.

More generally, the calculations in Appendix F.2 show that when utility has a constant coefficient of relative risk aversion η, $\frac{m'(w_1/2)}{2m'(w_1)} = 2^{\eta-1}$, which shows that the approximation we suggest above is valid for η in a neighborhood of 1, which Appendix F.4 shows is the range of values consistent with our data. For the empirically reasonable splitting risk $\kappa = 0.9$, the approximation is not very sensitive to assumptions about η: the term $\kappa + (1-\kappa)\frac{m'(w_1/2)}{2m'(w_1)}$ equals 0.97 when $\eta = 0.5$, it equals 1 when $\eta = 1$, and equals 1.04 when $\eta = 1.5$.

Intuitively, this equivalence arises because under neo-additive decision weights, consumers place an extra weight b_0 on the largest prize, and because this weight does not depend on the probability of winning, it is unaffected by the risk of splitting. They additionally place weight b_1 on the expected value of the prize. Under prize splitting, the monetary gain from a larger jackpot is halved if the prize is split, but in that outcome the marginal utility of the winnings is correspondingly doubled (under logarithmic utility), due to the lower level of the prize. As a result, the total effect on utility, and thus the effect on demand, is the same as in the case where no splitting occurs. This insight suggests that for the purposes of our structural model, we should not impose the adjustment factor mentioned in Section 3.1. As a result, when calibrating the structural model, we do not adjust the jackpot and estimated semi-elasticities by the adjustment factor.

F.4 Curvature of m

The robust stylized fact, first postulated as part of the "fourfold pattern of risk attitudes" by Tversky and Kahneman (1992), is that individuals are risk-seeking over low-probability gains, but risk-averse over moderate to high probability gains. This pattern is consistent with typical probability weighting functions, but not with convex utility functions. To illustrate, we conducted a supplementary survey with 200 subjects, summarized in Appendix E.3. In this survey, subjects could choose between a certain prize and an option with a 50 percent chance of a higher prize that yielded slightly lower expected value than the certain option; thus, choosing the risky option implies risk-seeking preferences. We find that for gambles on the order of hundreds of dollars, 12 percent of respondents chose the risky option (13 percent among those who purchased a lotto ticket in the past 12 months), while for gambles on the order of hundreds of millions of dollars, 2 percent of respondents chose the risky option (6 percent among those who purchased a lotto ticket in the past 12 months). These results are consistent with the fourfold pattern of risk attitudes, and inconsistent with the convexity conjecture of Friedman and Savage (1948).

In our model, the CRRA parameter shapes WTP for lottery tickets. With more curvature, the value function $m(w)$ is less sensitive to variation in the jackpot, requiring a higher decision weight Φ_1 to rationalize our empirical estimates of $\hat{\hat{\zeta}}_1$. This implies more utility from the jackpot and a higher WTP. CRRA values below 0.9 imply low WTP for the representative lottery ticket, to the point that if the jackpot declines to the Powerball jackpot reset value, demand falls to zero. In our baseline specification with CRRA=1, individuals' average WTP for the representative lottery ticket conditional on purchase—which must be higher than the \$2 ticket price—is \$3.38. On the other hand, a CRRA value of 1.5 implies a higher WTP of \$3.93 for each purchased ticket. In the 200-subject supplementary survey described in Appendix E.3, we find that for a Mega Millions lottery with a \$250 million jackpot, participants have a mean and median WTP of \$6.11 (with 95 percent confidence interval $(\$5.25, \$6.97)$) and \$4.00, respectively. The mean and median WTP among those who have purchased a lotto ticket in the last 12 months are similar: \$6.22 (with 95 percent confidence interval $(\$4.52, \$7.92)$) and \$4.00, respectively. These estimates are in the ballpark of our model's predictions in our considered range of CRRA parameters, and reinforce our claim that alternative assumptions deliver implausible predictions about WTP for lottery tickets.

G Optimal Policy from Sufficient Statistics Formulas

From Proposition 1, under the optimal policy the lottery ticket's markup over the marginal cost is $\bar{\gamma}(1+\sigma) - Cov\left[g(\theta), s(\theta)\right]/|\bar{\zeta}_p|\bar{s}$. We can rearrange this to give an expression for the optimal lottery ticket price, into which we can substitute estimates for each of the embedded statistics—computed in the status quo—to get an approximation for the optimal price, provided that these statistics do not change very much between our observed economy and the optimum:

$$p = \bar{\gamma}(1+\sigma) - \frac{Cov\left[g(\theta), s(\theta)\right]}{|\bar{\zeta}_p|\bar{s}} + \sum_k \pi_k w_k + o \tag{54}$$

$$= 1.12(1+0.11) - \frac{0.34}{|-0.5150| \times 7.64} + 0.44 + 0.2 \tag{55}$$

$$\approx 1.80. \tag{56}$$

The first term on the right-hand side of equation (54) is the bias-correction term. We can approximate money-metric bias $\gamma(\theta)$ using our survey data from Section 4.3: we divide each individual's amount of consumption attributable to bias by our estimated price semi-elasticity of demand, $\gamma_i = \hat{\boldsymbol{\tau}}\tilde{\boldsymbol{b}}_i/|\bar{\zeta}_p|$. For example, if bias increases consumption by 60 percent and a \$1 price increase reduces consumption by 30 percent, then bias would be $\gamma_i = 60\%/(30\%/\$1) = \$2$. ALT formalizes this approach. This implies an average marginal bias of $\bar{\gamma} \approx \$1.12$ per ticket.[35] To estimate the progressivity of bias correction σ, we combine the bias estimates with each individual's welfare weight $g(z)$, computed as described in Section 5.1. This gives $\sigma = 0.11$, reflecting the higher bias among lower-income individuals.

The second term, $-\frac{Cov[g(\theta),s(\theta)]}{|\bar{\zeta}_p|\bar{s}}$, quantifies the optimal price reduction due to redistributive concerns. Since lottery spending doesn't decline much with income, this covariance is small. We can use this term to quantify the importance of causal income effects. Our two estimates of causal income elasticities from Appendix Table A11 suggest that either 82 percent or 275 percent of the downward slope in lottery spending across incomes is attributable to income-correlated preference heterogeneity, rather than causal income effects.[36] Assuming that these percentages are constant

[35] Specifically, we assume a homogeneous price semi-elasticity, so that $\bar{\gamma} = \frac{\mathbb{E}[\gamma(\theta)\bar{\zeta}_p s(\theta)]}{\bar{\zeta}_p \bar{s}}$. To align with the approach in the structural model and to limit the effect of extreme outliers, we compute this and the other statistics in this section by first collapsing our data into the three levels of income and three income-conditional levels of consumption (non-consumers, below-median, and above-median) and then compute population-weighted averages and covariances. Our survey measures expenditures, which must be converted into a measure of quantity $s(\theta)$ to compute the covariances in equation (54); we use $p = \$2$. The covariance terms in which $s(\theta)$ appears are divided by the mean of $s(\theta)$, so the results are insensitive to the price used for this conversion. By the same token, although these results are computed using total lotto spending for $s(\theta)$, they are not sensitive to instead using just spending on Powerball, since that effectively amounts to rescaling the numerator and denominator in equation (54) by the same factor.

[36] Causal income effects plus between-income preference heterogeneity must sum to the observed cross-sectional profile of spending in Figure 4. Thus our causal income elasticity of -0.02 accounts for 18 percent of the cross-sectional income elasticity (-0.111) reported in Appendix Table A11, implying that the remaining 82 percent is attributable to preference heterogeneity. Our alternative causal income elasticity of 0.194 suggests that causal income effects have

across the income distribution, Proposition C1 in Appendix C shows that to account for causal income effects, we should rescale $Cov\left[g(\theta), s(\theta)\right]$ by either 0.82 or 2.75 in the optimal price formula. But because $Cov\left[g(z), s(z)\right]$ is small, these adjustments would change the optimal price by less than \$0.15.

The final two terms in equation (54) reflect the lottery ticket's marginal cost. $\sum_k \pi_k w_k$ is the net-of-income-tax expected payout of prizes, which we set to reflect the current Powerball format in Table 1, reduced by the 30 percent income tax rate. o is the overhead cost, which we assume is 10 percent of the current \$2 price, following the discussion in Section 1.

This calculation gives an optimal price of \$1.80, which is close to the current Powerball ticket price of \$2. The estimate of money-metric bias matters a lot for the optimal price: the corrective term $\bar{\gamma}(1+\sigma)$ is about \$1.20, and so the optimal ticket price would be significantly lower in the absence of bias.

Similarly, we can use Proposition 1 to estimate the optimal jackpot amount. We rearrange equation (11) to isolate the jackpot expected value from the summation on the left-hand side, and we use the fact that the average cost of a ticket rises one-for-one with a change in the jackpot expected value, implying $\frac{\partial C}{\partial a} = \bar{s}$, where $a = \pi_1 w_1$ is the jackpot expected value. This gives the following result:

$$\pi_1 w_1 = -\bar{\gamma}(1+\sigma_1) + \frac{\bar{\kappa} - \bar{\rho} + Cov\left[g(\theta), \kappa(\theta) - \rho(\theta)\right] - \bar{s}}{\bar{\zeta}_1 \bar{s}} + p - \sum_{k=2}^{K} \pi_k w_k - o \tag{57}$$

$$= -1.12(1+0.11) + \frac{36.61 - 20.57 + (-0.61) - 7.64}{2.47 \times 7.64} + 2 - 0.22 - 0.2 \tag{58}$$

$$\approx 0.75. \tag{59}$$

The key new terms for this calculation are $\bar{\kappa}$, the average monthly willingness-to-pay to increase the jackpot expected value by \$1 (through an increase in the prize, w_1), and $\bar{\rho}$, the average portion of that WTP that is driven by bias. From Section 2.4, $\bar{\kappa} = -\bar{\zeta}_1/\bar{\zeta}_p \cdot \bar{s} = \$36.61$ per month. To estimate $\bar{\rho}$, we assume that the normative share of WTP for a higher jackpot is equal to $(p-\gamma)/p$, i.e., the normative share of WTP for a lottery ticket for the marginal consumer. This average normative share among lottery purchasers is 0.75, and the average normative WTP for a higher jackpot is $\bar{\rho} \approx \$20.57$ per month. $\bar{\gamma}$ and σ are computed as before, but weighting individuals by demand responses to jackpot expected value changes, rather than price changes.[37] $\bar{\zeta}_1$ is the net-of-tax jackpot semi-elasticity, computed as our estimate of the jackpot semi-elasticity from column 2 of Table 3a divided by one minus the income tax rate.

Using these values to compute equation (58), the optimal net-of-tax jackpot expected value is \$0.75, higher than Powerball's current average net-of-tax jackpot expected value of \$0.22.

the opposite sign of the cross-sectional profile—i.e., lotteries are a normal good—implying that the preference for lotteries is declining steeply enough with income as to more-than-offset the positive causal income effects.

[37] Specifically, we assume a homogeneous prize semi-elasticity, so that $\bar{\gamma} = \frac{\mathbb{E}[\gamma_i \bar{\zeta}_1 s_i]}{\bar{\zeta}_1 \bar{s}}$.