Consumption, Savings, and Earnings Responses to Financial Windfalls*

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Abstract

We estimate the causal effect of a financial windfall on (1) consumption (MPC) using credit report data on credit card and durables spending, (2) savings (MPS) using both tax data on financial assets and credit report data on debt repayments, and (3) labor earnings (MPE) using tax data. To do so, we merge data on 40,000 Canadian lottery winners to their income tax records and credit reports. We also flexibly estimate heterogeneity in the marginal propensities across income groups. Our findings reveal substantial heterogeneity in all three terms, with higher-income individuals having a larger MPE and MPS and lower-income individuals having a larger MPC. We develop a simple life-cycle model that allows individuals to vary in their earnings ability and rate of impatience, and show that our model can match our estimated heterogeneous responses if earnings ability and impatience are negatively correlated. Our results have implications for the design of multiple policy programs, including the design of fiscal stimulus programs, the introduction of a universal basic income program, and the optimal taxation of income and savings.

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1 Introduction

How does wealth affect individuals' economic decisions? This question has long interested economists and policymakers. Thomas Malthus observed that the "the laboring poor . . . seem always to live from hand to mouth," while John Maynard Keynes wrote that "the propensity to consume will be weaker in a rich community because it is well off, and stronger in a poor community because it is deprived."

On the policy side, individual-level heterogeneity in the response to financial windfalls is important for the design of optimal income taxes (Ferey, Lockwood, and Taubinsky, 2024) and fiscal stimulus programs (Auclert, 2019; Patterson, 2023) and for determining the effects of monetary policy on the macro economy (Acharya, Challe, and Dogra, 2023; Ampudia et al., 2024; Crawley and Kuchler, 2023). For example, if policymakers are primarily interested in stimulating consumption, targeting the intervention to the population with the highest marginal propensity to consume is the most efficient way to achieve their objectives.

While economists have good reasons to expect that a poor person and a rich person will use a dollar differently, demonstrating this empirically is challenging. In particular, one requires an exogenous income shock along with data on the potential choices available to households across the income distribution. In this paper, we provide new evidence on this research question using a novel dataset that links high-quality Canadian administrative data from income tax records and credit bureau reports to 40,000 individuals who received a plausibly random shock to wealth from winning the lottery. From tax records, we observe earnings from labor and financial assets; from credit bureau data, we observe total credit card spending and debt balances. The richness of our data allows us to fully characterize how households across the income distribution spend their lottery winnings on consumption (e.g., the marginal propensity to consume, or MPC), savings (the marginal propensity to save, or MPS) and earnings (the marginal propensity to earn, or MPE).[1]

[1] Strictly speaking, these reduced-form parameters should be interpreted as *wealth effects*. These are easier to estimate and require fewer assumptions than the MPC and MPE *out of unearned income*. We are currently working to obtain estimates from unearned income using lottery winnings as an instrument.

In our main analysis, we use an event-study design that takes advantage of both cross-sectional variation in the amount of lottery prizes between consumers, and the timing of the win, to estimate the MPC, MPS, and MPE out of lottery winnings. Our visual evidence reveals clear "on impact" effects of lottery winnings on consumption, savings (including debt repayment), and labor earnings in our full sample of lottery winners. Moreover, we do not find any evidence for pre-trends which supports our key assumption that the lottery amount is exogenous.

Turning to magnitudes, we find that on average, lottery winners consume about 19 cents out of each dollar of wealth over the two years after the win and reduce their labor earnings by 29 cents over the six-year period. This decline in earnings comes from both extensive and intensive margins, with individuals less likely to have a job and earning less conditional on employment. Lottery winners, on average, use 6 cents of each dollar of their lottery wealth to repay their debts, which implies a two-year MPS of 0.06 from debt repayment. We also find lottery winners save a substantial portion of lottery prizes, roughly 74 cents on every dollar earned, and increase their income from savings (capital gains, dividends, interest and investment) by 28 cents over six years. We find an economically small effect on retirement savings of 0.3 cents. Our overall average effects are broadly similar to those reported in several recent lottery studies, as well as other studies of exogenous cash transfers similar to lottery windfalls (Golosov et al., 2024; Bartik et al., 2024). Reassuringly, if we plug our estimates of the two-year MPC, MPS, and MPE into the accounting identity $MPC + MPS - MPE = 1$ (see equation 9 below), we come close to satisfying it.

Our findings indicate substantial differences in how lottery winnings are spent based on income. Specifically, we find that higher-income individuals generally have larger MPE and MPS estimates, while lower-income individuals generally have larger MPC estimates. In terms of magnitudes, the two-year MPC out of lottery windfalls is 0.59 for the first quartile of the income distribution (neighborhood income below CA $49,634) and 0.15 for the fourth quartile (neighborhood income above CA $120,161). We also find that lower income individuals repay less debt out of their lottery wins compared with higher income individuals. The two-year MPS (based on debt repayment) for the first quartile of the income distribution is 0.03, while the MPS for the fourth quartile of income

is 0.09. Thus, our evidence is consistent with the conjectures of Keynes and Malthus: lower-income individuals are more likely to be hand-to-mouth consumers who boost their spending in response to winning the lottery, while higher-income individuals are more likely to invest their winnings.

In order to interpret our reduced-form evidence, we develop a simple life-cycle model following Ferey, Lockwood, and Taubinsky (2024). In the model, individuals have heterogeneous earnings ability and vary in their rate of impatience. We simulate the model and find that a negative correlation between earnings ability and degree of impatience can rationalize the patterns we observe on spending, savings, and earnings across the income distribution. This suggests a "preference-based" explanation for the income heterogeneity that we document and relates to the findings of Aguiar, Bils, and Boar (2024).

Finally, in ongoing work, we illustrate how understanding heterogeneity in the MPC, MPS and MPE is important for several policy questions. First, we intend to study the labor market consequences of a universal basic income program paying particular attention to the role of income heterogeneity. Second, we plan to use the estimated correlation in the MPC, MPS and MPE to calibrate the optimal taxes on income and savings and compare our results to calibrations that ignore the correlated heterogeneity in our behavioral responses.

Our paper makes three main contributions to the literature. Our primary contribution is to jointly estimate the response of consumption, savings, and earnings to a common wealth shock for the same set of individuals and to study the heterogeneity of these responses by income. This is possible since we link lottery winnings to both credit report data and tax data. This contrasts with existing studies which typically consider either credit bureau data or tax data in isolation and hence focus only on a subset of the outcomes we examine. For example, studies using tax data cannot directly observe consumption, whereas studies using credit bureau data cannot observe labor earnings. Therefore, understanding where one dollar of lottery wealth goes necessarily involves mixing estimates across potentially heterogeneous populations.

A key advantage of accessing both tax and credit bureau data is that we can measure savings

more broadly and consequently study the MPS across the income distribution. As noted above, we observe financial assets in the tax data as well as debt balances in credit bureau data. As both the accumulation of financial assets and the reduction in debt balances contribute to savings, our data allow us to consider the full set of savings responses, compared to the literature examining the impact of income shocks only on credit bureau outcomes.[2] Importantly, our data and setting allow us to compare the impact of income shocks on both financial assets and financial liabilities across income levels. This can be important because rich and poor individuals may respond to wealth windfalls using different sides of their balance sheet, e.g., some may increase savings by repaying debt, while others may increase savings by increasing investment in financial assets. We can separately observe both debt repayment and investment as well as their aggregate effect on savings.[3]

Our second contribution to the literature is to estimate the MPC on average and across the income distribution using a more precise measure of consumption. Specifically, we use newly available data on credit card spending obtained from credit bureau data.[4] To the best of our knowledge, our study is the first to link an income shock to credit card consumption data. In addition, we use data on auto loans to measure consumer spending on durables following Ganong and Noel (2020). These data provide us with several advantages relative to other studies that estimate the

[2]Studies in this literature include Agarwal, Liu, and Souleles (2007), Agarwal and Qian (2014b), Agarwal and Qian (2014a), Agarwal, Qian, and Zou (2021), Cookson, Gilje, and Heimer (2022), Di Maggio, Kalda, and Yao (forthcoming), Koşar et al. (2023), Sahm, Shapiro, and Slemrod (2010), Coibion, Gorodnichenko, and Weber (2020), Parker et al. (2022), Brown (2021), Boutros (2020), and Hisnanick and Kern (2018). Although these studies use credit bureau data to test whether income shocks cause a reduction in debt, they do not test whether the same shocks cause an increase in ownership of financial assets.

[3]It is worth noting that our measures of financial assets using tax data is broader than what is typically measured in the literature. In addition to examining various forms of investment income in tax data (as in Golosov et al., 2024), our tax data records individuals' contribution to and withdrawal from tax-advantaged retirement accounts (which in Canada are called Registered Retirement Savings Plans, RRSPs). Canadian tax policy incentivizes individuals to initially purchase financial assets in tax-advantaged RRSP accounts, up to the regulatory cap. Only after the financial assets have exceeded this tax-exempt cap will individuals purchase financial assets in accounts which are subject to taxation. This distinction is particularly important given our focus on heterogeneity in the ownership of financial assets across income levels.

[4]Credit Bureaus have traditionally only reported data on credit card balances, taken from the month end statement. With only data on balances, it is difficult to separate out the various transactions on credit cards that occurred during the month, including consumption and debt repayment by the consumer. However, starting in 2014, the credit bureau in Canada, from whom we obtained our data, began to provide their clients with additional data specifically on consumption on the credit card. These data have been made available to us.

MPC. Some lottery studies have used survey data to measure consumption (e.g., Imbens, Rubin, and Sacerdote, 2001; Kuhn et al., 2011). This can be problematic because of sample response bias and concerns about respondent recall. Other studies that estimate the MPC using lotteries have used tax data to impute the consumption response as a residual using the earnings response (MPE) and the change in labor earnings taxes (MPT) along with the budget constraint (e.g., Fagereng, Holm, and Natvik, 2021 and Golosov et al., 2024).[5]

Third, we extend the large literature in labor economics on the labor supply responses to financial windfalls (Imbens, Rubin, and Sacerdote, 2001; Cesarini et al., 2017; Picchio, Suetens, and van Ours, 2018; Golosov et al., 2024). Many lottery studies find reductions in employment and earnings, and our results in general align with them.[6] For example, we find higher MPE estimates for individuals with higher income levels, which match the results in Cesarini et al. (2017) and Golosov et al. (2024). Relative to the existing literature, we connect the labor supply responses to the spending and savings responses together based on the individual's predicted income at the time of lottery winning to learn whether the individuals with the largest MPE estimates also have the largest (or smallest) MPC and MPS estimates. We see heterogeneity and correlation in the responses as our key "value-added" relative to existing studies that have estimated wealth effects. Our lottery data also contain several advantages compared to the data in previous lottery studies. First, we observe the exact payment date and size of the amount won, which gives us precise information about the timing and size of the shock. This is especially valuable for estimating short-run consumption responses. Second, all prizes in the data are lump-sum, which avoids mixing lump-sum prizes and "annuity-like" prizes that are paid out gradually over time. Finally, the lottery winnings are non-taxable. As Golosov et al. (2024) show, studies using the pre-tax value can lead

[5]The budget constraint requires that $MPC - MPE = 1 - MPT$ where these marginal propensities are defined for a change in unearned income. Thus, the MPC out of unearned income is constructed as a residual. A key challenge with this approach is that one cannot observe non-taxable assets, such as housing. This approach additionally requires assuming a constant capitalization factor within asset classes for different wealth groups. This could be problematic if taxable rates of return vary across the income distribution, say through tax avoidance or different rates of capital income realization.

[6]Existing lottery studies have considered a wide range of outcomes, including entrepreneurship (d'Astous et al., 2025), stock market participation (Briggs et al., 2021), and bankruptcy filing (Hankins, Hoekstra, and Skiba, 2011; Agarwal, Mikhed, and Scholnick, 2020).

to a substantial underestimate of wealth effects.[7]

The remainder of our paper is organized as follows. Section 2 describes our data. Section 3 describes identification and estimation. Section 4 summarizes our empirical results. Section 5 considers a model to guide and interpret our results. Section 6 concludes.

2 Data

In this section, we describe how we constructed our data set. The data set consists of lottery data, credit bureau data, and administrative tax data from Statistics Canada. In the following subsections, we discuss each of these data sets separately and then describe the process of merging them.

2.1 Lottery Microdata

Our lottery data come from one Canadian province and cover all lottery prizes in this province between Q2:2003-Q2:2021. All lottery products in Canada are administered by Crown corporations and an anonymous corporation provided us with the lottery data. We do not disclose the name of the province or corporation due to our non-disclosure agreement.

Most lottery products in our data are classic lotteries with a winner decided by a random draw of numbers. For the most common lottery product, the player picks six numbers in sequence. The winning number is determined by a computer that randomly selects a sequence of numbers. A given lottery ticket is designated as a "lottery winner" if the sequence of numbers on the ticket partially matches the sequence of numbers that were drawn randomly. The prize amount is determined by several factors. First, it depends on the number of correct digits in the sequence. For example, suppose that the winning number drawn is 123456. A winning ticket could feature the sequence XXXXX6 (a smaller prize) or XXXX56 (a slightly larger prize). Second, the prize

[7] Unlike Cesarini et al. (2017) however, we do not observe precise information on the number of tickets purchased, so our research design is based on variation in the size of the prize conditional on timing. Since Cesarini et al. (2017) find very similar results when they exclude information on the number of lottery tickets purchased, we do not view this limitation as a source of bias, and our event-study results show strong support for the validity of lottery windfalls as a credible idiosyncratic wealth shock.

amount increases with the overall size of the lottery pool, which depends on the number of tickets purchased. Third, it decreases with the number of winning tickets.[8] Our data also contain other lottery products with fixed prize amounts (e.g., guess 3 numbers correctly and win $5,000), as well as "scratch" tickets with multiple possible fixed prizes and betting on professional sports.

The lottery data contain all winners of lottery prizes of $1,000 or more. Winners of prizes of less than $1,000 are not required to report their names and addresses to the lottery corporation, thus they are excluded from our data. For all winners in the data, the lottery corporation provided us with their first and last names, six-character postal codes, lottery payout date, lottery product information, amount won, and lottery ticket number. For all prizes with more than two winners, we do not observe all winners' names but have "in trust" information only (showing just one winner). Since we were unable to assign these prizes to individual winners, we did not include them in our sample. For prizes with two winners, we observe complete information on both individuals and their common ticket number. For such prizes, we assign 50% of the prize amount to each winner.

We restrict the sample to winners with one prize in the sample period. This restriction is designed to reduce the issue of multiple events (lottery prize wins) affecting the same person over a period of time. It allows us to identify the timing of each wealth shock precisely. After imposing these restrictions, we have 40,872 prizes and winners in our final sample. Table 1 provides summary statistics for these winners. On average, the prize amount is 16,549 Canadian dollars, which is winsorized at $350,000, (approximately the 99th percentile of lottery winnings). The data cover 69 quarters of winners between 2003 and 2021. We classify winners into "cohorts" based on the year-quarter they won the lottery to align with the frequency of our credit bureau. Figure A.1 shows the distribution of lottery prizes in our data.

[8] If there is no "jackpot" lottery winner, e.g., a winner who guesses all six digits correctly, the next lottery grows in size.

2.2 Credit Bureau Data

We obtained anonymous individual-level credit bureau data come from a national credit reporting agency that contains the population of Canadian credit users. The data are quarterly and cover the period Q1:2004 to Q1:2023. Table 1 presents summary statistics on credit bureau data for lottery winners and a sample of the general population. On average, winners are 48 years old. Three percent of lottery winners moved in the quarter prior to winning the lottery. The table also reports the number of accounts and sum of balances across the following credit types: credit cards, mortgages, auto loans, home equity lines of credit (HELOCs), unsecured lines of credit (LOCs), auto loans, student loans, and installment loans. Installment loans are defined as personal loans that are either made at the point of sale for a durable good, or an unsecured loan with a fixed interest rate (Equifax, 2025).

In addition to credit card balances, we also have a measure of credit card spending created by the credit bureau. Spending is constructed using a combination of balance changes from quarter to quarter and actual payments the cardholder makes as reported by each lender. Most credit card lenders began reporting actual payments in 2014, thus we have reliable coverage of card spending after this date. On average, Canadians spend roughly 56% of their total expenditures on credit cards and the remainder on a combination of debit cards, cash, checks, and other methods (Henry, Huynh, and Welte, 2018). Lottery winners spend $3,400 on average across their credit cards in the quarter before their win.

Measures of creditworthiness include a proprietary risk score measure that ranges from 300 to 900 with higher scores denoting better creditworthiness. The average risk score in our sample is 725, which is equivalent to a prime credit designation in the United States. Our data have flag indicators for if an individual filed for consumer bankruptcy (similar to chapter 7 bankruptcy in the United States) and consumer proposals (somewhat similar to chapter 13 bankruptcy), and whether any of their debts were sold to a collection agency and the amount in third-party collections. One percent of lottery winners had an account sold to collections and two percent filed for bankruptcy.

To address the external validity of our results, we provide evidence on the prevalence of gam-

bling in Canada and test if the sample of lottery winners is different from the general population. Based on surveys of the Canadian population, two thirds of Canadians gamble at least once per year, with an overwhelming majority of players participating in lotteries, instant lotteries, or gambling on professional sports(Marshall, 2011; Rotermann and Gilmour, 2022). These lottery products are included in our data. As Table 1 shows, lottery winners in our sample are similar to the general credit bureau population along many dimensions, including credit scores, individual's age, probability of moving, total debt balances, and the bankruptcy filing rate. Lottery winners have somewhat lower credit card spending. Overall, the lottery population is similar to the general population.

For identification, as we discuss below, we use plausibly random and exogenous variation in the lottery prize amount. To test that lottery amounts are indeed random, we examine if any credit bureau characteristics can predict the prize size. Table A.1 shows that credit bureau characteristics do not predict lottery win size. Agarwal, Mikhed, and Scholnick (2020) also show that neighborhood characteristics are not correlated with the lottery amount.

As our credit bureau data do not contain a measure of income, we match each winner to the neighborhood income of their Dissemination Area of residence (approximately 400-700 people) in the census year closest to the year before they won the lottery. These data were obtained from Statistics Canada's census data, and were matched by the credit bureau agency before being anonymized and returned.

2.3 Statistics Canada Tax and Employment Data

Statistics Canada's Canadian Employer-Employee Dynamics Database (CEEDD) provides us access to tax records of individuals and businesses. We use individual-level tax records data (T1 Personal Master File or T1PMF) from 2001 to 2018 to match lottery winner's annual personal tax data across a range of datasets, ultimately building an aggregate annual tax record for each individual including total labor, investment, or business income, as well as some demographic details such as age, sex, and marital status.

The individual tax record data also allow us to measure lottery winners' savings. In particular, we observe Dividend Income (tax return line 120), Interest and Other Investment Income (tax return line 121) and Taxable Capital Gains (tax return line 127). Dividend income represents profits received from an ownership share in a Canadian corporation. Two types of dividends are possible in Canada, with different tax treatments: eligible and non-eligible dividends. Eligible dividends include dividends from public and large private companies, while non-eligible dividends are from companies that benefit from small-business tax credits. In order to not double-tax equity earnings, eligible dividends receive a tax credit to compensate for the small-business tax credit non-eligible dividends receive. We sum both types of dividends in our dividend income measure. Interest and other investment income include foreign interest or dividend income, interest credited on bank accounts, term deposits or guaranteed investment certificates, Canada savings bonds, Treasury bills, and earnings on life insurance policies. Taxable capital gains represent the net capital gain on sold or transferred property such as land, buildings, shares, bonds, and fund and trust units. For some financial assets, in particular, retirement assets, we have data on contributions and withdrawals as well. We use contributions to employer-sponsored pension plans (RPP) and registered retirement saving plans (RRSP, which is similar to IRA in the U.S.) to measure individual's savings for retirement.

In addition to the aggregated tax information in the personal tax file, the T4 Record of Employment and Remuneration (T4ROE) provides the annual remuneration of each individual at each employer where they have worked in that year. We use these data to track all the different employers of a given individual each year and through time. Employers provide information on the employees, salary paid, reason of separation, contributions to pension programs, and number of days worked if there is a job separation. These data are also available from 2001 to 2018.

2.4 Data Matching and Sample Creation

We have two datasets available for our final analyses: a matched data set of lottery winners and their corresponding credit bureau information and a matched data set of lottery winners and their

tax information. While the underlying lottery data are the same (i.e., lottery winners from an unnamed Canadian province), we are unable to create an individually-matched sample of lottery winners' tax data and credit bureau information due to legal privacy restrictions in Canada.

The credit bureau agency used winners' first and last names, postal codes, and payout dates (when postal codes are recorded) to match lottery winners to their credit records. We use both full matches (based on first and last names) and partial matches (based on last names and a first initial). Because Canadian six-character postal codes are extremely small (15 households on average), these matching criteria enable us to precisely identify winners. After matching, all personally identifiable information (names and postal codes) are deleted from the data.

Statistics Canada used winners' first and last names, postal codes, and payout dates to match them to their tax records. This matching process results in a high match rate of 80%. Similar to the credit bureau data, all personally identifiable information is removed from the matched data, including first and last names and postal codes. All our final data are fully anonymized.

3 Identification and Estimation

This section describes our target parameter of interest. Our setting is one with a continuous and staggered treatment. We borrow from the framework of Callaway, Goodman-Bacon, and Sant'Anna (2024). We assume there are multiple time periods $t = 1, ..., T$. The period when individual i becomes treated for the first time (e.g., wins a lottery) is the unit's *timing group* and is denoted by $G_i \in \mathscr{G}$. If an individual never receives treatment, $G_i = \infty$. The treatment is defined by a dose $d \in \mathscr{D}$ where $\mathscr{D} = (0, \infty)$. The observed dose (lottery prize amount) for individual i is denoted by D_i. We can also define $W_{i,t} = D_i \mathbf{1}\{t \geq G_i\}$ which is the dose amount that unit i experiences in period t. For all units that are not yet treated by t, we have $W_{i,t} = 0$.

We define individual $i's$ potential outcome at time t as $Y_{i,t}(g,d)$. The untreated potential outcome is defined as $Y_{i,t}(0) \equiv Y_{i,t}(\infty, 0)$. For each unit i, we observe their outcome in period t, Y_{it}, which satisfies the following:

$$Y_{i,t} = Y_{i,t}(0)\mathbf{1}\{t < G_i\} + Y_{i,t}(G_i, D_i)\mathbf{1}\{t \geq G_i\}$$

Our main causal effects of interest are the marginal propensities to consume, save and earn. The treatment effect concepts that correspond to these terms are causal response parameters. In order to define these, we first define the average treatment effect on the treated:

$$ATT(g,t,d|g,d) \equiv \mathbb{E}[Y_t(g,d) - Y_t(0)|G = g, D = d]$$

The causal effect $ATT(g,t,d|g,d)$ is the average treatment effect of dose d, timing group g, in period t, among units in group g that experienced dose d. Given this, the average causal response parameter is defined as follows:

$$ACRT(g,t,d|g,d) \equiv \frac{\partial ATT(g,t,l|g,d)}{\partial l}|_{l=d} = \frac{\partial \mathbb{E}[Y_t(g,l)|G = g, D = d]}{\partial l}|_{l=d}$$

The key identification assumptions are as follows:

Assumption 1 (No Anticipation)**.** *For all $g \in \mathscr{G}$ and $t = 1, ..., T$ with $t < g$, $Y_{i,t}(g,d) = Y_{i,t}(0)$.*

This is the standard condition that the treatment cannot affect outcomes in the pre-treatment period.

Callaway, Goodman-Bacon, and Sant'Anna (2024) have several versions of the "common trends" assumption which we restate here.

Assumption 2 (Common Trends a)**.** *For all $g \in \mathscr{G}$ and $t = 2, ..., T$, $d \in \mathscr{D}$, $\mathbb{E}[\Delta Y_t(0)|G = g, D = d] = \mathbb{E}[\Delta Y_t(0)|D = 0]$ for all groups $k \in \mathscr{G}$ such that $t < k$.*

Assumption 3 (Common Trends b)**.** *For all $g \in \mathscr{G}$ and $t = g, ..., T$, $d \in \mathscr{D}$, $\mathbb{E}[\Delta Y_t(0)|G = g, D = d] = \mathbb{E}[\Delta Y_t(0)|G = k]$ for all groups $k \in \mathscr{G}$ such that $t < k$.*

Assumption 2 is the stronger parallel trends assumption and requires that the paths of untreated potential outcomes are the same for all groups, doses and periods. Assumption 3 weakens this and

requires that the path of untreated potential outcomes for group g in post-treatment periods is the same as the path of outcomes for all groups that are not treated in that period.

If Assumptions 1, and 2 or 3 hold, then we have the following:

$$ATT(g,t,d|g,d) = \mathbb{E}[Y_t - Y_{g-1}|G=g,D=d] - \mathbb{E}[Y_t - Y_{g-1}|W_t=0]$$

Next, if Assumptions 1 and 2 hold, then we have the following:

$$\frac{\partial}{\partial d}\mathbb{E}[Y_t - Y_{g-1}|G=g,D=d] = \frac{\partial}{\partial d}ATT(g,t,d|g,d) = ACRT(g,t,d|g,d) + \underbrace{\frac{\partial ATT(g,t,d|g,l)}{\partial l}|_{l=d}}_{\text{selection bias}}$$

To address selection bias, Callaway, Goodman-Bacon, and Sant'Anna (2024) further introduce a "strong parallel trends" assumption which can be stated as follows.

Assumption 4 (Strong Common Trends)**.** *For all* $g \in \mathscr{G}$ *and* $t = 2,...,T$, $d \in \mathscr{D}$, $\mathbb{E}[Y_t(g,d) - Y_{t-1}(g,d)|G=g,D=d] = \mathbb{E}[Y_t(g,d) - Y_{t-1}(g,d)|G=g]$ *and* $\mathbb{E}[\Delta Y_t(0)|G=g,D=d] = \mathbb{E}[\Delta Y_t(0)|D=0]$.

If we impose Assumptions 1, 2 and 4, then we obtain:

$$\frac{\partial}{\partial d}\mathbb{E}[Y_t - Y_{g-1}|G=g,D=d] = \frac{\partial}{\partial d}ATE(g,t,d) = ACR(g,t,d)$$

While both analyses of credit bureau (e.g., spending and borrowing) and tax (e.g., earning and saving) outcomes use a continuous difference-in-differences design, we currently rely on two slightly different estimators for each analysis, which we detail below. In ongoing work, we are working to harmonize our estimator across both credit bureau and tax outcomes.

3.1 Estimation: Credit Report Outcomes

For our preliminary credit bureau analysis, we estimate the following dynamic two-way fixed effects model:

$$Y_{it} = \alpha_i + \gamma_t + \sum_{\tau=-8, \tau \neq -1}^{\tau=8} \beta_\tau D_i \times \mathbf{1}\{\tau = t - G_i\} + \varepsilon_{it}. \tag{1}$$

The indicator $\mathbf{1}\{\tau = t - G_i\}$ are dummies for the eight quarters prior to and post lottery win (omitting the coefficient for the quarter immediately preceding the lottery win). We include two-way fixed effects for individual lottery winners (α_i) and time (γ_t) and cluster standard errors at the individual level. As our sample includes only individuals who win the lottery, there is no "never treated" group. Instead, our coefficients are identified based on exogenous variation in lottery win amount and the timing of the win (i.e., we compare early cohort winners to late cohort winners).

In their supplementary appendix, Callaway, Goodman-Bacon, and Sant'Anna (2024) consider the "static" two-way fixed effects (TWFE) estimand. They show that under the assumptions considered above, there are "nuissance terms" which show up related to treatment effect dynamics. Thus, in order for the TWFE estimand to identify a weighted-average causal response parameter, one has to restrict treatment effect heterogeneity. These restrictions involve imposing homogeneous treatment effects across time, across groups or across doses.[9]

Credit bureau outcomes include credit balances (to estimate the marginal propensity to save by repaying debt), and credit card spending (to estimate the marginal propensity to consume). We aggregate our quarterly event-time coefficients over two years (e.g. nine quarters including time zero) to provide marginal propensities which are more comparable to the existing literature.

3.2 Estimation: Tax Outcomes

For our preliminary tax analysis, we estimate the following stacked regression model:

[9] See Proposition S2 in Callaway, Goodman-Bacon, and Sant'Anna (2024). In ongoing work, we are working to implement estimators that avoid the potential pitfalls of the TWFE estimator.

$$Y_{i\tau g} = \alpha_{ig} + \gamma_{tg} + \sum_{\tau=-6,\tau\neq-1}^{\tau=6} [\beta_{0\tau} D_i + \beta_{1\tau} \mathbf{1}\{G_i = g\} + \beta_{2\tau} D_i \times \mathbf{1}\{G_i = g\}] \times \mathbf{1}\{\tau = t - G_i\} + \varepsilon_{i\tau g} \tag{2}$$

The indicator $\mathbf{1}\{\tau = t - G_i\}$ are dummies for the six years prior to and post lottery win (omitting the coefficient for the year immediately preceding the lottery win). We include fixed effects for individual lottery winners (α_{ig}) and time (γ_{tg}) which are both fully saturated with cohort-year fixed effects (Wing, Freedman, and Hollingsworth 2024). We cluster standard errors at the individual level in each cohort-year. Our cohort-specific analysis enables constructing a control group of not-yet-treated individuals, consisting of individuals who won the lottery in later cohorts $G_i > g$. Our coefficients are identified based on within-cohort exogenous variation in lottery win amount.

Our estimator aligns closely to a within-cohort, static TWFE estimator with a continuous treatment.[10] Callaway, Goodman-Bacon, and Sant'Anna (2024) show that under the assumptions considered above, the weights of average causal responses across doses are positive and equal to one, providing a (weakly) causal interpretation of TWFE. A pitfall is that the TWFE weighting scheme between doses is generally not equal to the dose distribution among the treated. The linearity of realized outcomes resolves such interpretation challenges.[11]

Tax outcomes include savings and income from financial assets (such as dividends, capital gains, interest and investment income) along with contributions to individual retirement accounts. For labor market outcomes, we consider total earnings and the probability of employment.

[10] For example, see Baker, Larcker, and Wang (2022) who consider a binary treatment setting and show such an estimator is equivalent to estimating treatment effects for each cohort of winners and then applying variance weighting to estimate average treatment effects across cohorts.

[11] See Theorem 3.4(a) in Callaway, Goodman-Bacon, and Sant'Anna (2024). As detailed in Footnote 9 and earlier in this section, we are working on implementing an estimator which avoids such potential pitfalls and is harmonized across our analyses.

4 Results

In this section, we describe our results for the three main choices made by households following a lottery win: (1) consumption (MPC); (2) savings (MPS), which we examine through both debt reduction and asset accumulation; and (3) earnings (MPE).

4.1 Marginal Propensity to Consume

Figure 1 shows the effect of $10,000 of lottery winnings on credit card spending. We find that total credit card spending increases by roughly $116 in each quarter. This spending increase occurs within two quarters of the win and persists for at least 8 quarters after the event. To create a comparable two-year MPC estimate with the literature, we aggregate our coefficients to include the quarter of the win and eight quarters post lottery win to find an MPC on credit card spending of 0.11. Since Canadians spend roughly 56% of their total spending on credit cards (Henry, Huynh, and Welte, 2018), this translates to a two-year MPC of 19 cents for every dollar won.

The average MPC of 19 cents masks substantial heterogeneity by income. Figure 2 plots credit card spending by quartile of neighborhood income. The first quartile of income (CA $49,634 and below) has a much larger increase in credit card spending, more than six times that of our average estimate. Coupled with the fact that borrowers in the first income quartile only put 19% of their spending on credit cards (Table A.2), this translates to an MPC of 0.59 (assuming their credit card spending remains the same share of their spending post-lottery win). The second income quartile (within quartile mean of CA $63,220) is more reflective of our average sample with an MPC of 0.23. The third and fourth neighborhood income quartiles, while spending much more of their income on credit cards (65% and 90% respectively), increase their spending by less, translating to an MPC of 0.15.

4.2 Marginal Propensity to Save

As described above, we can measure savings through both debt reduction (using credit data) and financial asset accumulation (using tax data). We discuss both in turn.

4.2.1 Debt Reduction

Figure 3 shows that, on average, borrowers repay roughly $860 for every $10,000 in winnings. Since total debt balance is a stock variable rather than the flow variable of consumer spending, we take the last-quarter coefficient as our estimate of the marginal propensity to save through debt repayment. This translates to a two-year marginal propensity to save through debt reduction of 0.06.

From Figure A.3, winners in the top quartile of neighborhood income pay down the most debt, approximately $1,000 per $10,000 won. This translates to a two-year MPS of 0.09. Their debt balance decreases sharply after the win and stays persistently lower for 8 quarters after the win, and becomes statistically insignificant only at the end of the two-year period. Borrowers in the bottom income quartile, or those with incomes below $50,000 lower their debt balances in the two quarters after the lottery win, but do not have statistically significant balance differences 3 quarters after the win. Their estimated MPS is 0.03, or roughly a third of the top quartile income borrowers. Borrowers in the third and second income quartiles also see statistically significant reductions in their balances that then rebound between a year to two years after the win, translating to an MPS of 0.05 for the second income quartile and 0.06 for the third income quartile.

Appendix A documents other potentially relevant credit bureau outcomes for winners. Despite the average treatment effect to repay debt, there is evidence that borrowers apply for more credit after a lottery win. Figure A.4 shows that credit inquiries increase by 0.01 percentage points per $1,000 of winnings, or 0.01% on a mean of 0.3 inquiries in the quarter before a win. Lenders are also willing to increase account credit limits: credit card limits increase by roughly $62 for every $10,000 won, on an average credit limit of $14,000 (Figure A.5), and HELOC limits increase by $167 for every $10,000 won on an average balance of $19,100. These effects account for both

the extensive margin of opening a new account and from increases in limits on existing accounts. Winners also improve their credit scores (Figure A.6) by about one point per $10,000 won.

4.2.2 Financial Asset Accumulation

Figure 5 shows event study estimates for each of our savings measures in the tax data. We find that an additional $10,000 in lottery wealth increases realized capital gains in each year following the lottery win, for a total of $729 over the six-year post-win period, in addition to the year of win (panel a). Similarly, panel (b) of Figure 5 shows that dividend income increases in each year post lottery win. In particular, for each $10,000 in lottery amount, dividend income increases on average $162 per year. While dividend income does not measure investment in equities directly, we can impute that winners increase their investment in this financial product and their stock market participation. This result is similar to the findings in Briggs et al. (2021).

Focusing on interest and investment income in panel (c) of Figure 5, we find that $10,000 in lottery wealth leads to between $100 and $180 of additional interest and investment income per year, or an extra $952 of such income over the six post-win years, in addition to the year of win.

In addition to these results on investment income, our tax return data also provide us with data on tax-advantaged investments, specifically individual retirement accounts and employer-sponsored pension plans. We report results for individual retirement account contributions in panel (d) . In our tax data, we are able to observe both retirement savings and pension plan contributions and withdrawals, as well as retirement savings plan contributions. One important caveat when examining tax-advantaged investments is that all of these tax-advantaged plans require that the individual can only contribute in these plans up to a ceiling defined by regulation (whereas there is no ceiling on investments in equities or fixed income assets).

In order to recover a MPS based on income from investment assets, we use a capitalization approach.[12] First, we calculate the average total investment income that lottery winners earned over

[12]We are working to also secure access to contributions to Tax-Free Savings Accounts or TFSAs to obtain a direct measure of MPS.

two years. In our case, this is roughly $400 per $10,000 in lottery winnings. In order to calculate the "savings base" that would generate such income, we use Saez and Zucman (2016)'s average pre-tax rate of return on taxable capital income of 5.4%. Then, $MPS = \frac{1}{r} \times$ investment income, or $\frac{1}{0.054} \times 400 = \$7,407$, or 74 cents per dollar.

We find that retirement contributions increase by $148 (for each $10,000 in lottery wealth) in the same year as the lottery win (year 0), and by $50 in year 1. After this immediate and significant increase in retirement contributions in response to a lottery win, contributions tail off and weakly fall in subsequent years. Overall, it seems that winners shift the timing of retirement contributions instead of permanently changing them. Over the entire post-win period, the average effect on retirement contributions is $4.72, or a MPS of 0.003.

We find no effects for any years on retirement savings withdrawals (panel (a) of Figure A.8) and a very small decrease in employer-sponsored pension contributions (panel b). Over the six-year period after a lottery win, employer-sponsored pension contributions decline by $5.55 on average (for each $10,000 in lottery wealth). This decrease may come from lottery winners decreasing their labor supply and earnings as we document in Section 4.3.

4.3 Marginal Propensity to Earn

We next report estimates of the marginal propensity to earn out of wealth by examining the effect of a $10,000 win on several labor supply outcomes: (1) labor earnings, (2) the probability of having a job, and (3) labor income conditional on employment. As discussed in Section 2.3, our measures of these various labor supply outcomes are taken from Statistics Canada's CEEDD data.[13]

Figure 6 presents our event-study estimates. Panel (a) shows that an extra $10,000 of lottery win reduces labor income by $411 on average per year. Aggregating over the post-treatment period (six years plus the year of win), labor income declines by $2,876 in response to an extra $10,000 in lottery wealth. Panel (b) of Figure 6 shows the estimates for the probability of having a job. There

[13] In particular, we use T4 Record of Employment and Remuneration tax files. Morissette, Qiu, and Chan (2013) report that Statistics Canada's definition of job quits could under report their true number. For this reason, we also measure the effect on the number of jobs, which counts the number of employment links and is free of under-reporting.

is a sharp reduction in the probability of having a job at the time of the lottery win. This effect grows over time and ranges between a 0.57 and 0.8 percentage point decline for each additional $10,000 in lottery wealth. On average, the probability of having a job decreases by 0.6 percentage points in the six years after the lottery win.[14]

Panel (c) shows our estimates for labor income conditional on employment. Labor income decreases by $328 on average per year for each $10,000 increase in wealth in the six years after the lottery win. Over this period, the total decline in labor earning is $2,294 for each $10,000 in extra wealth.

Taken together, our results in Figure 6 indicate that labor supply for winners responds immediately to a lottery win and that this occurs through both the extensive and intensive margins. Our annual MPE estimate of -$4.1 per $100 of lottery winnings compares to the wealth effect estimate in Golosov et al. (2024). They report an annual earnings effect of -$2.3 per $100 of lottery winnings. One reason why their headline estimate is smaller is their sample contains lottery winners who won larger prizes than our sample. In their appendix, they estimate MPE for smaller lottery sizes ($30,000-$300,000) which aligns more closely with our sample of lottery winners and find an average annual reduction around $5.5 per $100 of lottery winnings. Thus, our estimates are similar when reweighting their sample to similarly sized lottery prizes. Cesarini et al. (2017) on the other hand find a much smaller wealth effect on earnings corresponding to roughly -$1.31 per $100 in lottery winnings.

5 Model of Consumption, Savings and Earnings

In this section, we develop a simple two-period model of consumption, savings and earnings to interpret our evidence. The model follows Ferey, Lockwood, and Taubinsky (2024). Our main objective is to shed light on income heterogeneity in the MPC, MPS and MPE that we observed in

[14] In Figure A.9, we report a significant decrease in the number of jobs worked in each of the six years after the lottery win (relative to the year before the win) with a magnitude of between 0.01 and 0.012 fewer jobs for each additional $10,000 in lottery prize. On average, the number of jobs declines by 0.01 with each additional $10,000 in the lottery amount over the six years after the lottery win.

our reduced-form analysis. Although the model does not currently include credit constraints, we plan to incorporate this feature in future iterations.

Suppose individuals with heterogeneous earnings ability θ and discount factor δ earn labor income z after exerting an effort of z/θ and have unearned income y.[15] Preferences are given by:

$$U(c,S,z;\delta,\theta) = u(c) + \delta v(S) - k(z/\theta), \tag{3}$$

where consumption is given by $c = y+z-S$. We assume that u and v are increasing concave functions and k is an increasing convex function. The budget constraint implies that

$$\frac{dc}{dy} = 1 + \frac{dz}{dy} - \frac{dS}{dy} \tag{4}$$

so it is sufficient to characterize the relationship between the MPE and the MPS since these jointly determine the MPC.

The first-order condition for S is

$$-u'(y+z-S^*) + \delta v'(S^*) = 0 \tag{5}$$

The first-order condition for z is

$$u'(y+z^*-S) - \frac{1}{\theta}k'(z^*/\theta) = 0 \tag{6}$$

Totally differentiating the first-order conditions gives:

[15] In our two-period model, δ could reflect both exponential discounting and present-bias from self-control problems as in Laibson (1997).

$$\frac{dS^*}{dy} = \frac{1}{\frac{\delta v''(S)}{u''(c)(1+\alpha(\theta,y))} + 1} \tag{7}$$

$$\frac{dz^*}{dy} = \alpha(\theta,y)\left(\frac{\delta v''(S)}{\delta v''(s) + u''(c)\,(1+\alpha(\theta,y))}\right) \tag{8}$$

$$\frac{dc^*}{dy} = 1 + \frac{dz^*}{dy} - \frac{dS^*}{dy} \tag{9}$$

where $\alpha(\theta,y) \equiv -\frac{u''(c)}{u''(c)-\frac{1}{\theta^2}k''(z/\theta)} < 0$.

Equations 7, 8, and 9 characterize the MPS, MPE and the MPC.[16].

We next simulate the model in order to understand the key determinants of the MPC, MPS and MPE. For the simulation, we set $v(\cdot) = u(\cdot)$, and pick parameters for iso-elastic functions $u(\cdot)$ and $k(\cdot)$ to satisfy the regularity conditions.

$$u(c) = \frac{c^{1+\alpha}}{1+\alpha} \tag{10}$$

$$k(z/\theta) = \frac{(z/\theta)^{1+\gamma}}{1+\gamma} \tag{11}$$

With these functional forms, the optimal level of savings is given by:

$$S^* = \left(\frac{(z^*/\theta)^\gamma}{\delta\theta}\right)^{1/\alpha}, \tag{12}$$

and that the optimal level of labor earnings, z^*, for each θ are implicitly pinned down by

$$\left(y + z^* - \left(\frac{(z^*/\theta)^\gamma}{\delta\theta}\right)^{1/\alpha}\right)^\alpha = \frac{1}{\theta}(z^*/\theta)^\gamma \tag{13}$$

[16]Complete derivations for the MPs and S^*, z^*, c^* are in Appendix B.

for each θ. $c^*(\theta)$ can then be obtained through the budget constraint.

$$c^*(\theta) = y + z^*(\theta) - S^*(\theta) \tag{14}$$

We draw heterogeneous earnings ability θ from a Uniform$[1,5]$ and allow both unearned income, y, and discount factors, δ, to be positively correlated with earnings potential θ.

Figure 7 shows the marginal propensities across the income distribution. In line with our empirical evidence, the MPC is decreasing, the MPS is increasing and the MPE is decreasing in income. The relationship between the discount factor, δ, and the earnings potential, θ, modulates how these terms vary over the income distribution. In order to generate the patterns that are consistent with our empirical evidence, θ and δ must be positively correlated. This indicates that higher-income individuals tend to be more patient.

As shown in Ferey, Lockwood, and Taubinsky (2024), a sufficient statistic for "preference heterogeneity" is $s'(z) - s'_{inc}(z)$. The first term, $s'(z)$, is the across-income savings profile and the second term, $s'_{inc}(z)$, represents the causal income effect on savings. In the case where individual-type heterogeneity is uni-dimensional, this is equal to $\frac{\partial S}{\partial \delta}\frac{\partial \delta}{\partial z}$. In ongoing work, we plan to estimate this sufficient statistic and examine how it correlates with the MPC, MPS and MPE. This exercise reveals the role of preference heterogeneity for understanding the co-movement of spending, savings and earnings responses.

We also plan to link this preference heterogeneity to optimal taxes on income and savings. The celebrated result of Atkinson and Stiglitz (1976) states that savings should not be taxed in the presence of an optimal non-linear income tax. Ferey, Lockwood, and Taubinsky (2024) generalize this result and show that the key sufficient statistic for a non-zero tax on savings is $s'(z) - s'_{inc}(z)$. In particular, the optimal tax rate on savings varies positively with the degree of preference heterogeneity in the population. In ongoing work, we plan to calibrate optimal income and savings taxes using our empirical estimates, as well as consider broader policy implications related to the introduction of a universal basic income and the optimal targeting of fiscal policy.

6 Conclusion

In this paper, we construct a novel data set of lottery winners linked to their credit bureau and tax data to provide new estimates of the MPC, MPS and MPE out of financial windfalls. Our average effects mask considerable heterogeneity across the income distribution.

Our results on heterogeneity in the MPC, MPS and MPE have important policy implications. First, our results add to existing findings that fiscal stimulus should be targeted toward lower-income consumers with larger average MPCs. Second, our findings provide insights for effective monetary policy design. Understanding the MPC and MPS from labor income and wealth accumulation, which are affected by monetary policy, is critical to understanding transmission of monetary policy through the economy. In ongoing work, we plan to use our estimates to provide insights into the introduction of a universal basic income program and how our heterogeneity analysis changes the optimal tax calibrations relative to a benchmark where the wealth effect on labor supply is the same across the income distribution. We also plan to explore how the correlation in our estimates of the MPC, MPS and MPE by income are useful for calibrating optimal taxes on income and savings and compare our results to calibrations that ignore the correlated heterogeneity in behavioral responses.

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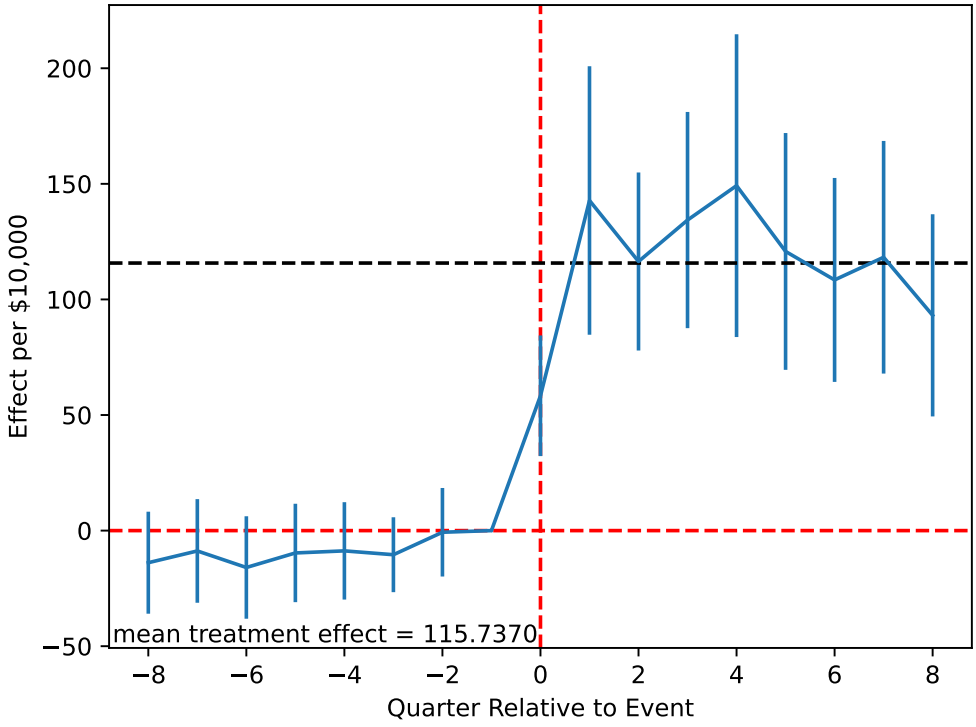
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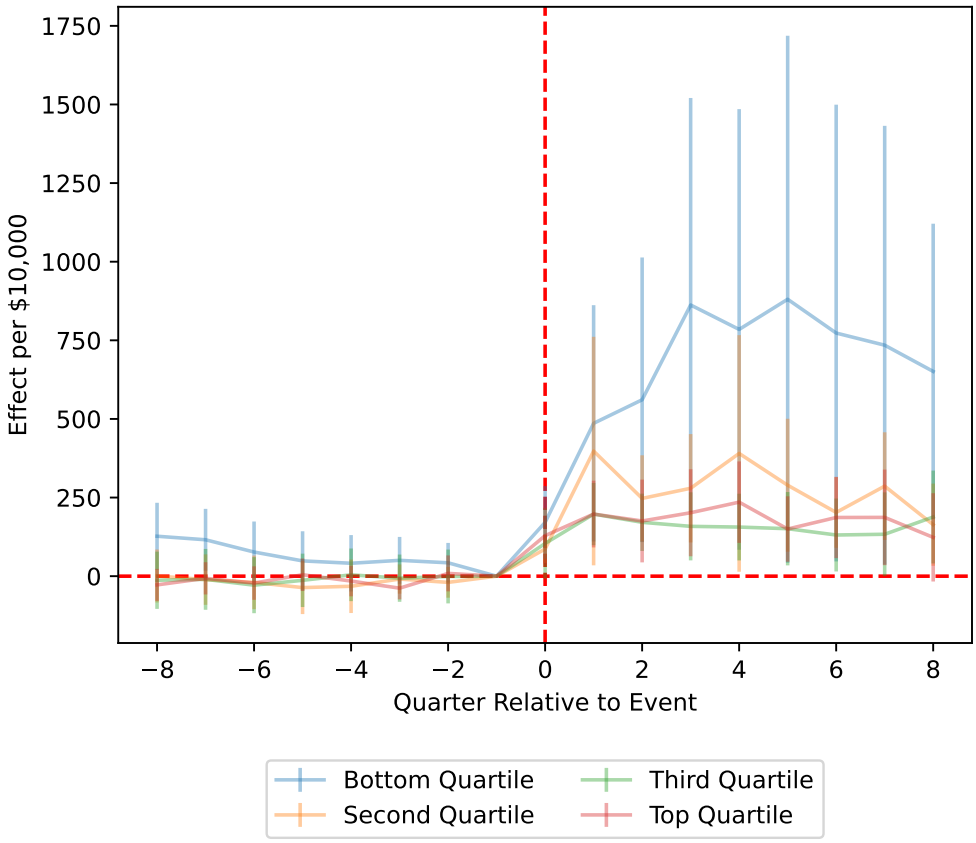
7 Figures and Tables

Figure 1: Marginal Propensity to Consume *on Credit Cards* from CA$10,000 of Lottery Winnings (credit bureau data)



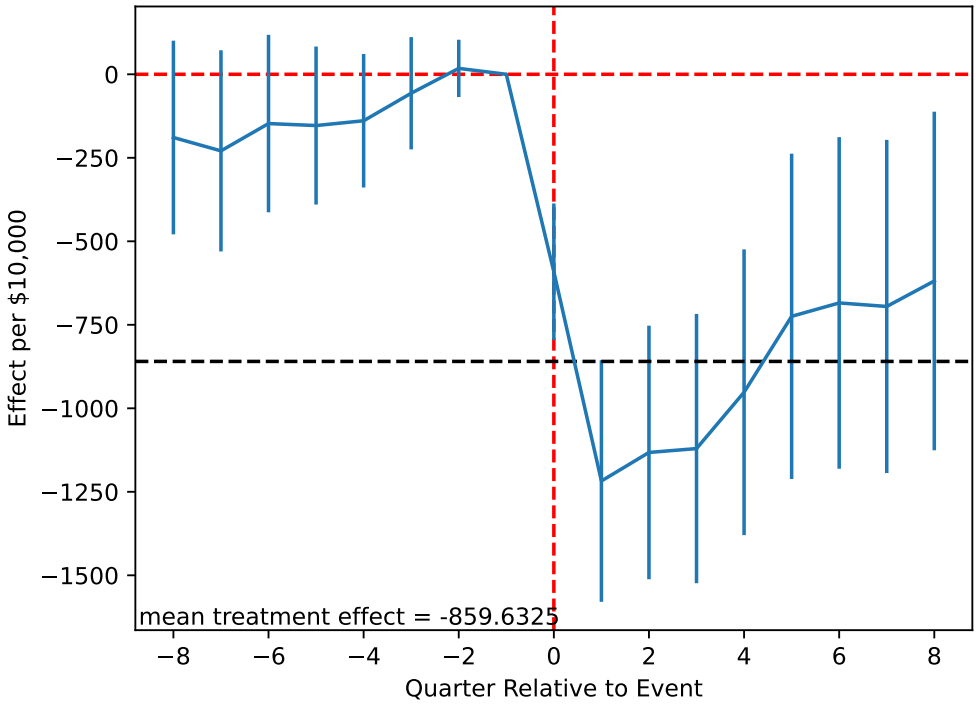
This figure shows event-study estimates of Equation (1) on total credit card spending. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample includes 13,413 individuals who won the lottery between January 2015 and March 2020. Lottery winnings are winsorized at CA$350,000. The mean treatment effect is calculated as the average across all post-treatment quarters and is depicted with the black dotted line. Credit card spending is imputed by the credit bureau based on credit card balances and (actual) payments made by individuals. We calculate the two-year MPC as the sum of post-treatment point estimates. These estimates aggregate to a two-year MPC *on credit cards* of 0.11. We define total spending as credit card spending scaled by the national average credit card share of spending of 0.56 (Henry, Huynh, and Welte 2018) implying a two-year MPC *overall* of 0.19.

Figure 2: Marginal Propensity to Consume *Overall* from CA$10,000 of Lottery Winnings, by Neighborhood Income (credit bureau data)



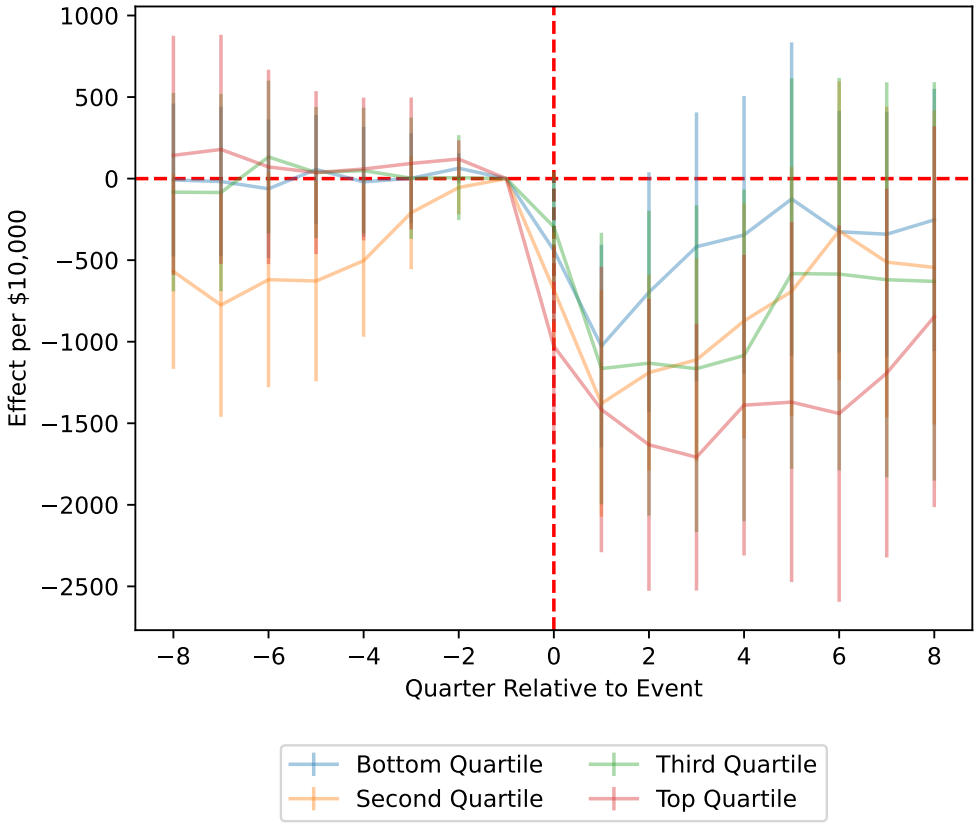
This figure shows event-study estimates of Equation (1) on total spending estimated separately by neighborhood income quartile. Point estimates are plotted along with the 95% confidence interval, where standard errors are clustered at the individual level. The overall sample includes 13,413 individuals who won the lottery between January 2015 and March 2020. Lottery winnings are winsorized at CA$350,000. Total spending is defined as total credit card spending—imputed by the credit bureau based on credit card balances and (actual) payments made—scaled by the credit card shares of spending reported in Table A.2. In practice, we estimate Equation (1) on credit card spending within income quartiles and then scale estimates based on the within-income quartile credit card share of spending. The first income quartile includes individuals with neighbourhood incomes below CA$49,634; the within quartile mean neighbourhood income is CA$38,612. The second income quartile includes individuals with neighbourhood incomes between CA$49,634 and CA$81,500; the within quartile mean neighbourhood income is CA$63,220. The third income quartile includes individuals with neighbourhood incomes between CA$81,500 and CA$120,161; the within quartile mean neighbourhood income is CA$101,147. The fourth income quartile includes individuals with neighbourhood incomes above CA$120,161; the within quartile mean neighbourhood income is CA$167,963. Individuals are assigned neighbourhood incomes based on their census Dissemination Area (DA) of residence in the closest census year prior to winning the lottery. DAs are small, stable geographic units with an average population of 400 to 700 persons (Government of Canada 2021). We calculate the two-year MPC as the sum of post-treatment point estimates. These results imply within-neighborhood income quartile two-year MPCs of: quartile 1 = 0.59; quartile 2 = 0.23; quartiles 3 and 4 $\approx$ 0.15.

Figure 3: Marginal Propensity to Save via Debt Repayment from CA$10,000 of Lottery Winnings (credit bureau data)



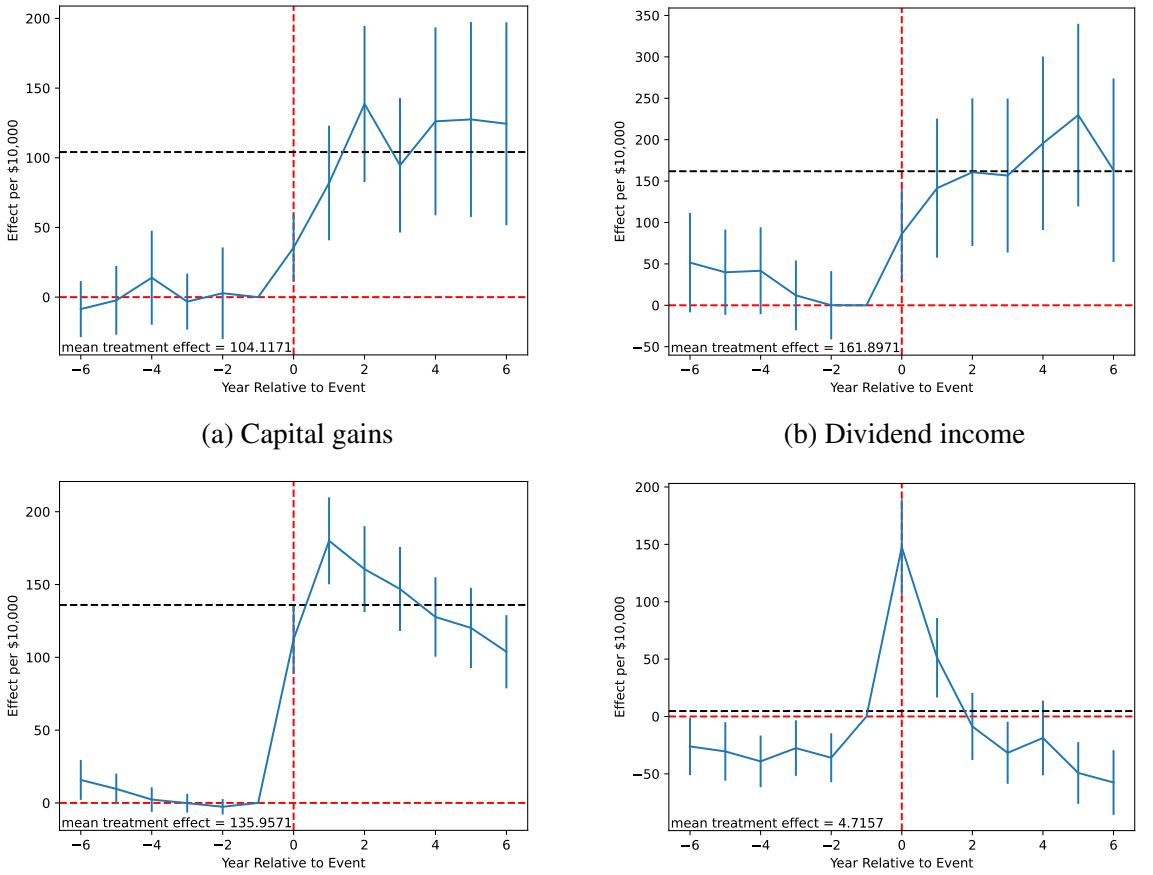
This figure shows event-study estimates of Equation (1) on total debt balance. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample includes 13,413 individuals who won the lottery between January 2015 and March 2020. Lottery winnings are winsorized at CA$350,000. The mean treatment effect is calculated as the average across all post-treatment quarters and is depicted with the black dotted line. Total debt balance is defined as the sum of the end of quarter principal balance owing across all non-revolving (mortgage, auto loan, installment loan, student loan and telephone loan) and revolving (home equity line of credit, unsecured line of credit and credit card) debt. We calculate the two-year MPS via debt repayment as the point estimate at eight quarters post-treatment. These estimates imply a two-year MPS via debt repayment of 0.06.

Figure 4: Marginal Propensity to Save via Debt Repayment from CA$10,000 of Lottery Winnings, by Neighborhood Income (credit bureau data)



This figure shows event-study estimates of Equation (1) on total debt balance estimated separately by neighborhood income quartile. Point estimates are plotted along with the 95% confidence interval, where standard errors are clustered at the individual level. The overall sample includes 13,413 individuals who won the lottery between January 2015 and March 2020. Lottery winnings are winsorized at CA$350,000. Total debt balance is defined as the sum of the end of quarter principal balance owing across all non-revolving (mortgage, auto loan, installment loan, student loan and telephone loan) and revolving (home equity line of credit, unsecured line of credit and credit card) debt. The first income quartile includes individuals with neighbourhood incomes below CA$49,634; the within quartile mean neighbourhood income is CA$38,612. The second income quartile includes individuals with neighbourhood incomes between CA$49,634 and CA$81,500; the within quartile mean neighbourhood income is CA$63,220. The third income quartile includes individuals with neighbourhood incomes between CA$81,500 and CA$120,161; the within quartile mean neighbourhood income is CA$101,147. The fourth income quartile includes individuals with neighbourhood incomes above CA$120,161; the within quartile mean neighbourhood income is CA$167,963. Individuals are assigned neighbourhood incomes based on their census Dissemination Area (DA) of residence in the closest census year prior to winning the lottery. DAs are small, stable geographic units with an average population of 400 to 700 persons (Government of Canada 2021). We calculate the two-year MPS via debt repayment as the point estimate at eight quarters post-treatment. These results imply within-neighborhood income quartile two-year MPSs via debt repayment of: quartile 1 = 0.03; quartile 2 = 0.05; quartile 3 = 0.06; and quartile 4 = 0.09.

Figure 5: Marginal Propensity to Save via Investment from CA$10,000 of Lottery Winnings (tax data)



(a) Capital gains

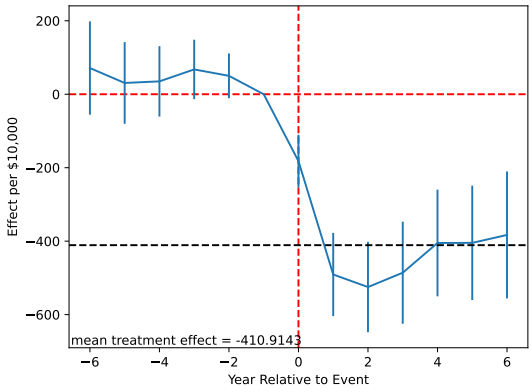
(b) Dividend income

(c) Interest and investment income

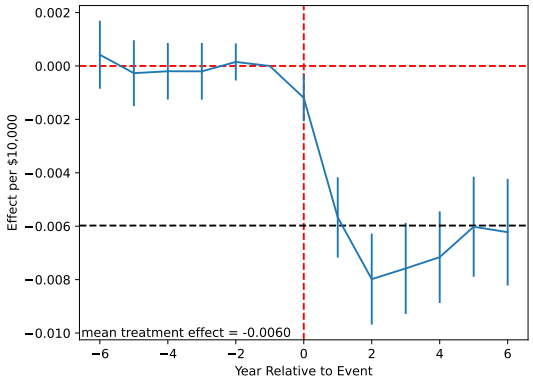
(d) Indiv. retirement account contributions

This Figure presents estimates from Equation (2) on various investment outcomes. All specifications include individual and calendar-year fixed effects, both of which we fully saturate with cohort-year fixed effects. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level in each cohort year. The sample is constructed based on Section 2. Lottery winnings are winsorized at CA$350,000. The mean treatment effect is calculated as the average across all post-treatment quarters and is depicted with the black dotted line. Capital gains is defined as the net taxable capital gains resulting from the sale or transfer of assets. Dividend income is defined as the taxable amount of dividends (eligible and other than eligible) from taxable Canadian corporations. Investment income is defined as interest, foreign interest, foreign dividend income, foreign income, and foreign non-business income. Individual retirement account contributions are defined as the amount contributed to a Registered Retirement Saving Plan. Summing post-treatment estimates per CA$10,000 of lottery winnings: capital gains increase by CA$729; dividend income increases by CA$1,133; interest and investment income increases by CA$952; and individual retirement account contributions increase by CA$33.

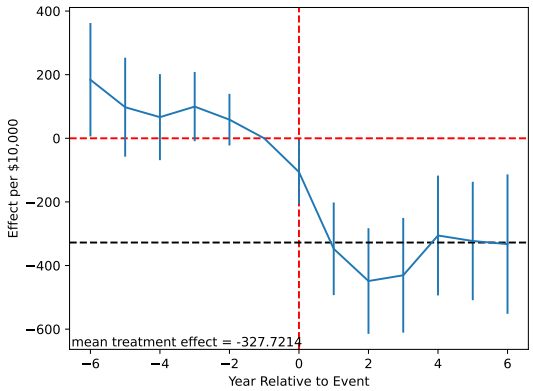
Figure 6: Marginal Propensity to Earn (intensive and extensive margin) from CA$10,000 of Lottery Winnings (tax data)



(a) Labor income



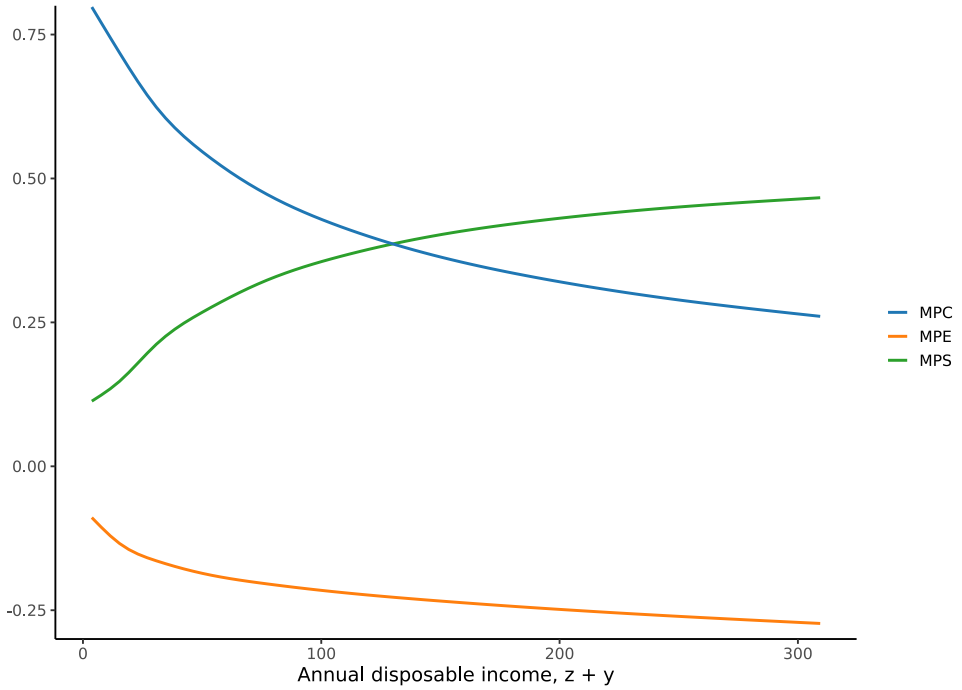
(b) $\mathbb{I}$(Have a job)



(c) Labor income | no quit

This Figure presents estimates from Equation (2) on various labor supply outcomes. All specifications include individual and calendar-year fixed effects, both of which we fully saturate with cohort-year fixed effects. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level in each cohort year. The sample is constructed based on Section 2. Lottery winnings are winsorized at CA$350,000. The mean treatment effect is calculated as the average across all post-treatment quarters and is depicted with the black dotted line. Labor income is defined as employment income received from a business enterprise, including wages, salaries, and commissions, before deductions, and excluding self-employment income. The probability of having a job is defined as an indicator variable equal to one if the individual has a job in the observed year. Labor income | no quit is defined as labor income for those lottery winners who do not quit their jobs after winning a lottery. We calculate the six-year MPE as the sum of post-treatment estimates. Estimates from panel (6a) aggregate to a six-year MPE of -0.29.

Figure 7: Model simulation



This Figure presents the simulated MPs over the income distribution, as described in Section 5. The iso-elastic parameter, α, for $u(\cdot)$ is -0.5 and the iso-elastic parameter, γ, for $k(z/\theta)$ is 0.5. We take 10,000 draws from Uniform$[1,5]$ for the earnings potential θ. Unearned income is positively correlated with θ and is generated as $y = \sqrt{\theta}$. The discount factor, δ, is generated as $\delta = 0.5 \cdot \theta$. z and S are pinned down using the first-order conditions. We can then use the budget constraint to obtain c. These quantities, in conjunction with the functional forms for $u(\cdot)$ and $k(\cdot)$, return the MPs through Equations 7, 8, and 9.

Table 1: Quarterly Summary Statistics in Quarter Prior to Treatment for Lottery Winners

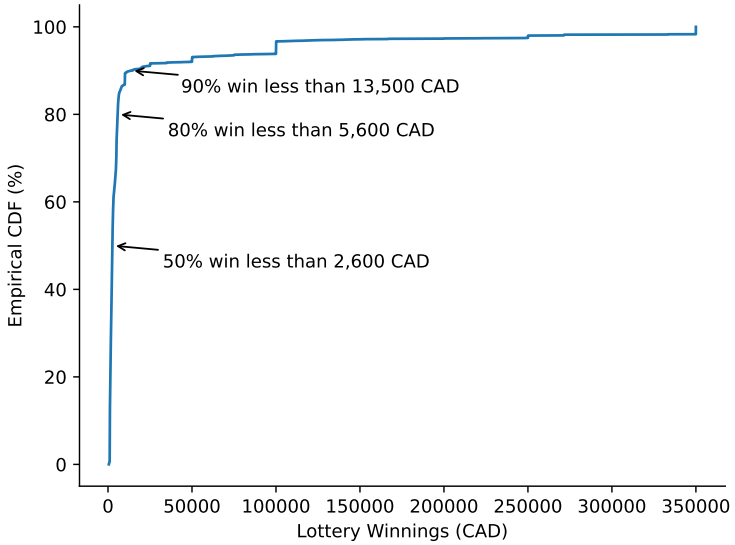
	Lotteries		General Population	
	Mean	Standard Deviation	Mean	Standard Deviation
Lottery winnings	16,548.64	54,387.86	0.00	0.00
Age	47.95	14.43	48.65	13.98
Neighborhood mobility rate	0.03	0.17	0.03	0.17
Credit characteristics				
Total quarterly credit card spending	3,400.17	9,165.34	4,378.85	13,057.46
Total debt balance	108,959.64	179,786.05	114,123.50	209,113.60
Risk score	725.34	110.19	756.81	99.45
Share in collection	0.01	0.08	0.00	0.06
Share in bankruptcy	0.02	0.12	0.01	0.11

This table shows summary statistics for key demographic variables and our main outcome variables for lottery winners in the quarter prior to winning and a 0.1% random sample from the Canadian population. Lottery winnings are winsorized at CA$350,000. Age is defined based on the midpoint of 5 year age bands. Neighborhood mobility is an indicator defined by the credit bureau based on whether an individual's address has changed since the previous quarter. Total credit card spending is the sum of credit card spending within a quarter across all credit cards; the credit bureau imputes credit card spending based on credit card balances and (actual) payments made. Total debt balance is defined as the sum of the end of quarter principal balance owing across all non-revolving (mortgage, auto loan, installment loan, student loan and telephone loan) and revolving (home equity line of credit, unsecured line of credit and credit card) debt. The risk score is calculated by the credit bureau using a proprietary formula and ranges from 300 to 900. Risk scores below 499 indicate serious credit issues; risk scores from 500 to 574 indicate a high risk individual; risk scores from 575 to 649 indicate an above average risk individual; risk scores from 650 to 749 indicate a fairly safe credit risk individual; risk scores above 750 indicate a safe credit risk individual. Collection is an indicator for if any of an individual's credit accounts have been sold to a collection agency by the original lender. Bankruptcy is an indicator if an individual is in consumer bankruptcy (similar to chapter 7 bankruptcy in the United States) and also includes consumer proposals (roughly similar to chapter 13 bankruptcy in the United States).

Appendix A Additional Figures and Tables

A.1 Additional Descriptive Figures

Figure A.1: Empirical CDF Lottery Winnings

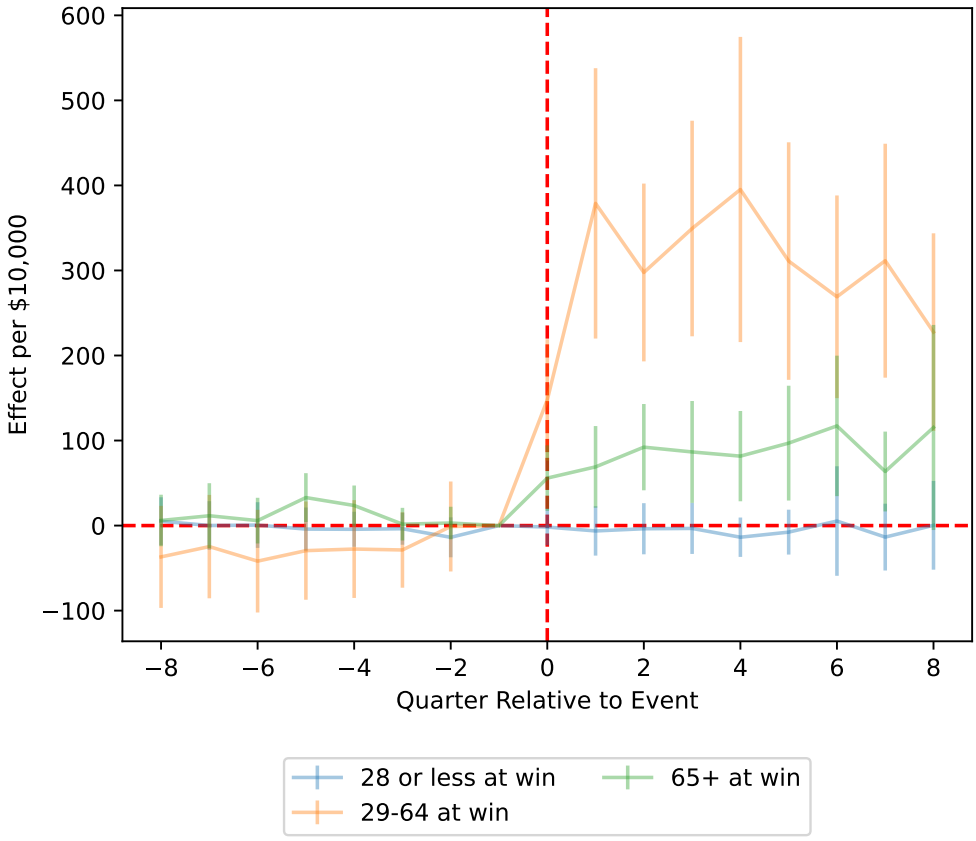


This figure shows the empirical cumulative distribution function of lottery winnings which are winsorized at CA$350,000 which is approximately equivalent to the 99th percentile. The mean lottery win amount was CA$16,549.

A.2 Additional Outcomes: Credit Bureau Data

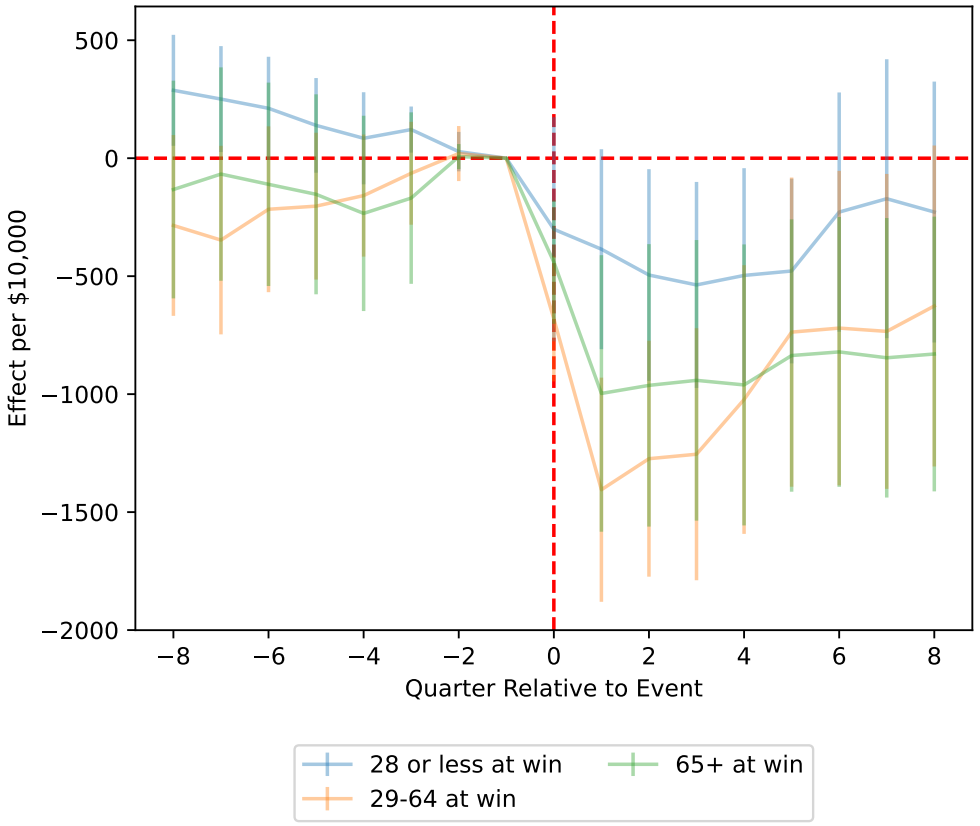
A.2.1 Heterogeneity by Age

Figure A.2: Marginal Propensity to Consume *Overall* from CA$10,000 of Lottery Winnings, by Age Group (credit bureau data)



This figure shows event-study estimates of Equation (1) on total spending estimated separately by age group. Point estimates are plotted along with the 95% confidence interval, where standard errors are clustered at the individual level. The overall sample includes 13,413 individuals who won the lottery between January 2015 and March 2020. Lottery winnings are winsorized at CA$350,000. Total spending is defined as total credit card spending—imputed by the credit bureau based on credit card balances and (actual) payments made—scaled by the credit card shares of spending reported in Table A.2. In practice, we estimate Equation (1) on credit card spending within age groups and then scale estimates based on the within-age group credit card share of spending. We calculate the two-year MPC as the sum of post-treatment point estimates. These results imply within-age group two-year MPCs of: ages 28 or less ≈ 0; ages 29-64 $= 0.27$; and ages 65 and above $= 0.08$. The MPC for individuals less than 28 is attenuated due to 56% of this age group not having credit cards (for whom spending is mechanically zero).

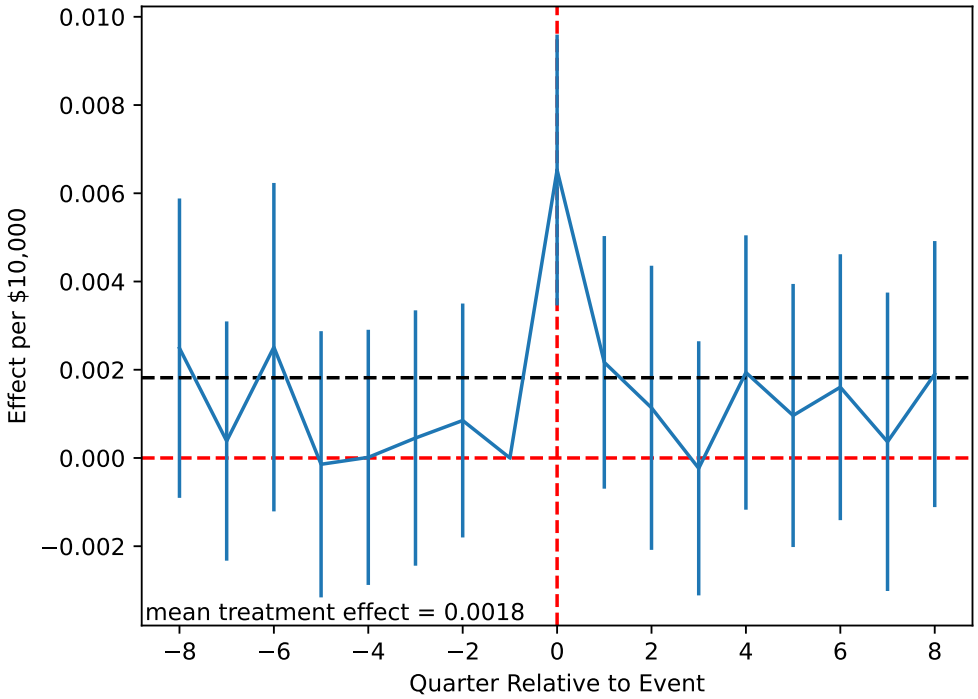
Figure A.3: Marginal Propensity to Save via Debt Repayment from CA$10,000 of Lottery Winnings, by Age Group (credit bureau data)



This figure shows event-study estimates of Equation (1) on total debt balance estimated separately by age group. Point estimates are plotted along with the 95% confidence interval, where standard errors are clustered at the individual level. The overall sample includes 13,413 individuals who won the lottery between January 2015 and March 2020. Lottery winnings are winsorized at CA$350,000. Total debt balance is defined as the sum of the end of quarter principal balance owing across all non-revolving (mortgage, auto loan, installment loan, student loan and telephone loan) and revolving (home equity line of credit, unsecured line of credit and credit card) debt. We calculate the two-year MPS via debt repayment as the point estimate at eight quarters post-treatment. These results imply within-age group two-year MPSs via debt repayment of: ages 28 or less $= -0.02$; ages 29-64 $= -0.06$; and ages 65 and above $= -0.08$.

A.2.2 Credit Demand

Figure A.4: Credit Inquiries

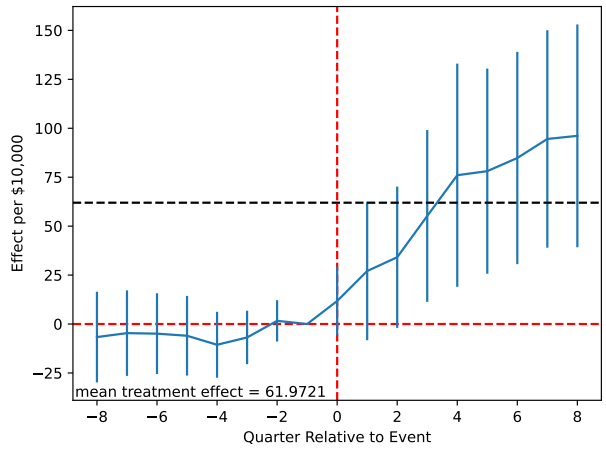


This figure shows event-study estimates of Equation (1) on credit inquiries. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample includes 13,413 individuals who won the lottery between January 2015 and March 2020. Lottery winnings are winsorized at CA$350,000. The mean treatment effect is calculated as the average across all post-treatment quarters and is depicted with the black dotted line. Credit inquiries are measured as the number of credit applications across any non-revolving (mortgage, auto loan, installment loan, student loan and telephone loan) and revolving (home equity line of credit, unsecured line of credit and credit card) debt.

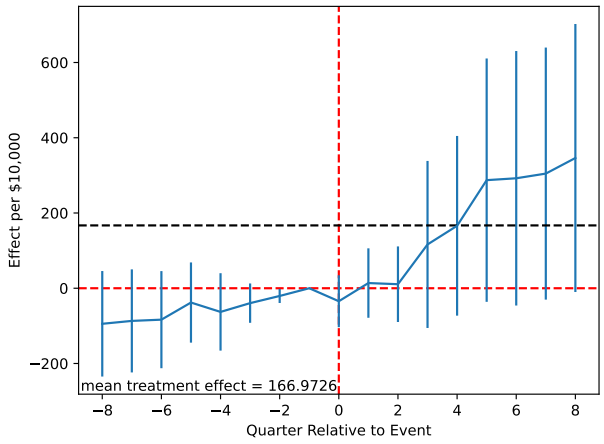
A.2.3 Credit Supply

Figure A.5: Credit Limits

(a) Total credit limit across credit cards



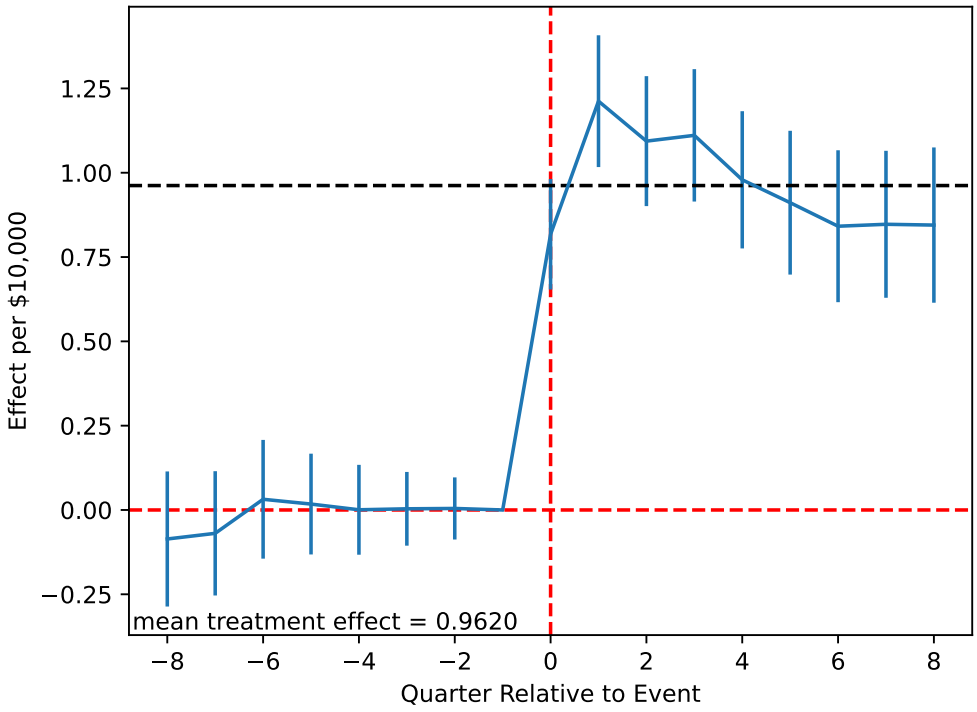
(b) Total HELOC credit limit



This figure shows event-study estimates of Equation (1) on credit limits. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample includes 13,413 individuals who won the lottery between January 2015 and March 2020. Lottery winnings are winsorized at CA$350,000. The mean treatment effect is calculated as the average across all post-treatment quarters and is depicted with the black dotted line. Credit card limits are calculated as the sum of all limits on an individual's credit cards. HELOC credit limits are calculated as the sum of all limits on an individual's HELOC accounts.

A.2.4 Financial Health

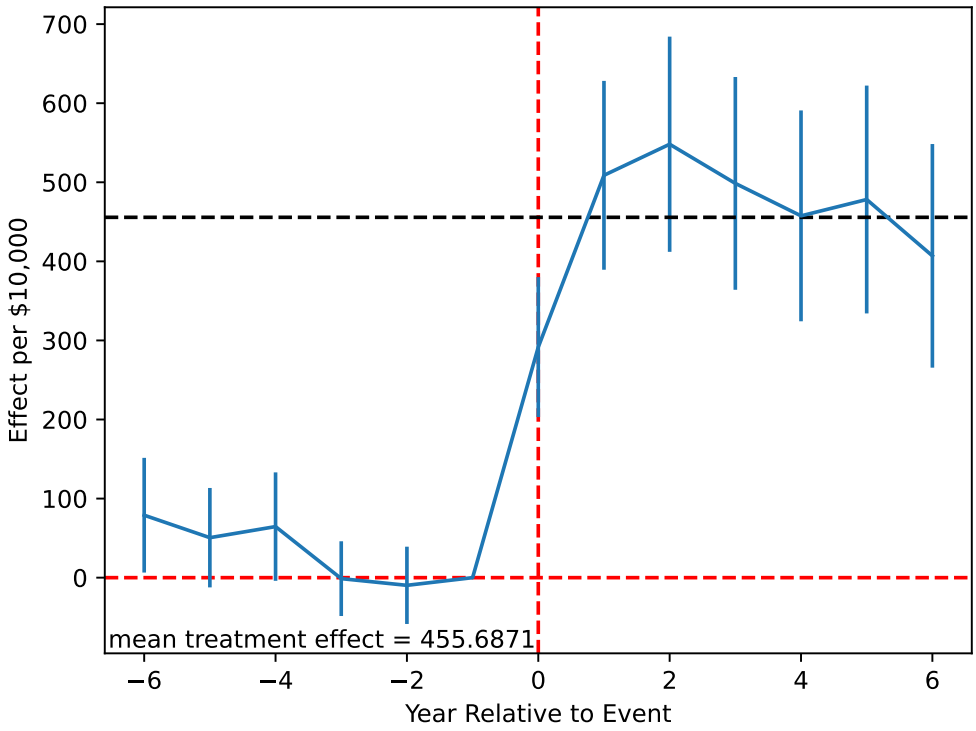
Figure A.6: Risk Score



This figure shows event-study estimates of Equation (1) on risk score. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample includes 13,413 individuals who won the lottery between January 2015 and March 2020. Lottery winnings are winsorized at CA$350,000. The mean treatment effect is calculated as the average across all post-treatment quarters and is depicted with the black dotted line. The risk score is calculated by the credit bureau using a proprietary formula and ranges from 300 to 900. Risk scores below 499 indicate serious credit issues; risk scores from 500 to 574 indicate a high risk individual; risk scores from 575 to 649 indicate an above average risk individual; risk scores from 650 to 749 indicate a fairly safe credit risk individual; risk scores above 750 indicate a safe credit risk individual.

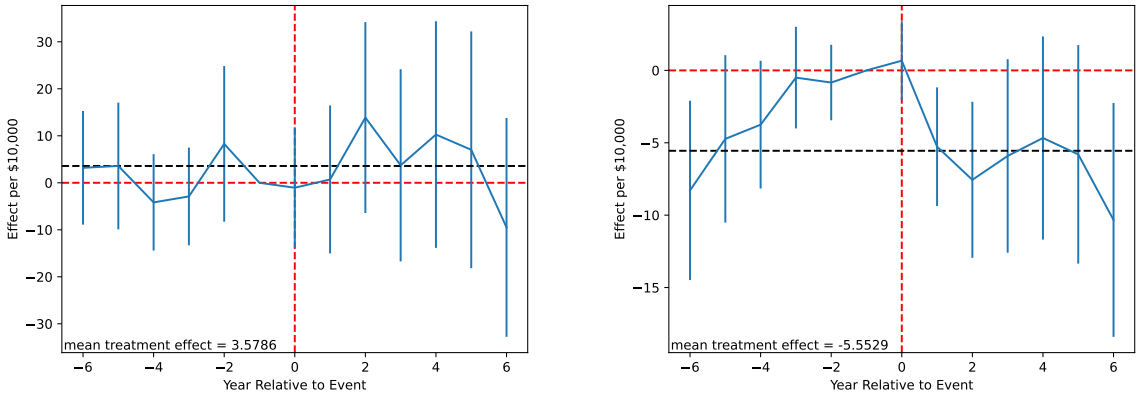
A.3 Additional Outcomes: Tax Data

Figure A.7: Total Investment Income (tax data)



This Figure presents estimates from Equation (2) on total investment income. All specifications include individual and calendar-year fixed effects, both of which we fully saturate with cohort-year fixed effects. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level in each cohort year. The sample is constructed based on Section 2. Lottery winnings are winsorized at CA$350,000. The mean treatment effect is calculated as the average across all post-treatment quarters and is depicted with the black dotted line. Total investment income is the sum of dividend income, capital gains, and investment income. Dividend income is defined as the taxable amount of dividends (eligible and other than eligible) from taxable Canadian corporations. Capital gains is defined as the net taxable capital gains resulting from the sale or transfer of assets. Investment income is defined as interest, foreign interest, foreign dividend income, foreign income, and foreign non-business income.

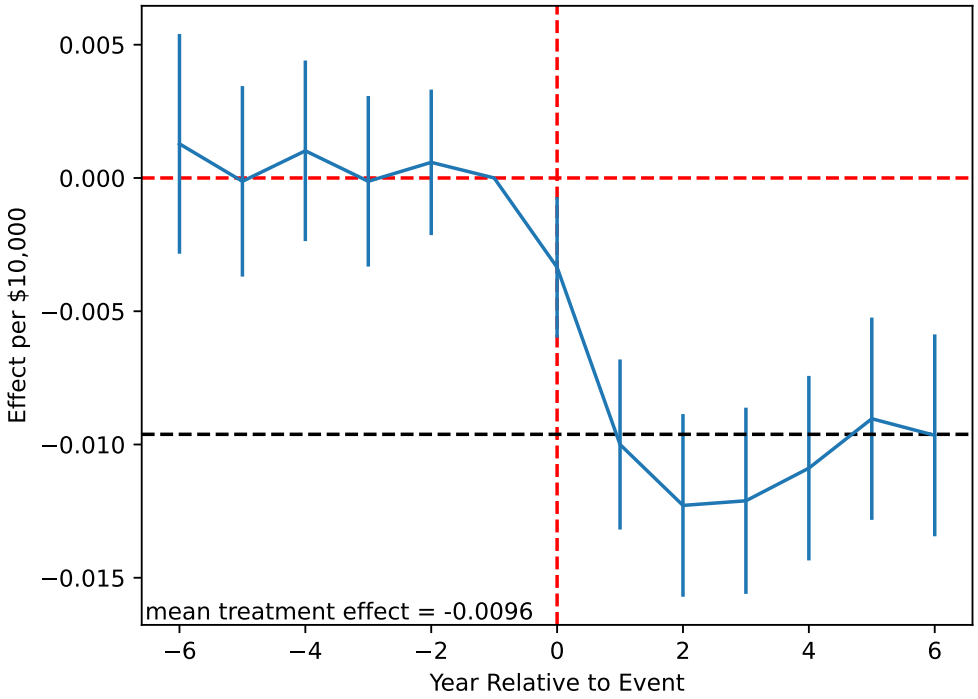
Figure A.8: Employer Pension Contributions and Retirement Account Withdrawals



(a) Indiv. retirement account withdrawal (b) Employer-sponsored ret. account contributions

This Figure presents estimates from Equation (2) on individual retirement account withdrawals and employer pension contributions. All specifications include individual and calendar-year fixed effects, both of which we fully saturate with cohort-year fixed effects. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level in each cohort year. The sample is constructed based on Section 2. Lottery winnings are winsorized at CA$350,000. The mean treatment effect is calculated as the average across all post-treatment quarters and is depicted with the black dotted line. An individual retirement account withdrawal is defined as the income received from a Registered Retirement Savings Plan. Employer-sponsored retirement account contributions is defined as the amount contributed to a Registered Pension Fund.

Figure A.9: Number of Jobs (tax data)



This Figure presents estimates from Equation (2) on number of jobs. All specifications include individual and calendar-year fixed effects, both of which we fully saturate with cohort-year fixed effects. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level in each cohort year. The sample is constructed based on Section 2. Lottery winnings are winsorized at CA$350,000. The mean treatment effect is calculated as the average across all post-treatment quarters and is depicted with the black dotted line. Number of jobs is defined as the number of jobs held by the individual in a tax year using employer-employee pairing derived from the employer-employee matched data.

A.4 Additional Descriptive Tables

Table A.1: Predictive Characteristics of Lottery Win Amount

Predictive Credit Characteristic	Coefficient (Standard Error)
Auto Loan Balance	-0.05 (0.08)
Auto Loan Count	77.94 (1729.69)
Auto Loan Credit Limit	0.03 (0.07)
Auto Loan Delinquency Count	-2659.80 (3707.41)
Auto Loan Utilization	16.60 (25.78)
Credit Card Amt. Past Due	1.46 (0.53)
Credit Card Balance	0.02 (0.06)
Credit Card Balance (spend not null during quarter)	-0.23 (0.23)
Credit Card Balance (spend not null end of quarter)	0.27 (0.23)
Credit Card Count	-154.82 (365.64)
Credit Card Credit Limit	-0.03 (0.03)
Credit Card Delinquency Count	-2208.36 (1571.16)
Credit Card Spend Amount	-0.02 (0.06)
Credit Card Utilization	11.97 (13.06)
Risk Score	6.55 (5.14)
HELOC Balance	0.02 (0.01)
HELOC Count	-196.33 (1791.43)
HELOC Credit Limit	-0.00 (0.01)
HELOC Delinquency Count	50706.94 (14222.54)
HELOC Utilization	-22.71 (29.31)
Inquiry Count	-110.17 (371.19)

Continued on next page

Table A.1: Predictive Characteristics of Lottery Win Amount

Predictive Credit Characteristic	Coefficient (Standard Error)
Installment Loan Balance	-0.05 (0.06)
Installment Loan Count	-728.80 (1186.98)
Installment Loan Credit Limit	0.05 (0.05)
Installment Loan Delinquency Count	-992.43 (3443.77)
Installment Loan Utilization	-6.53 (19.95)
Mortgage Balance	-0.05 (0.01)
Mortgage Count	-467.79 (1272.27)
Mortgage Credit Limit	0.04 (0.01)
Mortgage Delinquency Count	-8695.62 (8648.17)
Mortgage Utilization	0.00 (0.00)
Moved in Last 2 Months	-1404.62 (1902.50)
Propensity to be in Bankruptcy	-1067.45 (2766.43)
Propensity to be in Collection	-2855.53 (5940.15)
Propensity to have Consumer Proposal	-6812.56 (3923.86)
Student Loan Balance	0.27 (0.30)
Student Loan Count	-2375.23 (2240.50)
Student Loan Credit Limit	-0.12 (0.24)
Student Loan Delinquency Count	-2257.56 (5804.06)
Student Loan Utilization	-15.56 (34.37)
Telephone Loan Balance	0.42 (2.38)
Telephone Loan Count	-841.61 (896.02)
Telephone Loan Credit Limit	1.62 (1.17)

Continued on next page

Table A.1: Predictive Characteristics of Lottery Win Amount

Predictive Credit Characteristic	Coefficient (Standard Error)
Telephone Loan Delinquency Count	-2546.58 (2617.23)
Telephone Loan Utilization	46.81 (18.38)
Unsecured LOC Balance	-0.02 (0.06)
Unsecured LOC Count	958.27 (486.43)
Unsecured LOC Credit Limit	-0.03 (0.04)
Unsecured LOC Delinquency Count	-892.11 (2790.69)
Unsecured LOC Utilization	-6.78 (14.97)
R-squared	0.02
R-squared Adj.	0.01

This table shows estimates from a within cohort of win (defined as quarter of lottery win) regression of lottery winnings on all credit characteristics provided by the credit bureau in the quarter prior to winning the lottery. The inability of credit characteristics to predict lottery win amount—indicated by an adjusted R-squared= 0.01 and 44 of 50 coefficients being statistically insignificant at the 95% level of confidence—is consistent with random assignment of the lottery win amount.

Table A.2: Credit Card Spending Share by Neighborhood Income Quartiles and Age Groups

	Credit Card Spending Share (Value)
Income	
Quartile 1	0.19
Quartile 2	0.49
Quartile 3	0.65
Quartile 4	0.90
Age	
Less than 28	0.56
29 – 64	0.50
Greater than 65	0.62
National Average	0.56

Table A.2 provides average credit card spending shares per neighborhood income quartile, age group and overall. Overall and per age group average spending shares are provided by Henry, Huynh, and Welte, 2018; 2017 is the approximate midpoint of our analysis sample for credit bureau outcomes. Per neighborhood income group spending shares are provided by Arango and Welte, 2012 and scaled so the average credit card spending share across income groups equals the 2017 overall average credit card spending share. The first income quartile includes individuals with neighbourhood incomes below CA$49,634; the within quartile mean neighbourhood income is CA$38,612. The second income quartile includes individuals with neighbourhood incomes between CA$49,634 and CA$81,500; the within quartile mean neighbourhood income is CA$63,220. The third income quartile includes individuals with neighbourhood incomes between CA$81,500 and CA$120,161; the within quartile mean neighbourhood income is CA$101,147. The fourth income quartile includes individuals with neighbourhood incomes above CA$120,161; the within quartile mean neighbourhood income is CA$167,963. Individuals are assigned neighbourhood incomes based on their census Dissemination Area (DA) of residence in the closest census year prior to winning the lottery. DAs are small, stable geographic units with an average population of 400 to 700 persons (Government of Canada 2021).

Appendix B Model derivations

Deriving the MPs.
Differentiating the FOCs with respect to y:

$$z: u''(c)\left(1+\frac{dz}{dy}-\frac{dS}{dy}\right)-\frac{1}{\theta^2}k''(z/\theta)\frac{dz}{dy}=0 \tag{15}$$

$$S: -u''(c)\left(1+\frac{dz}{dy}-\frac{dS}{dy}\right)+\delta v''(S)\frac{dS}{dy}=0 \tag{16}$$

Rearranging 15:

$$-u''(c)\left(1-\frac{dS}{dy}\right)=\left(u''(c)-\frac{1}{\theta^2}k''(z/\theta)\right)\frac{dz}{dy} \tag{17}$$

Solving for dz/dy at a given bundle (c,z,S) of a given individual:

$$\frac{dz}{dy}=\underbrace{-\frac{u''(c)}{u''(c)-\frac{1}{\theta^2}k''(z/\theta)}}_{\equiv\alpha(\theta,y)}\left(1-\frac{dS}{dy}\right) \tag{18}$$

This pins down the relationship between the MPE and the MPS. Plug this into 16:

$$-u''(c)\left(1+\alpha(\theta,y)-(\alpha(\theta,y)+1)\frac{dS}{dy}\right)+\delta v''(S)\frac{dS}{dy}=0 \tag{19}$$

Rearranging 19,

$$\frac{dS}{dy}=\frac{1}{\frac{\delta v''(s)}{u''(c)(1+\alpha(\theta,y))}+1} \tag{20}$$

Plugging equation 20 into 18,

$$\frac{dz}{dy}=\alpha(\theta,y)\left(\frac{\delta v''(s)}{\delta v''(s)+u''(c)\,(1+\alpha(\theta,y))}\right) \tag{21}$$

The MPC can then be obtained through the budget constraint:

$$\frac{dc^*}{dy}=1+\frac{dz^*}{dy}-\frac{dS^*}{dy} \tag{22}$$

Solving for S^*, z^*, c^*.
Rewriting the FOC for z (6),

$$(y+z-S)^\alpha-\frac{1}{\theta}(z/\theta)^\gamma=0, \tag{23}$$

and the FOC for S (5),

$$(y+z-S)^\alpha-\delta S\alpha=0 \tag{24}$$

Dividing 5 by 6,

$$\delta\theta\frac{S^{\alpha}}{(z/\theta)^{\gamma}}=1 \tag{25}$$

$$S^{*}=\left(\frac{(z^{*}/\theta)^{\gamma}}{\delta\theta}\right)^{1/\alpha} \tag{26}$$

Plugging 26 into 23, we get an equation which implicitly defines z^{*} for each θ,

$$\left(y+z^{*}-\left(\frac{(z^{*}/\theta)^{\gamma}}{\delta\theta}\right)^{1/\alpha}\right)^{\alpha}=\frac{1}{\theta}(z^{*}/\theta)^{\gamma} \tag{27}$$

We can rewrite this as $f(z^{*})=0$ and use Newton's method to find the root z^{*} of the non-linear equation. This pins down $S^{*}(\theta)$ through 26 and $c^{*}(\theta)$ through the budget constraint.

$$c^{*}(\theta)=y+z^{*}(\theta)-S^{*}(\theta) \tag{28}$$