The Optimal Taxation of Lotteries

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Abstract

The average American household spends $665 per year playing state-run lottery games. There is a long-standing debate as to whether these lotteries are a regressive "tax on people who are bad at math" or a "win-win" that generates both consumer surplus and government revenues. We study optimal lottery policy through the lens of optimal taxation, where lotteries are a taxed good whose consumers may be subject to behavioral biases. We derive new sufficient statistics formulas for optimal pricing and attributes of a government-provided good. We then estimate the key parameters using lottery prizes and sales data and a large new nationally representative survey. Individual-level lottery spending is highly correlated with survey measures of innumeracy and poor statistical reasoning, but our observable measures of behavioral bias statistically explain only about 21 percent of lottery purchases for the average household. We estimate that lottery demand is highly responsive to ticket prices and jackpot amounts, but not to smaller prizes. Using these empirical moments, we calibrate a structural model of lottery demand. In the model, lotteries are indeed a welfare-improving "win-win," and the optimal implicit tax is similar to the current norms in U.S. states.

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> "[A lottery] preys upon the hard earnings of the poor; it plunders the ignorant and simple."
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> – U.S. Supreme Court, in Phalen v. Virginia (1850)

> "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 (2020)

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

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 percent of leading economists believe that state-run lotteries increase social welfare, 28 percent disagree, and 45 percent were uncertain or had no opinion.[1]

These debates matter. Americans spent $85 billion, or a remarkable $665 per household, on lottery tickets in 2018 (NASPL 2020). This contributed $23 billion to state and local governments that year (NASPL 2020). This is more than the revenue raised by federal estate or tobacco taxes, and just less than the revenue raised by the federal gas tax. 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 deeper empirical and theoretical questions. How much of lottery consumption is driven by entertainment and other normatively respectable preferences versus ignorance, innumeracy, and other behavioral factors that a social planner might want to mitigate? Do lower-income people really spend more on lottery tickets, and is this a good thing (because it reflects consumer surplus for people with higher marginal utility) or a bad thing (because it reflects exploitation of behavioral bias)? Broadly, how does one consider normative questions around lotteries in a principled way?

This paper considers state-run lotteries in a public finance framework, extended to incorporate possible behavioral bias. We present new empirical data and analyses that identify a set of statistics that determine optimal policy. We then use the empirical parameters to simulate the welfare effects

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

of lotteries and different design choices. In doing so, we provide the first benefit-cost analysis of state-run lotteries that theoretically and quantitatively considers the alleged behavioral biases at the heart of the policy discussion.

In our model, consumers with heterogeneous earning ability choose labor supply, lottery purchases, and numeraire good consumption to maximize their perceived utility. We leave utility general, so that a rational consumer might play the lottery because of anticipatory utility, entertainment value, the consumption from the possible lottery winnings, and/or any other reason. However, lottery consumption might also be affected by perceptual distortions, such as misunderstanding of small probabilities, overconfidence, self-control problems, and other behavioral biases that the social planner does not consider to be normatively relevant. The social planner has a lottery with exogenous prize structure, and sets the lottery purchase price, net lottery payout, and a non-linear income tax to maximize normative utility subject to a revenue raising constraint. The planner is inequality averse, placing higher welfare weights on people with lower earning ability. Setting a 100 percent implicit tax is equivalent to eliminating the lottery altogether.

The closest parallel to our model is the "optimal sin tax" framework of Allcott, Lockwood, and Taubinsky (2019). In the language of that framework, lottery tickets are a potential "sin good" (like alcohol, cigarettes, or sugary drinks) whose consumption may be affected by behavioral bias. A key difference is that in the framework in this paper, the state has direct control over a key product attribute: the lottery payout. Thus, policy directly targeting consumption of this potential "sin good" is multidimensional.

Put another way, the planner has two ways to change the implicit tax on lotteries: increase the price or decrease the payout. This introduces several important nuances, including the fact that biases such as perceptual distortions of probabilities would imply that mis-estimation of the normative utility of a lottery ticket is endogenous to the lottery payout. The optimal choice depends on which is a more progressive way of collecting revenue and reducing bias.

Generally, the social welfare effect of a state-run lottery depends on several sufficient statistics. More behavioral bias generally implies a higher implicit tax on lottery revenues. Relatively more behavioral bias among lower-income people implies a higher implicit tax because the corrective benefits of the implicit tax accrue to the poor. However, relatively more consumption among lower-income people implies a lower implicit tax because the mechanical utility losses from taxation accrue to the poor. The relative importance of the corrective benefits versus the mechanical losses depends on the demand slope: more responsive demand means that the corrective benefits of demand changes outweigh the mechanical losses, whereas less responsive demand means that the corrective benefits will be relatively small.

We gather a novel and extensive array of data to estimate the empirical parameters required by the theory. While lotteries have changed substantially in the past two decades with the growth of instant and multi-state lotto games, to our knowledge there are no nationally representative surveys of lottery spending since Clotfelter et al. (1999), and .[2] Using a new nationally representative survey on the high-quality AmeriSpeak panel, we provide updated estimates of Americans' lottery spending by income. The spending distribution is highly skewed, generating some imprecision in the estimated means, but point estimates suggest that lottery spending declines moderately with income. Individuals with household income less than $50,000 spend an average of $26 per month, while those with household income above $100,000 spend an average of $21.

We use the survey to provide new evidence on the relationship between lottery expenditures and proxies for behavioral bias. 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, even after controlling for demographics, risk aversion, and other survey-based measures of preferences for lottery play. Interestingly, not all of these relationships suggest that bias leads to overconsumption: the average person in our survey reports feeling she plays the lottery "too little" (instead of "too much" or "the right amount") and actually underestimates the share of lottery revenues that is returned to winners.

Overall, regression predictions suggest that Americans might spend about 21 percent less on the lottery if they perceived no self-control problems, had the financial literacy and statistical ability scores of the highest-scorers in the sample, and had correct beliefs about expected returns.[3] Since financial illiteracy and statistical mistakes are more prevalent at lower incomes, these predictions suggest that the share of consumption attributable to bias is higher at lower incomes. This is consistent with the Supreme Court's 1850 argument that a lottery "plunders the ignorant" and "preys upon the hard earnings of the poor."

The theory also requires us to identify the elasticity of lottery demand with respect to both prize amounts and prices. We collect a new nationwide dataset of lottery purchases, prize structures, and jackpot and other prize amounts from state sources and La Fleur's, a large data provider. To identify the effect of ticket prices on demand, we study two recent cases where multi-state lotto games increased ticket prices from $1 to $2. To identify the effect of prize amounts on demand, we exploit random variation in lotto prize amounts over time as prizes are won (returning the prize to some reset value) or not (rolling over the prize into the next drawing). We find that demand is much more responsive to the expected value of prize winnings from the jackpot than from the second largest prize. This is the opposite of what would be expected for risk-averse consumers, but it could be explained by probability weighting or other factors that cause variation in the jackpot to be more salient than variation in smaller prizes.

[2] The Consumer Expenditure Survey significantly under-counts lottery purchases (Kearney 2005).

[3] This is a statistical prediction, not a causal estimate: although we control for a rich array of demographic and preference measures, our bias proxies are not randomly assigned and may be incomplete and noisy measures of the full range of behavioral biases that might affect lottery play.

Finally, we calibrate a structural model of lottery demand to match the reduced form empirical moments, and we simulate welfare at different prices and implicit taxes under different assumptions about bias. Even without behavioral bias—that is, if the social planner fully respects the revealed preferences of lottery consumers—an implicit tax on the order of 0 percent is optimal. This is because higher-income people consume more lottery tickets, so higher lottery taxes are a useful form of redistribution.

If we assume that more consumption is explained by behavioral bias, the optimal implicit tax increases in order to offset the overconsumption caused by bias. However, even if we calibrate bias to explain a share of consumption that is four times larger than our surveys suggest, our simulations still suggest lotteries raise welfare on the whole. Bias would have to be substantially larger than this for our model to predict that lotteries reduce welfare. Indeed, our preferred calibrations suggest that the current implicit tax rate for Powerball and Mega Millions, the two large multi-state lotteries, is close to the level that maximizes social welfare.

Our work connects to three existing literatures. The first is the literature in behavioral economics, judgement and decision-making, psychology, and other fields on decision-making under risk in general and with lottery purchases in particular (Kahneman and Tversky 1979; Haisley, Mostafa, and Loewenstein 2008a; Haisley, Mostafa, and Loewenstein 2008b; Guryan and Kearney 2008; Post et al. 2008; Snowberg and Wolfers 2010; Aruoba and Kearney 2011; etc.). Our work adapts the insights from this literature into a quantitative welfare analysis.

The second area of related literature is on the public economics of lotteries (Clotfelter and Cook 1987, 1989, 1990; Price and Novak 1999, 2000; Grote and Matheson 2011; etc.). To our knowledge, our paper is the first to embed lottery policy questions into an optimal taxation model that accounts for behavioral bias.

The third area is the recent line of work evaluating behaviorally motivated public policy decisions.[4] Our paper extends this work to consider lotteries, and lays out a framework that we hope can provide the basis for a line of future work on economically optimal lottery design.

Sections 1, 2, 3, and 4 present the model, data, empirical results, and optimal policy simulations, respectively.

1 Framework

1.1 A static model of lottery demand

We begin by setting lottery consumption in a standard optimal tax setting, where we treat lottery tickets as a standard consumption good. In the body of the paper we consider a simplified model

[4] See, e.g., Gruber and Kőszegi (2001); Handel (2013); Allcott and Taubinsky (2015); Handel and Kolstad (2015); Handel, Kolstand, and Spinnewijn (2016); Taubinsky and Rees-Jones (2018); Allcott, Lockwood, and Taubinsky (2019); Allcott et al. (2020); Allcott and Rafkin (2020); Lockwood (forthcoming); and Rees-Jones and Taubinsky (forthcoming).

in which exogenous windfalls of money do not significantly affect lottery demand or labor supply, and in which demand for a particular type of lottery is binary.

We consider the binary demand assumption to correspond to our modeling of lottery purchases in a particular week for a particular game. Individuals rarely buy more than several lottery tickets at a time, perhaps because the "fun" of having a chance to win does not increase with the number of tickets. Empirically, we also do not find that shocks to individuals' incomes have a meaningful impact on lottery demand, consistent with our modeling. Finally, the negligible labor supply income effects assumption is supported by Gruber and Saez (2002), who find small and insignificant income effects on labor supply, and by Saez, Slemrod, and Giertz (2012), who review the empirical literature on labor supply elasticities and argue that "in the absence of compelling evidence about significant income effects in the case of overall reported income, it seems reasonable to consider the case with no income effects."

Formally, individuals choose earnings z, numeraire consumption c, and lottery consumption $x_s \in \{0, 1\}$. Earnings are subject to a nonlinear income tax $T(z)$, and the price of the lottery ticket is denoted p. The price of numeraire consumption is normalized to one.

Individuals have heterogeneous earnings ability, preferences, and behavioral biases. Heterogeneity is indexed by $\theta \in \Theta$. Types are distributed according to F_θ. A second dimension of heterogeneity, $\varepsilon \in \mathbb{R}$, determines the share of θ-types who purchase a lottery ticket, and is assumed to have a continuous distribution conditional on θ, denoted $F_{\varepsilon|\theta}$.

We focus on the case for which there are no (causal) income effects on lottery purchases. That is, we assume individuals' decisions can be approximated as maximizing a decision utility function

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

where $u(\boldsymbol{a}; \theta, \varepsilon)$ is the perceived subutility from purchasing a lottery ticket, and $\psi(z; \theta)$ is the labor disutility of generating earnings z, which is decreasing in ability and which does not vary with the preference shock ε. Numeraire consumption c is equal to $z - T(z) - ps$, due to the consumer's budget constraint. The parameter $\boldsymbol{a}$ represents a vector of lottery attributes which can be adjusted by the policy maker. These include advertising, prize amounts, probabilities, other attributes of game design.

Using the model above, individual binary demand is written as a function of lottery ticket price, lottery attributes, and consumer type:

$$x_s(p, \boldsymbol{a}; \theta, \varepsilon) = \begin{cases} 0 & \text{if } u(\boldsymbol{a}; \theta, \varepsilon) < p \\ 1 & \text{if } u(\boldsymbol{a}; \theta, \varepsilon) > p \end{cases} \tag{2}$$

We transform this binary choice model into a continuous one by aggregating over the preference shocks ε. We therefore define

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

(in which ε is not an argument) to denote the continuous share of θ-type consumers who purchase lottery tickets for a given price and attribute vector. As in many binary choice models, this share can also be interpreted as the share of choice occasions on which a θ-type consumer purchases a lottery ticket, and thus the average consumption per period in steady state—indeed, we will ultimately calibrate $s(p, \boldsymbol{a}; \theta)$ to match average daily expenditure at the individual level—but we will employ the language of the binary static model here for concreteness. The distribution of preference shocks ε is assumed to be continuously distributed, so that demand $s(p, \boldsymbol{a}; \theta)$ is a continuous function of p and continuous components of $\boldsymbol{a}$. We further define $\bar{s}(p, \boldsymbol{a}) := \int s(p, \boldsymbol{a}; \theta) dF_\theta(\theta)$ to represent aggregate demand for lotteries at the population level.

In our structural model, we assume that preference shocks are additive, so that

$$u(\boldsymbol{a}; \theta, \varepsilon) = m(\boldsymbol{a}; \theta) - \varepsilon, \tag{4}$$

where m is a smooth function of $\boldsymbol{a}$ and ε is the hassle cost of going to the store to buy the lottery ticket. As we shall dicsuss below, this assumption simplifies some of the

The function u can reflect a number of possible motives for playing the lottery. First, u of course includes the expectation of utility from material financial winnings. Second, it includes any entertainment derived from playing the lottery (Conlisk 1993; Kearney 2005), or anticipatory utility from thinking about a chance of winning (e.g., Loewenstein 1987; Caplin and Leahy 2001; Brunnermeier and Parker 2005). Third, we 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). Probability weighting (Kahneman and Tversky 1979; Tversky and Kahneman 1992) could be generated either by normatively relevant preferences, such as anticipatory utility (Brunnermeier and Parker 2005; Gottlieb 2014), or by perceptual distortions (Woodford 2012; Steiner and Stewart 2016). To formalize this third possibility, we draw a distinction between the decision utility function in equation 1, and the individual's normative utility function:

$$V = G(c + s \cdot v(\boldsymbol{a}; \theta, \varepsilon) - \psi(z; \theta)). \tag{5}$$

We let $s^V(p, a; \theta) := Pr\left(u(\boldsymbol{a}; \theta, \varepsilon) > p\right)$ to denote the aggregate demand function that would obtain if consumers maximized the normative utility function in equation 5

For simplicity, in the core theoretical analysis and simulations we restrict focus to a unidimensional attribute a. An example we will return to often, including in our numerical simulations, is one in which a represents the net-of-tax expected value of the lottery ticket. Concretely, consider a lottery with prize winnings $aw_1, aw_2, \ldots, aw_K$ and associated probabilities π_k, where we have normalized $\sum_k \pi_k w_k = 1$. Then by construction, a is equal to the expected value of the lottery, and variations in a trace out a univariate range of possible lottery designs which result from rescaling all prizes proportionally.[5] More generally, $\boldsymbol{a}$ could also include attributes such as the finer details of the prize distribution, or other policy choices which affect lottery spending, such as the level of advertising.

At a given price per ticket p, total expenditures on lotteries are $p\bar{s}$. The total amount of prize winnings paid out is $a\bar{s}$, implying that the share of expenditures retained by the state, which we call "the implicit lottery tax rate," is $1 - a/p$.

The cost to the state of selling a lottery tickets includes the expected prize payout, as well as administrative costs and vendor incentives. We use $C(a, \bar{s})$ to denote the cost to the government of selling $\bar{s}$ tickets with attributes a. For example, in the case where a represents the net-of-tax expected value of the lottery ticket and administrative costs scale with total ticket sales, we have $C(a, \bar{s}) = (a + o)\bar{s}$, where o is the administration cost per ticket. In the case where a represents advertising, $C(a, \bar{s}) = C_a(a) + o\bar{s}$, where $C_a(a)$ is the cost of advertising level a.

The policymaker selects T, p and a to maximize normative utility, aggregated across consumers using type-specific pareto weights $\mu(\theta, \varepsilon)$:

$$\max_{T,p,a} \left[\int_{\theta,\varepsilon} \mu(\theta, \varepsilon) V(c, s, a, z; \theta, \varepsilon) dF_\theta(\theta) dF_{\varepsilon|\theta}(\varepsilon|\theta) \right], \tag{6}$$

subject to a government budget constraint,

$$\int_\theta (ps(\theta) + T(z(\theta))) dF_\theta(\theta) - C(a, \bar{s}) \geq R \tag{7}$$

and to consumer optimization of U. We assume that consumers first choose z before learning the draw of ε from $F_{\varepsilon|\theta}$. This timing assumption is immaterial when preferences are weakly separable in lottery purchases, numeraire consumption and labor, but it plays a larger role in the general model in appendix A. Note that when no ambiguity arises, we sometimes suppress the arguments p, a, and T in the demand functions (e.g., $s(\theta)$, $z(\theta)$, etc.).

We let λ denote the marginal value of public funds (i.e., the multiplier on the government budget constraint in equation (7) at the optimum), and we define $g(\theta, \varepsilon) := \mu(\theta, \varepsilon) U'_c$ to denote the weighted marginal utility from consumption for a consumer of type θ, ε. Following Saez (2002) 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) under the optimal tax system. We thus use both $g(\theta)$ and $g(z)$ to denote social marginal welfare weights as a function of θ type or of income. Under the assumption of negligible income effects on labor supply, $E[g(z)] = 1$.

[5] Note that this representation is without loss of generality: beginning with any lottery with prize winnings $\tilde{w}_k$ and probabilities π_k, define $w_k := \tilde{w}_k / \sum_k \pi_k \tilde{w}_k$, then proceed as in the text.

1.1.1 Elasticity concepts and sufficient statistics

The optimal sin tax depends on three types of sufficient statistics: elasticities, money-metric measure of bias, and the "progressivity of bias correction." These statistics are understood to be endogenous to the tax regime, though we suppress those arguments for notational simplicity. Because we assume that social marginal welfare weights depend only on income, the relevant statistics are functions of income z, rather than of types θ. We write $\bar{s}(z)$ to denote lottery demand of z-earners, and we use $\bar{s}$ to denote population-wide demand.

We first define demand responses to lottery ticket price and attributes. We define the semi-elasticity of demand with respect to ticket price, $\zeta_p(z) := \frac{d \ln s(z)}{dp}$, and the semi-elasticity of demand with respect to expected value, $\zeta_a(z) := \frac{d \ln s(z)}{da}$. We use $\bar{\zeta}_p$ and $\bar{\zeta}_a$ to denote population-wide semi-elasticities. When relevant, we also us semi-elasticities to quantify the response to a change in the expected value of a particular prize level: $\zeta_{ak}(z) := \frac{d \ln s(z)}{dx_k}$.

We define $\kappa(\theta)$ and $\kappa(z)$ to be the average willingness to pay for a marginal increase in a of θ-types and z-earners, respectively. When $u'_a(a;\theta,\varepsilon)$ does not depend on ε, $\kappa(\theta) = -\zeta_a(\theta)/\zeta_p(\theta) \cdot s(\theta)$, and is thus directly obtained from empirical estimates. When $\boldsymbol{a}$ is an attribute that can be varied in experiments—such as a prize amount—κ can also be obtained by eliciting willingness-to-pay for different lotteries. We let $\bar{\kappa} := E[\kappa(z)]$ denote the average willingness to pay of all buyers of the lottery ticket.

We quantify bias as the wedge between decision utility and normative utility from lottery consumption: $\gamma(a;\theta,\varepsilon) := u(a;\theta,\varepsilon) - v(a;\theta,\varepsilon)$. To simplify exposition for the body of the paper only, we assume here that γ does not depend on the random taste shock ε, a property that is consistent with the additive structure in equation (4).

This definition of bias has a simple price-metric interpretation, consistent with the bias definition in ALT: γ is equal to the price reduction that would produce the same change in demand as the bias does. Formally, γ satisfies the equation $s^V(p-\gamma, a;\theta) = s(p,a;\theta)$. Figure 1 provides a graphical illustration of this definition of bias: it is the vertical distance between between the demand curves $s(p,a;\theta)$ and $s^V(p,a;\theta)$. The horizontal difference between $s(p,a;\theta)$ and $s^V(p,a;\theta)$, denoted $\Delta\bar{s}$, is the difference in demand induced by the bias. Notice that once $\Delta\bar{s}$ is known, the vertical distance can be approximated by dividing by the estimated the price elasticity of demand. Our empirical strategy for quantifying bias will proceed along these lines.

Following ALT, we define $\bar{\gamma}(z) := \frac{\mathbb{E}\left[\gamma(\theta)\frac{ds(\theta)}{dp}|z(\theta)=z\right]}{\mathbb{E}\left[\frac{ds(\theta)}{dp}|z(\theta)=z\right]}$ to be the average bias of marginal z earners, and we define $\bar{\gamma} := \frac{\mathbb{E}\left[\bar{\gamma}(z)\frac{ds(z)}{dp}\right]}{\mathbb{E}\left[\frac{ds(z)}{dp}\right]}$ to be the average bias of all individuals who are marginal to a price change at price p (for a given attribute a).

Because our framework includes redistributive motives, and because our bias definition is in money-metric terms, the welfare effects of behavior change will depend not just on the average bias but on whose behavior is being changed. All else equal, the welfare change is more positive when the benefits of counteracting individuals' biases are concentrated on low-income individuals. To take these redistributive concerns into account, we express the "progressivity of bias correction" from a change in price, using the statistic $\sigma_p := Cov\left[g(z), \frac{\bar{\gamma}(z)}{\bar{\gamma}}\frac{ds(z)}{dp}\right]/\frac{ds}{dp}$. Likewise, the analogous statistic for a change in attribute a is $\sigma_a = Cov\left[g(z), \frac{\bar{\gamma}(z)}{\bar{\gamma}}\frac{ds(z)}{da}\right]/\frac{ds}{da}$. These statistics quantify the extent to which the benefits of bias correction accrue to low-income individuals, per unit change in $\bar{s}$.

Finally, because biases may be endogenous to the attribute a, individuals' valuations of a may be biased. The bias in z-earners' valuation of a marginal increase in a is given by $\rho(z) := \mathbb{E}\left[\frac{d}{da}\gamma(a;\theta)\cdot s(\theta)|z(\theta)=z\right]$. We define $\bar{\rho} := \mathbb{E}\left[\rho(z)s(z)\right]$ to be the population average bias in the valuation of a. By definition, $\bar{\kappa}-\bar{\rho}$ is the average impact of increasing a on individuals' *normative* utility, measured in dollars per lottery ticket.

1.1.2 Simple example

We consider a simple example for purposes of illustration, to which we will later return in order to interpret our optimal tax formulas. Suppose that utility is linear in the numeraire consumption, and that the lottery offers a single large prize aw with a small probability π. Taking into account anticipatory utility, consumers' perceived utility from a lottery ticket is given by $u = (1+\phi)\pi m(aw)+\varepsilon$, where m is a concave function representing the utility gain for type θ from winning a prize of size aw. The term $1+\phi$ represents the decision weight that the consumer applies to the possibility of winning the prize, when deciding whether to purchase. The taste-shock ε could correspond to fluctuating tastes for the entertainment value of the lottery. If $\phi \equiv 0$ and $\varepsilon \equiv 0$, the consumer is an expected utility maximizer. We consider the relevant case in which $\phi > 0$ and ε has a continuous density function. This setup allows for the possibility that consumers misperceive the probability of winning. If the normative decision weight (under accurate perception) is $1+\phi^V$, then normative utility from lottery consumption is given by $v(a) = (1+\phi^V)\pi m(aw)+\varepsilon$, and bias is $\gamma(a) = (\phi-\phi^V)\pi m(aw)$. On the other hand, this framework also accommodates other forms of bias. For example, suppose consumers overestimate the happiness they would gain from winning a prize aw by a factor of b. Then $u = (1+\phi)\pi(1+b)m(aw)+\varepsilon$ while $v = (1+\phi)\pi m(aw)+\varepsilon$. In this case, bias is $\gamma(a) = (1+\phi)\pi b m(aw)$.

1.2 A formula for the optimal lottery "tax"

To obtain intuition for our main result, consider first how a change dp in the price p affects social welfare:

- First, it mechanically reduces individuals' incomes by $s(z)dp$, and mechanically increases government revenues by $dp\bar{s}$. The net mechanical effect is thus $E[\bar{s}-s(z)g(z)]dp = -Cov[s(z), g(z)]dp$.

- Second, it leads to substitution away from lottery purchases, which changes government revenue by $(p - C'_s(a, \bar{s})) \frac{d\bar{s}}{dp} dp$.

- Third, the substitution has a net bias correction benefit of $-\bar{\gamma}(1+\sigma_p)\frac{d\bar{s}}{dp}dp$.

Taking these terms together, the net effect on social welfare is

$$- Cov[s(z), g(z)]dp + \left(p - C'_s(a, \bar{s})\right) \frac{d\bar{s}}{dp} dp - \bar{\gamma}(1+\sigma_p)\frac{d\bar{s}}{dp}dp, \tag{8}$$

which implies that the optimal lottery price must satisfy the first-order condition

$$p - C'_s(a, \bar{s}) = \bar{\gamma}(1+\sigma_p) - \frac{Cov[s(z), g(z)]}{\left|\bar{\zeta}_p\right| \bar{s}}. \tag{9}$$

We next consider the impact of changing a. The welfare effects of this are as follows:

- First, there is a mechanical effect on lottery buyers' utilities. The impact on z-earners' normative utility is given by $(\kappa(z) - \rho(z))da$. The total impact on social welfare is therefore

$$E[(\kappa(z) - \rho(z))g(z)]da = (\bar{\kappa} - \bar{\rho})da + Cov[\kappa(z) - \rho(z), g(z)]da$$

- Second, this affects government revenue. The net affect is $p\frac{d\bar{s}}{da} - \frac{d}{da}C(a, \bar{s}(a))$, where $\frac{d}{da}C(a, \bar{s}(a))$ is the total derivative of costs with respect to a.

- Third, because a change in a affects behavior, it impacts social welfare through counteracting (or exacerbating) consumer bias. Analogous to the effect of changing the lottery price, this is given by $-\bar{\gamma}(1+\sigma_a)\frac{d\bar{s}}{da}da$.

Putting these effects together leads to the first-order condition

$$\bar{\kappa} - \bar{\rho} + Cov[\kappa(z) - \rho(z), g(z)] = \frac{d}{da}C(a, \bar{s}(a)) - p\frac{d\bar{s}}{da} + \bar{\gamma}(1+\sigma_a)\frac{d\bar{s}}{da} \tag{10}$$

In words, this condition states at the optimum, the direct affect on individuals' welfare has to equal the sum off the effects on costs and bias correction.

Combining the first-order conditions in (9) and (10), we have the following result:

Proposition 1. *If p and a are optimal and $a > 0$,*

$$p - C'_s(a, \bar{s}) = \bar{\gamma}(1+\sigma_p) - \frac{Cov[s(z), g(z)]}{\left|\bar{\zeta}_p\right| \bar{s}} \tag{11}$$

$$\bar{\kappa} - \bar{\rho} = C'_a(a, \bar{s}) + \bar{\gamma}(\sigma_a - \sigma_p)\bar{\zeta}_a \bar{s} + \left(Cov[s(z), g(z)] \frac{\bar{\zeta}_a}{\left|\bar{\zeta}_p\right|} - Cov[\kappa(z) - \rho(z), g(z)] \right) \tag{12}$$

If $a = 0$ is optimal then

$$\bar{\kappa} - \bar{\rho} < C_a'(a, \bar{s}) + \bar{\gamma}(\sigma_a - \sigma_p)\bar{\zeta}_a \bar{s} + \left(Cov[s(z), g(z)] \frac{\bar{\zeta}_a}{|\bar{\zeta}_p|} - Cov[\kappa(z) - \rho(z), g(z)] \right)$$

In the absence of biases ($\gamma(z) = 0$) and redistributive motives ($Cov[s(z), g(z)] = 0$), condition (11) states that the optimal lottery ticket price p must equal the marginal cost of a lottery ticket. When the marginal costs are constant, as in our simple example in Section 1.1.2, this implies that the price of the ticket equals the cost of the ticket. Thus, the state breaks even at the optimum.

It is optimal for the state to set a net tax—i.e., set a price above marginal cost—if the lottery is preferred by higher-income consumers, because such a tax is progressive. The extent to which it is optimal to tax depends on the elasticity of demand, and the degree to which the subsidy is regressive, $Cov[s(z), g(z)]$. When the elasticity is high, the tax is highly distortionary of behavior, and thus the redistributive motive does not receive significant weight. When the elasticity is low, the tax is a well-targeted tool for redistribution with minimal distortionary costs.

It is also optimal to price lottery tickets above marginal costs if individuals overvalue the lottery tickets. This is particularly true when $\sigma_p > 0$ because low-income individuals overvalue lottery tickets the most.

The economic content of equation (12) concerns the optimal value of the attribute a, and is as follows. The left-hand-side of the equality corresponds to the marginal impact on consumer surplus from an increase in a. The right-hand side consists of three terms. The first term is the direct marginal cost of increasing a, keeping lottery demand constant. For example, it is the marginal cost of increasing advertising, or it is the mechanical revenue loss from increasing the lottery prizes.

The second term is the degree to which increasing per-ticket state revenue by decreasing a leads to more progressive bias correction than increasing the ticket price p. For example, if a corresponds to the expected payout of the lottery ticket, a large value of this term implies that decreasing the value of the prizes is a more targeted means of counteracting individuals' biases than increasing the ticket price p. When this term is large, there is a strong policy motive to counteract individuals' biases by decreasing a, as opposed to by increasing p. Thus, the higher the term, the higher are the marginal social welfare costs of increasing a at the optimal policy.

The third term is the degree to which a decrease in a leads to a more progressive (or less regressive) change in consumer surplus than a decrease in p, per unit change in $\bar{s}$. The factor $\frac{\bar{\zeta}_a}{|\bar{\zeta}_p|}$ multiplying $Cov[s(z), g(z)]$ in the third term ensures that the comparison between the progressivity of changing a and the progressivity of changing p holds constant the total change in demand induced by decrease of da versus an increase of dp. When this term is large, it means that increasing per-ticket state revenue by reducing a is more progressive than increasing per-ticket state revenue by increasing the -ticket price p. For example, if a corresponds to the expected value of a lottery ticket, a large value of the third term implies that it is more progressive to decreases the prizes rather than to increase the price of the ticket.

1.2.1 Special cases of the formula

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, the result reduces to $p = C_s'(a, \bar{s})$ and $\bar{s}\bar{\kappa}(a) = C_a'(a, \bar{s})$. 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. When a corresponds to the expected payout of a lottery ticket, the conditions reduce to $p = a$ and $\bar{\kappa}(a) = 1$.

In the simple example where there is a single prize of size aw and $u(a) = (1 + \phi)\pi m(aw)$, this implies that p and a are determined by the conditions $p = a + o$ and $(1 + \phi)\pi w m'(aw) = 1$, where o is the additional administration cost form each lottery ticket. The second condition uniquely determines a, which then determines the price p. For example, if $m(x) = \ln(1 + x)$, then the optimal lottery structure is $p - o = a = \max\left\{\frac{1}{w}((1 + \phi)\pi w - 1), 0\right\}$. Since we normalize $\pi w = 1$, this implies that $a > 0$ at the optimum if and only if $\phi(\pi) > 0$; i.e., if additional entertainment utility leads individuals to value lotteries above their monetary value.

No bias, heterogeneous preferences. When $\gamma(\theta) \equiv 0$, the result reduces to $p - C_s'(a, \bar{s}) = -\frac{Cov[s(z), g(z)]}{|\bar{\zeta}_p|\bar{s}}$ and $\bar{\kappa} = C_a'(a, \bar{s}) + Cov[s(z), g(z)]\frac{\bar{\zeta}_a}{|\bar{\zeta}_p|} - Cov[\kappa(z) - \rho(z), g(z)]$. The first condition is analogous to Diamond's (1975) "many-person Ramsey tax rule", which states the tax is proportional to its degree of progressivity and is inversely proportional to the elasticity. The second, and more novel condition for $\bar{\kappa}$ 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, the first-order conditions reduce to $p - C_s'(a, \bar{s}) = \bar{\gamma}$ and $\bar{\kappa}(a) = C_a'(a, \bar{s}) + \bar{\rho}(a)$. In this case, the price is set above a lottery ticket's expected value when $\bar{\gamma} > 0$, so as to discourage lottery consumption. Moreover, the optimal amount of prize winnings retained by individuals, a, is set such that $\bar{\kappa}(a) > C_a'$ when $\bar{\rho}(a) > 0$ (individuals not only overvalue the lottery ticket, but also changes in a). This implies that a budget neutral reform that increases price and expected ticket value would raise total demand. In other words, the expected value is held below the value that would be optimal absent bias.

In the simple example where $u = (1 + \phi)\pi m(aw)$ and $v = (1 + \phi^V)\pi m(aw)$, we have $\bar{\kappa}(a)/\bar{s} = (1 + \phi)m'(aw)$, $\bar{\rho}(a)/\bar{s} = (\phi - \phi^V)m'(aw)$, and $\gamma = (\phi - \phi^V)\pi m(aw)$. At an interior optimum, we thus have the first-order conditions $p-a=(\phi-\phi^V)\pi m(aw)$ and $(1+\phi)m'(aw)=1+(\phi-\phi^V)m'(aw)$. When γ is sufficiently high, it is instead 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. This leads to the conditions $p-C_s'(a,\bar{s})=\frac{1}{\left|\bar{\zeta}_p\right|}$ and $\frac{d}{da}C(a,\bar{s}(a))=p\left|\bar{\zeta}_p\right|\bar{s}$. Using the first condition, the second condition can be reduced to $\frac{C_a'(a,\bar{s})}{\bar{s}}=\frac{\bar{\zeta}_a}{\left|\bar{\zeta}_p\right|}$. 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. Intuitively, at the optimal policy structure, increasing a by da and increasing p by $dp=da\frac{C_a'(a,\bar{s})}{\bar{s}}$—so that the net direct effect on government revenue is constant—cannot increase or decrease consumer demand for the lotteries.

For example, when a corresponds to expected payout of a lottery ticket, so that $C_s'=a$ and $C_a'/\bar{s}=1$, we have that at the optimum, $p-a=1/\left|\bar{\zeta}_p\right|$ and $\left|\bar{\zeta}_p\right|=\bar{\zeta}_a$.

2 Data

There are three major categories of state-run lottery games. The first is "lotto" games, in which players pick a set of numbers, and they win if their numbers match those drawn in prize drawings, which are typically held daily, bi-weekly, or weekly. If no player wins the jackpot, the jackpot rolls over to be included in the next drawing. If one or more players win the jackpot, they split the jackpot and jackpot returns to some reset value in the next drawing. The largest lotto games in the U.S. are the two major multi-state lotto games, Mega Millions and Powerball, but many states also run their own games. Tickets typically cost \$1 or \$2.

The second category is instant or "scratch-off" games. Players buy a paper card and scratch off parts of it to reveal hidden numbers, letters, or signs. Players win if the hidden values match some pattern, for example if all symbols in a given row are the same. Tickets typically cost \$1 to \$20. The third category is all other games, including Keno and video lottery terminals. Instant game consumption has grown substantially since the mid-1990s, while lotto consumption has dropped slightly, and other games grew during the late 2000s but have returned to their 1990s levels; see Appendix Figure A1.

2.1 AmeriSpeak Survey

We carried out a survey in April and May 2020 to measure lottery spending and proxies for preferences and biases related to lottery purchases. We fielded the survey on AmeriSpeak, a high-quality survey panel managed by the National Opinion Research Corporation (NORC). Unlike internet panels that allow anyone to opt in, NORC randomly selects U.S. households to be invited to participate. This helps to reduce sample selection biases that can make surveys unrepresentative on unobserved characteristics. All results presented below are weighted for national representativeness on age, sex, race, education, geography, and other key characteristics.

Table 1 presents descriptive statistics. 3,013 people completed the survey, of whom 2,887 had sufficient non-missing data and passed basic data quality checks. Sample sizes differ on individual questions due to item non-response. Panel (a) presents panelist demographics, Panel (b) presents survey questions on spending and income effects, and Panel (c) presents questions that proxy for preferences and bias. Appendix B presents the text of the survey questions.

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 panelists to "please include MegaMillions, 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 was asked to explicitly confirm or update their response. The average spending of $23 per month multiplied by 255 million American adults gives $59 billion, moderately smaller than the $85 billion total nationwide sales reported by the National Association of State and Provincial Lotteries (2020).

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*).

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 after standardizing each to have 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."

Using a number of underlying survey questions, we construct proxies for six biases that might be related to lottery purchases.

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).

Financial illiteracy. Financial illiteracy and innumeracy might affect 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.

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) 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 percent. *Gambler's Fallacy* is the share of answers that differ from 50 percent; Table 1 reports that people gave some other answer 31 percent of the time. Second, we measured non-belief in the Law of Large Numbers (Benjamin, Rabin, and Raymond 2016; Benjamin, Moore, and Rabin 2017) 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. Our *statistical mistakes* bias proxy is the average of these three variables after standardizing each to have standard deviation equal to one.

Overconfidence. Overconfidence 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 $1000 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. *Overconfidence* is the difference between own and average person expected winnings per $1 spent.

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?"

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, Ostling, and Cesarini (forthcoming) 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 panelists about the Lindqvist, Ostling, and Cesarini (forthcoming) study, 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.

2.2 Lottery Sales and Prizes

We have four separate data sources on lottery sales and prizes. Table 2 presents descriptive statistics. All monetary amounts are in real 2019 dollars.

First, we purchased weekly lottery sales data disaggregated by game and state from 1994 to 2017 from La Fleur's. The data include 275 unique games plus total sales of instant games by state and week, for 41 states plus D.C. The data cover approximately 96 percent of state-run lottery sales reported in the Census of Governments over 1995–2017. There is occasional missing data in early years, and the data do not include games in Arkansas, North Carolina, and Tennessee.

Second, we collect draw-level sales data from C

Second, we have imputed lottery sales at the draw-game level in California from 2003 to 2017. As described in Section **??**, California has an unusual lottery regulation requiring all prizes to evolve over time—a feature we exploit to identify the semi-elasticity of demand with respect to small prizes. Moreover, we can use the evolution of these pari-mutuel prizes to impute game sales for each drawing in California, even when there are multiple drawings per week. These draw-level data are important in addition to the La Fleur's data because many lotto games have multiple draws (typically with different jackpots) in each week, so weekly data are not sufficiently precise. We use these data in the sub-jackpot demand elasticity analysis.

Specifically, the California data include draw-level sales data for California's SuperLotto Plus from 2003 to 2017, Mega Millions from 2005 to 2017, and Powerball from 2013 to 2017. California joined Mega Millions in 2005 and Powerball in 2013, while SuperLotto Plus, a state-specific game, began before 2003. The data span three different structures of Mega Millions, two of Powerball, and one of SuperLotto Plus. Within our complete dataset, these are the only three games that are both pari-mutuel—resulting in variation in their sub-jackpot prize values—and that regularly experience rollovers and hence significant build-ups in the second prize pool, allowing us to identify a sub-jackpot elasticity off of significant variation in the second prize.

We impute sales using prize pool amounts, prize pool allocation, and La Fleur's weekly sales data. Each game has nine prize pools, one for the jackpot and each smaller prize. The amount in each prize's pool is either reported when the prize rolls over or equals the product of the number of winners and prize amount per winner when won by at least one player. The increase in the prize pool from one draw to the next when a rollover occurs or from zero to the next draw's prize amount when the prize is won (since the pool is depleted by the winners' prizes) is a function of sales. Administrators allocate a portion of the sales in each draw, typically around 50% ($\sim$45-67%), to prizes. They then allocate a portion of the total allocation to prizes to each of the nine prize pools in proportions fixed by regulation, for which we have data. In each game-format, we use prize data to obtain prize-specific allocations and then use the regulatory data to estimate the total allocation to prizes. We then compare the week-averaged La Fleur's data and week averages of the total allocation to estimate the portion of sales within each draw allocated to prizes. We assume this portion remains fixed within each game-format. Finally, we use our estimates of the total allocation to prizes in each draw and share of sales allocated to prizes in each game-format to estimate the sales in each draw. We complete this exercise for each of the three games.

Third, we have lottery sales at the draw-game level from 2005 to 2018 at the national level for Mega Millions and Powerball from the Lotto Report (lottoreport.com). The data span three different formats of each game. We use these data to study one structural change in Mega Millions and two structural changes in Powerball. In addition, we employ it in our sub-jackpot analysis to accurately compute the jackpot expected value of Mega Millions and Powerball in each draw, as the risk of splitting the jackpot is increasing in national sales.

These data also include draw-level data for Louisiana and the U.S. Virgin Islands for Mega Millions only from October 2010 to August 2012. We use these data to maintain a constant composition of states within Mega Millions's national sales in the Powerball price change event analysis.

Fourth, we have lottery prize and probability data at the state-game-draw level from 1994 to 2017. We collected the data directly from state lottery commissions and the Multi-State Lottery Association as well as scraped online from "are your numbers lucky?" tools and results pages. The data include 16 unique games and span 41 states and D.C.[6]

Only jackpot prizes and probabilities are used in the national demand elasticity analysis. Sub-jackpot prizes and probabilities for Mega Millions, Powerball, and SuperLotto Plus are used in the California draw sales imputation exercise, the Mega Millions and Powerball price elasticity and structural change analyses, and the sub-jackpot demand elasticity analysis. Jackpot prize amounts are reported as advertised when there is a difference between an estimate advertised and the actual prize awarded.

3 Empirical Evidence on Lottery Demand

In this section, we gather the empirical parameters needed to calibrate our model of optimal lottery policies. First, we show how lottery spending varies by income, measuring $\bar{s}$ and $\bar{s}(z)$. Second, we present descriptive evidence on how our survey-based bias proxies correlate with lottery spending,

[6]In addition to Mega Millions and Powerball, we have Fantasy 5 and The Pick from Arizona; SuperLotto Plus from California; Lotto from Connecticut; Lotto, Lucky Money, and Mega Money from Florida; Lotto from Illinois; Lotto and Easy 5 from Louisiana; Classic Lotto and Rolling Cash 5 from Ohio; Lotto Texas from Texas; and Lotto from Washington.

which we will later use to estimate bias γ. Third, we estimate prize semi-elasticities ζ_a. Fourth, we estimate the price semi-elasticity ζ_p.

3.1 Lottery Spending by Income

The distribution of lottery spending is skewed: the top 10 percent of spenders account for 71 percent of spending, while over 40 percent of people report no spending at all. Average spending conditional on non-zero spending in 2019 is \$39.98. See Appendix Figure A2 for the histogram of monthly spending.

Figure 2 presents average monthly lottery spending by income, after winsorizing at \$500 per month. Monthly spending declines slightly with income, from about \$25 for individuals with less than \$50,000 household income to about \$20 for individuals with higher incomes. The share of people with non-zero spending also declines slightly with income; see Appendix Figure A3. The results are similar but slightly less precise if we do not winsorize; see Appendix Figure 2.

These results are broadly consistent with data from the National Survey on Gambling Behavior carried out 20 years earlier by NORC: Clotfelter et al. (1999) found that about 52 percent of people had played the lottery in the last year, and that expenditures declined by income. However, lottery spending per capita has grown over time, even after adjusting for inflation, and our point estimates suggest slightly less decline in spending by income than in the 1999 study.

The theory in Section 1 distinguishes two reasons why consumption might vary with income: a 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 an income elasticity of 0.20; see Appendix Table A2 for formal regression results. This should be interpreted cautiously because changes in life circumstances correlated with income changes might also change lottery consumption preferences—for example, if getting a new job increases income and reduces leisure time for playing the lottery. Second, the average of *self-reported income effect* (the amount by which people thought their lottery spending would change if their income doubled) is -1.7 percent, suggesting an income elasticity of -0.017. This should be interpreted cautiously because the question was hypothetical. Both of these strategies are broadly consistent in suggesting limited income effects, and neither explains the pattern of declining expenditures by income in Figure 2.

3.2 Association Between Bias Proxies and Lottery Purchases

Are our six bias proxies described in Section 2.1 correlated with lottery spending? Does this correlation survive controls for preferences and demographics? And what share of lottery consumption is statistically explained by survey measures of bias?

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 overconfident, 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 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. Thus, $\tilde{b}_{ik} > 0$ implies that proxy k should cause person i to overconsume lottery tickets, while $\tilde{b}_{ik} < 0$ implies that proxy k should cause person i to underconsume. Finally, define $\boldsymbol{a}_i$ as a vector of the three preference proxies (*risk avesion*, *lottery seems fun*, and *enjoy thinking about winning*), and define $\boldsymbol{x}_i$ as a vector of the demographic characteristics presented in Panel (a) of Table 1 plus state fixed effects.

Descriptive correlations. Figure 3 presents binned scatter plots of the relationship between (unstandardized) bias proxies b_{ik} and $\ln(1 + s_i)$. In each of the six panels, a vertical line indicates the unbiased benchmark b_k^V, and the area of each circle corresponds to the share of people in each bin. 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 best fit line's upward slope means that people who report playing "too much" indeed spend more on lotteries. However, 67 percent 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; for *statistical mistakes*, we recenter so that 0 is the best score in the sample. The best fit lines' upward slopes mean that people with lower financial illiteracy and 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 *overconfidence*, 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 overconfidence may not contribute much to overconsumption: there is little relationship between overconfidence and spending, and about 64 percent of people reported the same expected earnings for themselves and the average player.

For *expected returns*, the unbiased benchmark b_k^V is 61 percent: the true share of state lottery winnings that are given out as prizes. 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 percent of lottery spending is returned to winners. This suggests that people might play *more* if they didn't underestimate the expected returns.

Finally, the unbiased benchmark b_k^V for *predicted life satisfaction* is the actual effect from Lindqvist, Ostling, and Cesarini (forthcoming): 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 7 percent more on lottery tickets.

Regression estimates. Do these relationships survive controls for demographics and preferences? To answer this question, we estimate the following regression:

$$\ln(s_i + 1) = \boldsymbol{\tau}\tilde{\boldsymbol{b}}_i + \beta_a \boldsymbol{a}_i + \beta_x \boldsymbol{x}_i + \epsilon_i. \tag{13}$$

Table 3 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 most of the unconditional relationships from Figure 3 survive controls: *self-control problems*, *financial illiteracy*, *statistical mistakes*, and *expected returns* are all strongly conditionally associated with lottery spending, while *overconfidence* 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 0.37. 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.

Share of consumption explained by bias. We can use the regression results to predict what lottery spending would be without systematic bias, i.e. if the average bias proxies b_{ik} equaled the unbiased benchmarks b_k^V . The predicted effect of bias k on consumption is $\hat{\tau}_k\bar{\tilde{b}}_k$, where $\hat{\tau}_k$ is from the primary estimates in Column 1 of Table 3 and $\bar{\tilde{b}}_k$ is the sample average of $\tilde{b}_{ik}$. These predictions should be thought of as descriptive instead of causal: although we control for observable preferences and demographics, the bias proxies are not randomly assigned and may be noisy measures of actual biases, and thus $\hat{\tau}_k$ is not the causal effect of bias on consumption.

Figure 4 presents the estimates for the six bias proxies. As discussed above, on average people perceive that they play the lottery "too little" and underestimate the expected lottery returns. Thus, $\bar{\tilde{b}}_k < 0$ for *self-control problems* and *expected returns*, and the regression predictions suggest that these biases each *reduce* lottery spending by about 10–12 percent. The $\hat{\tau}_k$ coefficients for *overconfidence* and *predicted life satisfaction* are both very close to zero, so the regression predictions suggest little effect on spending. For *financial literacy* and *statistical mistakes*, $\bar{\tilde{b}}_k > 0$ and $\hat{\tau}$ is positive, and the regression predictions suggest that these biases each increase lottery spending by 20–25 percent. The regression prediction of the total effect of bias on consumption is the sum of $\hat{\tau}_k\bar{\tilde{b}}_k$ across the six bias proxies, or $\hat{\boldsymbol{\tau}}\bar{\tilde{\boldsymbol{b}}} \approx 21$ percent.

As highlighted in Section 1, optimal policy depends on the relationship between bias and income. Figure A5 presents binned scatter plots of each bias proxy by income.

Using the differences in bias proxies by income, we construct the predicted total effect of bias on consumption $\hat{\boldsymbol{\tau}}\bar{\bar{\boldsymbol{b}}}$ separately for each income group. Figure 5 shows that the predicted effect is positive for all incomes, but it is markedly lower for higher-income people: the predicted effect is is 32 and 9 percent for household incomes below \$20,000 and above \$100,000, respectively. While these descriptive results are not causal, they provide suggestive evidence that innumeracy might play a role in lottery spending, and that bias might contribute more to overconsumption for lower-income consumers.

3.3 Prize Semi-Elasticities

In this section, we estimate the semi-elasticity of lottery demand with respect to jackpots and lower prizes, ζ_a. Figure 6 illustrates the identifying variation for an example game and year: Powerball in California in 2014. Over that year, the jackpot prize pool varied from \$40 million to \$400 million. In most drawings, nobody wins the jackpot, so a predetermined share of revenues are added to the jackpot prize pool and it rolls over to the next drawing. When someone does win the jackpot, the jackpot pool returns to the \$40 million "reset value" in the next drawing. Since the odds of winning the jackpot are 1 in 175,223,510, the expected value of the jackpot component of a Powerball ticket ranged from \$0.22 to \$1.71 over the year, as illustrated by the dashed series on the figure.

Since the winning number is randomly drawn, there is randomness in whether the jackpot is won, and thus randomness in the size of the next jackpot. We exploit this randomness to identify the semi-elasticity of demand with respect to jackpot amounts.

Estimating the elasticity with respect to lower prizes presents a separate challenge: while jackpots vary over time, almost all lotto games across the country hold lower prize amounts constant. To address this challenge, we exploit California's unusual parimutuel rule. In 1996, the California Supreme Court ruled that the California Lottery Act allows "lotteries," where players play against other players, but not "house-banked games," where players play against the house. As a result, all California lotto prize levels have parimutuel pools that roll over to the next draw if they are not won. Furthermore, Mega Millions and Powerball have California-specific parimutuel sub-jackpot prizes.

The third and lower prizes rarely roll over, so there is little variation in the expected value of those prizes. The second prizes, however, regularly roll over, generating variation in the expected value of the second prize, as illustrated by the solid line on Figure 6. The second prize pool evolves independently of the jackpot pool. Furthermore, while most of the expected value of a ticket is determined by the jackpot, the second prize pool can also contribute substantially to the overall expected value and even exceed the jackpot's contribution, as it did in June and July. Thus, we can limit our analysis to California and estimate the elasticity with respect to both the jackpot and the second prize.

Estimation strategy. We continue to index prizes by k, with $k = 1$ being the jackpot and $k = 2$ being the second prize. We index lottery games by j and time by t. For nationwide analyses using La Fleur's weekly data, t indexes weeks. For California-specific estimates using draw-level data, t indexes draws. s_{jt} denotes ticket sales for game j at time t, and w_{kjt} denotes the amount of prize k, both in units of millions of dollars. π_{kj} is the the probability of winning prize k in game j, $\boldsymbol{H}_{jt-1}$ is a vector of controls described below, ξ_j is a vector of fixed effects for each game-state-format combination, and $\phi_{q(t)}$ as a vector of quarter-of-sample fixed effects.[7] We would like to estimate the semi-elasticity of demand with respect to prizes by regressing the natural log of sales on the expected value of the first and second prizes:

$$\ln s_{jt} = \zeta_{a1}\pi_{1j}w_{1jt}\,(+\zeta_{a2}\pi_{2j}w_{2jt}) + \boldsymbol{\beta}_H \boldsymbol{H}_{jt-1} + \xi_j + \phi_{q(t)} + \epsilon_{jt}. \tag{14}$$

The second prize elasticity term in parentheses is included only in our California-specific estimates. For nationwide analyses, we cluster standard errors on two dimensions: state and time. For our California-specific estimates, we have only three lotto games (Mega Millions, Powerball, and California's SuperLotto Plus), so we use Newey-West standard errors.

equation (14) would deliver biased estimates of ζ_{ak} for two reasons. First, the period t jackpot pool is directly determined by ticket sales in period t, generating simultaneity bias. Second, previous period sales directly affect expected period t jackpot pools due to rollovers, and they may also be correlated with period t demand if demand shocks are

To address these endogeneity problems, we instrument for the prize expected value $\pi_{kj}w_{kjt}$ with a forecast $\pi_{kj}z_{kjt}$ based on whether or not the prize rolled over from the previous period. We define a rollover indicator as

$$r_{kjt-1} = \begin{cases} 1 & \text{if prize } k \text{ rolls over from } t-1 \\ 0 & \text{if prize } k \text{ was won in } t-1 \end{cases}. \tag{15}$$

The rollover r_{kjt-1} depends on ticket sales s_{jt-1}, but the realization is random conditional on s_{jt-1}. Let ι_{kj} denote the observed average percent increase in the jackpot for prize k in game j conditional on a rollover, and let $\underline{w}_{kj}$ denote prize k's reset value in game j. The prize pool forecast z_{kjt} is

$$z_{kjt} = \begin{cases} (1+\iota_{kj})w_{kjt-1} & \text{if } r_{kjt-1} = 1 \\ \underline{w}_{kj} & \text{if } r_{kjt-1} = 0 \end{cases} \tag{16}$$

Because demand shocks may be serially correlated and both rollovers r_{kjt-1} and the previous jackpot w_{1jt-1} depend on previous demand, we include a vector of controls $\boldsymbol{H}_{jt-1}$ for demand in periods $t-1$ and earlier. In our primary specifications, $\boldsymbol{H}_{jt-1}$ is the vector of sales s_{jl} and jackpots w_{kjl} in previous periods $l = \{t-1, t-2, t-3, t-4\}$, as well as the squares of those variables.[8]

[7]The expected value also depends on the probability of sharing a prize, but this is relatively rare for the jackpot and second prizes, so we assume that π_{kj} is constant and that prizes are never shared.

[8]This regression is related to a dynamic panel regression in the sense that$\boldsymbol{H}_{jt-1}$ includes lags of sales and the

Thus, after controlling for on $\boldsymbol{H}_{jt-1}$, we identify only off of conditionally random variation in the prize pool forecast z_{kjt} delivered by randomness in whether the prize rolled over.

Results. Figure 7 presents binned scatter plots of the variation identifying equation (14), using California data. Panel (a) shows that ticket sales are highly responsive to $\pi_{1j}z_{1jt}$, the jackpot expected value forecast. The slope is about 0.8, meaning that a \$0.10 increase in the expected value of the jackpot increases sales by about 8 percent. However, Panel (b) shows that ticket sales are not responsive to $\pi_{2j}z_{2jt}$, the second prize expected value forecast.

Table 4 presents estimates of prize elasticities using equation (14).[9] Panel (a) presents the jackpot elasticity across all lotto games nationwide, while Panel (b) presents the jackpot and second prize elasticities using California data only. In both panels, column 1 presents our primary IV estimates with the richest control vector $\boldsymbol{H}_{jt-1}$ (four lags and quadratic terms), while column 2 presents estimates with only two lags in $\boldsymbol{H}_{jt-1}$ and no quadratic terms. The fact that the coefficients move little between columns 1 and 2 suggests that any additional controls in $\boldsymbol{H}_{jt-1}$ would have little impact. Column 3 presents OLS results. The jackpot expected value coefficients are slightly larger (although not statistically significantly different in Panel (a)). This is consistent with moderate upward biases from simultaneity and serially correlated demand shocks causing larger sales and larger jackpots.

The regression results match the binned scatter plots in Figure 7. In both panels of Table 4, the jackpot semi-elasticity is around 0.8. In Panel (b), the second prize semi-elasticity is statistically indistinguishable from 0, and the 95 percent confidence intervals exclude values larger than about 0.3.

If consumers were risk-neutral, these two semi-elasticities would be the same: sales would respond equally to variation in expected value coming from the jackpot versus the second prize. The difference between the jackpot and second prize semi-elasticities could arise for several reasons. First, consumers could (in theory) be risk-seeking, although this would be inconsistent purchasing insurance and many decisions in other domains. Second, probability weighting could cause consumers to perceive that the jackpot probability is a larger proportion of its true probability than for the more likely lower prizes. Third, consumers could derive larger anticipatory utility from larger prizes, and anticipatory utility might be insensitive to probabilities. Fourth, the jackpots may be more heavily advertised and promoted, inducing consumers to pay more attention.

These estimates and our model in Section 1 consider individual lottery games in a static framework, meaning that there is no substitution across time or across games. In reality, one might worry about dynamics: for example, buying tickets when jackpots are large could cause people to tire of lotteries and be less likely to buy tickets when the jackpot resets. Furthermore, one

dependent variable is the natural log of sales. While serial correlation would bias our estimate of the coefficient $\boldsymbol{\beta}_H$, this does not affect our analysis because we do not interpret that coefficient. Instead, our parameter of interest is $\bar{\zeta}^a$, and $\boldsymbol{H}_{jt-1}$ are simply included as control variables.

[9] The first stages are very strong; see Appendix Table tk.

might wonder whether people substitute across games, for example buying fewer scratch-offs when lotto jackpots are high. Appendix C.1 shows that there is no statistically detectable substitution across time or across games. Furthermore, Kearney (2005) shows that new state lotteries don't affect other gambling spending, for example in casinos. This suggests that it is not unreasonable to model individual lotto games in isolation using the elasticity ζ^a that we have estimated.

3.4 Price Elasticity

In this section, we estimate the semi-elasticity of lottery demand with respect to price, ζ_p. The key challenge is that unlike prizes, prices change little over time: tickets for most lotto games cost \$1. To address this challenge, we exploit two price changes implemented by the major multi-state lotteries. First, the Powerball ticket price increased from \$1 to \$2 in January 2012. In addition to this price change, the probabilities rose by a ratio of 39/35 for some prizes, and the jackpot reset value doubled to \$40 million. Second, the Mega Millions price increased from \$1 to \$2 in October 2017. In addition, the odds of winning some of the prizes (those that require matching the "Mega Ball" value, five of the nine prize levels) increased by about 20 percent, while the odds of winning other prize levels decreased by a similar amount, shifting the overall prize allocation toward the jackpot.

Panels (a) and (b) of Figure 8 show ticket sales over time for Mega Millions and Powerball in event study frameworks. In each case, the raw data suggest that ticket sales drop after the price change relative to the other game, whose price does not change at that time. There is no large apparent increase in sales of the other game, suggesting that substitution is negligible, so we use the game whose price does not change as a control. Our estimation strategy implements this event study identification but also accounts for changes in demand due to simultaneous changes in the jackpots and lower prizes.

Empirical strategy. p_{jt} is the purchase price of game j tickets at time t, and $\eta_{d(t)}$ is a day-of-week fixed effect. $\hat{\zeta}_{a2} \sum_{k\geq 2} \pi_{kjt} w_{kjt}$ is the predicted effect of the sub-jackpot prizes on sales, where $\hat{\zeta}_2^a$ is the second prize semi-elasticity from column 1 of Panel (b) of Table 4 and $\sum_{k\geq 2} \pi_{kjt} w_{kjt}$ is the expected value of the sub-jackpot prizes. We estimate the following regression:

$$\ln s_{jt} - \hat{\zeta}_{a2} \sum_{k\geq 2} \pi_{kjt} w_{kjt} = \zeta_p p_{jt} + \beta_w w_{1jt} + \boldsymbol{\beta}_H \boldsymbol{H}_{jt-1} + \xi_j + \eta_{d(t)} + \phi_{q(t)} + \epsilon_{jt}, \qquad (17)$$

instrumenting for the jackpot w_{1jt} with the jackpot forecast z_{1jt}.

The jackpot amount w_{1jt} and the adjustment for sub-jackpot prizes $\hat{\zeta}_{a2} \sum_{k\geq 2} \pi_{kjt} w_{kjt}$ control for format changes implemented at the same time as the prize change. This primary specification uses the jackpot amount w_{1jt} instead of the jackpot expected value $\pi_{1jt} w_{1jt}$. Appendix C.2 considers a third event study in which Powerball changed its format in 2015 without changing the purchase price. In that appendix, we find that the jackpot pool control explains changes in sales after the format change better than the jackpot expected value control. This is why we use the jackpot pool control in our preferred estimates of price elasticity ζ_p, although it makes little difference for the estimate of ζ_p.

Results.

Figure 9 presents the event studies after residualizing on the covariates (other than price) in equation (17). In both event studies, the price increase from \$1 to \$2 appears to cause sales to drop by about 50 log points relative to the other multi-state game.

Table 5 presents estimates of equation (17). Columns 1 and 2 combine the two event studies, controlling for the jackpot amount or the jackpot expected value, respectively. Columns 3 and 4 consider each event study individually. The estimates of ζ_p between -0.5 and -0.6 imply that a price increase of \$0.10 per ticket reduces demand by 5–6 percent.

4 Calibrations

4.1 Setup

We now turn to the question of welfare and counterfactual policies. Progress here requires imposing some additional structure, for although the optimal policy conditions derived in Proposition 1 must hold at the optimum, the statistics on which they depend are endogenous to policy.

Turning to the choice of decision weights, we adopt as our starting point a representation for utility commonly used in the literature on decision making under risk,

$$\sum_k \Phi(\pi_k;\theta) m\left(aw_k;\theta\right), \tag{18}$$

where aw_k and π_k denote the prizes and associated probabilities for a given lottery, ranked by index k. (As in Section 1, we normalize $\sum_k \pi_k w_k = 1$ so that a is the expected value of the lottery.) The term $\Phi(\pi_k;\theta)$ represents the decision weight applied to each outcome, while m denotes the value function, representing the utility gained by type θ from winning each potential prize. This representation spans expected utility (the special case in which $\Phi(\pi_k;\theta) = \pi_k$) as well as many modifications proposed in the literature on prospect theory and cumulative prospect theory, including Kahneman and Tversky (1979), Tversky and Kahneman (1992), Prelec (1998), and Chateauneuf, Eichberger, and Grant (2007). (See Bernheim and Sprenger (2020) for a discussion.)

We assume that the value function m arises from an underlying (homogeneous) utility function over continuation wealth, and we normalize the utility gain by θ's local marginal utility of consumption, so that equation 18 can be interepreted in dollar terms as θ's certainty equivalent of lottery L.[10]

[10]Formally, if $\mathcal{U}(W)$ is the utility function over continuation wealth W, and $y(\theta)$ denotes θ's (net) continuation wealth if the prize is not won, then $m(x;\theta) = \frac{\mathcal{U}(y(\theta)+x)-\mathcal{U}(y(\theta))}{\mathcal{U}'(y(\theta))}$.

To adapt the representation in equation (18) to our setting in which lottery ticket purchase is a binary choice, we assume there is an additional random component of utility that determines whether an agent purchases on any particular occasion. For tractability, and to align with standard discrete choice demand models, we assume this preference shock takes the form of an additively separable term ε_t:

$$U(L;\theta,\varepsilon_t) = \sum_k \Phi(\pi_k;\theta) m\left(aw_k;\theta\right) + \varepsilon_t. \tag{19}$$

The agent purchases a ticket lottery ticket on occasion t if $U(L;\theta,\varepsilon_t) > p$. We assume ε_t is drawn from a type-specific distribution $F_{\varepsilon|\theta}(\varepsilon)$ and is independent across choice occasions. We can therefore define demand $s(\theta)$ as the share of θ-types who purchase a lottery ticket at price p on a given occasion, or equivalently, the average number of tickets purchased by θ-types per occasion:

$$s(\theta) = Pr\left(p < \sum_k \Phi(\pi_k;\theta) m\left(aw_k;\theta\right) + \varepsilon_t\right) \tag{20}$$

$$= 1 - F_{\varepsilon|\theta}\left[p - \sum_k \Phi(\pi_k;\theta) m\left(aw_k;\theta\right)\right] \tag{21}$$

We assume $F_{\varepsilon|\theta}$ is such that $0 < s(\theta) < 1$ for lotteries with a positive price and positive prizes, and that $F_{\varepsilon|\theta}$ is differentiable, so that $s(\theta)$ is continuous in p and a. We further assume that no agents are willing to pay a positive price for a lottery with prizes that are all zero. This implies that the preference shock ε_t has negative support: $F_{\varepsilon|\theta}(0) = 1$. We therefore think of ε_t as the hassle cost of purchasing a lottery ticket on occasion t; it represents the amount an agent would need to be paid to obtain a degenerate lottery ticket with $p = 0$ and $a = 0$. (This cost might be larger on days when one is not already entering an establishment that sells tickets, for example.) In the simulations below, we explore sensitivity to a vareity of assumptions about the parameteric form of $F_{\varepsilon|\theta}$. But first, we study the restrictions that our empirical results place on the admissible decision weights Φ for any distribution $F_{\varepsilon|\theta}$.

4.2 What is the Shape of Decision Weights?

The demand function in equation (20) imposes some restrictions on the relationship between the elasticity of demand with respect to price and to lottery prizes which hold for *any* differentiable distribution of preference shocks $F_{\varepsilon|\theta}$. We use these restrictions to explore which decision weighting functions $\Phi(\pi_k;\theta)$ appear to be consistent with the empirical findings in Section 3. Here we find a striking result: many such weighting functions cannot match key qualitative findings in Section 3 under any conventional parameter values. However, one class of functions, studied theoretically in Chateauneuf, Eichberger, and Grant (2007), can match these findings quite well. Although this calibration exercise is useful for our structural simulations, it also contributes directly to the literature empirically estimating the shape of probability weighting functions, in two ways. First, many previous empirical calibrations have relied on variation generated by laboratory experiments. By studying decision weights in a large and economically important field setting, we can examine which insights from the existing literature appear to apply in this market. Second, the lotteries studied here have outcomes involving very high prizes and low probabilities—an area of the decision space not feasibly studied by the sorts of incentivized experiments that have conventionally been used to calibrate probability weighting functions.

We begin by noting that the demand function in equation (20) imposes a constraint on the ratio of the demand response to a change in price vs. a change in the size of prize k. Specifically, letting $\zeta_p(\theta) = \frac{d \ln s(\theta)}{dp}$ denote the semi-elasticity of demand with respect to price, and letting $\zeta_k(\theta) = \frac{d \ln s(\theta)}{d(aw_k)} \cdot \frac{1}{\pi_k}$ denote the semi-elasticity of demand with respect to the expected value of prize k, individual lottery demand satisfies[11]

$$\frac{\zeta_k(\theta)}{|\zeta_p(\theta)|} = \frac{\Phi(\pi_k;\theta)}{\pi_k} m'(aw_k;\theta). \tag{22}$$

The empirical results in Section 3 provide strong evidence about the relative magnitudes of these elasticities at the population level. Our point estimates for $\bar{\zeta}_1$ and $\bar{\zeta}_p$ are 0.79 and -0.57, respectively. Accounting for the standard errors reported in Tables 4 and 5, we take this as evidence that the ratio $\bar{\zeta}_1/|\bar{\zeta}_p|$ lies between 1 and 2.[12]

Next, we consider the magnitude of the jackpot semi-elasticity compared to the second prize semi-elasticity, quantified by the ratio $\bar{\zeta}_1/\bar{\zeta}_2$. Our point estimate for $\bar{\zeta}_2$, based on second prize variation in California, is 0.077, suggesting a ratio of $\bar{\zeta}_1/\bar{\zeta}_2 = 10.26$. As we note in Section **??**, this source of variation may underestimate the semi-elasticy of demand with respect to the steady state second prize, if variation in the second prize is less salient than variation in the jackpot pool, for example due to advertising. This could lead us to overestimate the ratio $\bar{\zeta}_1/\bar{\zeta}_2$. However, there is also a natural lower bound for $\bar{\zeta}_1/\bar{\zeta}_2$, suggested by lottery administrator's incentives. If the second prize semi-elasticity were higher than the jackpot semi-elasticity (i.e., if $\bar{\zeta}_1/\bar{\zeta}_2 < 1$), then an administrator could raise sales at zero cost by reallocating resources from the jackpot pool to the second prize, or by reallocating advertising from the jackpot to the second prize. Yet in each of the

[11] To see this, note that changing the ticket price by $-dp < 0$ induces an increase in lottery purchases among θ-types equal to $ds(\theta) = |\zeta_p(\theta)|\, s(\theta) \cdot dp$. The increase in the expected value of prize level k, denoted dx_k, that would generate the same rise in demand satisfies $dp = \frac{\Phi(\pi_k)}{\pi_k} m'(aw_k;\theta) dx_k$. The change in demand generated by this jackpot increase is $ds(\theta) = \zeta_k(\theta) s(\theta) \cdot dx_k$. Therefore we have $|\zeta_p(\theta)|\, s(\theta) \frac{\Phi(\pi_k)}{\pi_k} m'(aw_k;\theta) \cdot dx_k = \zeta_k(\theta) s(\theta) \cdot dx_k$, which gives the equation in the text.

[12] Note that if the lottery administrator were to adjust price and jackpot in a budget-neutral fashion to maximize sales, this ratio would be 1. Our estimated range for this ratio therefore suggests that these values are close to jointly maximizing sales, though sales could potentially be increased by simultaneously raising prices and average jackpots. This implication is consistent with the lottery format reforms, discussed in Section 3.4 and reported in Appendix Table A3, which adjusted Mega Millions and Powerball in that direction.

three format changes described in Appendix Table A3, the jackpot pool expected value increased relative to the second prize expected value, and Appendix Table A8, which considers the effect of a format change wherein Powerball reallocated the prize share away from smaller prizes and toward the jackpot, indicates that demand actually increased following the reform. Therefore, we interpret our data to suggest that the ratio $\bar{\zeta}_1/\bar{\zeta}_2$ lies between 1 and 10.26.

Finally, an obvious feature of the data, which nevertheless imposes restrictions on admissible decision weights, is the fact that lottery demand is positive at all. The price of virtually all lottery tickets is higher than the expected value of winnings, yet lottery purchases are widespread. Intuitively, this suggests that for purchasers, the decision-weighted utility must not be less than the price of a ticket. Formally, the condition (discussed above) that the taste shock ϵ is negative implies that if a positive share of θ-types purchases lottery tickets, then $\sum_k \Phi(\pi_k;\theta)m\left(aw_k;\theta\right) > p$. Of course there may be heterogeneity across agents in this willingness to pay, but it suggests that in order to rationalize widespread lottery demand, we need a weighting function that can generate a certainty equivalent higher than the ticket price for a representative agent under conventional parameter values.

Together, these observations provide three desiderata for a decision weighting function, when evaluated for a representative agent, using conventional parameter values: (1) a jackpot semi-elasticity of demand between one and two times as large as the price semi-elasticity; (2) a jackpot semi-elasticity less than 11 times as large as the second prize semi-elasticity; and (3) a certainty equivalent higher than price.

To illustrate why many familiar probability weighting functions cannot produce the ranking $\bar{\zeta}_1 > |\bar{\zeta}_p| > \bar{\zeta}_2$, we consider the well-known specification proposed in Tversky and Kahneman (1992):

$$\mathcal{W}_{TK}(\pi) = \frac{\pi^{\beta}}{(\pi^{\beta} + (1-\pi)^{\beta})^{1/\beta}}. \tag{23}$$

This function has a familiar S-shape, the nonlinearity of which is controlled by the parameter $\beta \in (0,1]$; Appendix Figure A10 plots this function for several values of β. As presented in Tversky and Kahneman (1992), this weighting is applied cumulatively, so that the decision weight on the jackpot is $\mathcal{W}_{TK}(\pi_1)$, the weight on the second prize is $\mathcal{W}_{TK}(\pi_1+\pi_2)-\mathcal{W}_{TK}(\pi_1)$, and more generally,

$$\Phi_{TK}(\pi_k) = \mathcal{W}_{TK}\left(\sum_{j=1}^{k}\pi_j\right) - \mathcal{W}_{TK}\left(\sum_{j=1}^{k-1}\pi_j\right). \tag{24}$$

Using this weighting function, and a conventional calibration of the value function based on CRRA utility, we compute the ratios $\zeta_1(\theta)/|\zeta_p(\theta)|$ and $\zeta_1(\theta)/\zeta_2(\theta)$, and the certainty equivalent $\sum_k \Phi(\pi_k;\theta)m\left(aw_k;\theta\right)$ for a representative agent. (See Appendix D for details of this calibration exercise.) Setting $\beta = 0.61$, the median value estimated in Tversky and Kahneman (1992), see p.

312), this calibration produces the following values:

$$\frac{\zeta_1}{|\zeta_p|} = \frac{\Phi_{TK}(1/302,000,000)}{1/302,000,000} \cdot \left(\frac{1,000,000}{1,000,000 + 0.6 \times 300,000,000}\right) = 11.2, \tag{25}$$

$$\frac{\zeta_1}{\zeta_2} = \frac{\Phi_{TK}(1/12,600,000)}{\Phi_{TK}(1/302,000,000)} \cdot \frac{1/12,600,000}{1/302,000,000} \cdot \left(\frac{1,000,000 + 0.6 \times 1,000,000}{1,000,000 + 0.6 \times 300,000,000}\right) = 0.03, \tag{26}$$

$$\sum_k \Phi_{TK}(\pi_k;\theta) m\left(aw_k;\theta\right) = 56.3, \tag{27}$$

An immediate observation is that this calibration, based on a value of β that performs well in incentivized experiments with much higher probabilities and smaller prizes, fails to match our criteria. The calibration predicts a jackpot semi-elasticity that is too high relative to the price semi-elasticity, and a second prize that is two orders of magnitude *larger* than the jackpot semi-elasticity. The third criterion is satisfied — the certainty equivalent is higher than the price — but the certainty equivalent nevertheless appears implausibly high, as it implies that a representative agent would be willing to pay over \$50 for a ticket if they could do so at no hassle cost.

The results of the above calibration depend on a number of assumptions, including about the curvature of utility over continuation wealth and the parameter β, which governs the nonlinearity of the Tversky and Kahneman probability weighting function. Table A9 demonstrates, however, that this limitation is not an artifact of a particular choice of parameter values. For example, maintaining $\beta = 0.61$, if the curvature of utility is increased (higher CRRA), as is necessary to reduce the ratio $\zeta_1(\theta)/\zeta_2(\theta)$ and generate a more plausible certainty equivalent, the second prize semi-elasticity grows larger, violating the second condition even more extremely. Changing the parameter β also fails to resolve the issue: for each of the values of β ranging from 0.4 to 1 (the case of expected utility), shown in separate columns in Table A9, we see that any curvature which satisfies our first condition violates the second. This is a result of the fact that the Tversky and Kahneman weighting function is continuous across low probabilities. The mechanism can be seen visually in Appendix Figure A10: in order to increase the decision weight on very low probabilities, as is necessary to raise the semi-elasticity of demand with respect to the jackpot, the weighting function must be made more S-shaped, which simultaneously raises the weight on higher (though still very low) probabilities, thus raising the second prize semi-elasticity. This issue persists with other more flexible (yet still continuous) functional forms for probability weighting functions, like those proposed in Prelec (1998).

An alternative parameterization which can successfully match the observed features of lottery demand is the "neo-additive capacities model" presented in Chateauneuf, Eichberger, and Grant (2007). In contrast to the functions $\mathcal{W}_{TK}$ and $\mathcal{W}_{Prelec}$, this weighting function parameterization is neither continuous nor differentiable at zero. Instead, it features a linear weighting function which is discontinuous at the points of impossibility and certainty:

$$\mathcal{W}_C(\pi) = \begin{cases} 0 & \text{if } \pi = 0 \\ \beta_1 + \beta_2\pi & \text{if } 0 < \pi < 1 \\ \beta_1 + \beta_2 + \beta_3 & \text{if } \pi = 1 \end{cases}$$

with $\beta_1,\ \beta_2,\ \beta_3 > 0$, and with weights again applied cumulatively as in equation 24.[13] In our setting, the utility gain from the worst outcome is mechanically $m(0) = 0$, rendering the parameter β_3 irrelevant, and implying that for our purposes this specification has only two parameters of interest, β_1 and β_2.

A broad range of values of β_1 and β_2 can satisfy the relative elasticity magnitudes in the empirical data. Note that in this specification,

$$\frac{\zeta_1}{|\zeta_p|} = \frac{\mathcal{W}_C(\pi_1)}{\pi_1} m'(aw_1) = \frac{\beta_1 + \beta_2\pi_1}{\pi_1} m'(aw_1)$$

and

$$\frac{\zeta_1}{\zeta_2} = \frac{\mathcal{W}_C(\pi_1)}{\mathcal{W}_C(\pi_1 + \pi_2) - \mathcal{W}_C(\pi_1)} \cdot \frac{\pi_2}{\pi_1} \cdot \frac{m'(aw_1)}{m'(aw_2)} = \frac{\beta_1 + \beta_2\pi_1}{\beta_2\pi_2} \cdot \frac{\pi_2}{\pi_1} \cdot \frac{m'(aw_1)}{m'(aw_2)}.$$

Thus it is immediately apparent that for any candidate value function m, the ratio $\zeta_1/|\zeta_p|$ can be made arbitrarily large by choosing β_1 sufficiently high, while for any β_1, the ratio ζ_1/ζ_2 can be lowered arbitrarily close to one by choosing a value of β_2 sufficiently high. In fact, even a simpler single parameter specification, in which β_2 is fixed at the expected utility benchmark value of $\beta_2 = 1$, can match the empirical patterns observed in the data. Panel (b) of Appendix Table A9 reports the ratios $\zeta_1/|\zeta_p|$ and ζ_1/ζ_2 and the certainty equivalent for a range of values of the CRRA and β_1 when $\beta_2 = 1$. For each CRRA value in the conventional range of 0.5 to 2, there is a value of β_1 that jointly satisfies all three criteria. (When the CRRA parameter is equal to two, the certainty equivalent does become implausibly large, although this can be altered by allowing for $\beta_2 \neq 1$.) We defer a formal calibration to the next section; here we simply note that the simple single-parameter weighting function adapted from Chateauneuf, Eichberger, and Grant (2007) can match the general empirical features of lottery demand with ease—whereas other conventional probability weighting function specifications cannot—and on that basis we adopt this specification for our structural simulations.

[13] In Chateauneuf, Eichberger, and Grant (2007), a neo-additive capacity decision maker maximizes "a weighted average of the expected utility of a lottery and its maximal and minimal outcomes" (p. 539). That construction is equivalent to the formulation here, with weight β_2 on expected utility, and weights β_1 and β_3 on the best and worst outcomes, respectively.

4.3 Structural Simulations

We assume demand takes the form in equation (20), with

$$\varepsilon_t = \xi(\theta) + \alpha(\theta)\epsilon_t,$$

where $\xi(\theta)$ controls the mean hassle cost of obtaining a lottery ticket, $\alpha(\theta)$ controls the price elasticity of demand, and ϵ_t is a mean-zero an iid random variable. For tractability and simplicity, we perform calibrations assuming ϵ_t is a logit error term. Taken literally, this assumption unrealistically implies that the distribution of ε_t does not have purely negative support, yet as we show below, the estimated model finds a negative value for $\xi(\theta)$, with only a small share of ε_t falling in the positive domain. As a result, we can also interpret ε_t as being truncated above at zero, with the missing mass representing an atom of consumers with $\varepsilon_t = 0$.[14]

Taking the lottery expected value a and the ticket price p to be the policy instruments of interest for the government, we can write representative utility (i.e., averaged across all ϵ_t) for type θ as

$$\tilde{U}(a, p; \theta) := -p + \sum_k \Phi(\pi_k; \theta) m(aw_k; \theta) + \xi(\theta).$$

Due to the assumed logit distribution of ϵ_t, demand can be written in closed form:

$$s(p, a; \theta) = \frac{\exp\left(\tilde{U}(\theta)/\alpha(\theta)\right)}{1 + \exp\left(\tilde{U}(\theta)/\alpha(\theta)\right)}, \tag{28}$$

with population average $\bar{s}(p, a)$. The average decision utility from lotteries among θ-type agents also has an analytic solution:

$$\begin{aligned}\bar{U}(a, p; \theta) :=& E\left[\max\left\{0, -p + \sum_k \Phi(\pi_k; \theta)\pi_k m(aw_k; \theta) + \xi(\theta) + \alpha(\theta)\varepsilon_t\right\}\right] \\ =& \alpha(\theta) \ln\left(1 + \exp\left(\tilde{U}(a, p; \theta)/\alpha(\theta)\right)\right) \end{aligned} \tag{29}$$

This expectation may not represent normative welfare, for the decision weights $\Phi(\pi_k; \theta)$ may be distorted by behavioral biases. Yet we also allow that decision weights may diverge from expected utility due for normatively valid reasons, like anticipatory utility. To flexibly allow for this distinction, we define $\chi_k(\theta)$ to denote the share of the difference $\Phi(\pi_k; \theta) - \pi_k$ that is a normative mistake

[14] Consumers with such a truncated nonpositive distribution of ε_t behave identically to those with logit distributed shocks, except that demand falls discretely to zero if price rises above the consumer's certainty equivalent. We confirm that this is not the case for any of our calibrations in equilibrium. Although the truncation does affect the expected welfare derived from purchasing tickets, this difference is constant with respect to the policy instruments a and p, and thus the optimal policy simulations are unaffected.

or bias. Then we can write normative utility as

$$\bar{V}(a,p;\theta) = \bar{U}(a,p;\theta) - s(p,a;\theta)\sum_k \chi_k(\theta)\left(\Phi(\pi_k;\theta) - \pi_k\right) m(aw_k;\theta). \tag{30}$$

In the notation of Section (1), $\gamma(a;\theta)$ is equal to the summed term in equation (30).

We now turn to the government's welfare maximization problem. Our baseline assumption is that labor supply decisions are not affected by lottery policy, so that we can treat each agent's choice of earnings $z(\theta)$ as exogenous. In this case, lottery design does not affect the government's income tax receipts, and labor supply decisions can be ignored when considering optimal lottery design. However, earnings are relevant for the policymaker through their effect on the consumer's marginal utility of consumption, and the policymaker may wish to redistribute from higher to lower earning consumers at the margin. We encode this policy motive via reduced-form Pareto weights $\mu(\theta)$, which can be interpreted as the social marginal welfare weights under the prevailing income tax. The optimal lottery policy can be found by maximizing aggregate normative utility from lottery consumption, while accounting for any effects on total government revenues. Formally, the policy maker's objective function is

$$SW(a,p) = \int_\theta \mu(\theta)\bar{V}(a,p;\theta)dF_\theta(\theta) + \lambda\bar{s}(p,a)(p-a-o), \tag{31}$$

where λ represents the marginal value of public funds from lottery revenues, and o represents any overhead administration cost, which is assumed to scale with the number of tickets sold.

We impose a number of additional assumptions in order to calibrate this model using our empirical data. First, we assume that all consumers have homogeneous constant relative risk aversion (CRRA) utility over continuation wealth, and we further assume that the taste shock parameters are homogeneous across types: $\xi(\theta) \equiv \xi$ and $\alpha(\theta) \equiv \alpha$. Second, we assume the weighting function $\Phi(\pi_k;\theta)$ takes the form proposed in Chateauneuf, Eichberger, and Grant (2007) and discussed above, with $\beta_1(\theta)$ and $\beta_2(\theta)$ defined to denote the weights placed on the best outcome and on expected utility, respectively. To the extent that $\beta_1(\theta)$ differs from 0 and $\beta_2(\theta)$ differs from 1, θ differs from an expected utility maximizer. To reduce the dimensionality of the calibration problem, we calibrate the average values of $\bar{\beta}_1$ and $\bar{\beta}_2$, and we define a unidimensional measure $\phi(\theta)$, which quantifies θ's departure from expected utility in the direction $(\bar{\beta}_1, \bar{\beta}_2)$. That is, we define $\beta_1(\theta) = \phi(\theta)\bar{\beta}_1$ and $\beta_2(\theta) = 1 + \phi(\theta)(\bar{\beta}_2 - 1)$.[15] Thus an expected utility maximizer would have $\phi(\theta) = 0$, an agent behaving like the average consumer would have $\phi(\theta) = 1$, and an agent whose decision weighting is more extreme than the reference type would have $\phi(\theta) > 1$. We assume the bias share $\chi(\theta)$ is heterogeneous across types, but constant across levels, so the money-metric

[15] On the assumption that inattention to smaller prizes is bounded at $\beta_2(\theta) = 0$, we constrain $\beta_2(\theta)$ to be nonnegative.

bias term, corresponding to the summation in equation (30) above, simplifies to

$$\gamma(\theta) = \chi(\theta)\left[\beta_1(\theta)m(aw_1;\theta) + \sum_k \left(\beta_2(\theta)-1\right)\pi_k m(aw_k;\theta)\right]$$
$$= \chi(\theta)\phi(\theta)\left[\bar{\beta}_1 m(aw_1;\theta) + \sum_k \left(\bar{\beta}_2-1\right)\pi_k m(aw_k;\theta)\right].$$

We calibrate these bias shares based on the results from Section 3.2, using the counterfactual normative consumer strategy described at length in Allcott, Lockwood, and Taubinsky (2019). Specifically, we assume that the coefficients on bias proxies in Table 3 represent the causal effect of individuals' biases on lottery spending, controlling for normative preferences as captured by the controls specified in Column (1). We then compute the counterfactual level of lottery spending that would arise if each agent were debiased, by computing predicted expenditure when each agents bias covariates are replaced with the normative benchmark, while their preference and demographic controls are retained. Like in Allcott, Lockwood, and Taubinsky (2019), the validity of this approach depends on the assumption that other factors affecting lottery purchases, including unobserved normative preferences, are orthogonal to our measured bias proxies conditional on the included controls.

We discretize the income distribution into N types. (In one of the robustness specifications below we also allow for additional heterogeneity within income bins.) In total, then, we use our empirical data to calibrate four homogeneous parameters, ξ, α, $\bar{\beta}_1$, and $\bar{\beta}_2$, and two heterogeneous parameters, the decision-weighting strengths $\phi(\theta)$ and the bias shares $\chi(\theta)$. We calibrate these parameters using the population level elasticities $\bar{\zeta}_1$, $\bar{\zeta}_2$, and $\bar{\zeta}_p$, heterogeneous consumption levels $s(\theta)$, and heterogeneous values of the quantity effect of bias, $s(\theta) - s^V(\theta)$.[16]

We calibrate the model assuming the same single representative lottery game from the preceding subsection, equivalent to a current Mega Millions lottery ticket with a price of \$2 and a jackpot pool of \$300 million. We treat the policy choice of lottery expected value as a univariate decision, incorporating both the implicit tax rate and expected explicit income taxes paid on winnings. Therefore we include both factors in expected value parameter a, and we assume an income tax rate on lottery winnings of 40%. This leads to a status quo expected value of $a = 0.74$. 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. Finally, we use a conventional calibration of pareto weights, proportional to $1/c(\theta)$, where $c(\theta)$ is status quo income (net of taxes), to encode normative redistributive preferences.[17]

[16] The bias shares $\chi(\theta)$ have N degrees of freedom, while the decision-weighting strengths $\phi(\theta)$ have $N-1$ degrees of freedom, since the fact that $\bar{\beta}_1$ and $\bar{\beta}_2$ are averages implies that $\phi(\theta) = 1$ by construction. Thus the model is exactly identified with $4 + 2N - 1$ degrees of freedom.

[17] We convert our measure of pre-tax income to post-tax income using the schedules from Piketty, Saez, and Zucman

4.4 Results

The primary results of our baseline calibrations are reported in Figure 10. Both panels display plots of social welfare (relative to a benchmark with no available lottery) across a range of possible lottery parameters. Panel (a) varies the expected value of the lottery by scaling up or down all prizes proportionally, holding fixed the status quo price of the lottery. Panel (b) holds fixed status quo prices, and instead varies the price of the lottery ticket.

In both panels, we display results for three different assumptions about bias. The first case assumes all observed demand is fully normatively justified, that is, $\chi(\theta) = 0$ for all types. In this case it is unsurprising that lotteries generate surplus, as the usual revealed preference logic implies that consumers are made better off by the option to purchase a good from which they derive utility. The optimal implicit lottery tax is very close to zero, with an expected value equal to price minus overhead costs.

The blue lines in Figure 10 shows the welfare gain from lotteries under our estimated degree of behavioral bias. Although the total welfare generated by the lottery is somewhat lower, it remains positive across the range of plotted expected values.

The red lines plot the welfare gains assuming biases account for a much larger share of demand than we estimate. (For this specification we assume that the quantity effect of bias is four times as large as we estimate at each level of income.) Even under this more extreme assumption, welfare remains positive under the current design of lottery tickets, though by much less than in the previous specifications.

Panel (b) indicates that welfare declines to zero as the price grows large, reflecting the fact that a sufficiently high price discourages nearly all consumption and thus resembles a market with no lottery. Very low prices generate substantial welfare when consumers are unbiased, reflecting the fact that the fiscal cost to the government is offset by the transfer received by consumers, who derive anticipatory utility greater than the marginal social cost of providing the lottery. In contrast, in the presence of bias, welfare falls as prices decline. This reflects that low prices induce many consumers to purchase lottery tickets even when their net normative utility from that purchase decision is negative.

Although Figure 10 varies expected value while holding fixed price (and vice versa), it is also possible to jointly solve for the optimal expected value and price. We perform this computation using a nonlinear solver, and we find the optimal price of a lottery ticket is \$1.95, and the optimal expected value (rescaling all prizes in fixed proportion) is 1.34. Together, these result in an implicit tax rate of 21%, somewhat lower than the prevailing design of current lotto games like Powerball and Mega Millions. Figure 11 plots the jointly optimal price and expected value across a range of assumptions about the share of the decision weight that is due to bias.[18] When bias accounts for a

(2018).

[18] For the purposes of this figure, the bias share is assumed to be homogeneous across incomes.

larger share of demand, the lottery is optimally made less attractive via a lower expected value and higher price. The line is discontinued at points where the lottery is sufficiently unattractive that consumers would cease purchasing altogether under the truncated logit distribution of ε_t discussed above.

Table 6 reports these results across a range of alternative specifications and robustness checks. The right two columns report the jointly optimal expected value and ticket price in each specification; the left column reports the optimal implicit lottery tax, calculated as the share of price that is a markup over expected value plus overhead. After our baseline specification, the next two rows report results for lower and higher utility curvature (CRRA parameters 0.5 and 2). The row labeled "Higher value of $\bar{\zeta}_2$" calibrates the simulation assuming that the second-prize semi-elasticity is equal to the jackpot semi-elasticity, to allow for the possibility that our point estimate from Section **??** is an underestimate. The next two lines of the table report results under the two alternative assumptions about bias which considered in Figure 10: an "unbiased" specification in which all lottery demand is assumed to be driven by normative preferences, and a specification calibrated assuming the quantity effect of bias is four times as large as our estimates from Section **??**. Finally, the last row of the table reports results when we allow for additional heterogeneity conditional on income—specifically, we assume two types of consumers at each income level: those who are expected utility maximizers (represented by those who purchase no lottery tickets in our data) and a second type with positive lottery spending, calibrated to match the average total lottery spending in each income bin.

5 Conclusion

There is a long-standing debate as to whether these lotteries are a regressive "tax on people who are bad at math" or a "win-win" that generates both consumer surplus and government revenues. In this paper, we derive new formulas that deliver optimal prices and attributes for a government-regulated good as a function of a set of sufficient statistics. We then provide new descriptive evidence on lottery consumption, behavioral biases, and demand elasticities. We find that individual-level lottery expenditures are highly correlated with survey measures of innumeracy and poor statistical reasoning, but our observable measures of behavioral bias statistically explain only about 21 percent of lottery purchases for the average household. Using these empirical moments, we calibrated a model that predicts that lotteries are indeed a welfare-improving "win-win," and the socially optimal implicit tax is similar to the current norms in U.S. states. There are many caveats to our results, and we think of this paper as just a first step toward a new literature studying lotteries through the lens of optimal taxation.

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Table 1: **Descriptive Statistics: Survey Data**

(a) **Demographics**

	Obs.	Mean	Std. dev.	Min	Max
Household income ($000s)	2,887	69.92	54.45	5	250
Years of education	2,887	14.00	2.57	4	20
Age	2,887	47.70	17.48	18	91
1(Male)	2,887	0.48	0.50	0	1
1(White)	2,887	0.65	0.48	0	1
1(Black)	2,887	0.11	0.31	0	1
1(Hispanic)	2,887	0.16	0.36	0	1
Household size	2,887	3.04	1.59	1	6
1(Married)	2,887	0.51	0.50	0	1
1(Employed)	2,887	0.59	0.49	0	1
1(Urban)	2,887	0.80	0.40	0	1
1(Attend church)	2,887	0.36	0.48	0	1
Political ideology	2,886	3.88	1.54	1	7

(b) **Spending and Income Effects**

	Obs.	Mean	Std. dev.	Min	Max
Monthly lottery spending ($)	2,885	23.22	80.03	0	1,900
Income change (%)	2,879	-0.27	19.62	-50	50
Spending change (%)	2,877	-5.59	20.02	-50	50
Self-reported income effect (%)	2,862	-1.70	16.56	-50	50

(c) **Proxies for Preferences and Biases**

	Obs.	Mean	Std. dev.	Min	Max
Unwillingness to take risks	2,887	-3.95	1.40	-7	-1
Financial risk aversion	2,882	3.08	0.82	1	4
Lottery seems fun	2,883	0.19	1.87	-3	3
Enjoy thinking about winning	2,878	0.83	1.99	-3	3
Self-control problems	2,881	-0.38	1.15	-3	3
Financial literacy	2,887	0.75	0.26	0	1
Financial numeracy	2,887	0.61	0.33	0	1
Gambler's Fallacy	2,887	0.31	0.40	0	1
Non-belief in Law of Large Numbers	2,887	0.42	0.18	0.00	0.93
Expected value miscalculation	2,887	0.70	0.36	0	1
Overconfidence	2,871	0.00	0.57	-4.95	4.95
Expected returns	2,879	0.29	0.20	0.05	0.95
Predicted life satisfaction	2,855	2.49	4.82	-10	10

Notes: This table presents descriptive statistics for our AmeriSpeak survey. Panel (a) presents demographics, Panel (b) presents spending and income effects, and Panel (c) presents proxies for preferences and biases. Section 2.1 summarizes the coding of these variables. Observations are weighted for national representativeness.

Table 2: **Descriptive Statistics: Lottery Sales and Prize Data**

	Years	Geo.	Obs.	Mean	Std. dev.	Min	Max
LaFleur's sales ($millions)	1994-2017	State	322,848	3.31	8.38	0.00	178.61
Jackpot pool ($millions)	1994-2017	State	125,971	64.03	80.29	0.05	1,500.00
Jackpot odds (1 in ... million)	1994-2017	State	125,971	142.62	87.08	0.44	302.58
Lotto Report sales ($millions)	2005-2018	National	2,209	31.85	45.91	10.55	1,270.21
Imputed sales ($millions)	2003-2017	CA	3,202	4.69	5.54	1.69	178.37
2nd prize pool ($millions)	2003-2017	CA	3,202	0.42	0.70	0.03	7.66
2nd prize odds (1 in ... million)	2003-2017	CA	3,202	5.52	5.71	1.59	18.49

Notes: All means, standard deviations, minimums, and maximums are reported in millions. Variables for which the geographic level is "State" have coverage over 41 states and D.C. We use La Fleur's sales and jackpot pool and odds data in our national demand elasticity analysis and Lotto Report and imputed sales and second prize pool and odds data in our price and format change analyses as well as our California-level sub-jackpot demand elasticity analysis.

Table 3: **Regressions of Monthly Lottery Spending on Bias Proxies**

	(1)	(2)	(3)	(4)
Self-control problems	0.313***	0.397***	0.304***	0.303***
	(0.035)	(0.046)	(0.039)	(0.037)
Financial illiteracy	0.208***	0.316***	0.219***	0.215***
	(0.045)	(0.051)	(0.044)	(0.047)
Statistical mistakes	0.095***	0.184***	0.130***	0.087**
	(0.036)	(0.044)	(0.037)	(0.037)
Overconfidence	0.017	0.031	0.024	0.021
	(0.031)	(0.042)	(0.036)	(0.031)
Expected returns	0.109***	0.225***	0.119***	0.085***
	(0.032)	(0.040)	(0.034)	(0.033)
Predicted life satisfaction	0.005	0.194***	0.029	0.015
	(0.033)	(0.039)	(0.035)	(0.034)
Risk aversion	-0.033		-0.053	-0.037
	(0.036)		(0.037)	(0.037)
Lottery seems fun	0.633***		0.634***	0.638***
	(0.042)		(0.045)	(0.042)
Enjoy thinking about winning	0.243***		0.227***	0.242***
	(0.042)		(0.043)	(0.041)
ln(household income)	0.103**			0.092**
	(0.047)			(0.047)
ln(years of education)	-0.660***			-0.688***
	(0.235)			(0.259)
Other demographics	Yes	No	No	Yes
State fixed effects	Yes	No	No	No
R^2	0.44	0.16	0.37	0.41
Observations	2,810	2,810	2,810	2,810

Notes: This table presents estimates of equation (13), a regression of ln(1+monthly lottery spending) on bias proxies, preference proxies, and demographic controls using data from our AmeriSpeak survey. "Other demographics" includes age, household size, political ideology, and indicators for male, black, white, Hispanic, married, employed, urban area, and attends religious services at least once a month. Observations are weighted for national representativeness. Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 4: **Prize Semi-Elasticity Estimates**

(a) **Jackpot Semi-Elasticity: All Lotto Games Nationwide**

	(1) IV	(2) IV	(3) OLS
Jackpot expected value ($)	0.7931***	0.7986***	0.9058***
	(0.0875)	(0.0833)	(0.0755)
Lags in $\boldsymbol{H}$	4	2	0
Quadratic terms in $\boldsymbol{H}$	Yes	No	No
R^2	0.57	0.56	0.60
Observations	59,795	59,966	60,134

(b) **Jackpot and Second Prize Semi-Elasticity: California Only**

	(1) IV	(2) IV	(3) OLS
Jackpot expected value ($)	0.7660***	0.7995***	0.9717***
	(0.0472)	(0.0485)	(0.0426)
2nd prize expected value ($)	0.0770	-0.1461*	-0.1609**
	(0.1296)	(0.0887)	(0.0674)
Lags included in $\boldsymbol{H}$	4	2	0
$\boldsymbol{H}$ includes quadratic terms	Yes	No	No
R^2	0.45	0.47	0.62
Observations	3,107	3,114	3,202

Notes: This table presents estimates of equation (14), a regression of the natural log of sales on prize expected values, controlling for a vector $\boldsymbol{H}$ of lagged sales and prize amounts as well as quarter-of-sample and state-game-format 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. Panel (a) presents estimates for all lotto games nationwide, using game-by-week data, using two-way clustered standard errors by state and time. Panel (b) presents estimates limited to California, where we also exploit variation in second prizes, using game-by-drawing data, using Newey-West standard errors with up to five lags. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

Table 5: **Price Semi-Elasticity**

	(1) Pooled	(2) Pooled	(3) Powerball	(4) Mega Millions
Price ($)	-0.5686***	-0.5466***	-0.6150***	-0.5602***
	(0.0441)	(0.0292)	(0.0294)	(0.0308)
Jackpot pool ($millions)	0.0040***		0.0059***	0.0037***
	(0.0002)		(0.0002)	(0.0001)
Jackpot expected value ($)		1.0240***		
		(0.0267)		
Observations	836	836	418	418

Notes: This table presents estimates of equation (17), a regression of the natural log of sales (adjusted for predicted change in demand from changes in sub-jackpot prizes) on ticket price, controlling for the jackpot amount, a vector of lagged sales and prize amounts, a post-price change indicator, and day-of-week and quarter-of-sample fixed effects. All regressions instrument for the jackpot amount with a forecast based on the previous period jackpot amount and an indicator for whether the jackpot was won in the previous period. Columns 1 and 2 pool the data from both the Powerball and Mega Millions price changes and also control for event-game fixed effects, while columns 3 and 4 consider each price change in isolation. We use Newey-West standard errors with up to five lags. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

Table 6: **Optimal Lottery Tax and Attributes Under Alternative Assumptions**

	Optimal implicit tax	Optimal expected value	Optimal ticket price
Baseline	0.21	1.34	1.95
CRRA = 0.5	0.20	2.09	2.86
CRRA = 2	0.26	0.96	1.58
Higher value of $\bar{\zeta}_2$	0.11	3.12	3.71
Completely unbiased	-0.02	1.39	1.56
4x estimated bias	0.56	1.23	3.22
Heterogeneity conditional on income	0.14	1.32	1.77

Notes: TK

Figure 1: **Graphical Illustration of Bias**

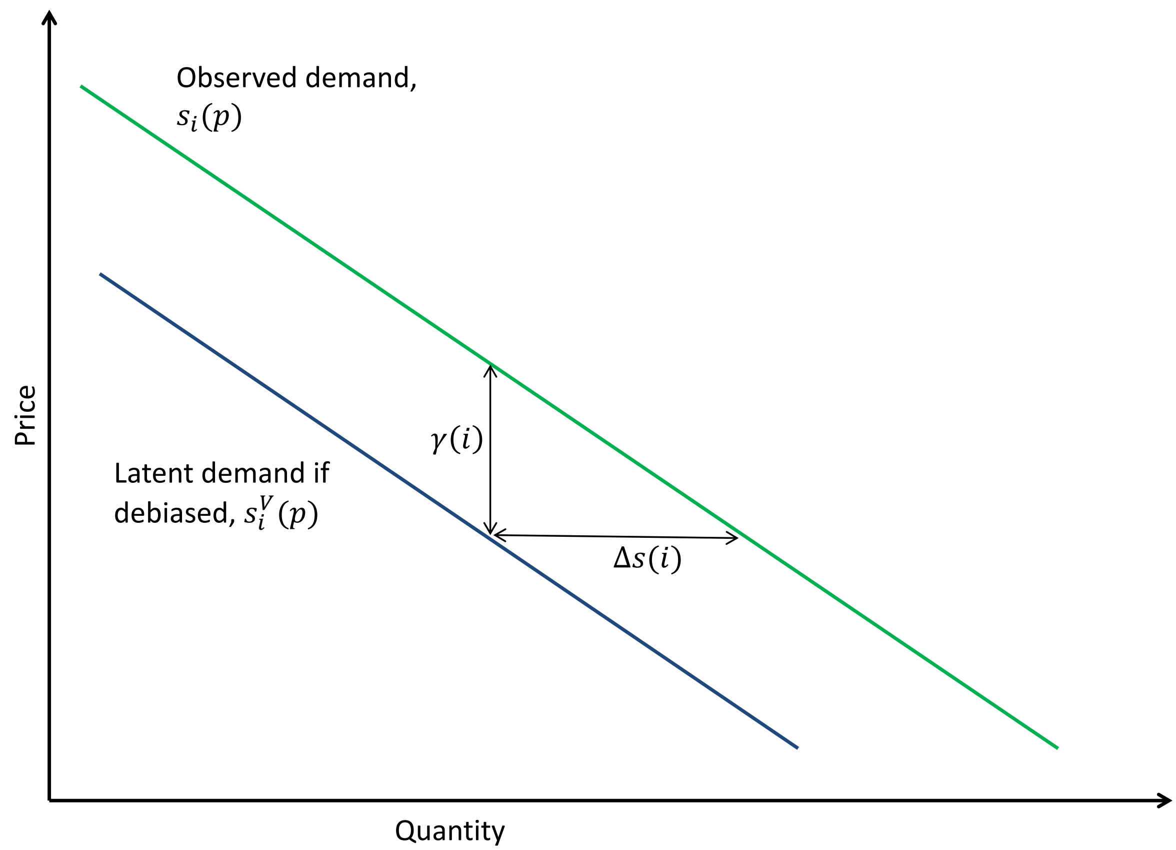
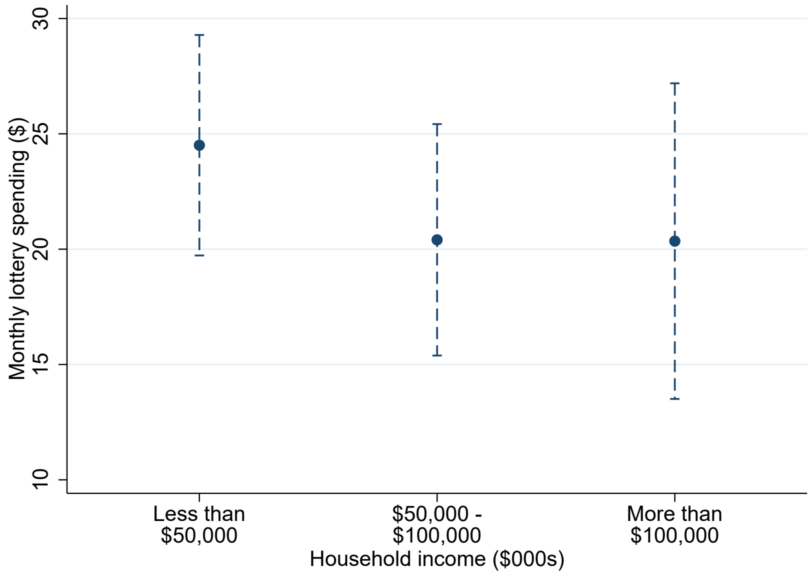
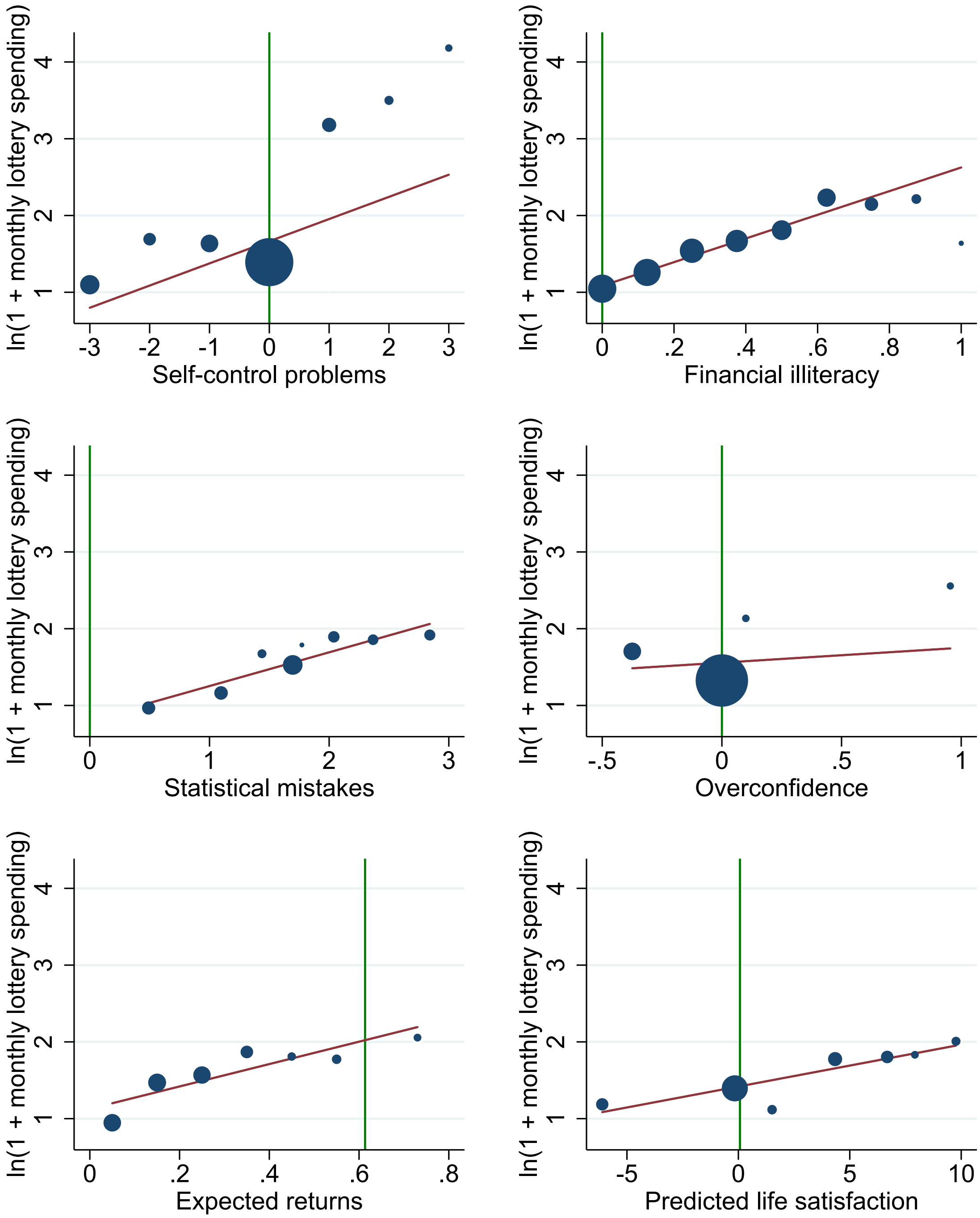


Figure 2: **Lottery Spending by Income**



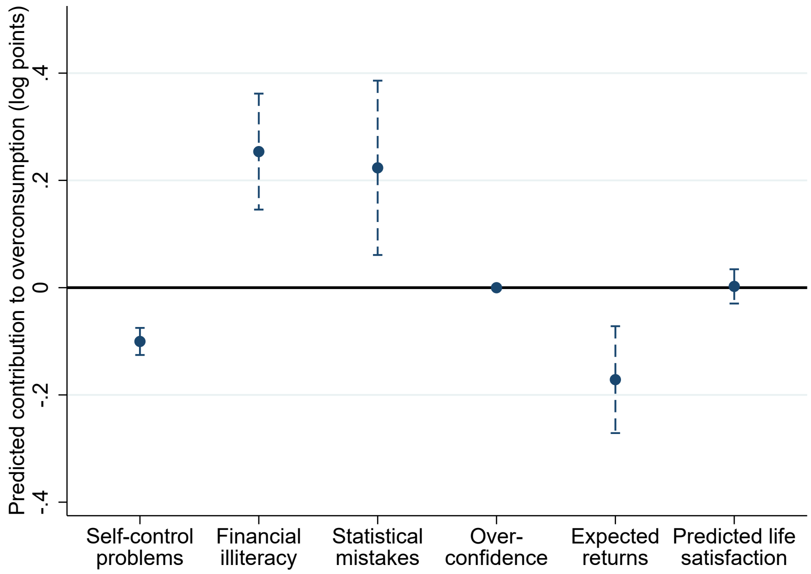
Notes: This figure presents monthly lottery spending by income, with 95 percent confidence intervals, using data from our AmeriSpeak survey. Spending is winsorized at $500 per month.

Figure 3: **Relationship Between Lottery Spending and Bias Proxies**



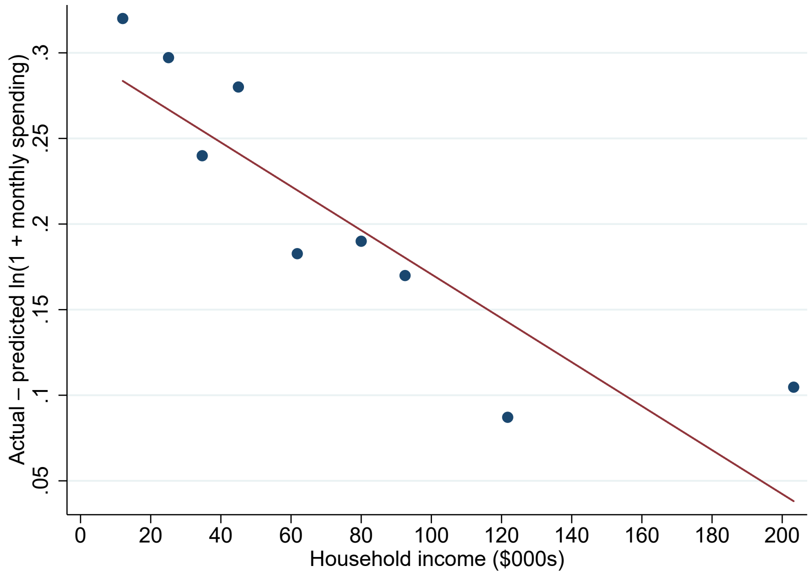
Notes: This figure presents binned scatter plots of ln(1+monthly lottery spending) versus our six bias proxies, using data from our AmeriSpeak survey. The vertical line on each panel corresponds to the correct or "unbiased" value of the bias proxy.

Figure 4: **Predicted Effect of Individual Biases on Lottery Spending**



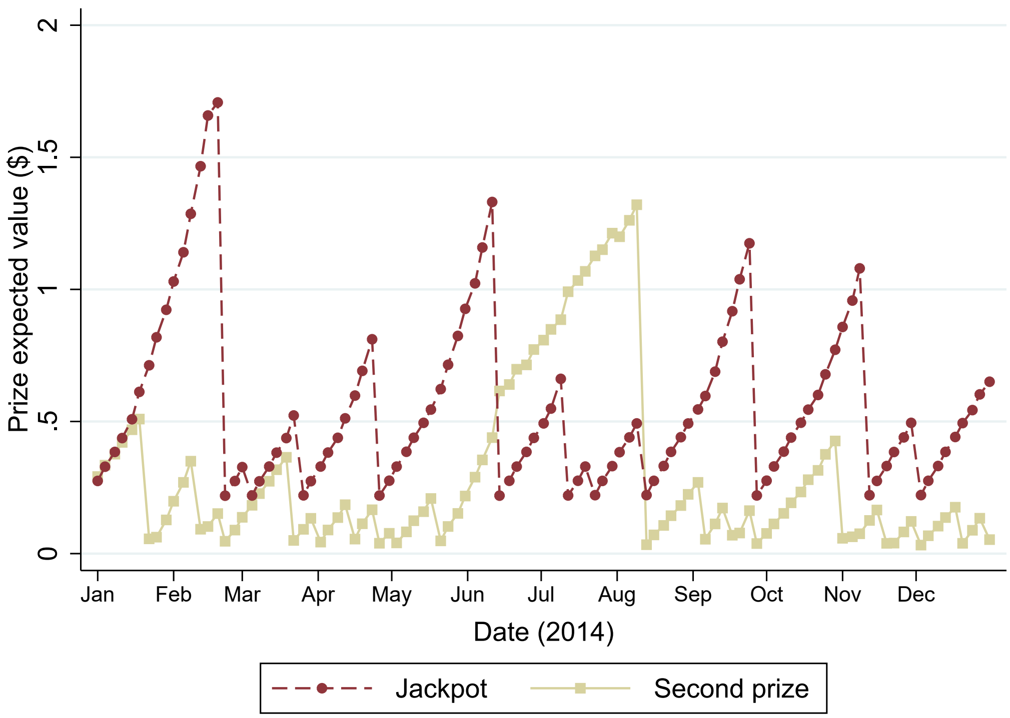
Notes: This figure plots $\hat{\tau}_k \bar{\tilde{b}}_k$, the predicted effect of bias on lottery spending for bias proxy k, for each of our six bias proxies. $\hat{\tau}_k$ is from column 1 of Table 3, $\tilde{b}_{ik} = \frac{b_{ik} - b_k^V}{SD(b_{ik})}$ is the difference between person i's proxy b_{ik} and the unbiased value b_k^V in standard deviation units, and $\bar{\tilde{b}}_k$ is the sample average of $\tilde{b}_{ik}$. 95 percent confidence intervals are calculated using the Delta method.

Figure 5: **Predicted Effect of Bias on Lottery Spending by Income**



Notes: This figure presents $\hat{\boldsymbol{\tau}}\bar{\tilde{\boldsymbol{b}}}$, the predicted effect of bias on lottery spending, by income. $\hat{\boldsymbol{\tau}}$ is from column 1 of Table 3, $\tilde{b}_{ik} = \frac{b_{ik}-b_k^V}{SD(b_{ik})}$ is the difference between person i's proxy b_{ik} and the unbiased value b_k^V in standard deviation units, and $\bar{\tilde{\boldsymbol{b}}}$ is the vector the averages of $\tilde{b}_{ik}$ for an income group.

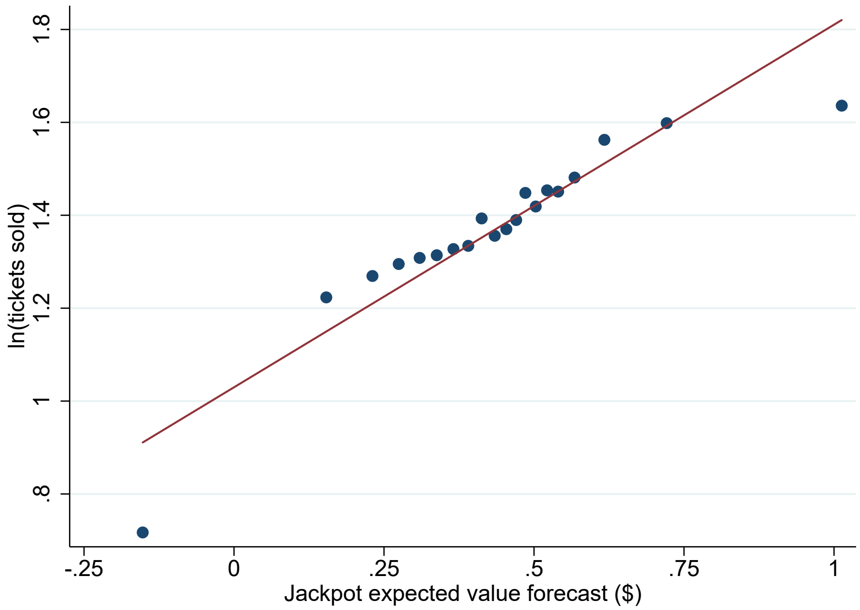
Figure 6: **California Powerball Jackpot and Second Prizes in an Example Year**



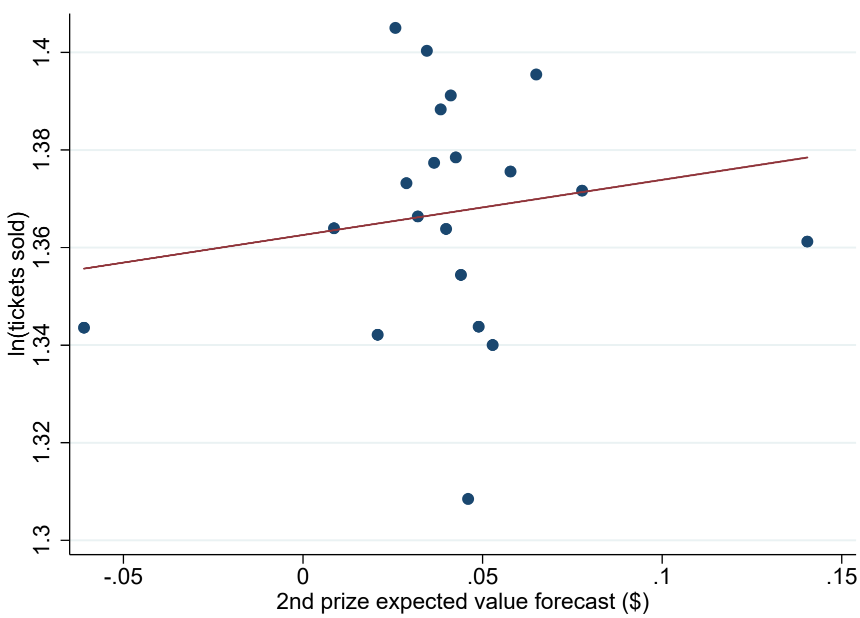
Notes: This figure presents jackpot and second prize expected values by drawing for Powerball in California in 2014.

Figure 7: **Ticket Sales versus Jackpot and Second Prize Expected Values in California**

(a) **Sales versus Jackpot Expected Value**



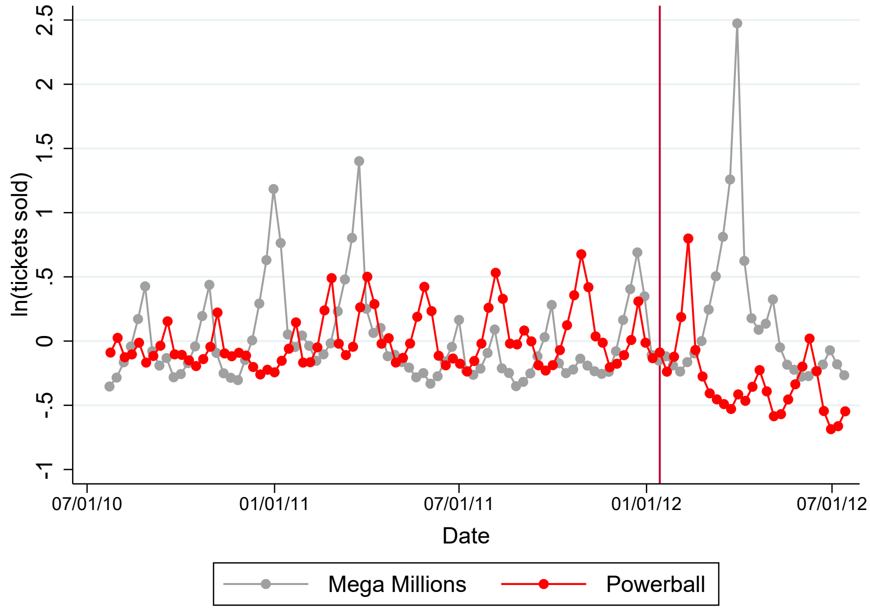
(b) **Sales versus Second Prize Expected Value**



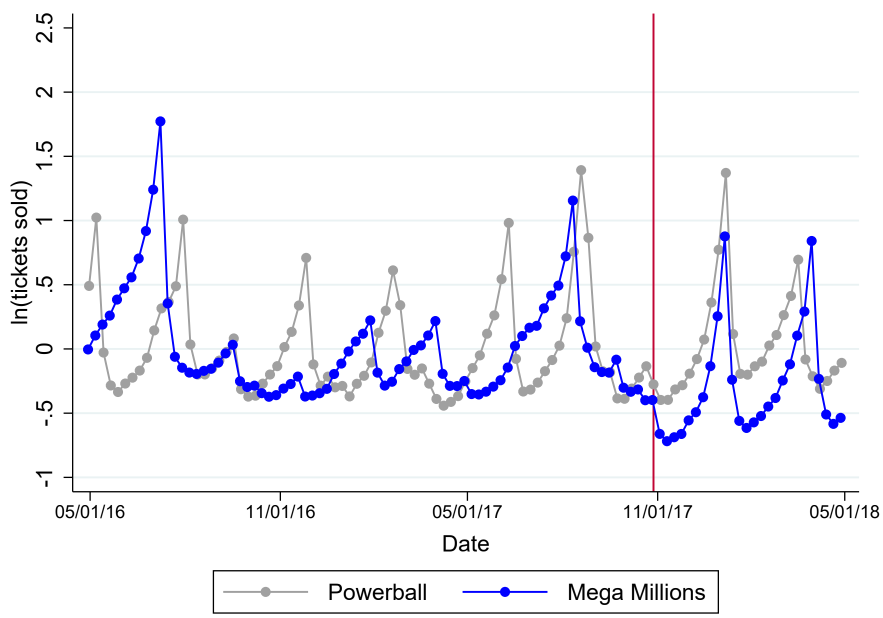
Notes: These figures present binned scatter plots of the natural log of ticket sales for California lotto games as a function of the jackpot expected value forecast (in Panel (a)) and the second prize expected value forecast (in Panel (b)), conditional on the other prize expected value forecast, a vector of lagged sales and prize amounts, and quarter-of-sample and state-game-format fixed effects.

Figure 8: **Price Change Event Studies**

(a) **Powerball**



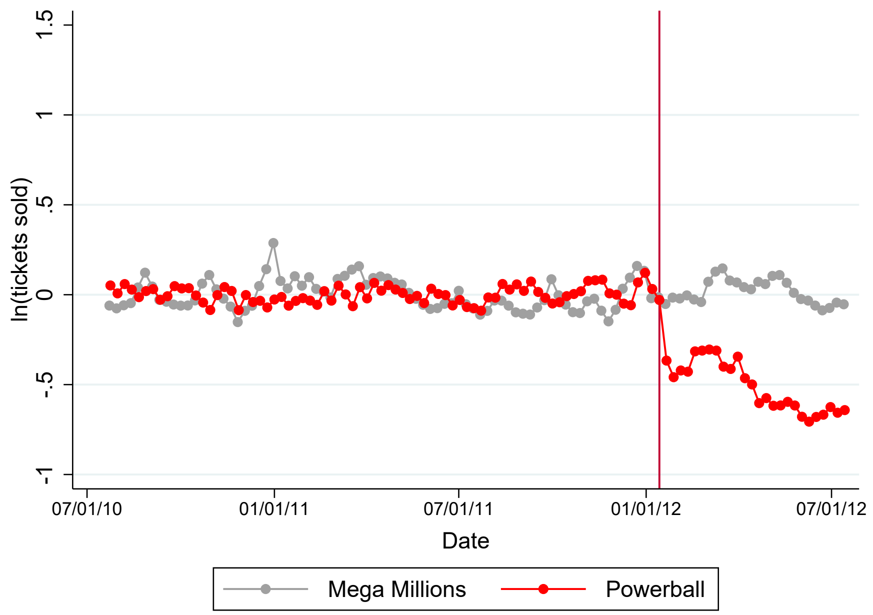
(b) **Mega Millions**



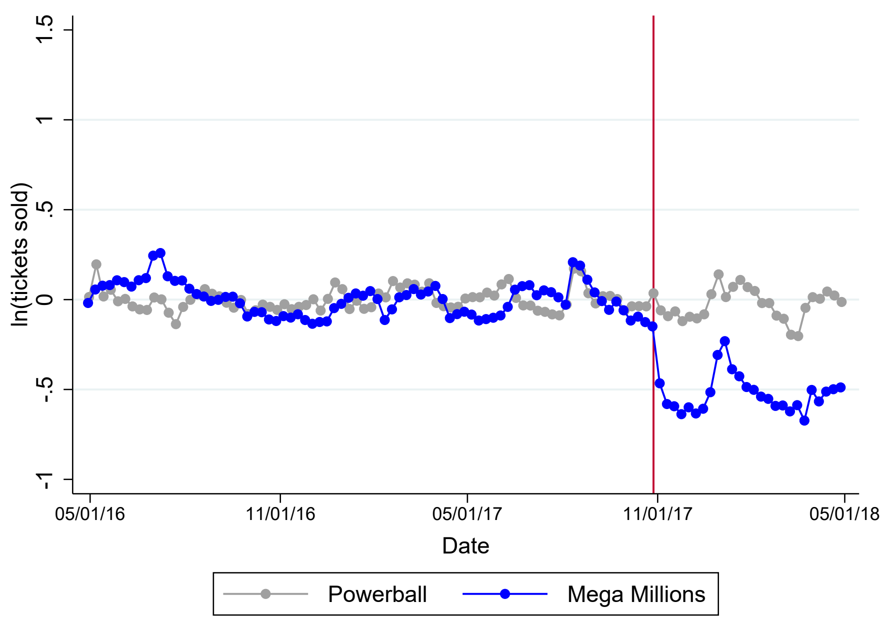
Notes: These figures present weekly averages of the natural log of ticket sales before and after price increases, which are indicated by the vertical red lines. The y-axis is adjusted so that the average for each game before the price change equals zero. In Panel (a), the Powerball ticket price increased from $1 to $2 in January 2012. In Panel (b), the Mega Millions ticket price increased from $1 to $2 in October 2017.

Figure 9: **Price Change Event Studies**

(a) **Powerball**



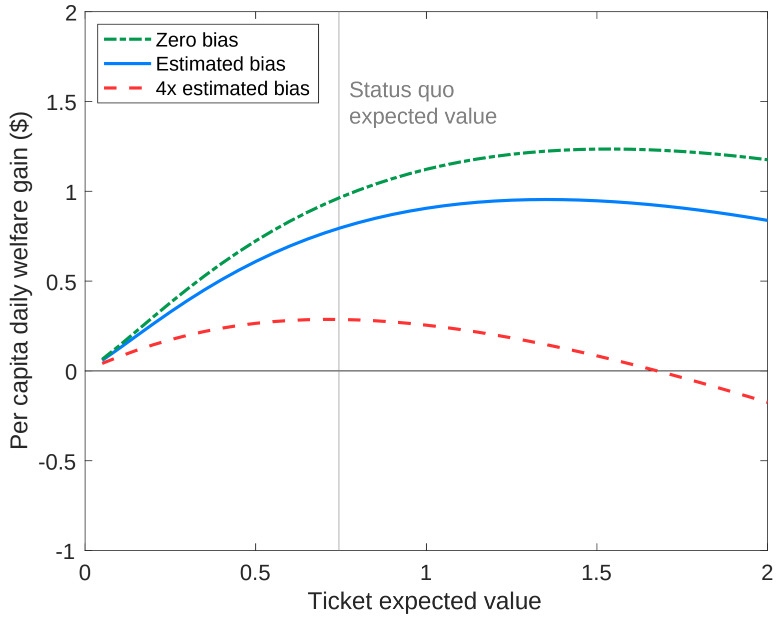
(b) **Mega Millions**



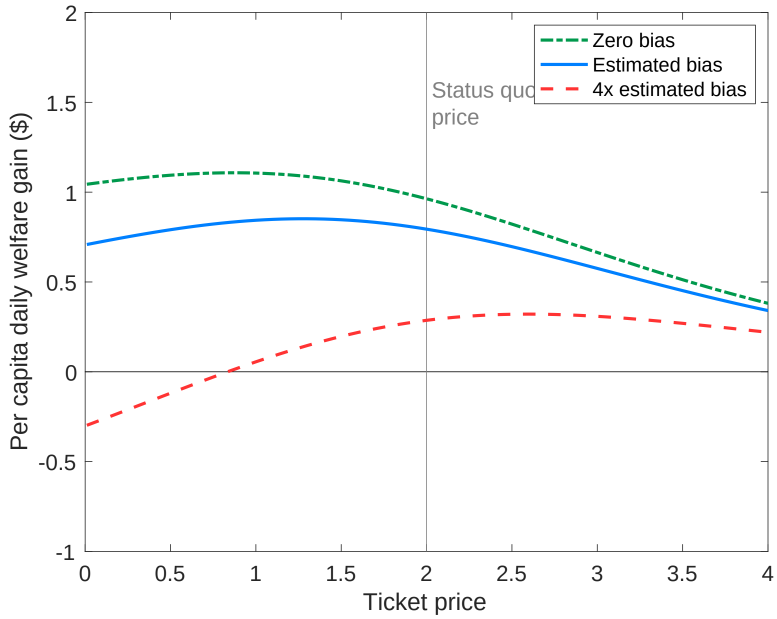
Notes: These figures present weekly average of the natural log of ticket sales (residual of controls in equation (17)) before and after price increases, which are indicated by the vertical red lines. The y-axis is adjusted so that the average for each game before the price change equals zero. In Panel (a), the Powerball ticket price increased from $1 to $2 in January 2012. In Panel (b), the Mega Millions ticket price increased from $1 to $2 in October 2017.

Figure 10: **Effect of Lottery Attributes on Social Welfare**

(a) **Variation in Ticket Expected Value**



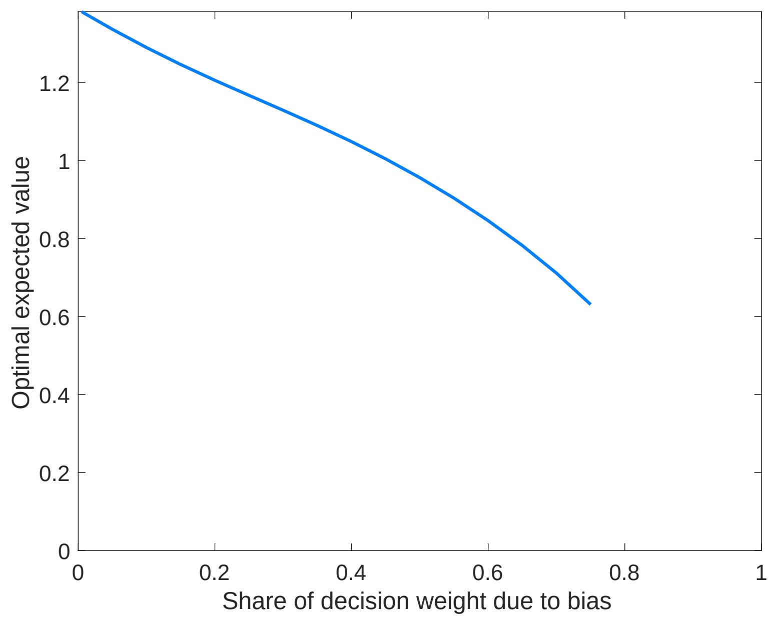
(b) **Variation in Ticket Price**



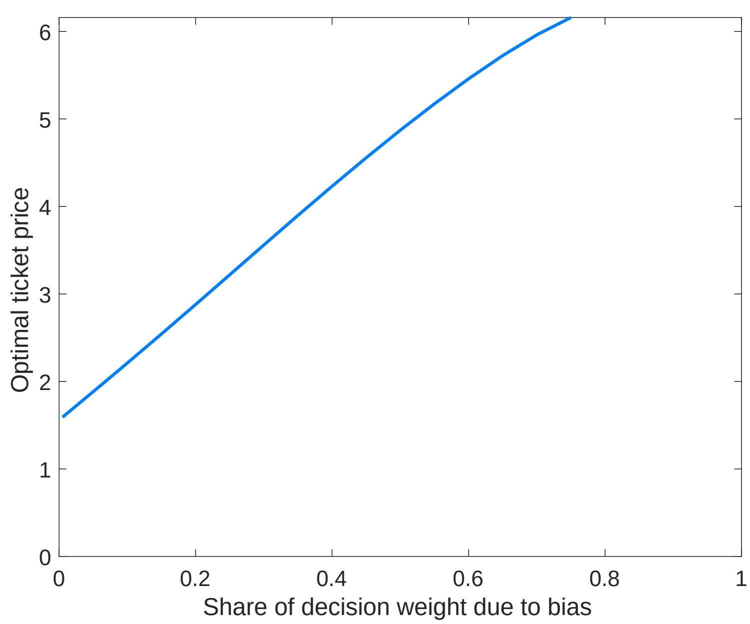
Notes: These figures plot the simulated social welfare gain, in dollars per person-day, from a representative lottery with varying expected value (Panel a) or price (Panel b). Values are computed relative to a hypothetical benchmark without a lottery product. The representative lottery is based on a standard $2 Mega Millions ticket with a jackpot pool of $300 million.

Figure 11: **Optimal Lottery Attributes as a Function of Bias**

(a) **Optimal Lottery Expected Value**



(b) **Optimal Ticket Price**



Notes: These figures plot the simulated social welfare gain, in dollars per person-day, from a representative lottery with varying expected value (Panel a) or price (Panel b). Values are computed relative to a hypothetical benchmark without a lottery product. The representative lottery is based on a standard $2 Mega Millions ticket with a jackpot pool of $300 million. Lines are discontinued where the lottery is optimally banned.

Online Appendix: Not for Publication

The Optimal Taxation of Lotteries

Hunt Allcott, Benjamin B. Lockwood, and Dmitry Taubinsky

A Theory Appendix

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 ocassions $t = 1, \dots, t^*$. Individuals realize a tasket chock ε_t at the beginning of each period that determines their utility from the lottery ticket, and we assume that the ε_t are i.i.d. conditional on θ. Individuals' utility given a vector of shocks $\boldsymbol{\varepsilon}$and x lottery tickets is given by $U(x, c, z; \boldsymbol{a}, \theta, \boldsymbol{\varepsilon})$. Lottery demand is a random variable $\boldsymbol{s}(\theta)$ that maps shock vectors $\boldsymbol{\varepsilon}$ to total number of lottery tickets purchased. We let $\bar{s}(\theta)$ denote expected lottery purchases.

We make the following assumptions

Assumption 1. *Lotteries are a sufficiently small share of expenditures such that terms of order* $U_c''\mathbb{E}[(p\boldsymbol{s}(\theta))^2]$ *and higher are negligible.*

Assumption 2. *Demand for lotteries is orthogonal to the income elasticity* ζ_z*, conditional on income.*

Assumption 3. $\kappa(a)$*, the valuation of the attribute* a*, is orthognal to the income elasticity* ζ_z*, conditional on income.*

Assumption 4. *Income effects on labor supply are negligible.*

Assumption 1 allows us to generalize Lemma 1 from Saez (2002). Intuitively, variation in lottery expenditures does not have a first order effect on marginal utility, and thus the first-order effect of a price increase p is $\approx U_c'(\bar{s}(\theta), z - T(z), z; \boldsymbol{a}, \theta, \boldsymbol{\varepsilon})\bar{s}(\theta)$. Similalry, the effect of increasing after-tax income is $\approx U_c'(\bar{s}(\theta), z - T(z), z; \boldsymbol{a}, \theta, \boldsymbol{\varepsilon})$. These two equations give us an approximate Roy identity, which recovers Lemma 1 from Saez (2002).

The assumption also implies that income effects on lottery expenditures are negligible, as in part (b) of Assumption 4 of ALT.

We define $s_{inc}'(z)$ as the causal effect on lottery demand of individuals changing their pre-tax income. We define $s_{pref}'(z) = s'(z) - s_{inc}'(z)$ and

$$s_{pref}(z) := \int_{x=z_{min}}^{z} s_{pref}'(x)dx. \tag{32}$$

Analogously, we define $\kappa_{inc}'(z)$ as the causal effect on willingness to pay for lottery attributes of individuals changing their pre-tax income. By the same logic as Lemma 1 of Saez (2002), it follows that if $\kappa(\theta)$ is the money-metric equivalent of perturbing a, then perturbing the marginal income tax rate by $\kappa_{inc}'(\theta)da$ has the same impact on type θ labor supply as does increasing a by da. We define $\kappa_{pref}'(z) = \kappa'(z) - \kappa_{inc}'(z)$ and

$$\kappa_{pref}(z) := \int_{x=z_{min}}^{z} \kappa'_{pref}(x)dx. \quad (33)$$

The intuition behind $\kappa_{pref}(z)$ is that it measures the extent to which WTP for a is driven by preference heterogeneity. The intuition for $\kappa_{inc}(z)$ is, roughly, the degree to which the WTP for a can be explained by income effects.

Under these assumptions and definitions we have the following:

Proposition 2. *If p and a are optimal and $a > 0$,*

$$p - C'_s(a, \bar{s}) = \bar{\gamma}(1 + \sigma_p) - \frac{Cov[s_{inc}(z), g(z)]}{\left|\bar{\zeta}_p\right| \bar{s}} \quad (34)$$

$$\bar{\kappa} - \bar{\rho} = C'_a(a, \bar{s}) + \bar{\gamma}(\sigma_a - \sigma_p)\bar{\zeta}_a \bar{s} + \left(Cov[s_{pref}(z), g(z)] \frac{\bar{\zeta}_a}{\left|\bar{\zeta}_p\right|} - Cov[\kappa_{pref}(z) - \rho(z), g(z)] \right) \quad (35)$$

If $a = 0$ is optimal then

$$\bar{\kappa} - \bar{\rho} < C'_a(a, \bar{s}) + \bar{\gamma}(\sigma_a - \sigma_p)\bar{\zeta}_a \bar{s} + \left(Cov[s_{pref}(z), g(z)] \frac{\bar{\zeta}_a}{\left|\bar{\zeta}_p\right|} - Cov[\kappa_{pref}(z) - \rho(z), g(z)] \right)$$

The intuition is for the comparative statics is to simply offset the labour supply effects of increase p and a by dp and da through income tax reforms that increase marginal tax rates by $s'_{inc}(z)$ and $\kappa'_{inc}(z)$, respectively.

B Survey Questions

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
Willingness 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. _%]

Overconfidence

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]

Predicted earnings

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.

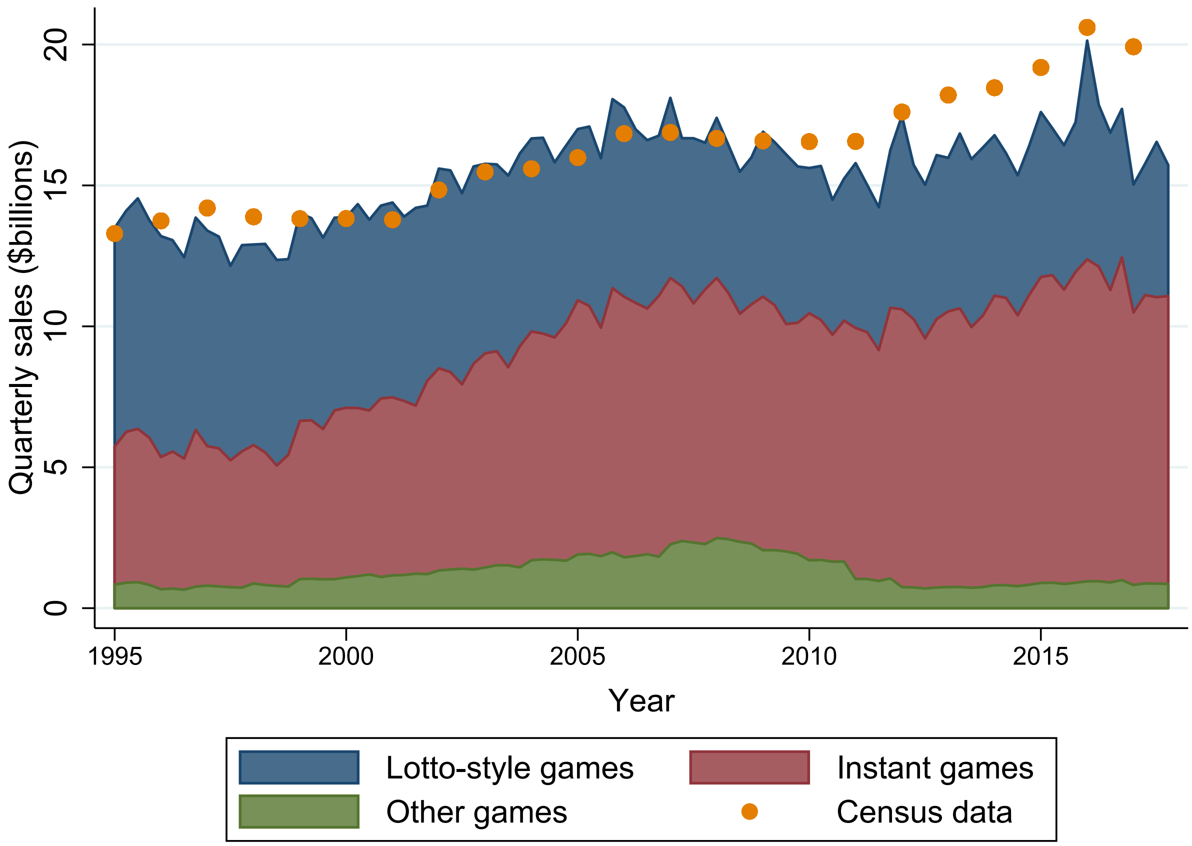
The survey asked the following question about life satisfaction: "Taking all things together in your life, how satisfied would you say that you are with your life these days?" People responded on a scale from 0 ("Extremely dissatisfied") to 10 ("Extremely satisfied"). The average response was 7.21 out 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?

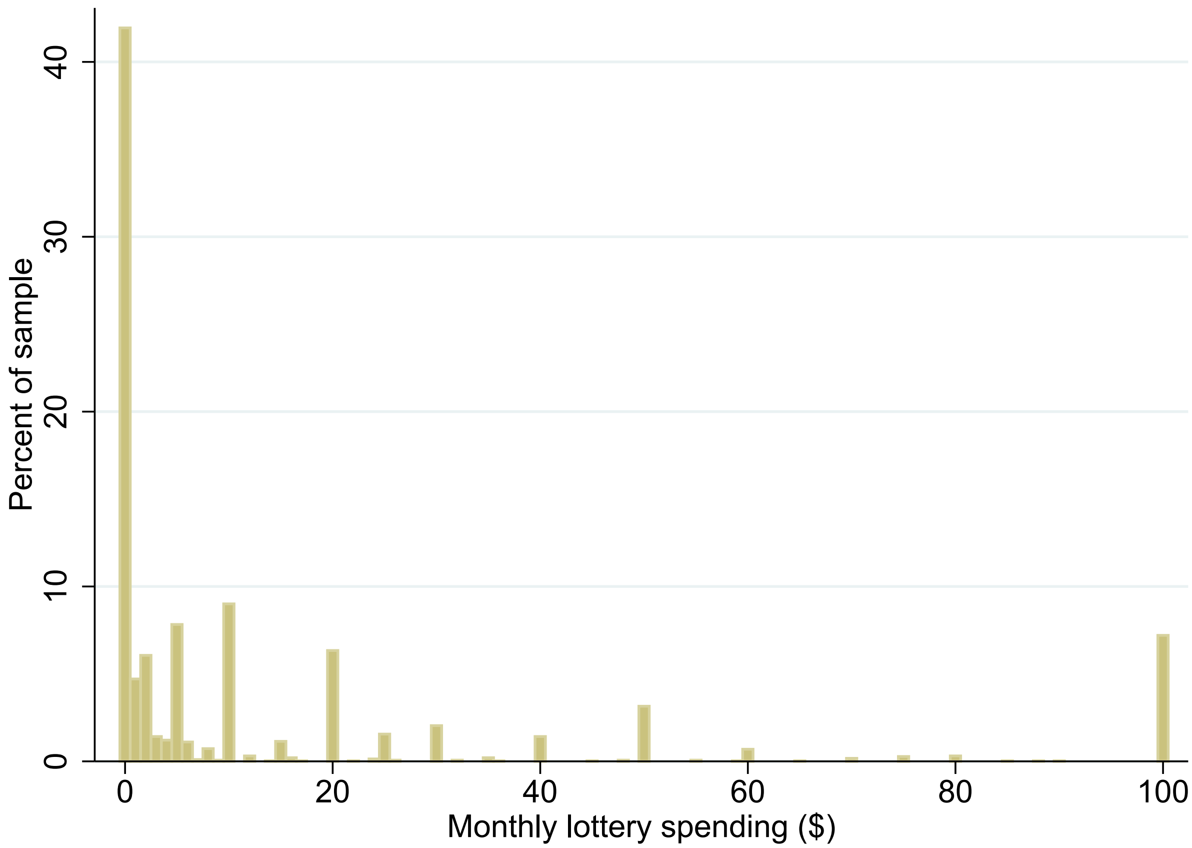
C Empirical Results Appendix

Figure A1: **Lottery Sales by Game Type over Time**



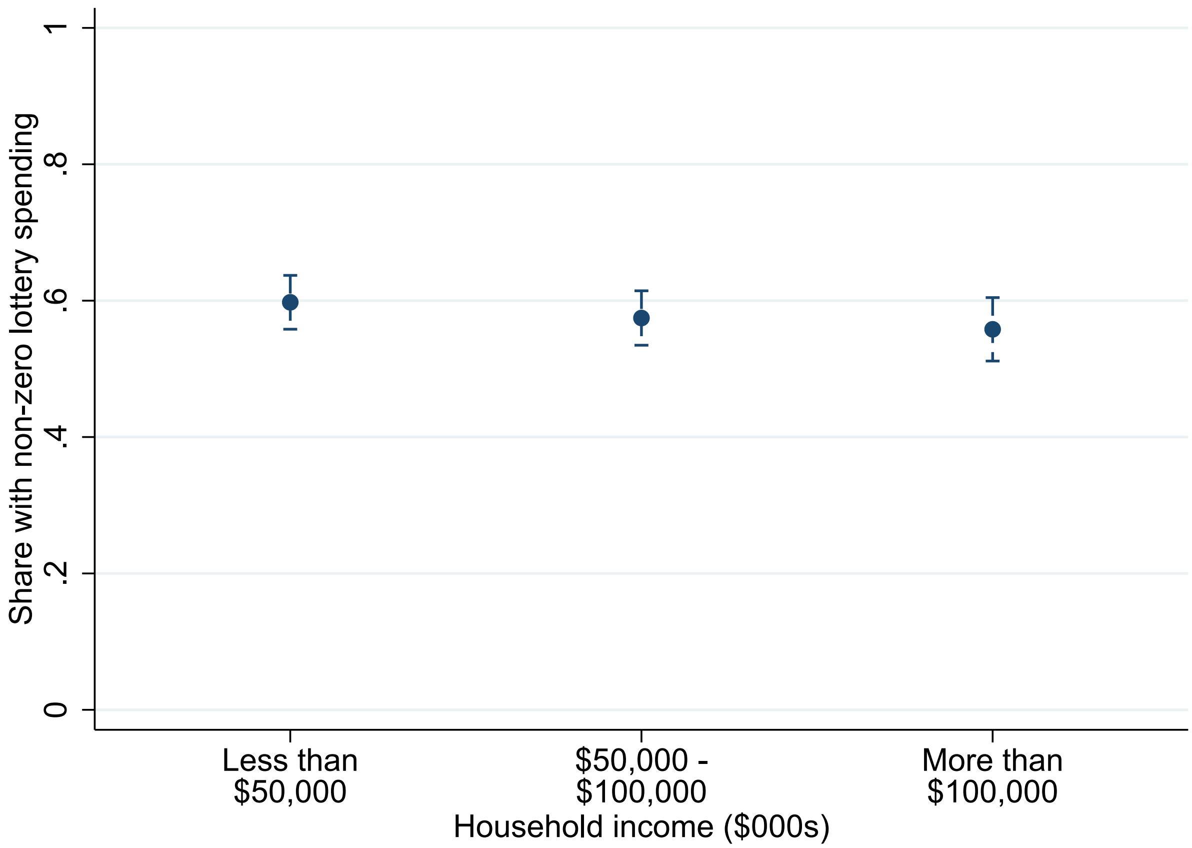
Notes: This figure presents total U.S. lottery sales by type of game, using data from La Fleur's. Census data are from the Census of Governments, inflated by six percent to account for the assumption that retailers receive six percent of sales as commission. Monetary amounts are in real 2019 dollars.

Figure A2: **Distribution of Monthly Lottery Spending**



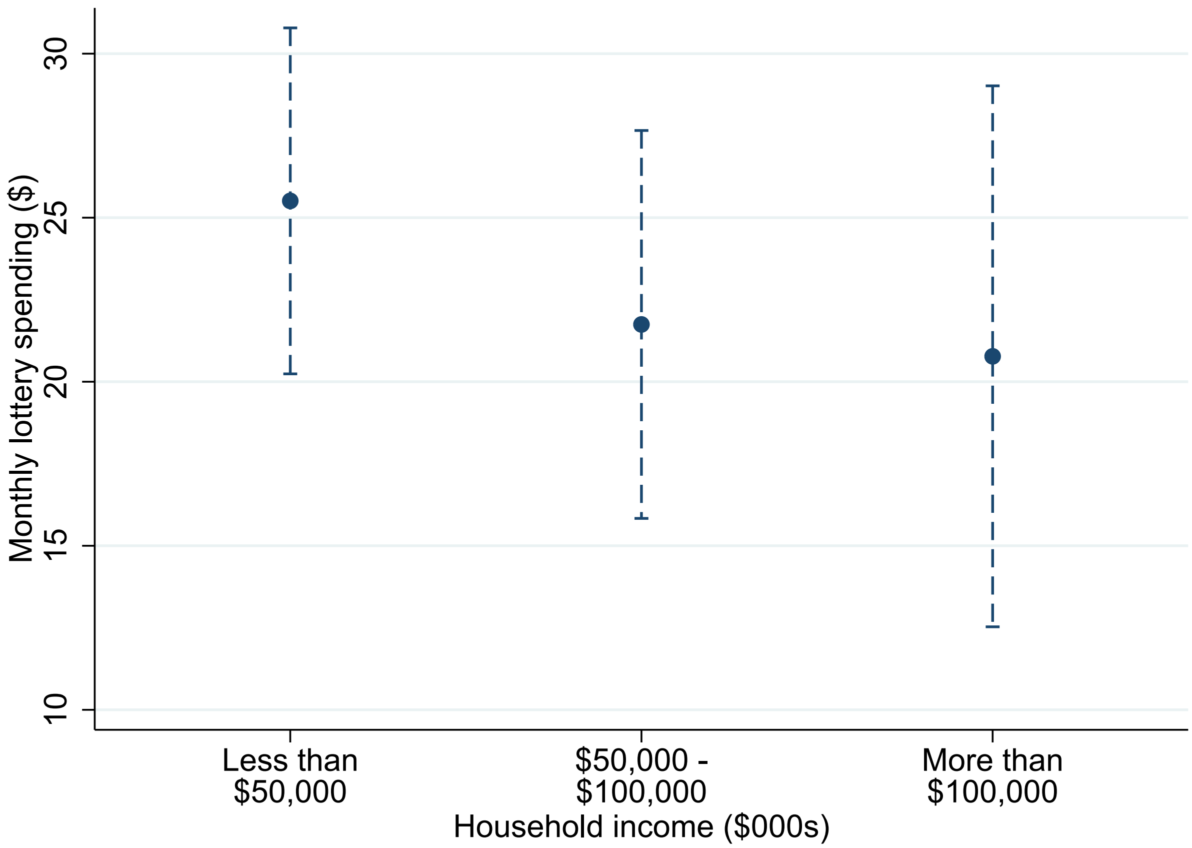
Notes: This figure presents a histogram of monthly lottery spending, using data from our AmeriSpeak survey. Spending is winsorized at $100 per month.

Figure A3: **Non-Zero Lottery Spending by Income**



Notes: This figure reports the share of people with non-zero monthly lottery spending in 2019 by income, with 95 percent confidence intervals, using data from our AmeriSpeak survey.

Figure A4: **Lottery Spending by Income without Winsorization**



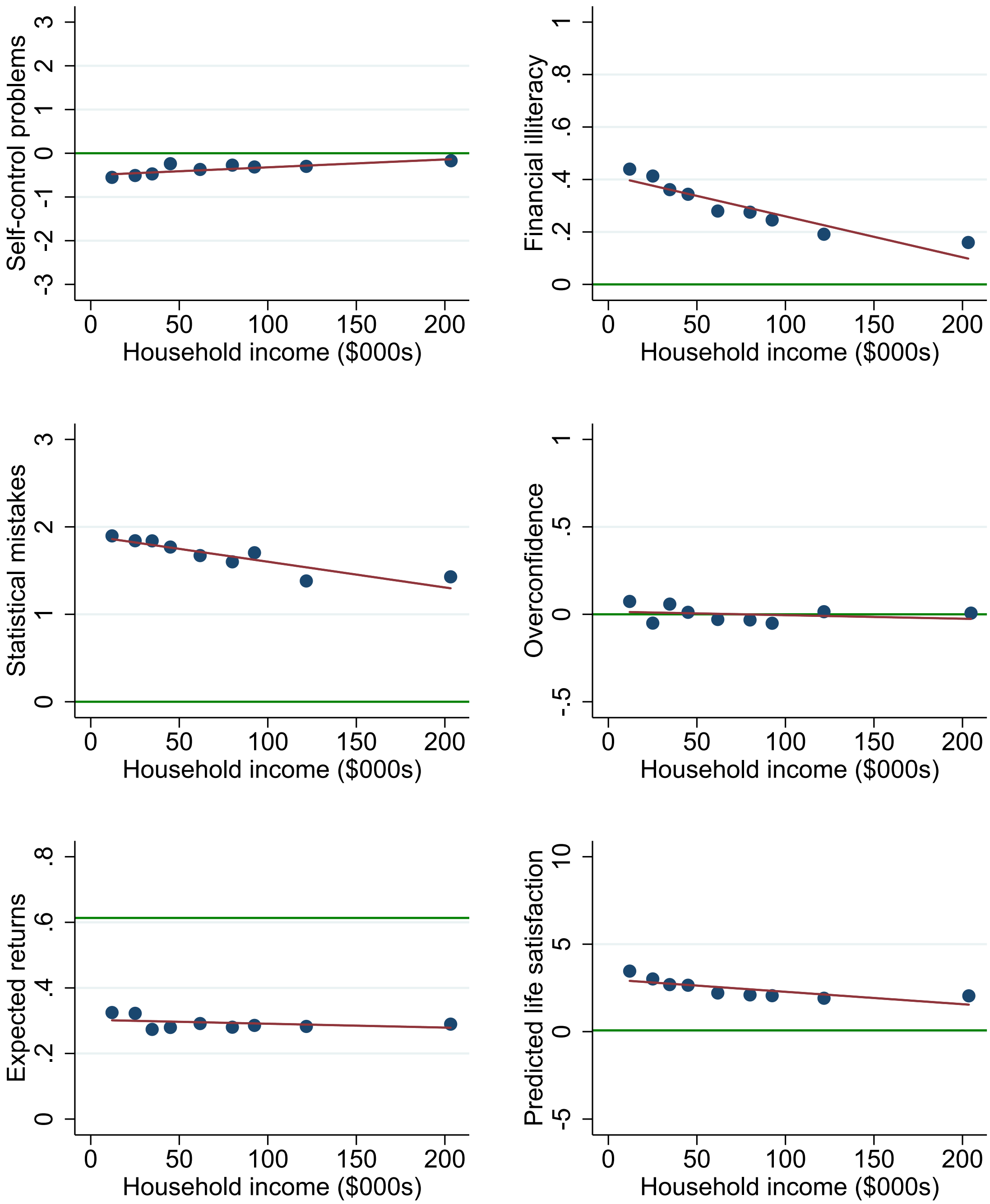
This figure presents monthly lottery spending by income, with 95 percent confidence intervals, using data from our AmeriSpeak survey. This parallels Figure 2, except that spending is not winsorized.

Table A2: **Income Effects**

	(1) Spending change	(2) Self-reported income effect
Income change	0.202***	
	(0.036)	
Constant	-5.529***	-0.017***
	(0.530)	(0.004)
Observations	2,869	2,862

Notes: This table reports two measures of the 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.

Figure A5: **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 AmeriSpeak survey.

Table A3: **Prizes and Probabilities by Game Format**

	Powerball			Mega Millions	
	2009–2012	2012–2015	2015–2017	2013–2017	2017
Ticket price	$1	$2	$2	$1	$2
Jackpot (average)	$74 million	$112 million	$172 million	$98 million	$147 million
Reset value	$20 million	$40 million	$40 million	$15 million	$40 million
Probability	1/195,249,054	1/175,223,510	1/292,201,338	1/258,890,850	1/302,575,350
Expected value	$0.38	$0.64	$0.59	$0.38	$0.49
Second prize	$200,000	$1 million	$1 million	$1 million	$1 million
Probability	1/5,138,133	1/5,153,633	1/11,688,054	1/18,492,204	1/12,607,306
Expected value	$0.04	$0.19	$0.09	$0.05	$0.08
Third prize	$10,000	$10,000	$50,000	$5,000	$10,000
Probability	1/723,145	1/648,976	1/913,129	1/739,688	1/931,001
Expected value	$0.01	$0.02	$0.05	$0.01	$0.01
Fourth prize	$100	$100	$100	$500	$500
Probability	1/19,030	1/19,088	1/36,525	1/52,835	1/38,792
Expected value	$0.01	$0.01	$0.00	$0.01	$0.01
Fifth prize	$100	$100	$100	$50	$200
Probability	1/13,644	1/12,245	1/14,494	1/10,720	1/14,547
Expected value	$0.01	$0.01	$0.01	$0.00	$0.01
Sixth prize	$7	$7	$7	$5	$10
Probability	1/359	1/360	1/580	1/766	1/606
Expected value	$0.02	$0.02	$0.01	$0.01	$0.02
Seventh prize	$7	$7	$7	$5	$10
Probability	1/787	1/706	1/701	1/473	1/693
Expected value	$0.01	$0.01	$0.01	$0.01	$0.01
Eighth prize	$4	$4	$4	$2	$4
Probability	1/123	1/111	1/92	1/56	1/89
Expected value	$0.03	$0.04	$0.04	$0.04	$0.04
Ninth prize	$3	$4	$4	$1	$2
Probability	1/62	1/55	1/38	1/21	1/37
Expected value	$0.05	$0.07	$0.10	$0.05	$0.05
Probability, any prize	1/35	1/32	1/25	1/15	1/24
Expected value, total	$0.55	$1.00	$0.91	$0.55	$0.73

Notes: This table reports the prizes, win probabilities, and expected values corresponding to each prize level and the overall ticket for a given Powerball or Mega Millions format. The expected value is computed simply as the prize (or average prize) multiplied by the win probability. Powerball changed its format on January 7, 2009; January 15, 2012; and October 4, 2015. Mega Millions changed its format on October 19, 2013, and October 28, 2017. The jackpot prize reported is the average approximate amount in the jackpot pool over the period beginning with the first draw under the format until the earlier of the last draw under the format and the last draw in 2017. All other prize levels reported are the fixed prizes offered in all states except California. An official record of these format change events with additional details can be found at the Pennsylvania Bulletin (http://www.pacodeandbulletin.gov/; Powerball notices: 38 Pa.B. 6571, 41 Pa.B. 6945, and 45 Pa.B. 5884; Mega Millions notices: 43 Pa.B. 5896 and 47 Pa.B. 6787).

Table A4: **First Stages for Prize Semi-Elasticity Estimates**

(a) **Jackpot Semi-Elasticity: All Lotto Games Nationwide**

	(1) Jackpot EV ($)	(2) Jackpot EV ($)
Jackpot expected value forecast ($)	0.9747***	0.9642***
	(0.0084)	(0.0079)
Lags included in $\boldsymbol{H}$	4	2
$\boldsymbol{H}$ includes quadratic terms	Yes	No
F-statistic	13,384	15,030
R^2	0.96	0.96
Observations	59,795	59,966

(b) **Jackpot and Second Prize Semi-Elasticity: California Only**

	(1) Jackpot EV ($)	(2) Jackpot EV ($)	(3) 2nd prize EV ($)	(4) 2nd prize EV ($)
Jackpot expected value forecast ($)	1.0193***	1.0369***	-0.0014	-0.0008
	(0.0051)	(0.0043)	(0.0011)	(0.0010)
2nd prize expected value forecast ($)	0.0459	0.0475	1.0122***	1.0101***
	(0.0474)	(0.0467)	(0.0110)	(0.0103)
Lags included in $\boldsymbol{H}$	4	2	4	2
$\boldsymbol{H}$ includes quadratic terms	Yes	No	Yes	No
F-statistic	63,900	62,048	8,745	9,721
R^2	0.99	0.99	0.97	0.98
Observations	3,107	3,114	3,107	3,114

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 a vector $\boldsymbol{H}$ of lagged sales and prize amounts as well as quarter-of-sample and state-game-format fixed effects. Panel (a) presents estimates for all lotto games nationwide, using game-by-week data, using two-way clustered standard errors by state and time. Panel (b) presents estimates limited to California, where we also exploit variation in second prizes, using game-by-drawing data, using Newey-West standard errors with up to five lags. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

C.1 Intertemporal and Cross-Game Substitution

In this appendix, we study intertemporal and cross-game substitution using nationwide data.

We first consider intertemporal substitution, testing whether previous jackpots affect current sales. To do so, we repeat estimates of equation (14), except including four additional lags of the jackpot expected value. We include one instrument for each lag $l \in \{1, ..., L\}$, constructed using the jackpot from the period before the earliest lag, w_{jt-L-1}, and rollovers between $t-L-1$ and $t-l$. The control vector $\boldsymbol{H}_{jt-L-1}$ includes only sales and jackpot pools from before the earliest lag. Appendix Table A5 shows that 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.

Appendix Table A6 presents results. Columns 1–5, respectively, present estimates with $L = \{4, 3, 2, 1, 0\}$ additional lags. The contemporaneous coefficient is much stronger than any of the lag coefficients, and the Akaike and Bayesian Information Criteria are minimized in column 5, the specification with zero lags. This suggests that any dynamic effects are limited.[19]

We now consider substitution between lottos and other games. To do this, we regress sales levels for different game types in the same state and week on the jackpot expected value for a given lotto game, using the same IV strategy and controls as in equation (14). Appendix Table A7 presents results. In column 1, the dependent variable is sales for the same lotto game. This parallels the results in Table 4, except that the dependent variable is in levels instead of logs. In column 2, the dependent variable is sales for all other games in that state and week. The ratio of coefficients in column 2 to column 1 is a diversion ratio: the dollars of expenditures that are diverted from all other games due to an exogenous $1 increase in expenditures on the average lotto game.

Different types of games might be more or less substitutable with lotto games. In particular, one might hypothesize that in states with multiple types of lotto games, the different lotto games are particularly close substitutes for each other. Columns 3 and 4 present estimates with all other lotto games and all instant (scratch-off) games as the dependent variables. In all of columns 2–4, we see no statistically detectable substitution toward or away from other games in the same state as lotto jackpots vary.

The results of Appendix Tables A6 and A7 suggest that it may be reasonable to consider individual lotto games in isolation, with the static prize elasticities as estimated in Table 4.

[19]Furthermore, the 2015 Powerball format change described in Appendix C.2 permanently increased average jackpots, as illustrated in Appendix Figure A6. However, column 1 of Appendix Table A8 shows that this sustained change had no detectable effect on demand after controlling for short-run variation in the jackpot pool, which again suggests that the prize elasticity is not different in the long run compared to the short run.

Table A5: **Regressions of Jackpot Expected Value on Forecast Instruments**

	(1) EV, t (\$)	(2) EV, $t-1$ (\$)	(3) EV, $t-2$ (\$)	(4) EV, $t-3$ (\$)	(5) EV, $t-4$ (\$)
Jackpot expected value forecast, t (\$)	0.6040***	-0.0808***	-0.0024	0.0079	0.0015
	(0.0256)	(0.0196)	(0.0131)	(0.0096)	(0.0014)
Jackpot expected value forecast, $t-1$ (\$)	0.0098	0.7564***	-0.0788***	-0.0081	-0.0023
	(0.0110)	(0.0216)	(0.0147)	(0.0063)	(0.0018)
Jackpot expected value forecast, $t-2$ (\$)	-0.0228	-0.0029	0.8575***	-0.0652***	-0.0065
	(0.0137)	(0.0148)	(0.0210)	(0.0155)	(0.0040)
Jackpot expected value forecast, $t-3$ (\$)	-0.0311	-0.0584***	-0.0409**	0.9175***	-0.0526***
	(0.0194)	(0.0188)	(0.0190)	(0.0215)	(0.0097)
Jackpot expected value forecast, $t-4$ (\$)	0.0773	0.0819	0.0570	0.0589	1.0147***
	(0.0657)	(0.0651)	(0.0631)	(0.0592)	(0.0130)
R^2	0.73	0.80	0.86	0.90	0.96
Observations	59,427	59,427	59,427	59,427	59,427

Notes: This table presents estimates of a regression of jackpot expected values on leads and lags of the jackpot expected value forecast, controlling for a vector $\boldsymbol{H}$ of lagged sales and jackpot amounts as well as quarter-of-sample and state-game-format fixed effects, using nationwide game-by-week data. We use two-way clustered standard errors by state and time. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

Table A6: **Intertemporal Substitution**

	(1)	(2)	(3)	(4)	(5)
Jackpot expected value, t (\$)	0.8976***	0.8943***	0.8803***	0.9254***	0.7931***
	(0.0461)	(0.0445)	(0.0473)	(0.0435)	(0.0875)
Jackpot expected value, $t-1$ (\$)	0.1058***	0.0930***	0.1446***	-0.0502	
	(0.0168)	(0.0192)	(0.0330)	(0.0879)	
Jackpot expected value, $t-2$ (\$)	-0.0170	0.0388*	-0.1341		
	(0.0196)	(0.0228)	(0.0904)		
Jackpot expected value, $t-3$ (\$)	0.0521**	-0.1145			
	(0.0213)	(0.0864)			
Jackpot expected value, $t-4$ (\$)	-0.1211				
	(0.0820)				
Observations	59,427	59,519	59,611	59,703	59,795
Akaike Information Criterion	-8,122	-8,161	-8,553	-9,115	-13,691
Bayesian Information Criterion	-8,077	-8,125	-8,526	-9,097	-13,682

Notes: This table presents estimates of a regression of the natural log of sales on current and lagged jackpot expected values, controlling for a vector $\boldsymbol{H}$ of lagged sales and jackpot amounts as well as quarter-of-sample and state-game-format fixed effects, using nationwide game-by-week data. We instrument for jackpot expected values with a forecast based on the previous period jackpot amount and an indicator for whether the jackpot was won in the previous period. We use two-way clustered standard errors by state and time. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

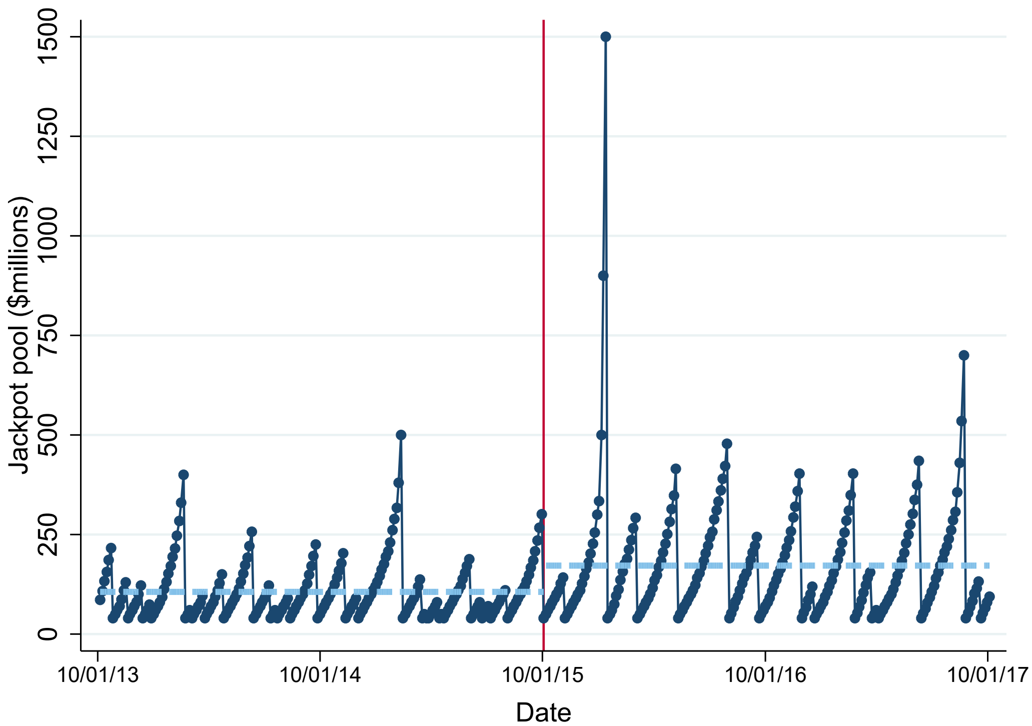
Table A7: **Cross-Game Substitution**

	(1) Own game sales ($millions)	(2) All other games sales ($millions)	(3) Other lotto games sales ($millions)	(4) Instant games sales ($millions)
Jackpot expected value ($)	1.6071***	0.0558	0.0271	0.0427
	(0.2986)	(0.1375)	(0.1166)	(0.0636)
Observations	58,762	58,762	58,762	58,762

Notes: This table presents estimates of a regression of the natural log of sales of lottery games indicated in each column on current and lagged jackpot expected values, controlling for a vector $\boldsymbol{H}$ of lagged sales and jackpot amounts as well as quarter-of-sample and state-game-format fixed effects, using nationwide game-by-week data. We instrument for jackpot expected values with a forecast based on the previous period jackpot amount and an indicator for whether the jackpot was won in the previous period. We use two-way clustered standard errors by state and time. *, **, ***: statistically significant with 90, 95, and 99 percent confidence, respectively.

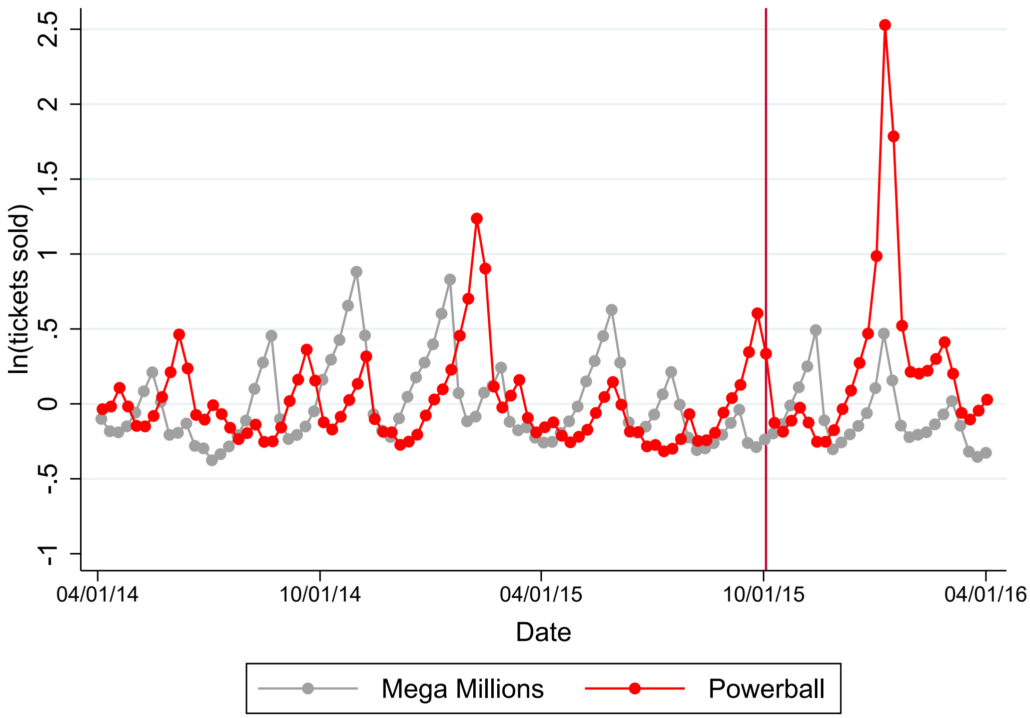
C.2 Powerball 2015 Format Change

Figure A6: **Powerball Jackpots Over Time**



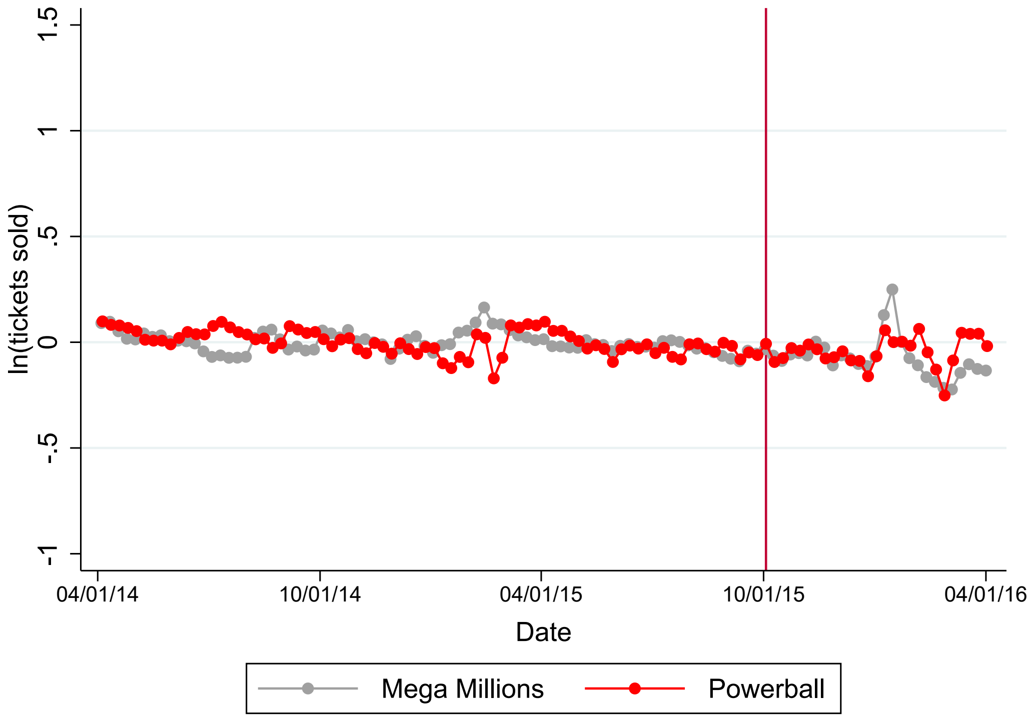
Notes: This figure presents the Powerball jackpot pool amounts before and after Powerball changed its format in October 2015. The dashed horizontal lines indicate the average amount of the jackpot pool in the two years before and after the format change event.

Figure A7: **Powerball Format Change Event Study**



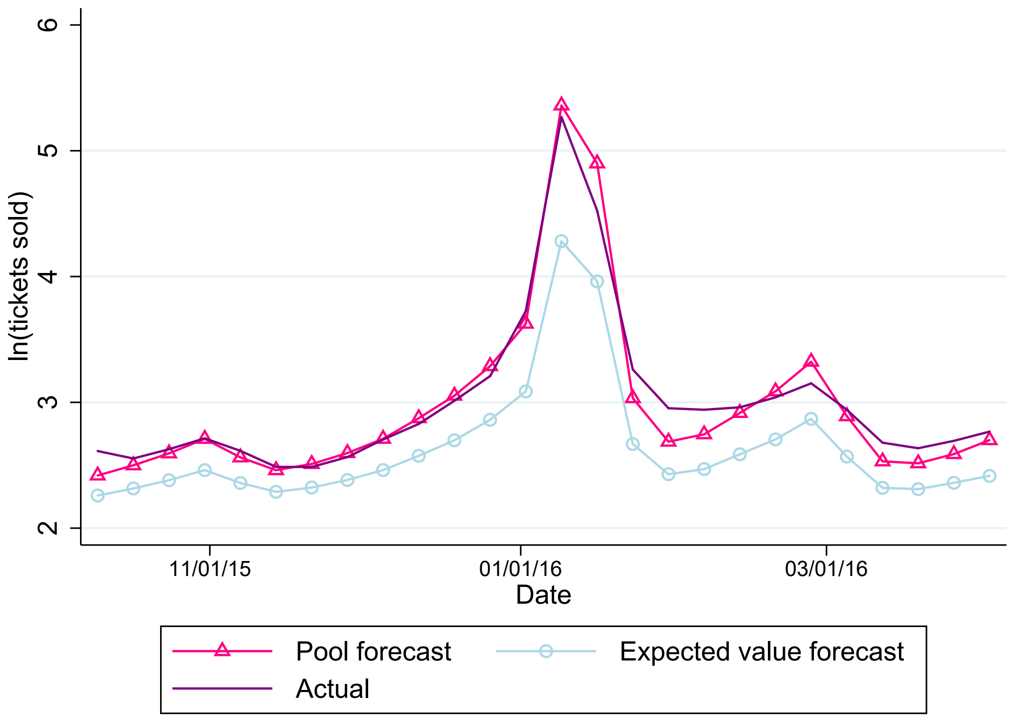
Notes: This figure presents weekly averages of the natural log of ticket sales before and after Powerball changed its format in October 2015. The y-axis is adjusted so that the average for each game before the price change equals zero.

Figure A8: **Powerball Format Change Event Study Residual of Controls**



Notes: This figure presents weekly averages of the natural log of ticket sales (residual of controls in equation 17) before and after Powerball changed its format in October 2015. The y-axis is adjusted so that the average for each game before the price change equals zero.

Figure A9: **Post-Format Change Forecasted Sales**



Notes: This figure presents weekly averages of the natural log of ticket sales after Powerball changed its format in October 2015. "Pool forecast" and "Expected value forecast" is a prediction of the natural log of ticket sales using quarter-of-sample and game fixed effects and either the jackpot pool or simple jackpot expected value. The predictions use jackpot semi-elasticities ζ_{a1} estimated from the previous year of Powerball data and the previous and contemporaneous year of Mega Millions data.

Table A8: **Difference-in-Differences: Format Change Event**

	(1) ln(tickets sold), adjusted	(2) ln(tickets sold), adjusted	(3) ln(tickets sold)
Powerball × Post	0.0326	0.2992***	0.1465**
	(0.0356)	(0.0427)	(0.0575)
Post	-0.0358	-0.0669**	0.2533
	(0.0343)	(0.0327)	(0.2797)
Jackpot pool ($millions)	0.0044***		
	(0.0003)		
Jackpot expected value ($)		0.8617***	
		(0.0456)	
R^2	0.96	0.94	0.74
Observations	418	418	418

Notes: The jackpot pool and simple jackpot expected value are instrumented by the jackpot forecast and simple jackpot expected value forecast in columns (1) and (2), respectively, as well as by the prior four draws' ticket sales, jackpot pools, and day-of-week, and quarter-of-sample fixed effects. Column (3) includes a linear time trend. "Post" is an indicator for observations after the Powerball format change event and "Powerball × Post" is an indicator for Powerball observations in the post-format change period. "ln(tickets sold), adjusted" is the natural log of sales adjusted by subtracting the estimated sales increase due to the increase in the sub-jackpot expected value using our preferred estimate of the sub-jackpot prize semi-elasticity. We use Newey-West standard errors with up to five lags. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

D Details of Numerical Calibrations

D.1 Details of Calibration Exercise in Section 4.2

To calibrate the value function m, we assume a CRRA parameter of 1 (log utility) and lifetime continuation wealth of $1 million. We compute elasticities using a representative lottery based on a Mega Millions game with a $300 million jackpot pool. The Mega Millions game has a prize vector of [jackpot; $1 million; $10,000; $500; $200; $10; $10; $4; $2], and vector of winning odds of one-in-[306 million; 12.6 million; 931,000; 38,700; 14,500; 693; 606; 89; 37]. The ticket price is $2. We assume a marginal income tax rate of 40% on prize winnings, implying that this game has an expected value of $0.74. (We abstract from the issue of annuitized payouts.)

D.2 Additional Derivations

Our specification assumes utility over expected continuation wealth W features a constant coefficient of relative risk aversion (CRRA), η:

$$\mathcal{U}(W) = \begin{cases} \ln(W) & \text{if } \eta = 1 \\ \frac{W^{1-\eta}-1}{1-\eta} & \text{if } \eta \neq 1 \end{cases} \tag{36}$$

Then the utility gain function for type θ, with (non-prize) lifetime expected continuation wealth $y(\theta)$, from winning a prize of size x is

$$m(x;\theta) = \frac{\mathcal{U}(y(\theta)+x) - \mathcal{U}(y(\theta))}{\mathcal{U}'(y(\theta))} \tag{37}$$

$$= \begin{cases} \frac{\ln(y(\theta)+x) - \ln y(\theta)}{y(\theta)^{-1}} & \text{if } \eta = 1 \\ \frac{\frac{1}{1-\eta}\left((y(\theta)+x)^{1-\eta} - y(\theta)^{1-\eta}\right)}{y(\theta)^{-\eta}} & \text{if } \eta \neq 1 \end{cases} \tag{38}$$

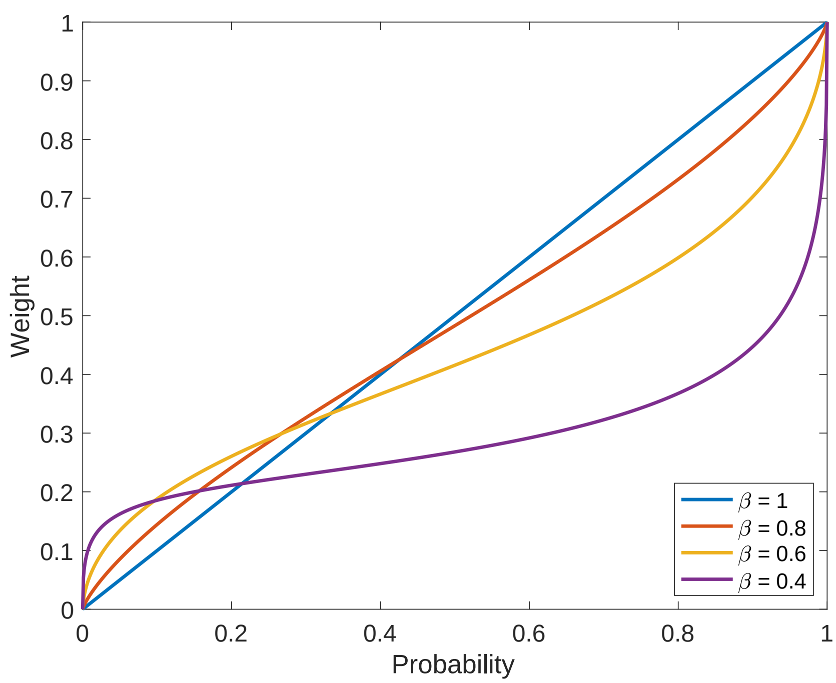
$$= \begin{cases} y(\theta)\ln\left(\frac{y(\theta)+x}{y(\theta)}\right) & \text{if } \eta = 1 \\ \frac{y(\theta)}{1-\eta}\left(\left(\frac{y(\theta)+x}{y(\theta)}\right)^{1-\eta} - 1\right) & \text{if } \eta \neq 1 \end{cases} \tag{39}$$

We can also thus compute the derivative, which figures prominently in the calibration section:

$$m'(x;\theta) = \frac{\mathcal{U}'(y(\theta)+x)}{\mathcal{U}'(y(\theta))} = \left(\frac{y(\theta)}{y(\theta)+x}\right)^{\eta}. \tag{40}$$

D.3 Additional Calibration Results

Figure A10: **Probability Weighting Function**



Notes: TK

Table A9: **Semi-elasticity Ratios Across CRRA and Weighting Function Parameter Values**

(a) Tversky and Kahneman (1992) weighting function calibration

		$\beta = 0.4$	$\beta = 0.61$	$\beta = 0.8$	$\beta = 1$
$\zeta_1/\lvert\zeta_p\rvert$	Linear utility	1.23×10^5	2.03×10^3	49.7	1
	CRRA = 0.2	4.33×10^4	718	17.6	0.354
	CRRA = 0.5	9.11×10^3	151	3.69	0.0743
	CRRA = 1 (log)	677	11.2	0.275	0.00553
	CRRA = 2	3.74	0.062	0.00152	3.05×10^{-5}
ζ_1/ζ_2	Linear utility	9.19	3.92	1.98	1
	CRRA = 0.2	3.57	1.52	0.769	0.388
	CRRA = 0.5	0.864	0.369	0.186	0.094
	CRRA = 1 (log)	0.0812	0.0347	0.0175	0.00884
	CRRA = 2	0.000718	0.000306	0.000155	7.81×10^{-5}
Certainty equivalent	Linear utility	7.35×10^4	1.23×10^3	31.1	0.742
	CRRA = 0.2	3.25×10^4	553	14.4	0.406
	CRRA = 0.5	1.07×10^4	191	5.5	0.225
	CRRA = 1 (log)	2.62×10^3	56.3	2.15	0.155
	CRRA = 2	820	24.2	1.27	0.133

(b) Chateauneuf, Eichberger, and Grant (2007) weighting function calibration

		$\beta_1 = 1.5 \times 10^{-8}$	$\beta_1 = 8 \times 10^{-8}$	$\beta_1 = 1 \times 10^{-6}$	$\beta_1 = 0.00011$
$\zeta_1/\lvert\zeta_p\rvert$	Linear utility	5.54	25.2	304	3.33×10^4
	CRRA = 0.2	1.96	8.92	107	1.18×10^4
	CRRA = 0.5	0.412	1.88	22.6	2.48×10^3
	CRRA = 1 (log)	0.0306	0.139	1.68	184
	CRRA = 2	0.000169	0.00077	0.00928	1.02
ζ_1/ζ_2	Linear utility	5.54	25.2	304	3.33×10^4
	CRRA = 0.2	2.15	9.8	118	1.29×10^4
	CRRA = 0.5	0.521	2.37	28.6	3.13×10^3
	CRRA = 1 (log)	0.049	0.223	2.69	295
	CRRA = 2	0.000433	0.00197	0.0238	2.6
Certainty equivalent	Linear utility	3.44	15.1	181	1.98×10^4
	CRRA = 0.2	1.59	6.71	79.1	8.66×10^3
	CRRA = 0.5	0.598	2.22	25.1	2.74×10^3
	CRRA = 1 (log)	0.233	0.571	5.35	572
	CRRA = 2	0.148	0.213	1.13	110

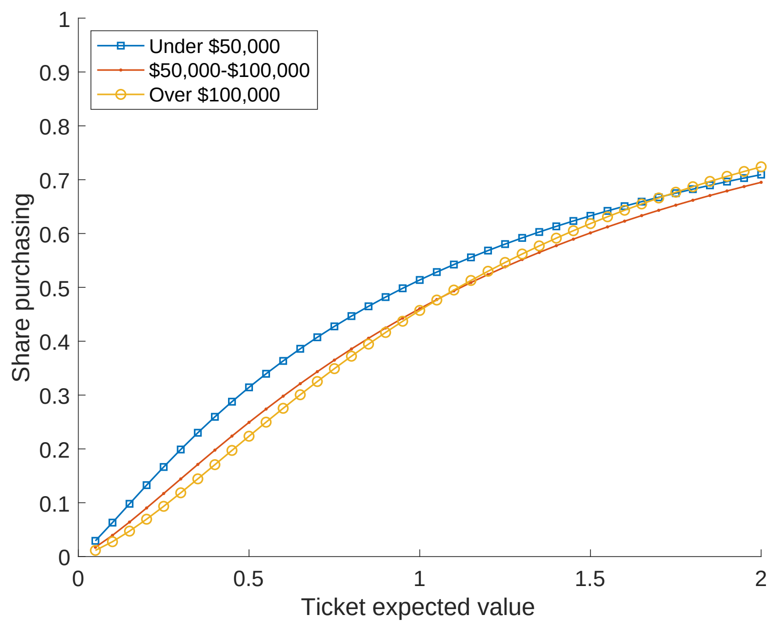
Notes: TK

D.4 Additional Simulation Figures

Figure plots the simulated share of consumers purchasing the representative lottery ticket within each income bin, across a range of ticket expected values.

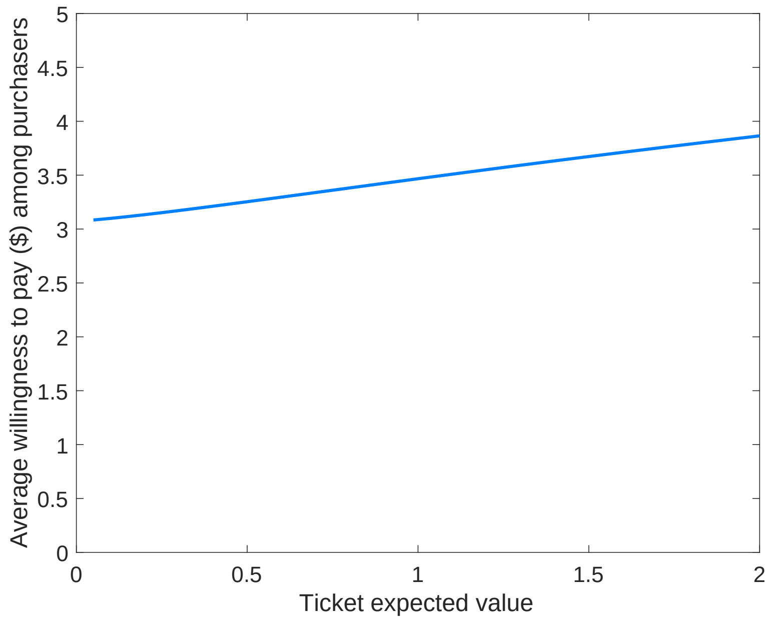
We do not directly target the willingness to pay for lottery tickets among lottery purchasers in our calibration. Computing this value can serve as a validation exercise, to check that the consumer surplus generated from our simulations seems reasonable. Figure A12 plots this willingness to pay, across the range of ticket expected values explored in our range of policy counterfactuals. By construction, the willingness to pay is higher than the price of the ticket, which is \$2 in these simulations.

Figure A11: **Simulated Share Purchasing Lottery Tickets, by Income Bin**



Notes: This figure plots the simulated share of consumers in each income bin who purchase lottery tickets.

Figure A12: **Simulated Willingness to Pay Among Purchasers**



Notes: This figure plots the simulated average willingness to pay for a lottery ticket among those purchasing a ticket, for a range of ticket expected values.