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 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 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 optimal design of various policies, including fiscal stimulus programs, a universal basic income, and the 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 front, heterogeneity in individuals' response to financial windfalls has important implications for optimal income tax design (Ferey, Lockwood, and Taubinsky, 2024), the effectiveness of fiscal stimulus (Auclert, 2019; Patterson, 2023) and the transmission of monetary policy to 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 groups with the highest marginal propensity to consume is the most efficient approach.

Establishing whether an extra dollar is used differently across income levels is empirically challenging. It requires an exogenous income shock combined with rich data on households' available choices (e.g., consumption, saving, debt repayment, investment and earnings) throughout the income distribution. This paper provides new evidence on this question using a novel Canadian administrative dataset that links income tax records and credit bureau reports to 40,000 lottery payments. 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, allocate their lottery winnings to 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]

For our main analysis, we use an event-study design that combines cross-sectional variation

[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 lottery prize size across winners and the timing of wins to estimate the MPC, MPS, and MPE. The event-study figures show sharp, immediate effects at the time of the win on consumption, savings (including debt repayment), and labor earnings. The pre-trends are flat which supports the identification assumption that prize amounts are exogenous. Averaged over the two years after the win, lottery recipients spend about 18.4 cents per dollar of wealth ($MPC = 0.18$), reduce labor earnings by roughly 10 cents per dollar ($MPE = -0.10$), and save 24 cents ($MPS = 0.24$). The savings response consists of 8 cents in debt repayment and 16 cents in investment. Summing across all responses yields a total response of 52 cents per dollar. Our 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., 2025).

Our findings indicate substantial differences in how lottery winnings are allocated based on income.[2] Specifically, higher-income individuals generally have larger MPE and MPS estimates, while lower-income individuals generally have larger MPC estimates. In terms of magnitudes, low-income (high-income) individuals have an $MPC = 0.29$ ($MPC = 0.15$), an $MPE = -0.05$ ($MPE = -0.16$) and an $MPS = 0.15$ ($MPS = 0.35$). 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 and consume more leisure.

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 (2025).

Finally, in ongoing work, we illustrate how understanding heterogeneity in the MPC, MPS and

[2]Our heterogeneity analysis is based on neighborhood income. High-income households are defined based on whether their income is above the median value of $80,502.

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. Third, we plan to estimate the sufficient statistics that characterize an aggregate consumption response function in macroeconomic models with heterogeneous agents as in Auclert (2019).

Our paper makes three main contributions to the literature. Our primary contribution is to jointly estimate the consumption, savings, and earnings responses to a common wealth shock for the same set of individuals and to study the heterogeneity in these responses throughout the income distribution. This is possible since we link lottery winnings to both credit report data and tax data and 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 with the literature examining the effect of income shocks only on credit bureau outcomes.[3] Importantly, our data and setting allow us to compare the effect 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

[3]Studies in this literature include Agarwal, Liu, and Souleles (2007), Agarwal and Qian (2014), Agarwal, Qian, and Zou (2021), Cookson, Gilje, and Heimer (2022), Di Maggio, Kalda, and Yao (2019), Koşar et al. (2023), Sahm, Shapiro, and Slemrod (2010), Coibion, Gorodnichenko, and Weber (2020), Parker et al. (2022), Brown (2021), Boutros and Mijakovic (2024), 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.

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.[4]

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.[5] 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 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).[6]

An important additional dimension we add to the literature is the estimation of MPCs *over*

[4]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.

[5]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.

[6]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.

time, also known in the literature as iMPCs, or intertemporal MPCs (Auclert, Rognlie, and Straub, 2024). The dynamic aspect of MPCs are very important for macroeconomic models: for example, if consumption responds immediately but transiently to a one-time transfer as in Boehm, Fize, and Jaravel (2025), then deficit spending will not have a fiscal multiplier effect, and stimulus payments are just as powerful at stimulating the economy as tax-financing. On the other hand, if spending remains persistently elevated after a one-time transfer, as we find, there can be scope for multiplier effects from deficit spending that are not present in tax-financed spending. The consumption impulse response functions we estimate is useful for disciplining macroeconomic models. In particular, our results favor certain types of heterogeneous-agent models (specifically, HANK models, two-agent bond-in-utility (or zero-liquidity) models) over more analytical models like single representative agent models, two-agent models, and bond-in-utility models.

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.[7] 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 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 with 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

[7] 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).

"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 to a substantial underestimate of wealth effects.[8]

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

This section describes how we constructed our dataset which consists of lottery data, credit bureau data, and administrative tax data. We begin by discussing each dataset separately, and then describe the merging process.

2.1 Lottery Microdata

Our lottery data consist of the universe of lottery winners in excess of $999.99 from 2003 through 2021 in a Canadian province.[9] The majority of the lottery products in our data are "classic lotteries" where a winner is decided by a random draw of numbers. For example, the most common lottery product in our dataset is called Lotto 6/49, where players pick six numbers (from one to 49) in sequence and a lottery ticket is designated a winner if the chosen sequence partially or fully matches a unique sequence of randomly drawn numbers. The prize amount is primarily dictated by two factors. First, the number of correct digits in a player's chosen sequence. For example, if the winning number is 123456, a winning ticket could feature the sequence XXXXX6 (a smaller

[8]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.

[9]All lottery products in Canada are administered by Crown corporations. Winners of prizes of less than $1,000 are not required to report their names and addresses to the lottery corporation and are thus excluded from our data. An anonymous corporation provided us with the lottery data; due to a non-disclosure agreement, we do not disclose the name of the province or lottery corporation.

prize) or XXXX56 (a slightly larger prize). Second, the prize amount decreases with the number of winning tickets, but increases with the overall size of the lottery pool. The overall size of the lottery pool primarily depends on the number of tickets purchased, however, it can also depend on prior lotteries, if those lotteries had no "jackpot" lottery winners (e.g., a winner who guesses all six numbers correctly). In this scenario, the ensuing lottery grows in size.

For all solo lottery winners we observe: first and last names, six-character postal codes,[10] lottery payment date, lottery product (e.g., Lotto 6/49) and lottery winnings. 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. For prizes with more than two winners, we do not observe all winners' names.[11] Since we are unable to assign prizes with more than two winners to all winning individuals, we did not include them in our sample. We also restrict our sample to winners who win one prize over the entire sample period to reduce the issue of multiple lottery prize wins affecting the same person. This restriction allows us to identify the timing of each wealth shock precisely.

Our final sample of lottery winners consists of 40,872 prizes and winners across 69 quarters from 2003 to 2021. We classify winners into "cohorts" based on the year-quarter they won the lottery to align with the frequency of our credit bureau data. Table 1 provides summary statistics for these winners. On average, the prize amount is 9,481 Canadian dollars after trimming prizes at $250,000. Figure A.1 shows the distribution of lottery prizes in our data.

2.2 Credit Bureau Data

We obtained anonymized, individual-level credit bureau data from a national credit reporting agency housing the population of Canadian credit users. The data are quarterly and cover our entire sample period of winners. Table 1 presents summary statistics on credit bureau data for our sample of lottery winners and a random 0.1% sample of the Canadian population. On average,

[10]Six-character postal codes are similar to ZIP+4 extensions (i.e., 9-digit ZIP codes) in the United States.

[11]More specifically, we observe a single winner's name and postal code who received the winnings "in trust" for all winners.

winners are 48 years of age and three percent of winners moved in the quarter prior to winning the lottery. The table also provides the summary statistics for the following credit outcomes: total card spending, total debt balance, credit card and mortgage balances, shares with cards and mortgages, risk score, shares in delinquency, collections and bankruptcy. Overall, lottery winners look similar to the general population for many of these outcomes, with them having similar card spending, debt balances and risk scores.

A novel feature of our credit bureau data is a measure of quarterly credit card spending created by the credit bureau. The credit bureau constructed quarterly spending using a combination of monthly balance changes and actual payments made by cardholders, both of which are reported by credit card lenders. As nearly all major credit card lenders began reporting actual payments by 2015, we have nearly universal coverage of credit card spending after this date. On average, Canadians spend roughly 56% of their non-housing expenditures on credit cards and the remainder on a combination of debit cards, cash, checks, and other methods (Henry, Huynh, and Welte, 2018). Non-housing expenditures account for approximately 72% of overall expenditures on average; thus, 40% of overall expenditures occur on credit cards. Notably, among non-housing expenditure, Canadians put roughly 60% of their durables spending on credit cards (Henry, Huynh, and Welte, 2018), so our MPC measures both non-durable and a portion of durables expenditure. Lottery winners spend $3,244 on average per quarter across their credit cards, in the quarter before their win. We use credit card spending to construct consumption expenditure; hence, it is important for us to have good data on this outcome. Therefore, in our credit bureau analyses, we focus on winners in 2015-2020.[12]

We also observe a proprietary risk score as a measure of creditworthiness; this score 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 also contain 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

[12]We exclude winners after 2020 to avoid the effects of the Covid-19 pandemic.

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 gambling 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, age, move probability, total debt balances, and bankruptcy filing probability. However, lottery winners are somewhat more likely to be delinquent and fewer of them have credit cards.

As will be detailed below, our identification strategy leverages 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 registered retirement savings 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

3.1 Identification

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:

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

Having defined our parameter of interest, the next section discusses our estimator.

3.2 Estimation

For all of our analyses, we use the following within-cohort estimator:

$$Y_{itg} = \alpha_i + \gamma_{tg} + \sum_{\tau, \tau \neq -1} \beta_\tau D_i \times \mathbf{1}\{\tau = t - G_i\} + \varepsilon_{itg}. \tag{1}$$

In our estimation of credit bureau outcomes (spending, saving via debt repayment), the indicators $\mathbf{1}\{\tau = t - G_i\}$ are dummies for the eight quarters prior to and post lottery win (omitting the coefficient for the quarter immediately preceding the lottery win). In our estimation of tax outcomes (earnings, saving via investment), the indicators $\mathbf{1}\{\tau = t - G_i\}$ 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_i) and time (γ_{tg}), where the latter are fully saturated with cohort (quarter of win) fixed effects (Wing, Freedman, and Hollingsworth, 2024). We cluster standard errors at the individual level. Our coefficients are identified based on within-cohort exogenous variation in lottery win amount.

Our estimator aligns closely to a within-cohort, static two way fixed effects (TWFE) estimator with a continuous treatment.[13] 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 may not equal to the dose distribution among the treated. Linearity of realized outcomes, however, resolves such interpretation challenges and fully restores a causal interpretation in terms of ACRs.[14] In ongoing work, we are exploring linearity.

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 (eight full quarters in addition to the partial quarter at "time zero") to provide marginal propensities which are comparable to the

[13]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.

[14]See Theorem 3.4(a) in Callaway, Goodman-Bacon, and Sant'Anna (2024).

existing literature.

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 (to estimate the marginal propensity to save). For labor market outcomes, we consider total earnings (to estimate the marginal propensity to earn).

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). For ease of reference, all two-year marginal propensity estimates referenced in this section are consolidated in Table 2.

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 $82 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 0.074. Since Canadians spend roughly 40% of their total spending on credit cards (Henry, Huynh, and Welte 2018), this translates to a two-year MPC of 18.4 cents for every dollar won. 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., 2025). Bartik et al. (2025) finds MPCs of non-durables to be between 0.38-0.5, which is higher than our estimate, but is consistent with our findings on income heterogeneity (Section 4.4) that MPCs are decreasing in income. Our below median average income is CA $50,259, whereas the average income in Bartik et al. (2025) is approximately US $29,000, so it is unsurprising that their MPC estimate is higher than ours.

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 2 shows that, on average, borrowers repay roughly $1,028 for every $10,000 in winnings per quarter. 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 0.084.

4.2.2 Financial Asset Accumulation

Figure 3 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 three years following the lottery win, for an average effect of $5 (panel a). Panel (b) of Figure 3 shows that dividend income does not increase in any year post lottery win. Focusing on interest and investment income in panel (c) of Figure 3, we find that $10,000 in lottery wealth leads to $11 of additional interest and investment income per year on average.

In addition to these results on investment income, the tax data also provide us with information on tax-advantaged investments, specifically individual retirement accounts.[15] We report results for individual retirement account contributions in panel (d). We find that retirement contributions increase by $50 (for each $10,000 in lottery wealth) in the same year as the lottery win (year 0). After this immediate and significant increase in retirement contributions in response to a lottery

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

win, contributions tail off and fall in subsequent years. Overall, it seems that winners shift the timing of retirement contributions instead of permanently changing them.

In order to recover a two-year MPS based on income from investment assets, we use a capitalization approach. First, we calculate the two-year post-treatment effect for each type of account: namely that $10,000 of lottery winnings increase capital gains income by $10, dividend income by $8, and interest and investment income by $17. Then, to calculate the "savings base" that would generate such income, we use Saez and Zucman (2016)'s approach of calculating MPS as $MPS_A = \frac{1}{r_A} \times$ asset income. We use Hempel (2025)'s estimates of asset-specific rates of return to then recover an aggregate MPS via investment summed over our asset classes. Specifically, we use a capitalization factor of 16.1% for capital gains, 27.3% for dividends and 71.8% for interest and other investment income. This method allows us to estimate an MPS of 0.02 for capital gains, 0.01 for dividend income, and 0.12 for interest and investment income. For individual retirement accounts contributions, we sum over the first two years of post-treatment estimates to get an MPS via retirement savings of 0.005. These estimates imply an aggregated two-year MPS via investment of 0.16.

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 labor earnings. Figure 4 presents our event-study estimates. We find that an extra $10,000 of lottery win reduces labor income by $323 on average per year. Aggregating over the post-treatment period (e.g., six years plus the year of win), we estimate a six-year MPE of -0.21 and a two-year MPE of -0.10. The effect declines over time and becomes statistically insignificant by year 6.

Panel (b) of Figure 4 shows the estimates for the probability of being employed (extensive margin). There is a sharp reduction in the probability of employment at the time of the lottery win. This effect declines over time and ranges between a 1 and 3 percentage point decline for each additional $100,000 in lottery wealth. On average, the probability of having a job decreases by percentage points in the six years after the lottery win.

Panel (c) shows our estimates for labor income conditional on employment (intensive margin). Labor income decreases by $268 on average per year for each $10,000 increase in wealth in the six years after the lottery win. Similar to total labor earnings, the effect of lottery wealth on income conditional on employment declines over time and becomes statistically insignificant by year 4 after the win.

Our one-year MPE estimate of -$3.2 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. Our estimate is also similar to Cesarini et al. (2017), who find a smaller wealth effect on earnings corresponding to roughly -$1.31 per $100 in lottery winnings.

4.4 Heterogeneity by Income

Figure C.1a presents estimates from equation (1) for winners above and below the median DA household income of $80,502.[16] While we do not see statistically significant differences in spending responses to a lottery windfall, we estimate two-year MPCs of 0.145 for above median income winners, and 0.290 for below median income winners. We also estimate equation (1) by quartiles of neighborhood income and find further differences in our MPC estimates by neighborhood income. Figure C.1b plots credit card spending by quartile of income. The first quartile of income ($49,117 and below) has an MPC of 0.519, which is more than five times larger than that of the fourth quartile (incomes greater than $120,009) MPC estimate of 0.088. The second and third income quartile (incomes between $49,117 and $80,502, and incomes between $80,502 and $120,009, respectively) MPCs are more reflective of our average sample with an MPC of 0.23.

Figure C.2 shows that above-median neighborhood income winners pay down more debt, approximately $1,800 per $10,000 won, which translates to a two-year MPS (debt reduction) of 0.12. Their debt balance decreases sharply after the win and stays persistently lower for 8 quarters after the win. Borrowers below the median income experience the same magnitude of decline in their

[16]All dollar-denominated cutoffs are based on constant 2015 dollars.

debt balances as the above-median income borrowers, but their debt balance slowly increases over the eight quarters, becoming statistically insignificant in quarter 5 after the win. As debt balances are a stock variable, we use the last coefficient in quarter 8 as their measure of MPS (debt reduction), which translates to 0.03 for the below-median income group and 0.12 for the above-median income group.

Figures C.3 and C.4 show MPS heterogeneity by income for different credit products. These results suggest that both below and above median income individuals reduce credit card and unsecured credit balances, but these effects are transitory. However, above median income individuals persistently reduce their installment loan balances and mortgage balances (MPS of 0.03 and 0.064, respectively).

We plot results for the income-based heterogeneity for savings in financial assets in Figure C.5. While we do not see statistically significant differences between above and below-median income winners, we see qualitative differences between the two groups. There do not seem to be consistent differences between the two groups for capital gains (panel a) or dividend income (panel b). While both groups of winners contribute to their RRSP accounts, above-median income winners contribute more than twice as much to their accounts in year zero than do below-median income winners, they then also taper off in their contributions by year six. Using our capitalization procedure described in Section 4.2.2, we estimate a two-year MPS via investment for below-median income groups of 0.12 and 0.23 for above-median income groups.

Panel (a) of Figure C.6 shows that above-median income winners have an aggregate six-year MPE of -0.29 (two-year MPE of -0.16), while below-median winners have an aggregate six-year MPE of -0.09 (two-year MPE of -0.052). Both groups reduce their labor earnings immediately after receiving lottery wealth and these effects persist for at least five years. Our results in panel (b) suggest that above-median income winners have a larger and more persistent effect on the extensive margin (probability of employment) compared with low-income individuals who have smaller and insignificant effects on this outcome.

To summarize, we document significant heterogeneity in how winners of different incomes react to lottery windfalls: lower-income individuals are more likely to spend their winnings than higher income prize recipients. In addition, higher-income individuals save a larger proportion of their lottery prizes and reduce their debts by a larger amount than lower-income winners. Below-median income individuals also have smaller responses in labor income than above-median income winners.

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 empirical results. 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 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.[17] Preferences are given by:

$$U(c,S,z;\delta,\theta) = u(c) + \delta v(S) - k(z/\theta), \tag{2}$$

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

$$\frac{dc}{dy} = 1 + \frac{dz}{dy} - \frac{dS}{dy} \tag{3}$$

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

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

The first-order condition for S is

$$-u'(y+z-S^*)+\delta v'(S^*)=0 \tag{4}$$

The first-order condition for z is

$$u'(y+z^*-S)-\frac{1}{\theta}k'(z^*/\theta)=0 \tag{5}$$

Totally differentiating the first-order conditions gives:

$$\frac{dS^*}{dy}=\frac{1}{\frac{\delta v''(S)}{u''(c)(1+\alpha(\theta,y))}+1} \tag{6}$$

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

$$\frac{dc^*}{dy}=1+\frac{dz^*}{dy}-\frac{dS^*}{dy} \tag{8}$$

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

Equations 6, 7, and 8 characterize the MPS, MPE and the MPC.[18]

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.

$$u(c)=\frac{c^{1+\alpha}}{1+\alpha} \tag{9}$$

$$k(z/\theta)=\frac{(z/\theta)^{1+\gamma}}{1+\gamma} \tag{10}$$

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

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

$$S^* = \left(\frac{(z^*/\theta)^\gamma}{\delta\theta}\right)^{1/\alpha}, \tag{11}$$

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

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

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

$$c^*(\theta) = y + z^*(\theta) - S^*(\theta) \tag{13}$$

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 5 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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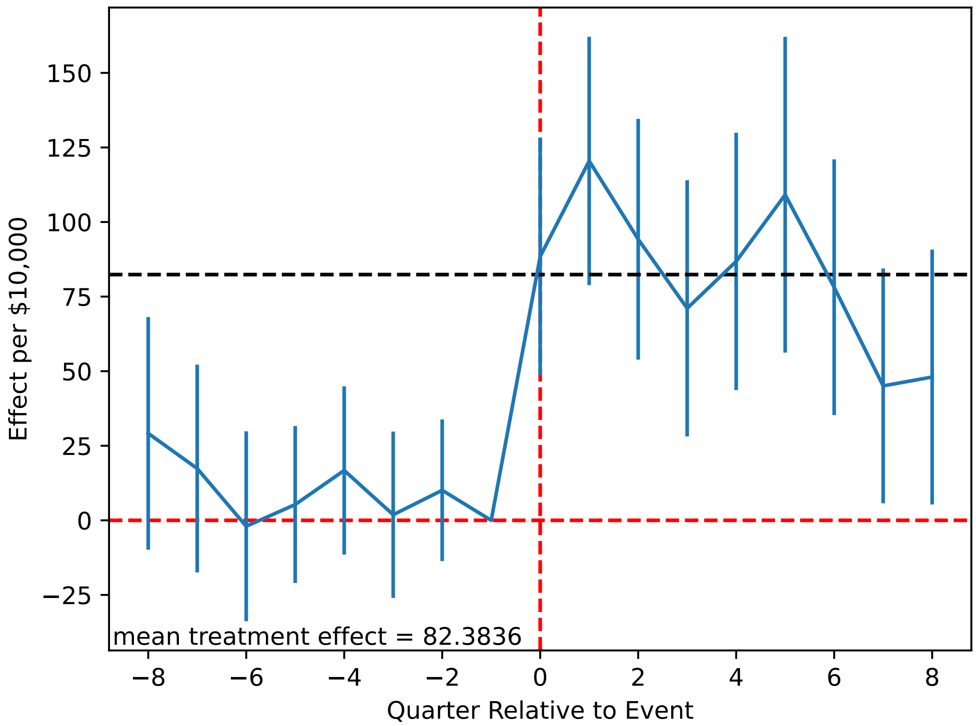
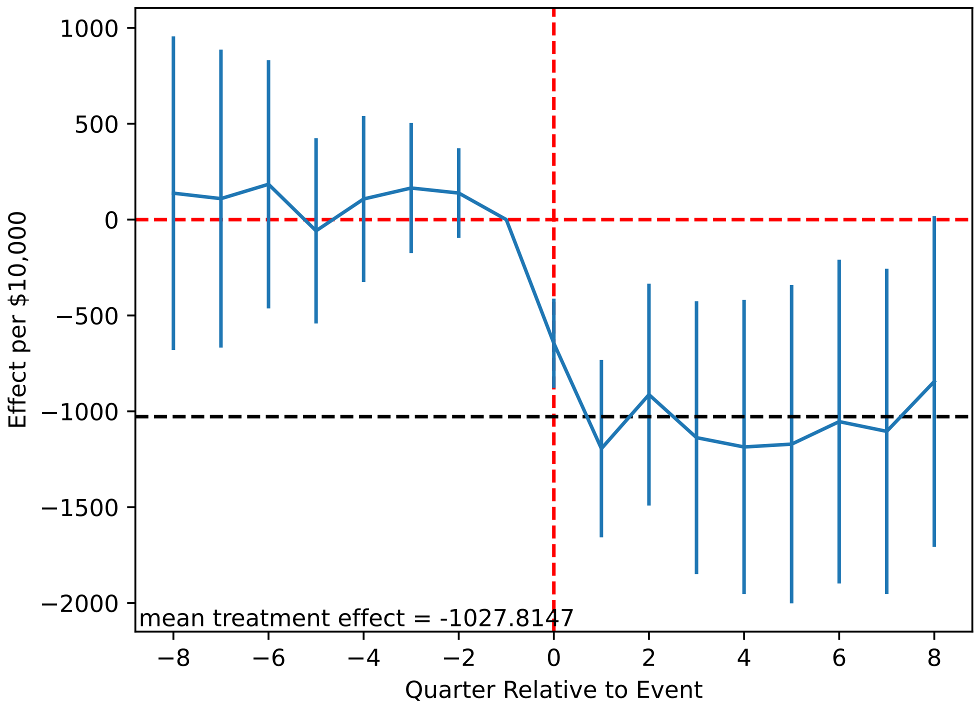
7 Figures and Tables

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



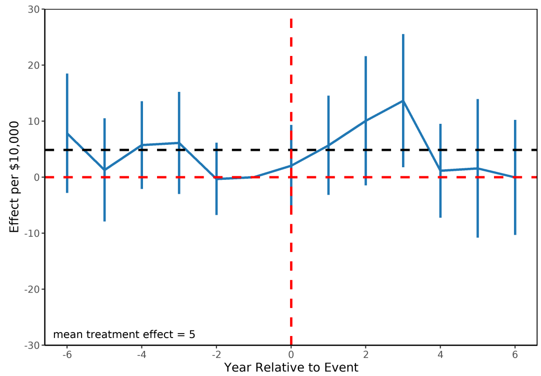
This figure shows event-study estimates of Equation (1) on total credit card spending. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample includes 11,926 individuals who won the lottery between January 2015 and March 2020. 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 winsorize credit card spending at 99.5% within each calendar-quarter. 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 0.074 (s.e. 0.014). We define total spending as credit card spending scaled by the national average credit card share of spending of 0.40 (Henry, Huynh, and Welte 2018; Statistics Canada 2017) implying a two-year MPC *overall* of 0.184 (s.e. 0.036).

Figure 2: Marginal Propensity to Save via Debt Repayment from \$10,000 of Lottery Winnings (credit bureau data)

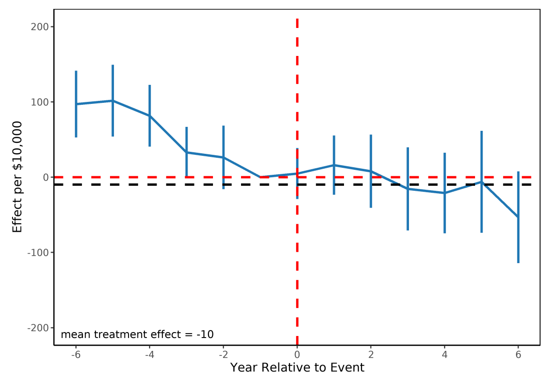


This figure shows event-study estimates of Equation (1) on total debt balance. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample includes 11,926 individuals who won the lottery between January 2015 and March 2020. 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 and student loan) and revolving (home equity line of credit, unsecured line of credit and credit card) debt. We winsorize individual debt balances at 99.5% within each calendar-quarter prior to aggregation. 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 0.084 (s.e. 0.044).

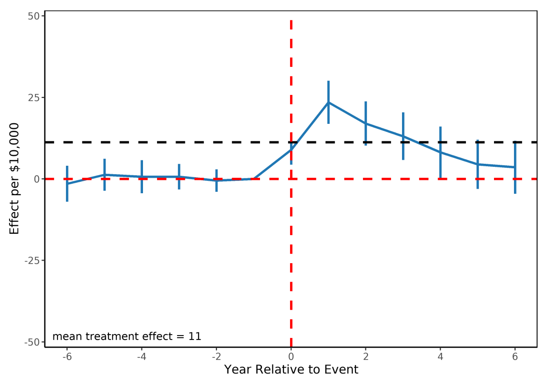
Figure 3: Marginal Propensity to Save via Investment from $10,000 of Lottery Winnings (tax data)



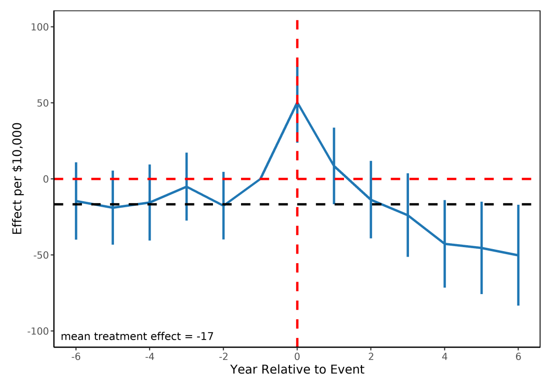
(a) Capital gains



(b) Dividend income



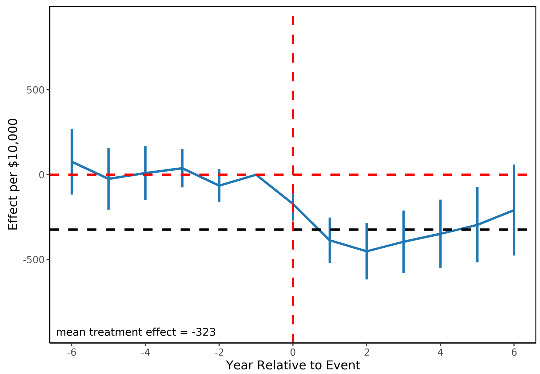
(c) Interest and other investment income



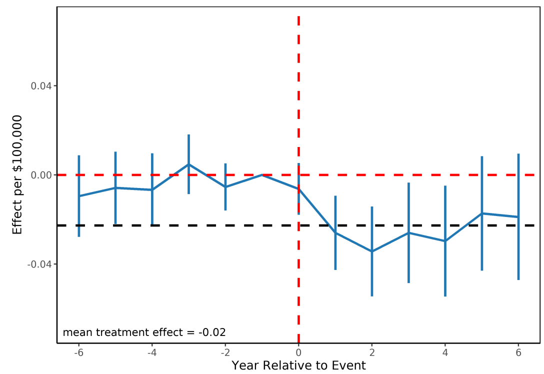
(d) Indiv. retirement account contributions

This Figure shows event-study estimates from Equation (1) on capital gains, dividend income, interest and investment income, and retirement contributions. All specifications include individual fixed effects and calendar-year fixed effects interacted with quarter-year of win cohort fixed effects. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample is constructed based on Section 2. Winners above $250,000 are dropped from the analysis sample. The mean treatment effect is calculated as the average across all post-treatment years 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. Interest and other investment income is defined as the sum of 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 Savings Plan. The two-year estimates per $10,0000 of lottery winnings are: taxable capital gains increase by $10; dividend income increases by $8; and interest and investment income increases by $17. Summing over the first two post-treatment estimates per $10,0000 of lottery winnings, individual retirement account contributions increase by $45. These two-year estimates imply an MPS of: 0.02 for capital gains using a capitalization factor of 16.1; 0.01 for dividend income using a capitalization factor of 27.3; 0.12 for interest and investment income using a capitalization factor of 71.8; and 0.005 for individual retirement account contributions. These imply an aggregated two-year MPS via investment of 0.16.

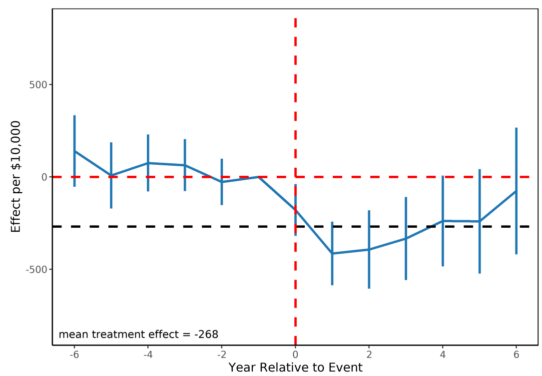
Figure 4: Labor Supply Responses to Lottery Winnings (tax data)



(a) Total Labor Earnings



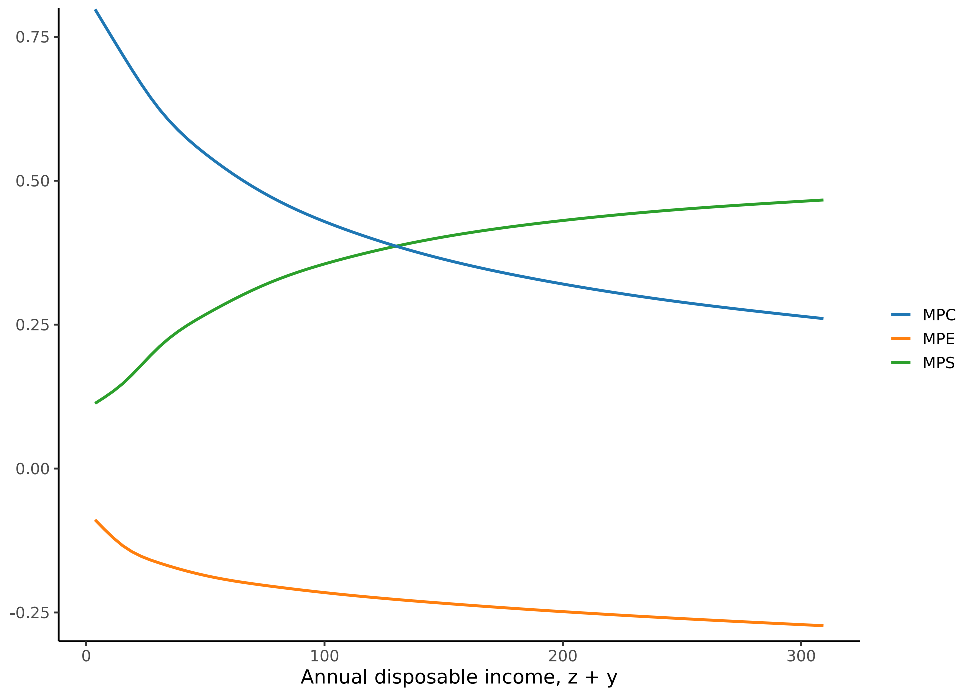
(b) Extensive Margin (Probability of Employment)



(c) Intensive Margin (Earnings Conditional on Employment)

This Figure shows event-study estimates from Equation (1) on labor earnings, the probability of employment, and labor earnings conditional on employment. All specifications include individual fixed effects and calendar-year fixed effects interacted with quarter-year of win cohort fixed effects. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample is constructed based on Section 2. Winners above $250,000 are dropped from the analysis sample. The mean treatment effect is calculated as the average across all post-treatment years and is depicted with the black dotted line. Estimates for the probability of employment are reported per $100,000; all other estimates are per $10,000 of lottery winnings. Total labor earnings is defined as employment income received from a business enterprise, including wages, salaries, and commissions, before deductions, and excluding self-employment income. We define employment in a year as reporting total labor earnings $\geq \$1,000$. We calculate the two-year MPE and six-year MPE as the sum of post-treatment estimates in the first two and six years, respectively. Estimates from Figure (4) aggregate to a two-year MPE of -0.10 and a six-year MPE of -0.21.

Figure 5: 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 6, 7, and 8.

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

	Lotteries		General Population	
	Mean	Standard Deviation	Mean	Standard Deviation
Lottery winnings	9,481.25	27,264.09	0.00	0.00
Age	48.00	14.37	48.20	14.02
Neighborhood mobility rate	0.03	0.17	0.03	0.16
Credit Portfolio				
Total quarterly credit card spending	3,243.99	6,582.86	3,614.90	6,461.68
Share with a credit card	0.70	0.46	0.83	0.37
Share with a mortgage	0.27	0.45	0.32	0.47
Total debt balance	107,416.92	169,151.87	103,435.20	171,714.70
Credit card balance	4,764.59	9,192.59	3,511.81	6,800.48
Mortgage balance	72,589.74	145,065.56	75,197.68	152,180.00
Credit Worthiness/Financial Well-being				
Risk score	725.34	110.19	754.95	99.00
Share in delinquency	0.07	0.25	0.04	0.19
Share in collection	0.01	0.08	0.00	0.06
Share in bankruptcy	0.02	0.12	0.01	0.12

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. 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. We winsorize credit card spending at 99.5% within each calendar-quarter. 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 and student loan) and revolving (home equity line of credit, unsecured line of credit and credit card) debt. We winsorize individual debt balances at 99.5% within each calendar-quarter prior to aggregation. 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. Delinquency is an indicator if an individual has any delinquent accounts across all types of revolving and non-revolving debt. 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).

Table 2: Marginal Propensities by Income Group

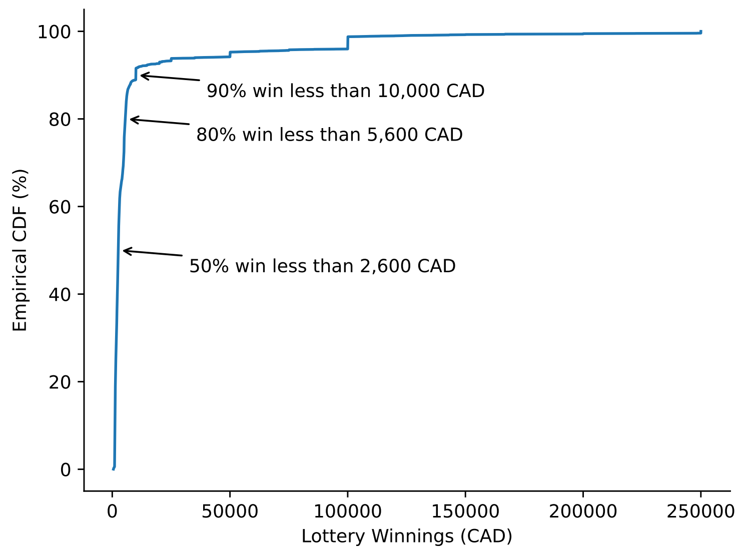
		Income	
	Overall	Below Median	Above Median
2-year Marginal Propensities			
MPC	0.18	0.29	0.15
MPE	-0.10	-0.05	-0.16
MPS			
via debt repayment	0.08	0.03	0.12
via investment	0.16	0.12	0.23
total	0.24	0.15	0.35
Total	0.52	0.49	0.66
5-year Marginal Propensities			
MPC	0.33	0.55	0.24
MPE	−0.21	−0.09	−0.29
MPS			
via debt repayment	0.08	0.03	0.12
via investment*	0.09	0.07	0.15
total	0.17	0.10	0.27
Total	0.71	0.74	0.80

This table shows 2- and 5-year marginal propensities to consume, save (via debt repayment and investment) and earn from lottery winnings. All marginal propensities are derived from event-study estimates of Equation (1). Marginal propensities to consume and save (via debt repayment) are estimated using our credit bureau data. In our credit bureau data, below median income includes individuals with neighborhood-average household incomes below $80,502; within this group the mean household income is $50,259. Above median income includes individuals with neighborhood-average household incomes above $80,502; within this group the mean household income is $134,405. Individuals are assigned neighborhood-average household 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). To obtain 5-year marginal propensities for consumption and saving via debt repayment, we extrapolate (constantly) from our event-study estimate 2 years post-lottery win. Marginal propensities to save (via investment) and earn are estimated using our tax data. At this project's current stage, we are not allowed to disclose summary statistics on the income distribution in the tax data. Event-study figures for marginal propensities estimated on our full sample (overall) can be found in Section 7; all other event-studies can be found in Appendix C.

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 in our sample; the maximum lottery prize in our sample is $250,000. The mean lottery win amount is $9,481.25 (s.d. $27,264.09).

A.2 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)
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)

Continued on next page

Table A.1: Predictive Characteristics of Lottery Win Amount

Predictive Credit Characteristic	Coefficient (Standard Error)
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)
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 (C.C.) Share of Overall Spending, by Neighborhood Household Income and Age

	Housing		Non-housing		Overall
	Consump. sh.	C.C. sh.	Consump. sh.	C.C. sh.	C.C. sh.
Household income quartile					
Bottom quartile	0.34	0.00	0.67	0.19	0.12
Second quartile	0.30	0.00	0.71	0.49	0.35
Third quartile	0.28	0.00	0.72	0.65	0.47
Top quartile	0.26	0.00	0.74	0.90	0.67
Age group					
Less than 28	0.28	0.00	0.72	0.56	0.41
29 – 53	0.29	0.00	0.71	0.50	0.35
54 – 64	0.26	0.00	0.74	0.62	0.46
Greater than 65	0.28	0.00	0.72	0.62	0.45
Overall	0.28	0.00	0.72	0.56	0.40

Table A.2 provides average credit card spending shares per neighborhood income quartile, age group and overall. Average credit card spending shares for above and below median neighborhood income are calculated as the average across above and below median quartiles, respectively. All shares of spending on housing are provided by the 2017 Survey of Household Spending (Statistics Canada 2017, 2017). Overall and by age group credit card spending shares of non-housing consumption are provided by Henry, Huynh, and Welte (2018). 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. 2017 is the approximate midpoint of our analysis sample for credit bureau outcomes. The first income quartile includes individuals with neighborhood-average household incomes below \$49,177; the within quartile mean household income is \$38,367. The second income quartile includes individuals with neighborhood-average household incomes between \$49,177 and \$80,502; the within quartile mean household income is \$62,146. The third income quartile includes individuals with neighborhood-average household incomes between \$80,502 and \$120,009; the within quartile mean household income is \$100,585. The fourth income quartile includes individuals with neighborhood-average household incomes above \$120,009; the within quartile mean household income is \$168,274. Individuals are assigned neighborhood-average household 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).

Table A.3: Comparison of Non-Housing Consumption from Survey of Household Spending and Microdata, Overall and by Neighborhood Income

		Household income quartile			
	Overall	Bottom	Second	Third	Top
Inputs					
Avg. C.C. spend/person (Microdata)	12,975.96	5,901.60	9,929.88	13,973.64	22,291.44
Share of spending on C.C. (Table A.2)	0.56	0.19	0.49	0.65	0.90
Avg. household size (Statistics Canada 2017)	2.48	1.53	2.15	2.78	3.47
Equivalence scale					
Additional person 1	0.80	0.80	0.80	0.80	0.80
Additional person 2	0.40	0.40	0.40	0.40	0.40
Additional person 3	0.30	0.30	0.30	0.30	0.30
Scaled household size	1.99	1.43	1.86	2.11	2.34
Comparison of non-housing household consumption					
Microdata	46,239.91	45,329.28	37,313.75	45,325.09	57,735.57
Statistics Canada 2017	46,017.00	23,908.00	36,402.20	49,257.80	74,161.20

Table A.3 compares non-housing expenditure from the 2017 Survey of Household Expenditure (Statistics Canada 2017, 2017) to non-housing consumption calculated using our microdata on credit card spending and scaling factors from Table A.2. We use an equivalence scale from Fréchet et al. 2010; future work will allow the equivalence scale to vary across the income distribution. The first income quartile includes individuals with neighborhood-average household incomes below \$49,177; the within quartile mean household income is \$38,367. The second income quartile includes individuals with neighborhood-average household incomes between \$49,177 and \$80,502; the within quartile mean household income is \$62,146. The third income quartile includes individuals with neighborhood-average household incomes between \$80,502 and \$120,009; the within quartile mean household income is \$100,585. The fourth income quartile includes individuals with neighborhood-average household incomes above \$120,009; the within quartile mean household income is \$168,274. Individuals are assigned neighborhood-average household 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:

$$z: u''(c)\left(1+\frac{dz}{dy}-\frac{dS}{dy}\right)-\frac{1}{\theta^2}k''(z/\theta)\frac{dz}{dy}=0 \tag{14}$$

$$S: -u''(c)\left(1+\frac{dz}{dy}-\frac{dS}{dy}\right)+\delta v''(S)\frac{dS}{dy}=0 \tag{15}$$

Rearranging 14:

$$-u''(c)\left(1-\frac{dS}{dy}\right)=\left(u''(c)-\frac{1}{\theta^2}k''(z/\theta)\right)\frac{dz}{dy} \tag{16}$$

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

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

This pins down the relationship between the MPE and the MPS. Plug this into 15:

$$-u''(c)\left(1+\alpha(\theta,y)-(\alpha(\theta,y)+1)\frac{dS}{dy}\right)+\delta v''(S)\frac{dS}{dy}=0 \tag{18}$$

Rearranging 18,

$$\frac{dS}{dy}=\frac{1}{\frac{\delta v''(s)}{u''(c)(1+\alpha(\theta,y))}+1} \tag{19}$$

Plugging equation 19 into 17,

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

The MPC can then be obtained through the budget constraint:

$$\frac{dc^*}{dy}=1+\frac{dz^*}{dy}-\frac{dS^*}{dy} \tag{21}$$

Solving for S^*, z^*, c^*.
Rewriting the FOC for z (5),

$$(y+z-S)^\alpha-\frac{1}{\theta}(z/\theta)^\gamma=0, \tag{22}$$

and the FOC for S (4),

$$(y+z-S)^\alpha-\delta S\alpha=0 \tag{23}$$

Dividing 4 by 5,

$$\delta\theta \frac{S^{\alpha}}{(z/\theta)^{\gamma}} = 1 \tag{24}$$

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

Plugging 25 into 22, we get an equation which implicitly defines z^{*} for each θ,

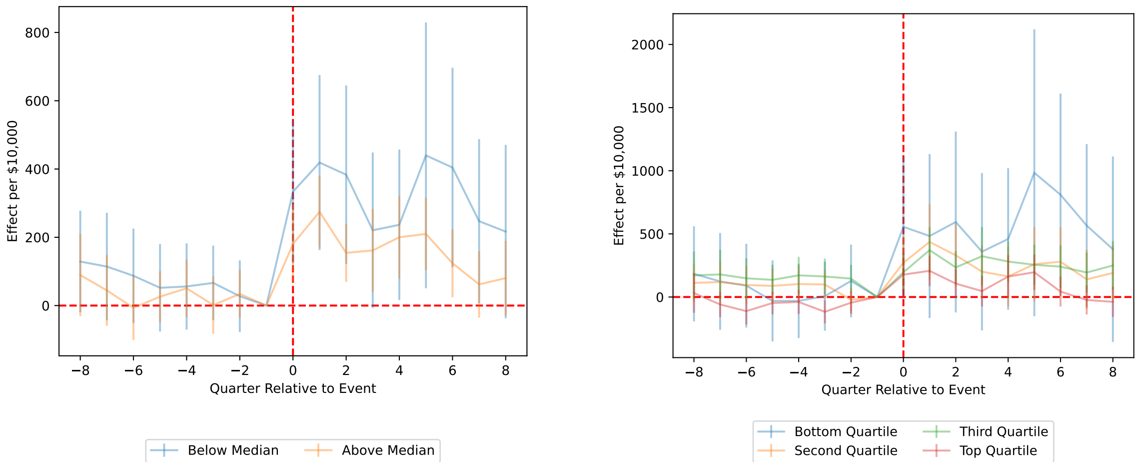
$$\left(y + z^{*} - \left(\frac{(z^{*}/\theta)^{\gamma}}{\delta\theta}\right)^{1/\alpha}\right)^{\alpha} = \frac{1}{\theta}(z^{*}/\theta)^{\gamma} \tag{26}$$

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 25 and $c^{*}(\theta)$ through the budget constraint.

$$c^{*}(\theta) = y + z^{*}(\theta) - S^{*}(\theta) \tag{27}$$

Appendix C Heterogeneity by Income

Figure C.1: Marginal Propensity to Consume *Overall* from \$10,000 of Lottery Winnings, by Neighborhood Income (credit bureau data)

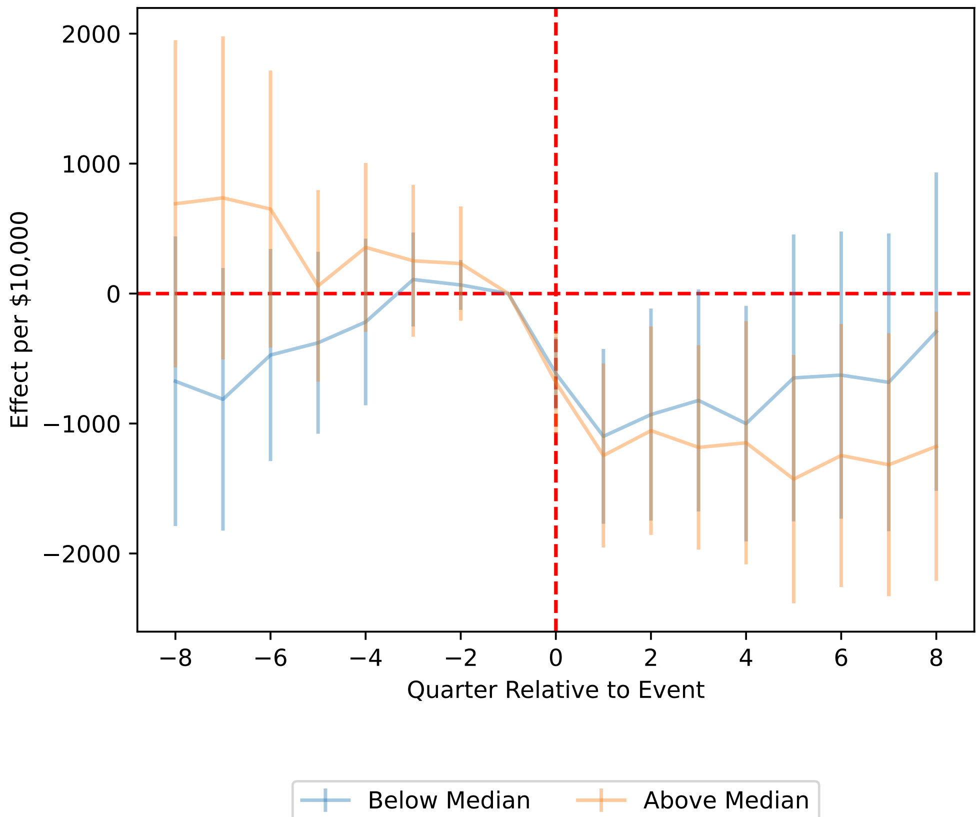


(a) Above and Below Median Income

(b) Income Quartiles

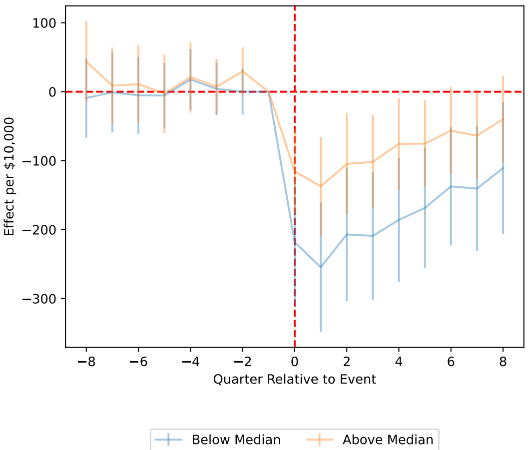
This figure shows event-study estimates of Equation (1) on total spending estimated separately by neighborhood-average household income. Point estimates are plotted along with the 95% confidence interval, where standard errors are clustered at the individual level. The overall sample includes 11,926 individuals who won the lottery between January 2015 and March 2020. 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. We winsorize credit card spending at 99.5% within each calendar-quarter. In practice, we estimate Equation (1) on credit card spending within income groups and then scale estimates based on the within-income group credit card share of spending. Panel (a) shows results for individuals above and below the median of neighborhood-average household income. Below median income includes individuals with neighborhood-average household incomes below \$80,502; within this group the mean household income is \$50,259. Above median income includes individuals with neighborhood-average household incomes above \$80,502; within this group the mean household income is \$134,405. Individuals are assigned neighborhood-average household 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-average household income group two-year MPCs of: below median $= 0.290$ (s.e. 0.090); above median $= 0.145$ (s.e. 0.035). Panel (b) shows results by quartile. The first income quartile includes individuals with neighborhood-average household incomes below \$49,177; the within quartile mean household income is \$38,367. The second income quartile includes individuals with neighborhood-average household incomes between \$49,177 and \$80,502; the within quartile mean household income is \$62,146. The third income quartile includes individuals with neighborhood-average household incomes between \$80,502 and \$120,009; the within quartile mean household income is \$100,585. The fourth income quartile includes individuals with neighborhood-average household incomes above \$120,009; the within quartile mean household income is \$168,274. These results imply within-neighborhood-average household income quartile two-year MPCs of: quartile $1 = 0.519$ (s.e. 0.255); quartiles 2 and $3 \approx 0.23$ (s.e. 0.07); quartile $4 \approx 0.088$ (s.e. 0.038).

Figure C.2: Marginal Propensity to Save via Debt Repayment from $10,000 of Lottery Winnings, by Neighborhood Income (credit bureau data)

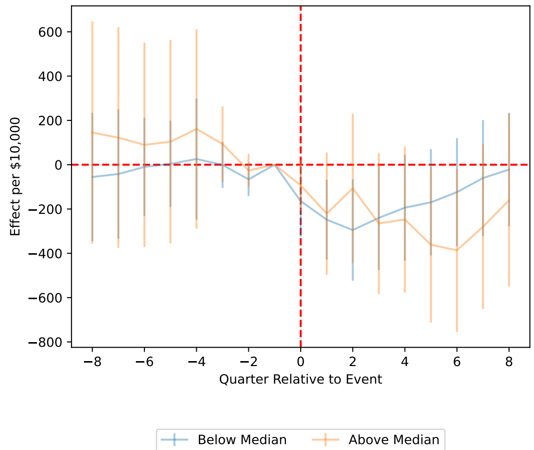


This figure shows event-study estimates of Equation (1) on total debt balance estimated separately by neighborhood-average household income. Point estimates are plotted along with the 95% confidence interval, where standard errors are clustered at the individual level. The overall sample includes 11,926 individuals who won the lottery between January 2015 and March 2020. 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 and student loan) and revolving (home equity line of credit, unsecured line of credit and credit card) debt. We winsorize individual debt balances at 99.5% within each calendar-quarter prior to aggregation. Below median income includes individuals with neighborhood-average household incomes below $80,502; within this group the mean household income is $50,259. Above median income includes individuals with neighborhood-average household incomes above $80,502; within this group the mean household income is $134,405. Individuals are assigned neighborhood-average household 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-average household income group two-year MPSs via debt repayment of: below median = 0.029 (s.e. 0.062); above median = 0.118 (s.e. 0.053).

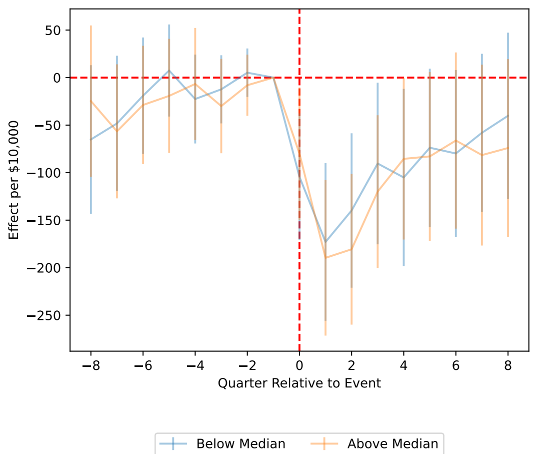
Figure C.3: MPS via Revolving Debt Repayment from $10,000 of Lottery Winnings, by Neighborhood Income (credit bureau data)



(a) Credit cards



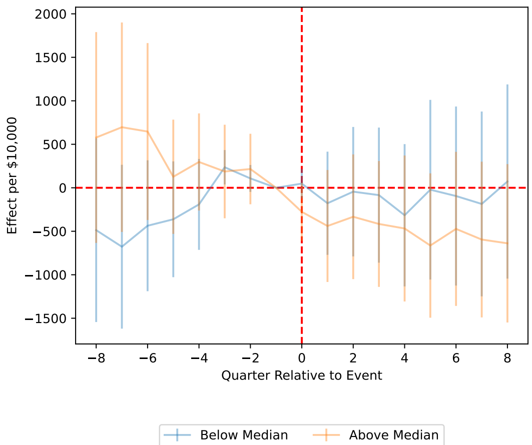
(b) Home equity lines of credit



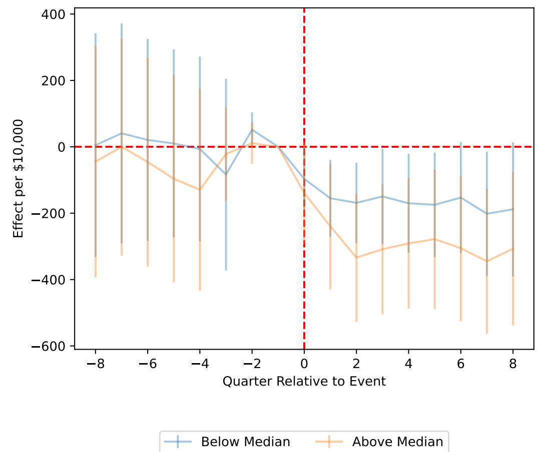
(c) Unsecured lines of credit

This figure shows event-study estimates of Equation (1) on revolving debt balances estimated separately by neighborhood-average household income. Point estimates are plotted along with the 95% confidence interval, where standard errors are clustered at the individual level. The overall sample includes 11,926 individuals who won the lottery between January 2015 and March 2020. Below median income includes individuals with neighborhood-average household incomes below $80,502; within this group the mean household income is $50,259. Above median income includes individuals with neighborhood-average household incomes above $80,502; within this group the mean household income is $134,405. Individuals are assigned neighborhood-average household 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-average household income group two-year MPSs via debt repayment of: (i) Credit cards: below median = 0.011 (s.e. 0.004); above median = 0.004 (s.e. 0.004) (ii) Home equity lines of credit: below median = 0.002 (s.e. 0.013); above median = 0.016 (s.e. 0.019) (iii) Unsecured lines of credit: below median = 0.004 (s.e. 0.004); above median = 0.007 (s.e. 0.005).

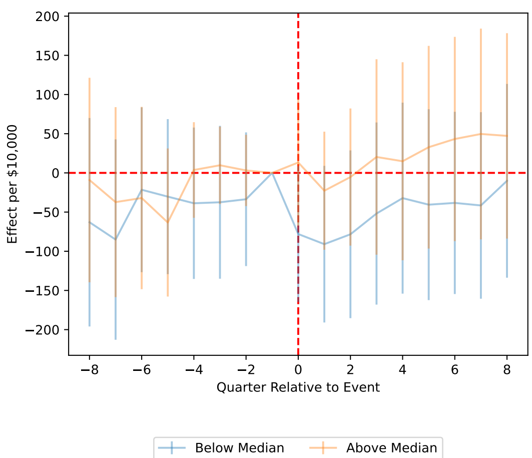
Figure C.4: MPS via Non-revolving Debt Repayment from $10,000 of Lottery Winnings, by Neighborhood Income (credit bureau data)



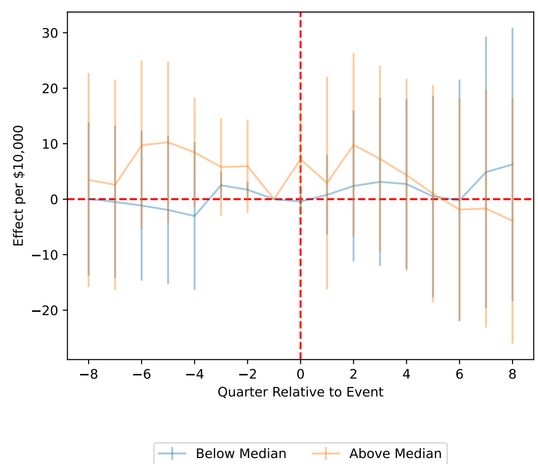
(a) Mortgages



(b) Installment loans



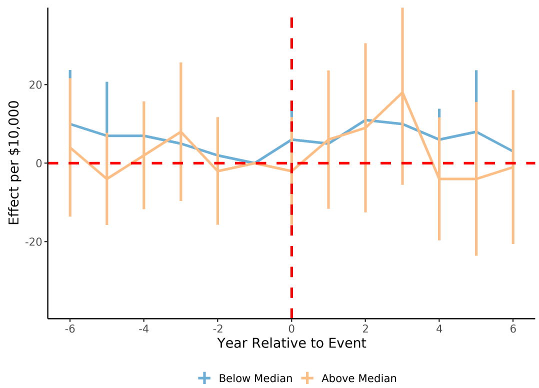
(c) Auto loans



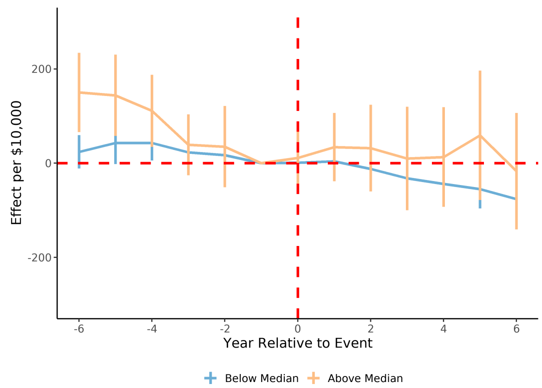
(d) Student loans

This figure shows event-study estimates of Equation (1) on non-revolving debt balances estimated separately by neighborhood-average household income. Point estimates are plotted along with the 95% confidence interval, where standard errors are clustered at the individual level. The overall sample includes 11,926 individuals who won the lottery between January 2015 and March 2020. Below median income includes individuals with neighborhood-average household incomes below $80,502; within this group the mean household income is $50,259. Above median income includes individuals with neighborhood-average household incomes above $80,502; within this group the mean household income is $134,405. Individuals are assigned neighborhood-average household 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-average household income group two-year MPSs via debt repayment of: (i) Mortgages: below median $= -0.007$ (s.e. 0.056); above median $= 0.064$ (s.e. 0.046). (ii) Installment loans: below median $= 0.018$ (s.e. 0.010); above median $= 0.031$ (s.e. 0.012). (iii) Auto loans: below median $= 0.001$ (s.e. 0.006); above median $= -0.004$ (s.e. 0.006). (iv) Student loans: below median ≈ 0 (s.e. 0.001); above median ≈ 0 (s.e. 0.001).

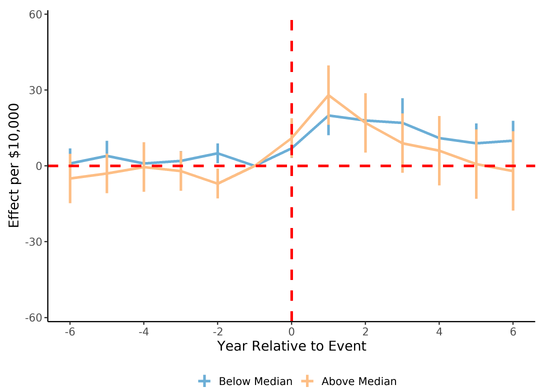
Figure C.5: Marginal Propensity to Save via Investment from $10,000 of Lottery Winnings, by Individual Income (tax data)



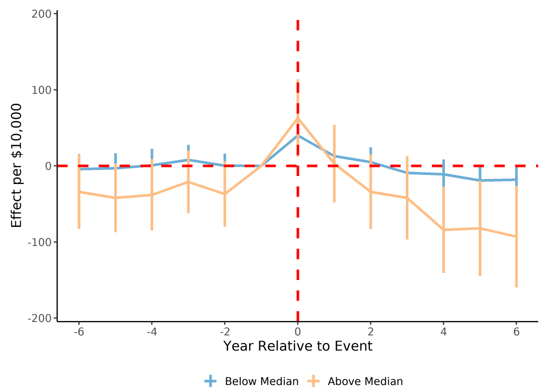
(a) Capital gains



(b) Dividend income



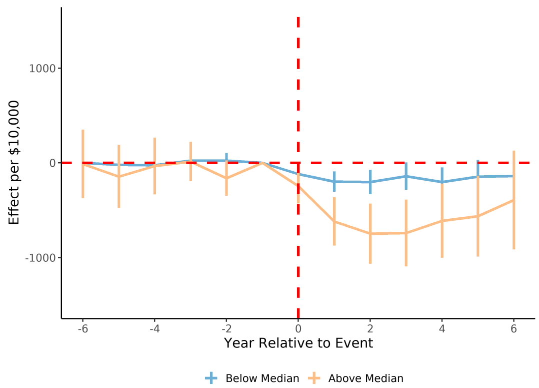
(c) Interest and other investment income



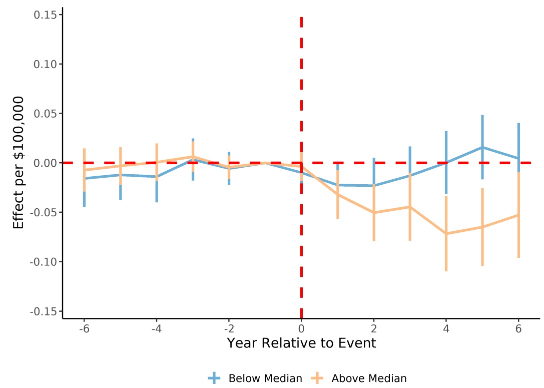
(d) Indiv. retirement account contributions

This Figure shows event-study estimates from Equation (1) on capital gains, dividend income, interest and investment income, and retirement contributions estimated separately by income group. All specifications include individual fixed effects and calendar-year fixed effects interacted with quarter-year of win cohort fixed effects. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample is constructed based on Section 2. Winners above $250,000 are dropped from the analysis sample. 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. Interest and other investment income is defined as the sum of 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 Savings Plan. We calculate the two-year MPS via investment as the point estimate at two years post-treatment for interest and investment income, capital gains, and dividend income and sum over the first two years of post-treatment estimates for individual retirement account contributions. These results imply individual income group two-year MPSs via investment of: below median income = 0.12; above median income = 0.23.

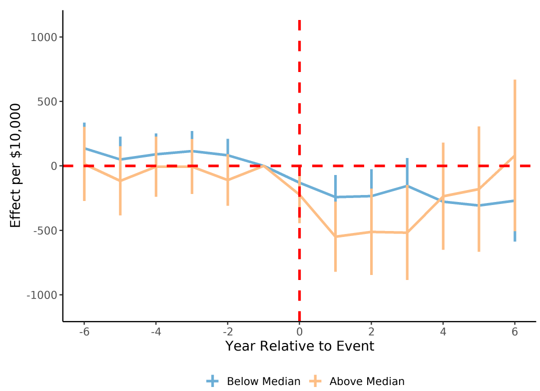
Figure C.6: Labor Supply Responses to Lottery Winnings, by Individual Income (tax data)



(a) Total Labor Earnings



(b) Extensive Margin (Probability of Employment)



(c) Intensive Margin (Earnings Conditional on Employment)

This Figure shows event-study estimates from Equation (1) on labor earnings, the probability of employment, and labor earnings conditional on employment estimated separately by income group. All specifications include individual fixed effects and calendar-year fixed effects interacted with quarter-year of win cohort fixed effects. Point estimates are plotted along with 95% confidence intervals, where standard errors are clustered at the individual level. The sample is constructed based on Section 2. Winners above $250,000 are dropped from the analysis sample. Estimates for the probability of employment are reported per $100,000; all other estimates are per $10,000 of lottery winnings. Total labor earnings are defined as employment income received from a business enterprise, including wages, salaries, and commissions, before deductions, and excluding self-employment income. We define employment in a year as reporting total labor earnings $\geq \$1,000$. We calculate the two-year MPE and six-year MPE as the sum of post-treatment estimates in the first two and six years, respectively. Estimates from Figure (C.6) aggregate to a two-year MPE of below median income = -0.052 and above median income = -0.16 and a six-year MPE of: below median income = -0.09 and above median income = -0.29.