MPCs Estimated from Tax Lottery, Survey and Administrative Data *

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Abstract

We estimate intertemporal marginal propensities to consume (iMPCs) from an unexpected fiscal transfer using both administrative and survey data for the same households. Leveraging random assignment from a tax lottery, we identify large causal effects of the income windfall, tracking iMPCs for eight months. *Revealed-preference* estimates from expenditure data align with *reported-preference* survey results for the same households, underscoring the validity of our data and methods. We observe substantial heterogeneity in MPCs and relate it to observable household characteristics. Households report a higher MPC for unexpected income losses compared to gains and prioritize debt repayment.

Keywords— Marginal Propensity to Consume; Heterogeneity; Consumer Finances; Tax Lottery; Fiscal Transfers; Consumption; Savings; Deficit-Financed Fiscal Policy; Causal Effects; Surveys.

JEL: D12; D15; E21; G51; H31.

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1 Introduction

Understanding the magnitude and heterogeneity of the responses of households' consumption to windfall income is critical for assessing the effectiveness of fiscal policy, the transmission of monetary policy, and aggregate economic fluctuations.[1] Numerous studies have sought to estimate the marginal propensity to consume (MPC) through different approaches. Empirical research using exogenous variation to causally identify the marginal propensity to consume (MPC) from actual fiscal transfers, giving *revealed-preference* estimates, has produced inconclusive findings regarding both the size and heterogeneity of the MPC (e.g. Parker et al. (2013), Orchard, Ramey, and Wieland (2023), Borusyak, Jaravel, and Spiess (2024) for the U.S experience). An alternative approach involves asking individuals to report their intended consumption behavior in hypothetical scenarios, providing *reported-preference* estimates of MPC (e.g. Christelis et al. (2019), Fuster, Kaplan, and Zafar (2021), Colarieti, Mei, and Stantcheva (2024), Bunn et al. (2018) and Coibion et al. (2024), among others). A major concern with this method is whether households' actual responses to fiscal transfers align with their self-reported intentions in surveys where they face hypothetical scenarios.

In this paper, we estimate intertemporal Marginal Propensities to Consume (iMPC) from an unexpected fiscal transfer using two methods: *revealed preferences* from administrative data on household spending and *ex-ante reported preferences* from a customized survey of the same households. We find that our *revealed-preference* estimates, based on actual monthly expenditures, align with the *reported-preference* estimates from the survey. Additionally, survey responses are consistent regardless of whether individuals were responding to a hypothetical or imminent windfall. The study leverages a unique setting—a tax lottery with random and simultaneous assignment—to identify the causal effects of unexpected fiscal transfers. We estimate intertemporal MPC (iMPC) on a monthly basis, tracking changes in spending for up to eight months after the income shock. We also examine the factors associated with heterogeneity in MPC across households and find that certain observable characteristics significantly differentiate spending behavior. Our analysis includes *reported-preference* estimates for the consumption, saving and debt repayment responses to both unexpected income gain and loss scenarios, offering insights into how these shocks impact household financial choices.

A major challenge in estimating the MPC is isolating and identifying the effects of large, unexpected, exogenous, and temporary shocks to household income. Our empirical approach addresses this challenge through four key features. First, our sample consists of 931 Greek households, some of whom won a tax-free lottery prize of €1,000 in December 2019,[2] while others, who did not win, were matched with the winners according to similar socioeconomic characteristics. The prize amount, €1,000, is substantial, equivalent to roughly two months' salary for an inexperienced worker earning the minimum wage. Importantly, all adults who made at least one electronic transaction in Greece in October 2019 were automatically entered into the lottery, allowing us to use random and simultaneous assignment to identify the causal effects of this unexpected, transitory income shock. The €1,000 transfer came from the Greek public revenues authority, making it similar to one-time, deficit-financed lump-sum transfers to households, like the 'stimulus checks' distributed in the U.S. and other countries. Our MPC estimates are not confounded by concerns that individuals might anticipate future

1. Kaplan and Violante (2022) conduct a systematic investigation of the size and determinants of the aggregate MPC in heterogeneous agent, incomplete markets models with nominal rigidities. Other papers include Kaplan and Violante (2014), and Auclert, Rognlie, and Straub (2024, forthcoming) on the size of fiscal multipliers, Auclert (2019), Kaplan, Moll, and Violante (2018), on monetary policy transmission, Angeletos, Lian, and Wolf (2024) on self-financing deficits, Angeletos, Collard, and Dellas (2020) on inattention, and Bilbiie (2020), Patterson (2019), Werning (2015), and Kekre and Lenel (2021) on the amplification mechanism.

2. The lottery took place on 30 November 2019. An extensive description of the lottery is given in Section 2.

taxes to cover the deficit created by this fiscal action, as the total prize pool was known to be small at only 1 million euros.

Second, to ensure that our estimates are representative of the broader Greek population, we applied weights derived from selection logits on the population of lottery ticket holders, which included about 5.7 million individuals. This step was crucial in ensuring the external validity of our results. Third, we designed and conducted with the help of the public revenues authority a survey of the households in our estimation sample, collecting detailed data on their consumption, saving, and debt behavior, as well as their expectations about future activity and other behavioral traits. In particular, we asked households how they would adjust their consumption, savings, and debt repayments in response to an unexpected one-time increase, or separately decrease, in income of €1,000. For the lottery winners, the income windfall was imminent and not hypothetical. Fourth, we obtained access to anonymized administrative tax, income, and wealth data from the Greek public revenues authority, providing a comprehensive view of these households' economic conditions dating back to 2006. This rich dataset enables us to identify heterogeneity in consumption and savings behavior across households with different observable characteristics.

Our analysis focuses on the same households, capturing their reported preferences *ex ante* through survey data and their revealed preferences *ex post* using administrative data, with random variation introduced by the tax lottery (random assignment). All treated and control households are part of the same cohort, and there is no "staggered rollout" in the design of the *revealed-preference* approach. To our knowledge, this is the first study to combine both *revealed-* and *reported-preference* methodologies to measure the MPC of the same households. For the *revealed-preference* estimates, we calculate Average Treatment Effects by analyzing administrative data on individuals' total monthly credit and debit card spending from December 2019 to July 2020, following the lottery. We estimate the causal effect of winning the lottery by comparing the treated group of winners to the control group of non-winners. A key distinction from previous studies is that in our study, identification is based on random and simultaneous assignment of the windfall, rather than random variation in prize size or timing of its distribution.

The *revealed-preference* estimates show that a significant portion of the spending response occurs in the first few months after treatment (front-loading), though notable spending continues later as well. In Table 3 we display the dynamics of the consumption response, tracking the path of intertemporal MPCs (iMPCs as discussed in Auclert, Rognlie, and Straub (2024, forthcoming)) over a period of about 8 months from the initial shock. The estimated MPC is €157 (out of €1,000) within the first 11 days after the treatment, rising to €406 in the first six weeks. By the eight-month mark, the MPC reaches €690, the longest horizon we observe. These substantial figures, even several months after the shock, lend support to arguments for self-financing deficits (Angeletos, Lian, and Wolf (2024)) and suggest persistent output effects from deficit-financed fiscal stimulus policies (Auclert, Rognlie, and Straub (2024, forthcoming)).

We also investigate the heterogeneity in MPC across observable characteristics, specifically household income, liquid wealth and illiquid wealth, as well as individual age, sex and arrears to the State in 2019. The first three characteristics—income, liquid wealth, and illiquid wealth—have been widely explored in previous research, while our inclusion of arrears to the extended public sector is a novel contribution. Our study is further distinguished by providing evidence of iMPC heterogeneity across multiple time horizons, setting it apart from previous findings. To explore heterogeneity, we segment our sample into terciles, separately for each characteristic, and estimate iMPCs for each group over various time horizons.

For current income, we find that the highest-income households exhibit the highest MPCs among the three groups across all time horizons. Six weeks after receiving the prize, their MPC is estimated at €747, and by the eight-month horizon, it reaches a striking €1,855. In contrast, the two lower-income groups show significantly lower MPCs across all observed horizons.

For liquid wealth, households with higher liquid assets exhibit the highest and statistically significant MPCs at all horizons. Those in the lowest liquidity tercile show an MPC of €478 in the first six weeks and €510 at the eight-month horizon, with most of the treatment effect occurring in the initial six weeks. While these figures are substantial, they are considerably lower than the MPC for the wealthiest group, which reaches €1,376 by the eight-month mark.

In terms of illiquid wealth, a non-monotonic relationship with cumulative MPC emerges. Households in the middle tercile of illiquid wealth display the highest MPCs, estimated with statistical precision across all horizons. The lowest tercile shows substantial but lower MPCs, with estimates becoming less precise beyond the six-week horizon. Interestingly, households in the highest illiquid wealth tercile have MPCs that are not statistically different from zero at any horizon, a stark contrast to the results for liquid wealth. This highlights the importance of distinguishing between liquid and illiquid wealth when analyzing consumption behavior.

Next, examine individuals' arrears to the extended public sector at the end of 2019, which serves as a key indicator of financial health or distress. Presumably, individuals would default on obligations to the State as a last resort after defaulting on privately-held debt. When categorizing individuals by their arrears levels, we observe a clear negative relationship between arrears and MPC. Households with no arrears—representing over half of the sample—show a strong consumption response, with an MPC of €547 at the six-week mark and an MPC of €1,062 at the eight-month horizon. These relatively financially healthier households increase their spending significantly in response to the windfall. In contrast, households with the highest arrears have MPCs that are statistically insignificant at all horizons. This suggests that financially fragile households, burdened by debt, are more likely to use the windfall for repaying obligations rather than increasing consumption. Meanwhile, individuals with low arrears display a strong initial consumption response, but their cumulative MPC approaches zero by the end of the observation period, indicating intertemporal substitution, where initial spending is offset by later reductions in consumption.

We also examine the heterogeneity in MPC based on two demographic factors: age and sex. The results show a clear negative relationship between age and MPC, with younger individuals having higher MPCs than older ones. Regarding sex, men tend to have higher MPCs than women. However, this difference appears to be influenced by marital status. Married women show strong and significant MPCs, whereas single women's MPCs are not statistically different from zero. This suggests that marital status may play a significant role in determining consumption responses among women.

We next move to estimating *reported-preference* MPCs. To this end, we employed a survey instrument like that in Christelis et al. (2019) and conducted with the help of the Greek public revenues authority telephone interviews of the same households in early December 2019, before payments were made to winners. Following Fuster, Kaplan, and Zafar (2021), we introduced some important differences in our instrument. We fixed the size of treatment at €1,000 income increase (GAIN scenario) or €1,000 income decrease (LOSS scenario) for all subjects, and the time horizon of observed behavior was set at four months. The average reported MPC for the GAIN scenario is €487, very close to the *revealed-preference* estimate of between €448 and €502 at the four-month horizon. This cross-validation exercise provides assurance of consistency between the two approaches and lends credence to the data from the survey instrument. It seems that respondents understand well what is asked about consumption, savings, and debt repayment decisions. In addition, the results provide general confidence in the use of survey instruments to elicit marginal propensities to consume, save and repay debt.

The treatment effect on non-durables (€360) is larger than that for durables (€127), which contrasts with previous studies, primarily focused on U.S. data. As reviewed by Laibson, Maxted, and Moll (2022) and Di Maggio, Kermani, and Majlesi (2020), prior research generally finds that nondurable Marginal Propensities to eXpend (MPX) make up about one-quarter to one-third of total MPX. In our estimates, however, nondurable MPX accounts for approximately three-quarters of the total. Consequently, the implied notional MPC for a model of the Greek economy will be very close to the total MPX estimates (using the terminology of Laibson, Maxted, and Moll (2022)). This contrasts with the rule of thumb for U.S. data advocated by Laibson, Maxted, and Moll (2022), where "MPC Times 3 Equals MPX."

We observe significant heterogeneity in marginal propensities to consume (MPC) across the two scenarios, revealing six distinct household types within our data. Focusing on the GAIN scenario and at the 4-month horizon, we find that the distribution of MPCs is trimodal, with modes at values of 0, 0.5 and 1. The first modal type, the *Spenders* (MPC = 1) are hand-to-mouth consumers, comprising 33 percent of the population. They allocate their spending between non-durables and durables at a 3-to-1 ratio. The second modal group seems to behave according to the Permanent Income Hypothesis with MPC = 0, making up 35 percent of the population. These households either save their windfalls, pay down debt, or do both. This group, therefore, is diverse, comprising three types. *Savers* allocate all their windfall to savings (with a marginal propensity to save, MPS, equal to 1); *Debt Servicers* allocate entirely to repaying their debt (with a marginal propensity to repay debt, MPRD, of 1), and *Mixed Saver/Servicers* who split their windfall between saving and debt repayment (MPS + MPRD = 1). On average, households in the Mixed group split their windfall equally between saving and debt repayment. Almost two-thirds of the households with MPC=0 are primarily involved in debt deleveraging. Finally, households with an MPC between 0 and 1 are divided into two types: the *Equal Splitters* (19 percent of the population), the third mode of the distribution, who split their windfall equally between consumption and net savings, and the *Unequal Splitters* (13 percent of the population) who allocate on average roughly equally between consumption and net savings. Both of these groups prioritize non-durables over durables in their spending choices.

We next address the question: "Do individuals' responses to hypothetical scenarios in surveys mirror how they would respond in comparable real-life situations?" Our survey uniquely includes both lottery winners, who will receive an actual income transfer, and non-winners, who were only presented with a hypothetical transfer scenario. This setup can be seen as a type of Randomized Control Trial (RCT). Both groups are asked identical questions regarding their marginal propensities to consume, save and repay debt. However, while the winners are in a real-life situation, non-winners are experiencing a controlled experimental setting. We observe similar responses in both groups regarding anticipated income changes, which, to our knowledge, is the first such comparison in the literature. The similarity in responses between these carefully balanced groups, matched on their observable characteristics, supports the view that hypothetical scenarios in survey research can effectively capture real-world spending and saving behaviors. Consequently, these responses may be applicable in real-world contexts, such as fiscal transfers.

Our survey instrument also has an unexpected one-time income LOSS scenario of €1,000, for which we do not have corresponding *revealed-preference* estimates. The average reported MPC for the LOSS scenario is €685, split between €433 in non-durables and €252 in durables. Consistent with the literature, we find that reported responses to losses are much larger and more widespread than to gains.

Respondents to the survey were asked how they would distribute their savings out of the windfall income in the GAIN scenario. On average, they would channel €194 to gross saving and €319 to repaying their debt. These responses show clearly that households are quite mindful about servicing their debt. When faced with unexpected income LOSS, household responses point to a substantial change in the allocation of their saving. On average, they would reduce gross saving by a similar amount as in the GAIN scenario (€143) but they would not reduce substantially their repayment of debt (€172). Again, these responses show that households are quite mindful about servicing their debt and this is in part the reason for the increased MPC in the LOSS scenario. This suggests that the debt overhang in the Greek economy is affecting the reported MPC of households.

Related Literature. Our analysis framework has the unique feature of random and simultaneous assignment in a tax lottery, administered by Greece's public revenues authority, which offers an ideal setting for identifying the causal effects of an unexpected fiscal transfer. In addition, to our knowledge, this is the first study to examine both *ex ante* reported preferences and *ex post* revealed preferences for the same households' consumption behavior. While many surveys assess *ex ante* preferences by placing individuals in hypothetical scenarios of unexpected income shocks, our study links these responses to actual consumption behavior by the same individuals using administrative data and finds consistency of results. Moreover, we find that individuals who were about to receive an actual transfer (lottery winners) reported *ex ante* preferences similar to those in a hypothetical situation (non-winners). Since surveys typically involve hypothetical scenarios, this novel finding is reassuring, suggesting that responses from such surveys may be applicable to real-world contexts like fiscal transfers.

This paper contributes to the literature on *revealed-preference* estimates of the marginal propensity to consume (MPC). One of the earliest studies, Bodkin (1959), found that World War II veterans spent up to 72 percent of unexpected dividend payments on nondurable goods. Several subsequent studies explored household consumption responses to tax rebates and fiscal stimulus payments in the U.S., such as those in 2001 and 2008 (e.g., Johnson, Parker, and Souleles (2006); Parker et al. (2013); Misra and Surico (2014); Broda and Parker (2014); Orchard, Ramey, and Wieland (2023); Borusyak, Jaravel, and Spiess (2024)). Agarwal, Liu, and Souleles (2007) used credit card data to show that consumers initially saved their 2001 tax rebates but increased spending over time, with low-liquidity consumers being most responsive. These innovative studies primarily leveraged near-random variation in the timing of payment receipt or in payment size, capturing only the spending caused by the arrival of the funds. Our approach differs in that we exploit random assignment between winners (treated) and non-winners (control) in the tax lottery, allowing us to capture not only the spending after receiving the prize but also any additional spending that may have occurred between the prize announcement and payout. This design resembles the study by Aydin (2022), though his setup is fully experimental. Furthermore, unlike Agarwal, Liu, and Souleles (2007) and Aydin (2022), we analyze comprehensive monthly credit and debit card transactions from the entire Greek financial system, including ATM withdrawals.

Compared with two key studies on lotteries and MPC, our design includes several distinct advantages. Imbens, Rubin, and Sacerdote (2001) collected survey data of individuals who played the lottery in Massachusetts in the mid-1980's, including both winners of large prizes and people who won small, one-time prizes. The critical assumption for identification of MPC that they made was that among lottery winners the magnitude of the prize was randomly assigned. Another lottery paper is Fagereng, Holm, and Natvik (2021). They examined how winners of sizable lottery prizes in Norway responded to transitory income shocks and found that more than 50 percent of the amount won was spent the first year and about 90 percent in the first five years.

Our study offers several key differences from these papers. In the previous studies, winning was tied to active behavioral decisions on betting and games activity, the propensity score (probability of winning) was not known, prize sizes varied significantly (from USD 1,100 to USD 150,000 in Fagereng, Holm, and Natvik (2021) and from USD 22,000 to USD 9.7 million in Imbens, Rubin, and Sacerdote (2001)), and consumption was either self-reported through recall by surveys (for Imbens, Rubin, and Sacerdote (2001)) or imputed at an annual frequency from income and wealth data (for Fagereng, Holm, and Natvik (2021)). In contrast, in our study, lottery participation was automatic, requiring only one electronic transaction in October 2019. The prize was a fixed amount of €1,000 for everyone, constituted a fiscal transfer as it was awarded by the public revenues authority, the propensity score is known with certainty, and consumption is directly measured from spending at a monthly frequency as registered in the financial accounts of the entire Greek banking system. These features ensure precise and uniform conditions for comparison.

Methodologically, our approach also diverges from these studies. Fagereng, Holm, and Natvik (2021) estimate MPC by comparing consumption before and after the prize, assuming the prize size and timing are exogenous. Imbens, Rubin, and Sacerdote (2001) compare the consumption of large-prize winners (designated as treated) to that of small-prize winners (designated as controls). We, on the other hand, rely on the random assignment of lottery winners and use a known propensity score to estimate average treatment effects by comparing winners' post-lottery consumption with that of a matched sample of non-winners. By providing responses at a monthly frequency and for an income shock originating from the public revenues authority and of magnitude tantamount to typical fiscal interventions, our study is especially relevant for policymakers aiming to stimulate economic activity through fiscal transfers and for researchers developing theoretical models.

Boehm, Fize, and Jaravel (2024), written contemporaneously with our paper, present experimental evidence on MPC, using random assignment to distribute prepaid debit cards with varying features. Our study differs by examining unanticipated, transitory transfers directly from the public revenues authority, and by analyzing the complete set of individuals' financial accounts -rather than from one banking group- over a longer period, extending eight months post-treatment. We are, thus, able to provide intertemporal MPCs over a longer horizon and provide evidence that significant additional spending occurs even as late as eight months after treatment. Furthermore, our study compares both *revealed-preference* and *reported-preference* estimates for the same households, introducing a novel cross-validation method between these approaches that supports the robustness of both our dataset and results.

The literature on survey-based *reported-preference* estimates of MPC is extensive, including studies such as Shapiro and Slemrod (1995), Shapiro and Slemrod (2003), Jappelli and Pistaferri (2014), Colarieti, Mei, and Stantcheva (2024), Bunn et al. (2018) and Coibion et al. (2024). Among these, two studies closely parallel ours in survey design. Christelis et al. (2019) estimate an MPC of 40 percent in a one-month income GAIN scenario, while Fuster, Kaplan, and Zafar (2021) report a much lower MPC of 7 percent for a $500 GAIN scenario over a three-month period. Our estimate, in comparison, is higher at 49 percent over a four-month period. This difference may reflect both the varying timeframes and the contrasting economic conditions of the samples. In 2019, Greek GDP per capita was still 20 percent below its 2008 peak, while in the U.S. sample used by Fuster, Kaplan, and Zafar (2021), GDP per capita was 35 percent higher than in 2008. A unique contribution of our paper is the implementation of two cross-validation approaches. First, we compare our survey-based estimates with *revealed-preference* estimates for the same households; second, we contrast survey responses to actual versus hypothetical income changes.[3]

This paper contributes to the recent literature examining the Greek Depression, a crisis of unprecedented scale and duration among advanced economies and past economic recessions. Previous studies, such as Gourinchas, Philippon, and Vayanos (2017), Ioannides and Pissarides (2015), Chodorow-Reich, Karabarbounis, and Kekre (2023), focus on macroeconomic analysis, while Fakos, Sakellaris, and Tavares (2022) and Giannoulakis and Sakellaris (2024) highlight the significance of firm heterogeneity using firm-level data. In contrast, our paper is the first to analyze household data on consumption and saving, offering new insights into the contractionary effects of austerity policies and the potential impact of fiscal stimulus on economic recovery.

The remainder of the paper is structured as follows: Section 2 describes the data and methodology used in our analysis, including details on the tax lottery, survey design, and administrative data. Section 3 presents our empirical findings that focus on *revealed-preference* estimates of MPC and their heterogeneity. Section 4 provides *reported-preference* estimates from our survey instrument. Finally, Section 5 concludes with policy implications and suggestions for future research.

2 Description of the Data

The dataset comprises administrative and survey data on 931 individuals in Greece, built around a lottery held on November 28th, 2019, which awarded a tax-free prize of €1,000 to 1,000 taxpayers. The lottery includes all individuals with a Greek Tax Identification Number (TIN) who made at least one electronic transaction in the previous month. Eligible transactions include credit and debit card purchases as well as bank transfers. However, individuals under 18 years old cannot participate. The pool of participants consisted of 5,695,732 individuals who used electronic payments in October 2019. Given that the minimum gross salary in Greece in December 2019 was € 650 gross (€ 546 net), this prize is substantial, equivalent to nearly two months' wages for minimum-wage workers. For most winners, the prize was credited to their accounts on December 20th, 2019, though a few received it in January or February 2020 (12 individuals).

Since 2017, the Independent Authority for Public Revenue (I.A.P.R.) of the Hellenic Republic has conducted monthly lotteries to encourage the use of electronic payments. The prize is tax-free and cannot be seized for unpaid tax debts even if the individual is not in a payment arrangement with the Revenue Authority. It is also protected from legal claims by private-sector creditors. The number of lottery tickets each person receives is based on a step function of their total transactions in euros during the previous month (e.g. October 2019), with the number of tickets per euro decreasing as spending increases. Eligible spending is capped at € 50,000, and each participant can win up to two times in a calendar year. If someone wins more than twice, the prize is awarded to the next person on a reserve list. Practically all tax payers in Greece have a bank account on file with the tax authorities for receiving tax refunds. Lottery winners have three months from the draw date to declare a payment account to receive the prize if they do already have one on record. The prize is credited interest-free. If no account is provided within the deadline, the prize is given to the next person on the reserve list.

With the support of the I.A.P.R., which administered our survey, we attempted to contact 942

3. Parker and Souleles (2019) run a different cross-validation exercise. They evaluate the consistency of *ex ante* reported intentions and *ex post* recall of behavior within the same households. Another cross-validation strategy is used by Colarieti, Mei, and Stantcheva (2024). They ask survey participants a series of questions intended to produce estimates that can be directly compared with those from observational studies in the literature.

of the 1,000 tax-lottery winners (W).[4] The remaining 58 individuals were not contacted because they either had not filed taxes or were listed as dependents on tax returns. Of the contacted individuals, 481 winners agreed to participate in the study, consented to share their personal data, and completed the survey. In parallel, we constructed a control sample of 533 non-winners (NW) who agreed to participate and answer the survey questions. This control group was drawn from a donor pool of 5,977 individuals, a sub-sample of the total non-winner population (5,694,732 individuals). Anticipating a high non-response rate and aiming for a final sample with well-balanced covariate distributions, we matched the donor pool *ex ante* to the 942 lottery winners based on observable characteristics.[5] To account for potential non-response, participation, and trimming biases, we use throughout our analysis inverse probability weights (IPWs), which we describe later in the paper.

To improve internal validity and ensure covariate balance, we trimmed the sample to ensure overlap in propensity scores (PS) between the treated and control groups. Specifically, we excluded winners with PS values higher than the maximum PS of non-winners, and non-winners with PS values lower than the minimum PS of winners (see Imbens and Rubin (2015) pp. 292-293). The PS reflects each individual's probability of winning one of the 1,000 lottery prizes, which is observed with certainty. After trimming, the final sample used for estimation included 440 winners (W) and 491 non-winners (NW). Importantly, this trimming did not compromise external validity, as the IPWs accounted for it in our analysis.

The anonymous administrative data were obtained from the I.A.P.R. and included monthly non-cash expenditures processed by the entire Greek financial system, broken down into credit card, debit card, and bank transfer transactions from January 2017 to July 2020. For the *revealed-preference* estimates presented in Section 3, we define expenditures as the total of credit and debit card transactions, excluding bank transfers, as these may include debt repayments. This exclusion could potentially bias our MPC estimates downward if some bank transfers were used for consumption. Appendix A.1 details the data cleaning process, which resulted in a final dataset of 931 individuals. While participants' tax arrears are not available in the tax returns, I.A.P.R. provided anonymous data on the exact amount of tax arrears owed to the extended public sector as of the end of 2019. Lastly, we obtained all household-level information from individual tax returns, including real estate holdings, and automobile and boat assets, dating back to 2006.

To supplement the administrative data, we set up a survey instrument that was conducted in various stages and with different rates of participation among the whole (pre-trimmed) sample of subjects. We first conducted, again with the help of I.A.P.R., a telephone survey of all individuals in our sample between the 2nd and 13th of December 2019 (with a limited number of telephone calls also made on the 19th and 20th of December 2019). Survey participants were asked to consider the current economic condition of their household and divide their (actual or hypothetical) tax-free one-time income windfall of €1,000 into saving, repaying debt, consuming non-durables, or consuming durables, with the time horizon for this decision set at 4 months (as in, among others, Fuster, Kaplan, and Zafar (2021)). We call this the GAIN scenario. We also subjected the individuals to a hypothetical LOSS scenario where the government unexpectedly imposed an additional (one-time) tax of €1,000 on their income effective immediately. The survey also involved several other stages that are not directly

4. Participants were informed that the survey was anonymous, they could withdraw at any time, and if they chose to withdraw, their data would be deleted. They were also informed that their responses, along with any relevant tax return information (for example, birth year, gender, family status, reported assets, income, arrears, and other tax details), would be forwarded anonymously to the research team, with confidentiality maintained throughout the process.

5. Details of the matching procedure can be found in Appendix A.1.

relevant for this paper. A detailed description of the survey methodology is contained in Appendix A.1 and the transcript of the questionnaires involved is given in Appendix C.

Table 1 provides information on some characteristics of the population that participated in the November 2019 lottery. This included about 5.7 million people, a bit over half of Greece's resident population and about 85 percent of the corresponding age group of the Greek population.[6] This is contrasted with the characteristics of the estimation sample of 931 individuals, weighted for participation and selection issues.[7] Examining moments of the weighted sample distribution we find that they are very close to the corresponding ones of the population distribution in terms of income, age, sex, and household size. Our sample participants had more electronic transactions in October 2019 than the lottery population and, thus, had more lottery tickets.[8] Table 2 compares the observable

Table 1: **Lottery Population & Estimation Sample Statistics**

Variables	Population			Sample		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Lottery Tickets	298.07	257.00	343.21	416.64	354.00	440.44
E-Transactions (€)	626.31	312.42	3,129.24	1,056.40	509.76	2,355.85
Age	49.59	48.00	17.27	50.00	49.00	14.55
Household Size	2.12	2.00	1.19	2.22	2.00	1.25
Individual Income 2019 (€)	17,651.13	13,262.20	38,341.43	16,520.13	14,340.34	17,511.77
Female	0.48			0.48		
Married Female	0.26			0.28		
Never Married Female	0.14			0.12		
Single Female	0.22			0.20		

Note: Lottery population size is 5,695,732 and our estimation sample size is 931. Household Size and Individual Income were available for 5,480,822 individuals in the population. Sample moments refer to the weighted distribution. For a description of the weighting procedure see Appendix B.7. For variable definitions, see Appendix A.2. For a description of the weighting procedure see Appendix B.7. Electronic transactions refer to the month of October 2019. Single Female include females that are never married, widowed, separated or divorced.

characteristics of our sample, which includes the treated group (W) and the control group (NW). To facilitate comparison, the last column shows the standardized difference in means between the two groups (treated minus control). The standardized differences indicate that the two groups are generally well-balanced in terms of observable characteristics, although variables related to October 2019 expenditures show slightly larger differences.

6. In 2021, the year of the latest Census of Population, the resident population in Greece was 10,432,481 of whom 6,773,700 were between 20 and 70 years old. A more comprehensive table on the distribution of the same characteristics is given in Appendix Table A.1.

7. A description of the construction of inverse probability weights used throughout the analysis is given in Appendix B.7.

8. In unreported results, we find that without weighting, the sample contains individuals with higher income, expenditures and lottery tickets on average than does the population.

Table 2: **Descriptive statistics for the estimation sample**

Variable	Mean	Median	Std.Dev	Norm. Diff.
October 2019 Expenditures	1,056.40	509.76	2,355.85	0.44
Lottery tickets	416.64	354.00	440.44	0.45
Linearized Propensity Score	-8.63	-8.48	0.81	0.44
Age	50.00	49.00	14.55	0.07
Female	0.48		0.50	0.09
Household Size 2019	2.22	2.00	1.25	0.17
Gross Individual Income 2019	16,520.13	14,340.34	17,511.77	0.10
Net Individual Income 2019	13,155.49	11,385.66	14,533.62	0.11
Gross Household Income 2019	22,029.97	17,543.87	21,334.74	0.14
Net Household Income 2019	17,499.25	13,991.21	17,433.54	0.15
Liquid Wealth 2019	42,967.11	347.06	526,236.23	-0.00
Illiquid Wealth 2019	118,084.19	60,106.03	198,902.77	0.26
Arrears to the State 2019	1,409.47	0.00	7,502.91	0.01
Single females	0.20			0.05
Married females	0.28			0.10

Note: The sample of 931 individuals that is used in the revealed-preference estimation contains 440 winners and 491 non-winners. Normalized mean differences refer to treated vs control observations. Sample moments refer to the weighted distribution. For variable definitions, see Appendix A.2. For a description of the weighting procedure see Appendix B.7. Single females include females that are unmarried, widowed, separated or divorced. The variables referring to expenditures, income and wealth are in euros.

3 *Revealed-preference* results

Starting with *revealed-preference* estimates of MPC, we use administrative data on total monthly credit- and debit-card spending by the individuals in our sample. The Weighted Average Treatment Effect (WATE) was estimated with the method of subclassification on the propensity score (PS), the probability of winning the lottery. Our study is a rare instance where the propensity score is known with certainty. We subclassify the sample of 931 observations into K blocks (strata) in ascending order of the PS, and denote membership in a block with the indicator variable B. The procedure is described in Appendix B.5. We calculate the following expressions, where z=0 or 1 denotes control or treated individual, Y is the outcome variable (expenditures), and S is the estimated inverse probability weight (IPW) of participation in the sample. Since we have data on the superpopulation from which our estimation sample was drawn, we can estimate IPW as described in Appendix B.7. We normalize the weights, S_i, by the sum of the weights for each treatment group, and use $\tilde{S}$, as defined below, for our estimations.

The WATE, denoted by τ^w, is given by

$$\tau^w = \frac{\sum_{k=1}^{K}\left[\left(\sum_{i:B_i=k;z=1}\tilde{S}_i + \sum_{i:B_i=k;z=0}\tilde{S}_i\right)\tau_k^w\right]}{\sum_{i=1}^{N}\tilde{S}_i}, \tag{1}$$

where

$$\tau_k^w = \frac{\sum_{i:B_i=k;z=1} Y_i\tilde{S}_i}{\sum_{i:B_i=k;z=1}\tilde{S}_i} - \frac{\sum_{i:B_i=k;z=0} Y_i\tilde{S}_i}{\sum_{i:B_i=k;z=0}\tilde{S}_i},$$

and

$$\tilde{S}_i = \begin{cases} \dfrac{S_i}{\sum_{i:z=1} S_i}, & \text{for } i : z = 1 \\ \\ \dfrac{S_i}{\sum_{i:z=0} S_i}, & \text{for } i : z = 0 \end{cases}.$$

3.1 MPC Estimates for the Estimating Sample

We now apply the above method of subclassification on the Propensity Score on our Estimating Sample. In Appendix Figure B.1 we show that no available observable characteristics can significantly predict treatment status in our sample. In Appendix B.5 we provide some statistics and evidence of balance in the propensity score between treated and controls in different blocks. The causal effects of winning the lottery on expenditures are presented in Table 3 and Figure 1. These correspond to MPCs out of €1,000 at different horizons.

The estimated MPC in December is strong at €157 (with a standard error of €62). The estimate for the month of December 2019 should be interpreted carefully. It contains only 11 days of treatment for W, as the prize was paid on December 20th. If treatment is considered to have coincided with the arrival of information rather than the payment, December contains 31 days of treatment, as messages were sent to winners on the 29th of November. In addition, December contains the Christmas and New Year's Eve special holiday expenditures.[9] January 2020, the first full month of treatment displays an even stronger MPC of €249 (with a standard error of €71). The MPCs for February and March are much lower even though February is a month when the retail sector holds its biannual sales in Greece. The cumulative MPC at the three-month horizon is €440, if December is counted as a full treatment month, or close to €445, if the first twenty days of March are used to complete a three-month period.[10] The MPC rises to between €448 and €502 at the four-month horizon,[11] and between €568 and €590 at the six-month horizon.[12] In July 2020, more than seven months after the receipt of the unexpected payment, the cumulative causal effect of winning the lottery is even more sizeable at €690 (s.e. €206).

We provide some remarks regarding the estimated causal effects of the lottery prize. First, the estimates account for all spending originating within the Greek financial system, including ATM

9. The tradition in Greece is to give presents on New Year's Eve and not on Christmas Day or Eve.

10. The MPC in March is estimated at €8. Under an assumption of uniform treatment effect in March the first 20 days would have an MPC of about €5.

11. The MPC in April is estimated at €81. Under an assumption of uniform treatment effect in April the first 20 days would have an MPC of about €54.

12. The MPC in June is estimated at €33. Under an assumption of uniform treatment effect in June the first 20 days would have an MPC of about €22.

Table 3: **Revealed-preference MPC from Card Expenditures**

Month	Monthly	Implied Cumulative
December 2019	157.31	
	(61.83)	
January 2020	248.78	406.09
	(71.49)	(113.72)
February 2020	34.22	440.30
	(81.60)	(166.35)
March 2020	7.76	448.07
	(61.40)	(202.25)
April 2020	81.08	529.15
	(38.40)	(203.25)
May 2020	38.84	567.99
	(58.67)	(204.25)
June 2020	32.57	600.56
	(50.80)	(205.25)
July 2020	89.21	689.77
	(57.21)	(206.25)

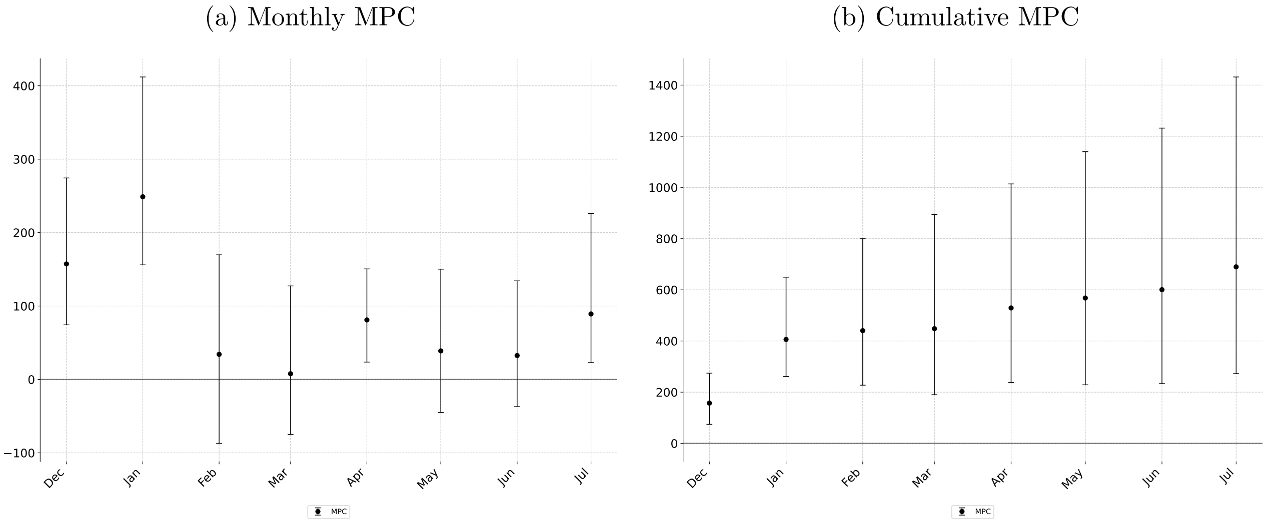
Note: Reported are Weighted Average Treatment Effects (WATE) estimated using the estimator described in (1). The outcome variable is total monthly expenditures on credit and debit cards for 931 individuals at different months after the November 2019 lottery. The prize payment date was the 20th of December 2019, and the notification of the prize was sent to winners on the 29th of November 2019. Bootstrap standard errors are in parentheses (calculated as described in Appendix B.3).

withdrawals used for cash expenditures. If individuals took on new debt to finance additional spending, that spending is also captured in these estimates. Second, if individuals held cash outside the formal financial system, these estimates might understate the total increase in spending, in the case that they used this external cash in addition to—or instead of—their financial system liquidity. Third, as the maximum horizon analyzed here is quite long at close to eight months, we can rule out concerns of intertemporal substitution of expenditure by the individuals. Thus, we can safely say that the increase in spending is concentrated in the short term with 59 percent (406/690) of the estimated total effect occurring in the first 43 days of treatment (20 December to 31 January). The estimated MPC for the month of July 2020 is €89, and statistically significant. This is consistent with continued increases in expenditure beyond the period observed here and towards an even higher long-term MPC.

Fourth, the use in the estimation of inverse participation probability weights (IPW) based on the lottery population makes the sample representative and provides external validity to the estimates. This is important when using these estimates in macroeconomic models or for macroeconomic policy design.[13] Fifth, the estimated effect for the month of April (€81 with s.e 38) is high and statistically significant. This month included Orthodox Easter (19 April 2020), the most significant holiday of

13. Laibson, Maxted, and Moll (2022) showed that the relevant target for macroeconomic models that include only a single consumption good is the "notional" MPC. In these models, notional consumption represents the flow of consumption that generates utility. Using their terminology, our estimates are for marginal propensities to expend (MPX), as they include spending on both durable and non-durable goods. Theoretically, the notional MPC is lower than the overall MPX (on both durable and non-durable purchases) that we estimate here. Ultimately, what matters for policymakers is how much GDP responds to fiscal stimulus, which in turn depends on the size of the *expenditure* response to such stimulus.

Figure 1: **Revealed-preference MPC Estimates for Card Expenditures**



Note: Panel A depicts the monthly MPC and Panel B the implied cumulative MPC based on the weighted average treatment effects (τ^w) defined in the text. The vertical lines report the 95 percent bias-corrected and accelerated bootstrap confidence intervals (calculated as described in Appendix B.3).

the year in Greece when households concentrate much of their non-usual expenditure, including trips. The school system has a two-week break around that Sunday. It is possible that treated households may have saved part of their prize in December planning to undertake expenditures during the Easter holiday. This expenditure may have been affected downwards by the first COVID-19 lockdown in Greece, which came into effect on the 23rd of March 2020 and started being gradually lifted on the 4th of May 2020. This may also have contributed to the strong MPC of July 2020.

The above estimates of MPC are higher than those found in much of the literature at similar horizons.[14] Johnson, Parker, and Souleles (2006) and Parker et al. (2013) examine the response of US households to economic stimulus programs during two recessions (2001 and 2008). In 2008, Parker et al. (2013) estimated that households spent approximately 12 to 30 percent of their stimulus payments on non-durables and services and a total of 50 to 90 percent of their checks on total additional spending in the three months following receipt. In 2001, approximately 20 to 40 percent of stimulus checks were spent on non-durables and services in the three months following receipt. Broda and Parker (2014) found that a household's spending on covered goods increased by approximately 10 percent in the week that it received a 2008 stimulus payment. However, a more recent literature using estimators that are robust to staggered treatment finds much smaller MPCs of about 25 percent over a quarter for the same fiscal stimulus episodes (Borusyak, Jaravel, and Spiess (2024), Orchard, Ramey, and Wieland (2023)). In contrast, our estimated three-month MPC for our sample is about 44 percent. Fagereng, Holm, and Natvik (2021) study responses to lottery earnings in Norwegian administrative data, and find an average MPC of about 51 percent for the year following the windfall. Bodkin (1959), looking at the consumption behavior of World War II veterans after the receipt of unexpected dividend payments, estimated MPC for nondurables of 72 percent. The relevant horizon varied across individuals in his sample between 9 and 12 months. The longest-horizon estimate included in our paper is 8 months and the corresponding MPC estimate is 69 percent.

14. See Browning and Lusardi (1996), Jappelli and Pistaferri (2010) and Krueger, Mitman, and Perri (2016) for surveys and Havranek and Sokolova (2020) for a meta-analysis.

3.2 Heterogeneity of MPC by observable characteristics

Whereas in the standard life-cycle model and the permanent income hypothesis MPC is the same for all households, models with precautionary savings, liquidity constraints, bequest motives, or heterogeneous preferences, predict considerable heterogeneity in MPC.[15] We now examine whether the Marginal Propensity to Consume (MPC) varies based on observable household characteristics. Specifically, we explore heterogeneity by household income, liquid wealth, illiquid wealth, age, sex, and arrears to the State in 2019. While income, liquid wealth, and illiquid wealth have been extensively studied in the literature, our inclusion of arrears to the State as a factor is a novel contribution of this analysis.

A key strength of our study is the use of administrative data from the Greek tax authority (I.A.P.R.) to measure these characteristics. Household gross income is recorded for the 2019 calendar year. Liquid wealth is constructed as the average level of household deposits in Greek financial institutions during 2019, while illiquid wealth is measured as the assessed value of household-owned real estate, vehicles, and boats as of the end of 2019. Arrears refer to outstanding debts to the Greek State and public-sector enterprises as of December 2019.

To maintain statistical precision given the sample size, we divided the sample in three groups (terciles of the weighted distribution) for each observable characteristic separately and estimated WATE within each group. Table 4 shows the means of weighted distribution terciles for each observable characteristic, with monetary amounts in euros and age in years. Note that group memberships differ across characteristics since terciles are defined independently for each variable's distribution. For arrears, Group 1 includes participants with zero arrears (N=498), while Groups 2 and 3 consist of those with non-zero arrears, divided at the weighted median. When estimating WATE for each group we trimmed observations within the group to ensure overlapping PS between treated and controls. Appendix Table B.4 provides the range of values in each group, along with the count of observations used in each group estimation.

We see that the distributions of income and wealth have quite broad support, including in the tails. The sample contains households both at the low and at the high end of income and wealth. As mentioned above, more than half the households in the sample have no arrears to the State. However, there are households in the sample with substantial arrears, with a mean of about €6,360 in the top half of the segment having positive arrears.

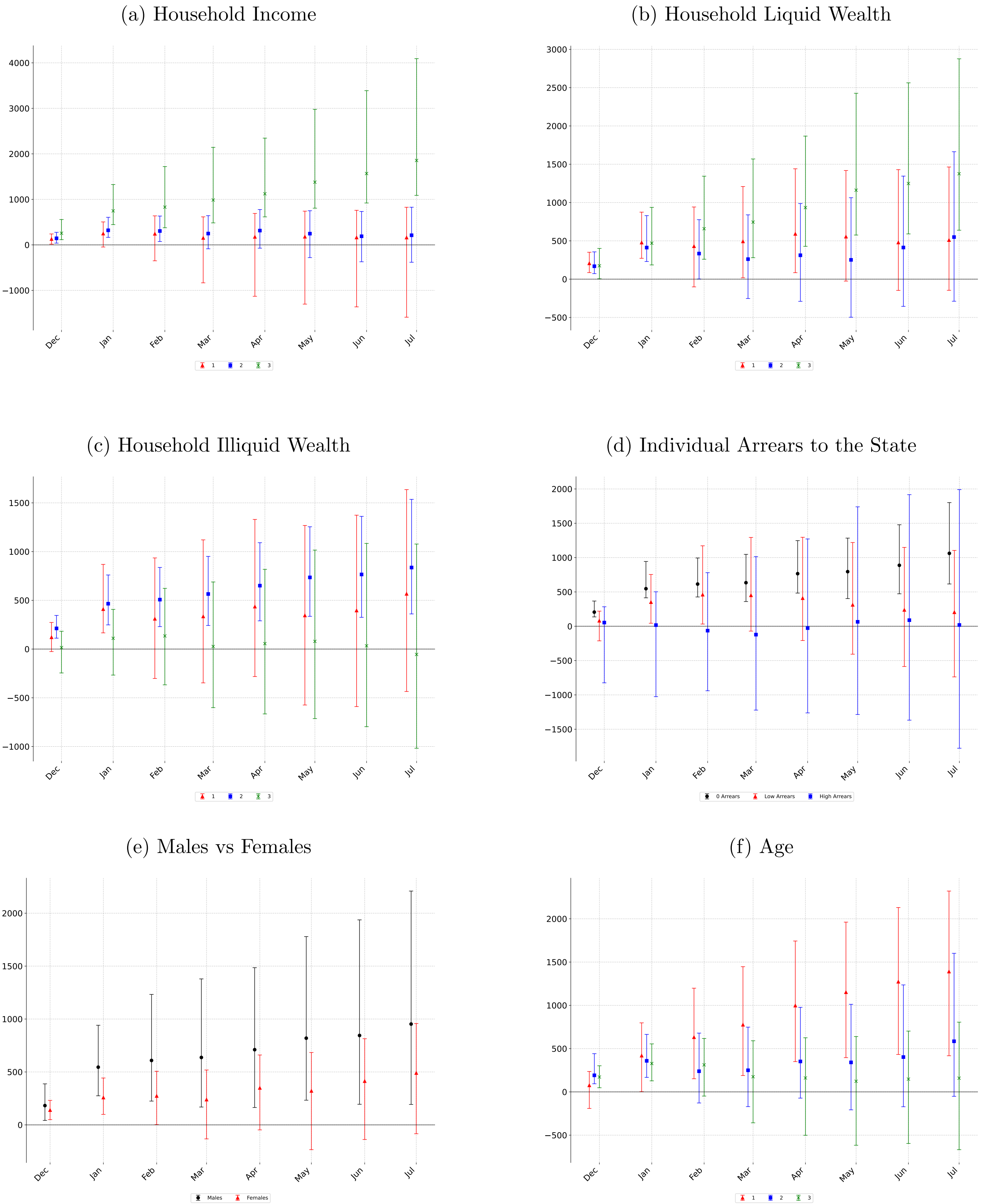
The discussion now turns to the estimated causal effects (WATE) of winning the lottery for different groups of observable characteristics. These effects are visualized in Figure 2 that displays the cumulative MPCs over different horizons, denoted by the month at the endpoint of the horizon. For ease of reference, we also display these cumulative MPCs in Table 5 for the January '20, March '20 and July '20 horizons only.[16]

Income. The estimates (Panel a of Figure 2) show that the highest-income households exhibit the largest MPCs among the three groups across all time horizons. At the end of January 2020, 42

15. Households with zero wealth, facing binding credit constraints, or wealthy households who hold the bulk of their wealth in illiquid assets will have high MPC in such models (see Kaplan and Violante (2014) for an example). In other models, precautionary saving motives induce a consumption function that is concave in wealth and MPCs that are heterogeneous across households. See Carroll (2001) and Carroll, Holm, and Kimball (2021) for explanations and surveys of the literature. In another set of models, households differing in preferences or income processes can display high MPCs (see Aguiar, Bils, and Boar (2020); Carroll et al. (2017)).

16. In Table B.3 we report the normalized mean differences of LPS between treated and control individuals within each group of observable characteristic. These indicate balance of covariate distributions within each group. In Appendix B.5 we provide some statistics and evidence of balance in the propensity score between treated and controls in different blocks within each group of observable characteristics.

Figure 2: **Cumulative MPC by Observable Characteristic**



Note: In this figure we report the cumulative treatment effects (in euros) for heterogeneous groups at different horizons, denoted by the month at the endpoint of the horizon. The sample is split into terciles using the estimated population quantile function (see Appendix B.1) for household income, liquid and illiquid wealth, and age (see Appendix A.2 for the description of the variables). Arrears to the State are split into those with zero arrears, and those with strictly positive arrears are split at the median. See Table B.4 in the Appendix for the number of observations in each tercile. The vertical lines report the 95 percent bias-corrected and accelerated bootstrap confidence intervals (calculated as described in Appendix B.3).

Table 4: **Mean Values of Observable Characteristics by Group**

Group	**Income**	**Liquid Wealth**	**Illiquid Wealth**	**Arrears**	**Age**
Group1	6,505.03	36.05	6,440.07	0.00	34.17
Group2	17,860.66	412.75	57,804.41	214.74	49.33
Group3	41,511.16	128,196.31	281,987.97	6,360.27	67.06

Note: In this table, we report the weighted average value of observable characteristics, separated into three groups. The sample is split into terciles of Household income, liquid and illiquid wealth, and individual age using the estimated population Quantile function (see Appendix B.1). See Appendix A.2 for the description of the variables. Arrears to the State are split into those with zero arrears (Group 1), and two equal-sized groups with strictly positive arrears (split at the weighted median of non-zero arrears). The amounts are in euros. Age is in years. See Table B.4 in the Appendix for the number of observations in each group. The groups for each column have a different membership as the terciles are defined separately for each distribution of observable characteristic.

days after receiving the €1,000 prize, the MPC is estimated at €747 (s.e. €269). By the end of March 2020, the MPC rises to €986 (s.e. 459). Even more strikingly, at the end of July '20, more than seven months after treatment, the MPC reaches €1855 (s.e. €773). In contrast, the two lower-income groups display significantly lower MPCs at every time point.

The relationship between income and MPC in the empirical literature is mixed. For example, Lewis, Melcangi, and Pilossoph (2024) and Boutros (2022) provide evidence of a positive correlation between income and MPC in the 2008 Economic Stimulus Act, originally studied by Parker et al. (2013). Kueng (2018) examines fixed payments from the Alaskan Permanent Fund and finds that MPC consistently increases with income. Other studies report substantial MPCs among high-income households, despite estimating a negative overall relationship between income and MPC. For instance, Parker et al. (2013), who look at income, and Jappelli and Pistaferri (2014) and Andreolli and Surico (2024) who examine cash-on-hand. In the case of Andreolli and Surico (2024), the negative relationship applies to smaller income changes similar to those analyzed in this study, but for larger changes, they find a positive correlation.

Other studies, such as Fagereng, Holm, and Natvik (2021), Parker and Souleles (2019), and Sahm, Shapiro, and Slemrod (2010), find no significant relationship between income and MPC. Chetty et al. (2023) report that MPC increased with income for U.S. stimulus payments in April 2020, but decreased with income for the stimulus payments in January 2021. The pattern we estimate in this paper is difficult to reconcile with liquidity constraints or precautionary saving motives. Andreolli and Surico (2024) demonstrate that this pattern can be explained by a model with no borrowing constraints and non-homothetic preferences for non-essential consumption. Another interpretation of the evidence, highlighted by Kueng (2018), points to near-rational behavior: since the prize is fixed at €1,000 regardless of income, the welfare loss from not smoothing consumption is minimal for high-income households, potentially leading to a higher MPC. A related explanation comes from Boutros (2022), who proposes a model of bounded intertemporal rationality, where the smaller the relative size of the payment, the more planning costs outweigh the benefits of smoothing consumption.

Liquid Wealth. Models of household consumption with financial frictions prompt us to investigate whether liquidity affects MPC. Such models predict that households with low levels of liquid

Table 5: **Heterogeneity - Cumulative MPCs**

Group	Month	Income	Liquid Wealth	Illiquid Wealth	Arrears	Female	Age	Single Female vs Married Female
1	Jan '20	248.44	477.80	409.74	547.01	545.32	418.86	181.36
		(167.98)	(167.13)	(198.42)	(125.50)	(200.26)	(245.76)	(174.02)
	Mar '20	152.67	493.10	334.99	634.43	636.97	776.16	74.92
		(398.84)	(356.61)	(449.29)	(201.77)	(356.69)	(380.09)	(400.02)
	Jul '20	161.22	510.30	566.78	1061.93	952.63	1390.41	333.73
		(604.31)	(484.79)	(632.53)	(342.49)	(581.59)	(585.32)	(704.49)
2	Jan '20	320.23	412.16	465.30	351.61	258.32	358.93	293.91
		(125.65)	(163.25)	(154.26)	(212.40)	(103.13)	(145.74)	(137.72)
	Mar '20	248.78	261.17	565.20	451.01	239.08	249.76	406.67
		(220.01)	(348.58)	(211.94)	(397.71)	(197.13)	(284.17)	(266.27)
	Jul '20	211.28	549.26	836.59	204.58	490.09	584.98	827.41
		(368.24)	(598.27)	(358.71)	(574.91)	(317.32)	(486.69)	(412.78)
3	Jan '20	746.92	469.56	110.46	17.04		327.90	
		(268.72)	(231.60)	(211.68)	(413.02)		(131.57)	
	Mar '20	985.78	744.99	26.69	-122.04		175.15	
		(458.82)	(384.93)	(400.38)	(702.18)		(293.16)	
	Jul '20	1854.72	1375.81	-55.01	18.44		158.78	
		(773.10)	(642.29)	(650.69)	(1173.44)		(451.56)	

Note: The table contains the cumulative MPCs for groups of observable characteristics at three horizons. Treatment of €1,000 occurred on the 20th of December 2019. The sample is split into terciles using the estimated population weighted Quantile function (see Appendix B.1) of Household income, liquid and illiquid wealth, and sample participant's age (see Appendix A.2 for the description of the variables). The groups for each column have a different membership as the terciles are defined separately for each distribution of observable characteristic. Arrears to the state are split into those with zero arrears (Group 1), and those with strictly positive arrears split at the median of the weighted distribution (Groups 2 and 3). See Table B.4 in the Appendix for the number of observations in each group. For "Female", Group 1 refers to male and Group 2 refers to female. Single Female is reported in Group 1 and Married Female in Group 2. Single females include those that are never married, widowed, divorced, and separated. Bootstrap standard errors are given below each estimate (calculated as described in Appendix B.3).

wealth fail to smooth consumption due to (occasionally) binding liquidity constraints or a high elasticity of precautionary saving with respect to cash on hand. As shown in Table 5 and Figure 2 (Panel b), we find that households with high liquid wealth have the highest MPCs and are statistically significant at all horizons. Those in the lowest liquidity tercile display MPC of €478 (s.e. €167) on impact and €493 (s.e. €357) at the horizon of March '20. At longer horizons their MPC remains relatively constant. It seems that almost all the treatment effect for this group takes place in December '20 and January '20. These are substantial numbers, yet much lower than the MPC of the wealthiest. Liquidity constraints or concave consumption functions cannot be an explanation for the higher MPC of the highest tercile, the highest-liquidity individuals, though it could explain the significant MPC of the lowest-liquidity individuals. The higher MPC of the highest tercile seems consistent with models of behavior incorporating rules of thumb, mental accounts, problems with self-control, or an important role for planning.

The evidence on the relationship between liquid wealth and marginal propensity to consume (MPC) in the literature is mixed. Some studies on U.S. tax rebates, using data from the Consumer Expenditure (CE) Survey, do not find strong evidence of a correlation between liquid wealth and MPC (e.g., Johnson, Parker, and Souleles (2006); Parker et al. (2013)). However, other research does report a significant correlation (e.g. Fagereng, Holm, and Natvik (2021); Baker (2018); Aydin (2022); Parker (2017); Olafsson and Pagel (2018); Baugh et al. (2021); Misra and Surico (2014) and Leth-Petersen (2010)).[17] There is evidence in the literature that MPC is high even among the most liquid households, and Fagereng, Holm, and Natvik (2021) argue that this result is difficult to reconcile with conventional buffer-stock saving models.

The high MPC observed among the wealthiest (i.e., most liquid) households cannot be explained by liquidity constraints or concave consumption functions, which may explain the high MPC among households with low liquidity. Instead, this evidence suggests behavioral factors, such as rules of thumb, mental accounting, self-control issues, or the role of financial planning, may be important (Karlsson, Gärling, and Selart (1997); Shefrin and Thaler (1988), and Bernheim, Skinner, and Weinberg (2001)).

We should be cautious when comparing our results on liquidity to those in the existing literature. Our measure of liquid wealth is based on average balances over the reference year, whereas much of the literature relies on point-in-time balances. Additionally, our liquid wealth data is derived from administrative records provided by the tax authority, while typical measures in the literature are self-reported and reflect balances at a specific moment.

Illiquid Wealth. The picture that emerges for illiquid wealth is a non-monotonic relationship to cumulative MPC (Table 5 and Figure 2, Panel c). The middle tercile of the distribution displays the highest MPCs, estimated with statistical precision at all horizons. The poorest (in terms of illiquid wealth) have substantial but lower MPCs, estimated imprecisely from February '20 and at longer horizons. An interesting finding is that the wealthiest (in terms of illiquid wealth) have MPCs that are not statistically different from zero at all horizons. This contrasts with our findings in liquid wealth and demonstrates the importance of separating these two sources of wealth in studying consumption.

Arrears. Arrears to the State and the extended public sector is a meaningful indicator of household financial health or distress. When splitting individuals by their level of arrears to the State there is strong evidence of a negative relationship to MPC. Individuals with zero arrears, constituting more than half the sample, have a MPC of €634 (s.e. €202) at the March '22 horizon and a MPC of €1062 (s.e. €342) at the July '22 horizon. These are relatively financially healthy individuals, and likely households, who respond strongly in their consumption. In contrast, the MPC of the segment with highest arrears is statistically insignificantly different than zero at all horizons. This is consistent with an explanation that high-arrears households are highly financially fragile, with high debt burdens that pose constraints on using the income windfall for extra consumption. The average level of arrears to the State for this group was €6,360 and it is likely that they have other outstanding balances or Non-Performing Loans. It is likely that the windfall is used for repaying part of their debt obligations.[18] Individuals with a low level of arrears to the State in Group 2 (with an average arrears level of €215) show strong MPCs in the first few months but seem to intertemporally substitute, as their cumulative MPC is near zero by the end of the observation horizon.

We examine next heterogeneity of MPC based on two demographic characteristics: sex and age.

Sex. It is clear from our results that males have higher MPCs than females at all horizons, though not statistically significantly so. This seems to be driven in part by sharply different MPCs within the group of females when we separate by marital status. As we see in Table 5, married

17. Andreolli and Surico (2024) find that families with low liquid wealth have a higher MPC in response to small windfalls, but for larger income changes, there is a positive relationship between liquid wealth and MPC.
18. In the section where we report *reported-preference* estimates, we will provide evidence that this group of individuals has a considerably higher marginal propensity to repay debt (MPRD) out of a €1,000 income windfall than the other groups.

females have strong MPCs of €294 (s.e. €138) and €407 (s.e. €266) at the January '20 and March '20 horizons respectively. At the end of July '20, the cumulative MPC was estimated at €827 (s.e.€413). In contrast, single females' MPCs at the same horizons are statistically insignificantly different than zero.[19] One possible explanation is that single women may lack the family safety nets available to married women. In Greece, family support usually complements social and public safety nets, which are relatively weaker than those in other European Union countries, especially during times of unemployment, health issues, or poverty. Due to the limited sample size, we cannot further divide these two groups by adding other observable characteristics to explore this hypothesis in more depth.

Age. The estimates show a monotonic negative relationship between age and MPC. The younger tercile has a wide range of ages between 22 and 42 (see Appendix Table B.4).

4 *Reported-preference* results

Do individuals on what they say they would or will do? Are individuals' financial responses to income windfalls symmetric to their responses to unexpected income losses? Are their financial responses to unexpected income gains and losses similar, or do they differ? To investigate these questions, as well as some other issues, we present *reported-preference* estimates for the same sample of individuals previously used to calculate *revealed-preference* estimates of MPC.

We used a survey similar to that in Christelis et al. (2019), conducting telephone interviews in December 2019. Following Fuster, Kaplan, and Zafar (2021), we introduced some key adjustments. Specifically, we standardized the size of the income change to €1,000—either as a gain (GAIN scenario) or a loss (LOSS scenario)—and set a four-month time horizon for observed behavior.[20]

The sample is identical to that used in the *revealed-preference* estimates, including 931 participants who consented to provide their household administrative data.[21] Figure 3 illustrates substantial variation in reported MPC across individuals for both scenarios. We will analyze this heterogeneity extensively in the following subsection. Tables 6 and 7 contain the results of our analysis for the GAIN and LOSS scenarios respectively. These may be best visualized in Figure 4.

The average reported MPC for the GAIN scenario is €487 very close to the *revealed-preference* effect estimate of between €448 and €502 at the four-month horizon. This provides substantial assurance of consistency between the two approaches and lends credence to the data from our survey instrument as well as the results from the transactions data. Individuals actually do what they say they would do, at least on average. The treatment effect on non-durables (€360) is greater than that for durables (€127).

We provide now a comparison of our estimates to those in some previous studies. This is not meant to be a consistency check as these use different datasets and MPC could vary depending on economic conditions or other factors. In addition, estimates could depend on the wording of questions asked. The MPC estimate from our survey is larger but close to that in the one-month income GAIN scenario in Christelis et al. (2019) (40 percent). As our horizon is also longer the comparison is not entirely revealing. Jappelli and Pistaferri (2014) report an average MPC of 48 percent in their sample, which, they note, is at the high end of *reported-preference* estimates based on survey data.[22] In

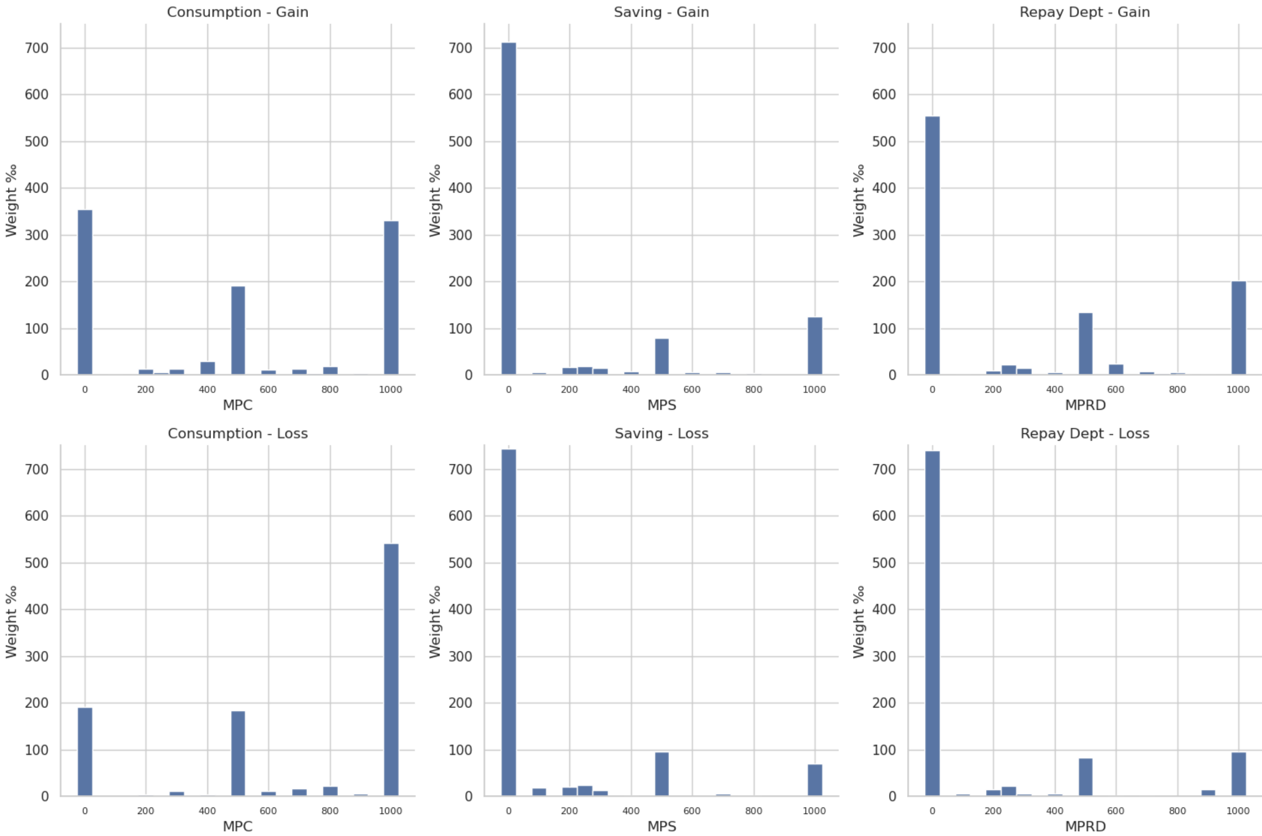
19. Single females include those that are never married, widowed, divorced, or separated.

20. Appendix A.1 provides a detailed description of the survey methodology, and Appendix C contains the questionnaire transcript.

21. Two participants did not respond to the LOSS scenario.

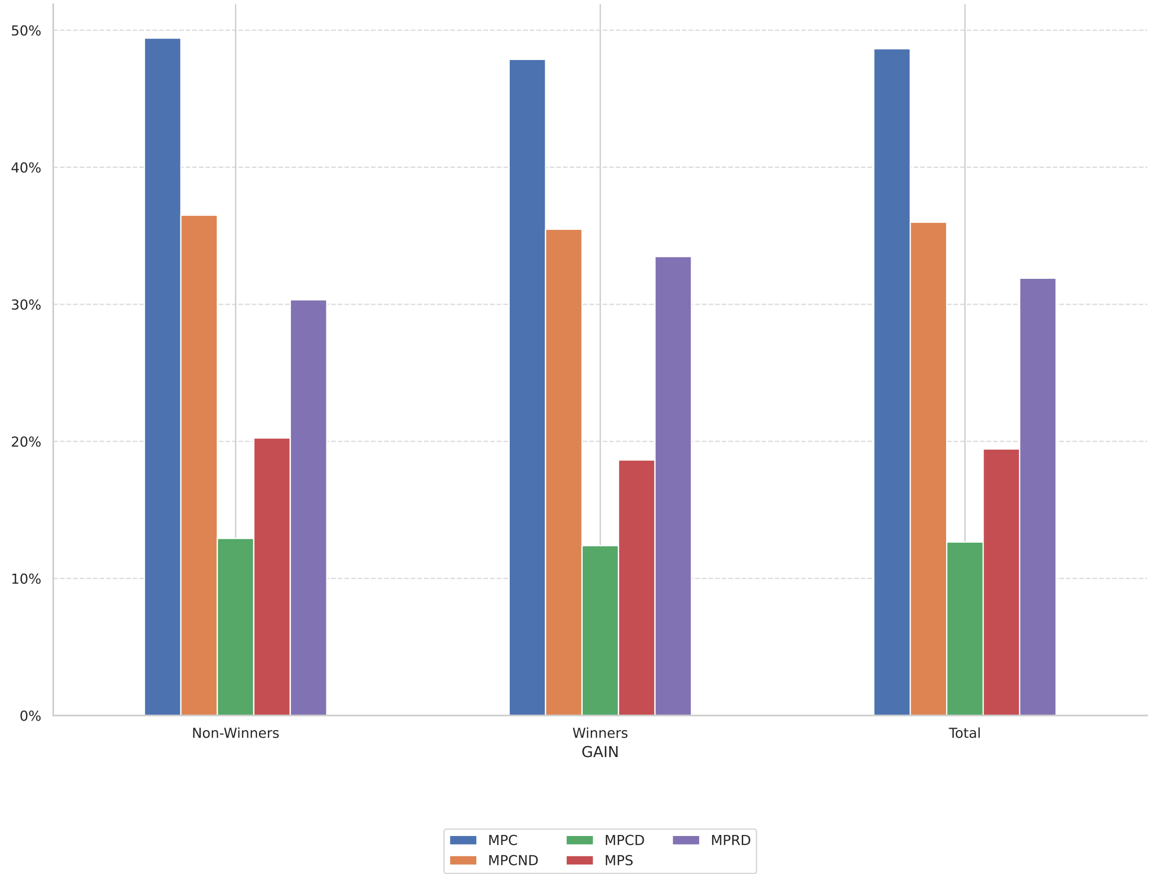
22. Jappelli and Pistaferri (2014) use responses to survey questions in the 2010 Italian Survey of Household Income and Wealth, which do not specify an action horizon. It is plausible that respondents would consider that to be longer than our horizon of four months.

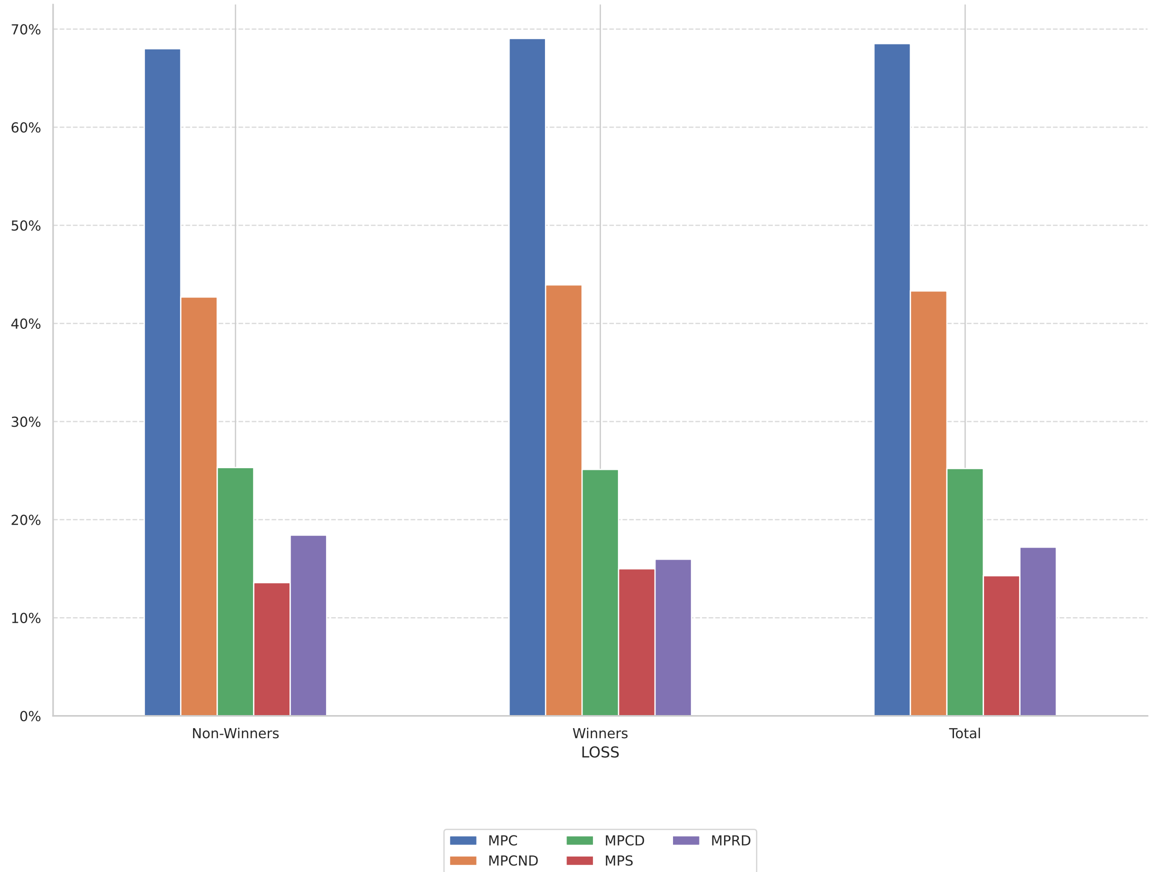
Figure 3: **Distributions of MPC, MPS, and MPRD (*Reported Preference*)**



Note: The figure contains the weighted distributions of responses on marginal propensities (in percent) to consume (MPC), save (MPS), or repay debt (MPRD) out of €1,000 unexpected, one-time tax-free transfer (GAIN) or €1,000 unexpected, one-time reduction on income (LOSS). The number of observations is 931 for GAIN and 929 for LOSS.

Figure 4: **Means of MPC, MPCND, MPCD, MPS, and MPRD (*Reported Preference*)**





Note: The figure contains the weighted means of responses to the telephone survey on marginal propensities (in percent) to consume (MPC), consume non-durables (MPCND), consume durables (MPCD), save (MPS), or repay debt (MPRD) out of €1,000 unexpected, one-time tax-free transfer (GAIN) or €1,000 unexpected, one-time reduction on income (LOSS). The number of observations is 931 for GAIN and 929 for LOSS.

Table 6: **Reported preferences - GAIN Scenario**

	MPC	MPCND	MPCD	MPS	MPRD
Mean	48.65	35.99	12.66	19.44	31.91
Std. Dev.	2.34	2.14	1.42	1.94	2.24
Mean (Winners)	47.87	35.48	12.39	18.64	33.49
Std. Dev. (Winners)	2.12	1.97	1.30	1.70	2.06
Mean (Non-Winners)	49.42	36.50	12.92	20.25	30.33
Std. Dev. (Non-Winners)	4.23	3.81	2.54	3.61	3.98

Note: The table contains reported Marginal Propensities at the four-month horizon in percentages of the €1,000 GAIN treatment. Means and standard deviations are weighted using the estimated weights IPW (see Appendix B.7). MPC is Marginal Propensity to Consume, MPCND is Marginal Propensity to Consume Non-Durables, MPCD is Marginal Propensity to Consume Durables, MPS is Marginal Propensity to Save, and MPRD is Marginal Propensity to Repay Debt. The number of observations is 931.

Table 7: **Reported preferences - LOSS Scenario**

	MPC	MPCND	MPCD	MPS	MPRD
Mean	68.52	43.31	25.21	14.28	17.19
Std. Dev.	2.18	2.11	1.73	1.61	1.83
Mean (Winners)	69.04	43.93	25.12	14.99	15.96
Std. Dev. (Winners)	1.99	1.99	1.69	1.52	1.63
Mean (Non-Winners)	68.00	42.69	25.31	13.58	18.42
Std. Dev. (Non-Winners)	3.92	3.66	2.88	2.77	3.35

Note: The table contains reported Marginal Propensities at the four-month horizon in percentages of the €1,000 LOSS treatment. Means and standard deviations are weighted using the estimated weights IPW (see Appendix B.7). MPC is Marginal Propensity to Consume, MPCND is Marginal Propensity to Consume Non-Durables, MPCD is Marginal Propensity to Consume Durables, MPS is Marginal Propensity to Save, and MPRD is Marginal Propensity to Repay Debt. The number of observations is 929.

contrast, Fuster, Kaplan, and Zafar (2021) estimate a much lower MPC of 7 percent for a $500 GAIN at a three-month horizon. One possibility for the difference with the latter paper could be the stark difference in the state of the economy from which the two samples were drawn. As noted earlier, in 2019 Greek GDP per capita was still 20 percent below its peak in 2008. In contrast, in the US economy that provided the Fuster, Kaplan, and Zafar (2021) sample, GDP per capita was 35 percent higher in 2019 than in 2008. Another difference is that the treatment of €1,000 in our survey instrument is comparatively higher when translated into average monthly salaries. Crossley et al. (2021) find an MPC of 11 percent for UK households during the COVID-19 pandemic. They attribute this relatively low estimate to a strong desire to deleverage due to the economic uncertainties associated with the pandemic. We show below that, in our sample, strong desire to deleverage coexists with high MPC.

Respondents to the survey were also asked how they would distribute their savings out of the windfall income. On average, they would channel €194 to gross saving and €319 to repaying their debt. These responses show clearly that households are quite mindful about servicing their debt.

Our survey instrument also has a LOSS scenario of €1,000, for which we do not have corresponding *revealed-preference* estimates. The average reported MPC for the LOSS scenario is €685, split between €433 in non-durables and €252 in durables. This is larger but close to the corresponding estimate in Christelis et al. (2019) (50 percent). Again, Fuster, Kaplan, and Zafar (2021) find a much lower estimate of 32 percent for a $500 LOSS scenario. Consistent with existing research, we find that individuals report significantly larger and more widespread responses to income losses than to gains (in addition to the above two studies see also Bunn et al. (2018) and Colarieti, Mei, and Stantcheva (2024)). This pattern is often interpreted as supporting models that incorporate precautionary saving or liquidity constraints. However, an alternative explanation, recently proposed by Mijakovic (2022), suggests that households may be averse to dissaving—a behavioral tendency linked to mental accounting practices.

When faced with income loss, household responses point to a substantial change in the allocation of their net saving. On average, they would reduce gross saving by €143 and they would reduce their repayment of debt by €172. There is a clear asymmetry in individuals' net saving decisions between the GAIN and the LOSS scenarios. The LOSS scenario entails a 26 percent reduction in MPS (143/194) but a 46 percent reduction in MPRD (172/319), compared to the GAIN scenario. Again, these responses show that households are quite mindful about servicing their debt and this is in part the reason for the increased MPC in the LOSS scenario. The debt overhang in the Greek economy seems to be affecting both the MPC of households and their financial decision regarding their net saving.

Another result indicative of the degree that financial distress is affecting individuals' consumption and saving decisions is obtained when we separate individuals by their arrears to the State in the same manner that we did earlier. In the GAIN scenario, individuals with zero arrears report about equal MPS and MPRD (€245 and €247 respectively), whereas individuals with high arrears, Group 3, report €117 and €472 correspondingly. Clearly, individuals with high arrears prioritize servicing their debt obligations at the expense of consumption and gross savings. For the LOSS scenario, individuals with zero arrears report MPS and MPRD of €166 and €129 respectively, whereas individuals with high arrears, Group 3, report €88 and €284 correspondingly. These numbers also demonstrate the added burden of debt servicing for financially fragile individuals.

A key finding from Tables 6 and 7 is that there are no significant differences in the average reported preferences between winners and non-winners. Additionally, Figure B.2 in Appendix B.8 shows that the entire distribution of responses on marginal propensities —not just the average— is similar between winners and non-winners. This consistency holds across both the GAIN and LOSS scenarios and for all marginal propensities examined. In other words, individuals who experienced an actual event (winning the lottery) reported preferences similar to those in a hypothetical scenario (non-winners). The treatment effect seems indistinguishable between the two groups. Given that surveys typically place individuals in hypothetical situations, this novel finding is reassuring, suggesting that these responses may be applicable in real-world contexts, such as fiscal transfers.

4.1 Heterogeneity of Reported MPC

Following Campbell and Mankiw (1989), the two-agent model, which combines hand-to-mouth and permanent-income households, has become a popular framework for introducing heterogeneity into macroeconomic models. However, in Figure 3, which shows the distribution of reported preferences from our survey, we find that the heterogeneity is much richer.[23]

Figure 3 shows that the distribution of MPCs is trimodal, with the three modes taking the

23. We thank Deniz Aydin for suggesting the analysis in this subsection.

values of 0, 0.5 and 1. We categorize this heterogeneity into six types and provide some statistics for the GAIN scenario in Table 8. Spenders, who have a MPC of 1, are hand-to-mouth consumers. They make up 33% of the population and allocate their consumption between non-durables and durables in a 3-to-1 ratio. The second modal group seems to behave according to the Permanent Income Hypothesis with MPC = 0, making up 35 percent of the population. These households either save their windfalls, pay down debt, or do both. This group, therefore, is diverse, comprising three types. *Savers* allocate all their windfall to savings (with a marginal propensity to save, MPS, equal to 1); *Debt Servicers* allocate entirely to repaying their debt (with a marginal propensity to repay debt, MPRD, of 1), and *Mixed Saver/Servicers* who split their windfall between saving and debt repayment (MPS + MPRD = 1). On average, households in the Mixed group split their windfall equally between saving and debt repayment. Almost two-thirds of the households with MPC=0 are primarily involved in debt deleveraging. Finally, households with an MPC between 0 and 1 are divided into two types: the *Equal Splitters* (19 percent of the population), the third mode of the distribution, who split their windfall equally between consumption and net savings, and the *Unequal Splitters* (13 percent of the population) who allocate on average roughly equally between consumption and net savings. Both of these groups prioritize non-durables over durables in their spending choices.

The propensities reported here reflect a 4-month horizon. In Appendix Table B.5, we classify consumers into six types based on their responses in the LOSS scenario. Notably, we observe that in this scenario hand-to-mouth consumers (with MPC=1) make up more than half of the population. Appendix Tables B.6 and B.7 show that the distribution of these consumer types are similar for both winners and non-winners within each scenario.

Table 8: **Heterogeneity of Agent Types according to their Survey Answers (GAIN Scenario)**

Type	**Frequency**	**MPC**	**MPCND**	**MPCD**	**MPS**	**MPRD**
Spender	0.330	1.000	0.729	0.271	0.000	0.000
Saver	0.126	0.000	0.000	0.000	1.000	0.000
Debt Servicer	0.203	0.000	0.000	0.000	0.000	1.000
Mixed Saver/Servicer	0.025	0.000	0.000	0.000	0.469	0.531
Equal Splitter	0.191	0.500	0.367	0.133	0.176	0.324
Unequal Splitter	0.125	0.489	0.395	0.094	0.185	0.327

Note: The table describes six different types of consumers based on their reported preferences. Frequency is weighted. The other columns contain the weighted averages of responses on marginal propensities (as a fraction of 1) to consume (MPC), consume non-durables (MPCND), consume durables (MPCD), save (MPS), or repay debt (MPRD) out of €1,000 unexpected, one-time tax-free transfer (GAIN scenario) at the four-month horizon. The types are defined as follows. Spender: MPC=1, Saver: MPS=1, Debt Servicer: MPRD=1, Mixed Saver/Servicer: MPS+MPRD=1 and MPS≠1 and MPRD≠1, Equal Splitter: MPC=0.5, Unequal Splitter: MPC≠0 and MPC≠0.5 and MPC≠1. The number of observations is 931.

5 Concluding remarks

This paper utilizes random and simultaneous assignment from a tax lottery to overcome the identification challenges in estimating *revealed-preference* intertemporal Marginal Propensity to Consume (iMPC). Using administrative data, we provide clear causal evidence of high iMPCs in Greece at the end of 2019, when the economy was experiencing a prolonged depression, with households facing limited credit access and substantial debt burdens. Our findings show that intertemporal MPCs remain significant even up to eight months after the initial shock. Our estimates suggest an MPC between 45% and 50% over the four-month period following unexpected income windfalls. These *revealed-preference* estimates closely align with the *reported-preference* MPC estimate of 49% derived from a tailored survey of the same households.

Over an eight-month period, the cumulative MPC from an income windfall rises to 69%, supporting the argument that deficit-financed fiscal stimulus could effectively sustain economic activity with lasting effects, potentially making such deficits self-financing (see Angeletos, Lian, and Wolf (2024) and Auclert, Rognlie, and Straub (2024, forthcoming). Because we provide iMPC estimates at a monthly frequency, these results can inform the calibration of macroeconomic models to yield policy-relevant outcomes. Additionally, our survey shows an MPC of 67% in response to unexpected income losses at the four-month horizon, indicating even larger multipliers for contractionary fiscal policies.

Through *revealed-preference* estimates, we document substantial heterogeneity in MPC across households based on observable characteristics, offering valuable insights for theoretical models of household behavior. Meanwhile, *reported-preference* estimates of MPC, MPS and MPRD identify six distinct household types. This diversity highlights the potential to develop more comprehensive models that capture the varied behaviors of different household types. The estimated moments we present in this paper can be used to calibrate such models.

This paper highlights the robustness of our approach in assessing consistency between two empirical methods—*revealed-preference* and *reported-preference* estimates—and in identifying the causal effects of one-time income shocks. The cross-validation of survey data with administrative transaction data, as well as the alignment of the estimates, strengthens the case for using household surveys to study consumption and saving behaviors. With the growing role of surveys in economic research, we argue that they offer a powerful complement to traditional data sources and methodologies.

Our findings have direct implications for designing more effective countercyclical policies. A key challenge for policymakers is that MPCs are not constant but rather responsive to the economic and policy context. Real-time MPC estimates, therefore, provide more accurate forecasts of the impact of stimulus payments than relying solely on historical data.[24] This paper demonstrates a framework where fiscal authorities can use a tax lottery and administrative expenditure data to produce *revealed-preference* estimates of current MPC. Greece is not alone in utilizing a tax lottery; by 2024, more than a dozen countries have implemented similar programs. Even in the absence of tax lotteries, fiscal authorities can employ surveys as demonstrated here. Our finding that *reported-preference* MPC estimates align with *revealed-preference* estimates suggests that surveys can reliably assess the economic effects of stimulus programs.

24. For example, Chetty et al. (2023) illustrates this point clearly in the context of the COVID-19 pandemic in the U.S.

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Appendix to "MPCs ESTIMATED FROM TAX LOTTERY SURVEY, AND ADMINISTRATIVE DATA"

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A The tax lottery in Greece.

Each month, starting in 2017, the Independent Authority for Public Revenue (I.A.P.R.) of the Hellenic Republic conducts a monthly lottery where 1,000 winners each receive €1,000. This prize is tax-free, and it is not considered income nor can it be confiscated in the case the individual has tax debts in arrears and is not under a payment arrangement with the Revenue Authority. All consumers with a Tax Identification Number who had executed at least one electronic transaction in the previous month are included in the monthly draw performed by the Revenue Authority. Electronic transactions are purchases with credit or debit cards, and bank transfers, towards purchases of goods or services. Consumers below the age of 18 cannot take part in the tax lottery, even if they are registered with the Revenue Authority and submit a tax return.

For winners of the lottery, the prize is credited in their account provided that the consumer has provided the Revenue Authority with a valid International Bank Account Number. The number of lottery tickets given to each person is a step function of the amount of total transactions in Euros with the number of lottery tickets per Euro spent decreasing in the value of spending. There is maximum eligible spending of €50,000. The probability of winning, therefore, is not constant across consumers but it depends on the amount of purchases made. Each participant can win up to two (2) times in the same calendar year. In case a participant wins more than two times, the amount corresponding to the prize is paid to the 1st, 2nd, and so on from a reserve list drawn. Taxpayers who have won in the lottery and have not declared a payment account are given three months from the date of the draw to declare the payment account to which they wish the prize money to be credited. The amount corresponding to the cash prize is credited interest-free. If a winner does not provide a bank account within the specified deadline, the amount corresponding to the prize is paid to the 1st, 2nd, and so on from a reserve list.

The following table provides some information on the number of e-transactions, lottery tickets, age of participants, household size, and declared household income (as of 2019) for the participants in the November 2019 lottery.

Table A.1: Descriptive statistics of the population of the tax lottery

Variable	**Count**	**Proportion**	**Mean**	**Std.Dev.**	**p1**	**p25**	**p50**	**p75**	**p99**
Lottery Tickets	5,695,732	100.00%	298.07	343.21	5	120	257	396	1200
E-Transactions (€)	5,695,732	100.00%	626.31	3,129.24	4.3	119.11	312.42	635.535	5,092.46
Age	5,695,732	100.00%	49.59	17.27	20	36	48	62	89
Household Size	5,480,822	96.23%	2.12	1.19	1	1	2	3	5
Individual Income 2019 (Declared)	5,480,822	96.23%	17,651.13	38,341.43	0	5,977.84	13,262.2	23,165.5	83,774.7

Note: Lottery population size is 5,695,732. Household Size and Individual Income were available for 5,480,822 individuals in the population. For variable definitions, see Appendix A.2. Electronic transactions refer to the month of October 2019.

A.1 Sample construction

The sample is based on the tax lottery that took place on 28 November 2019. The lottery pool included 5,695,732 individuals who had made transactions in October 2019 and had a Tax Identification Number (TIN). A TIN is required in order to open a Greek bank account or obtain a Greek-bank-issued credit card. The I.A.P.R. notified the 1,000 winners by email and SMS the following day. The €1,000 prize was credited in the winners' bank account on 20 December 2019, except for a few cases where this was done on 17 January 2020 and 21 February 2020. This delay occurred because some of the winners provided their bank account details in the system late. Two winners failed to provide their bank account details to I.A.P.R. until the 28th of February 2020 and thus were disqualified from receiving the prize and are not included in our sample. An important element in interpreting empirical results is that lottery prizes were paid 20 days after the announcement of the winners.

The objective was to contact all lottery winners (1,000), except those who had never filed a tax return (16) or were listed as dependent members of a household (35), or had filed a separate tax return from their spouse/partner (7). This left 942 winners in the pool to be contacted. For each of the 942 winners, we picked up to 10 matched non-winners from the population of lottery participants. The matching was performed according to the following procedure. For each winner, we generated the subset of the population that contained all exact matches on Sex, Region of Residence, Age, Marital Status, and Household Size. If this exact matching procedure selected fewer than five matches of non-winners, we would then relax the Household Size criterion by allowing the matching to be performed even when the non-winner's household had one more/less member than the winner's household. The next step was to select from this set only those individuals who belonged to the same "Declared Household Income for 2018" category as the winner. To do so, we separated the 2018 income distribution of the November 2019 lottery participants into 12 groups delineated by the following percentiles: minimum, 5%, 10%, 20%,...,80%, 90%, 95%, and maximum. If this procedure selected more than 10 matches among non-winners for each winner, the algorithm prioritized for contact those matches that had the closest absolute distance to the number of lottery tickets of the corresponding winner. Given the size of the population pool, matching was performed without replacement. This procedure created a donor pool of controls that consisted of 5,977 individuals.

The first stage of our survey commenced on Monday, 2 December 2019. A team of 15 highly specialized employees from the Customer Support Centre (CSC) of the I.A.P.R. was designated to work on the study. CSC is responsible for providing information to taxpayers regarding tax matters. All team members from CSC had been appropriately briefed so there would be a common response, should subjects want additional clarifications. A Q&A document was prepared by the CSC and the research team and was shared with all CSC team members. At first, through telephone contact, lottery winners were informed they had won in the 34th tax lottery conducted on 28 November 2019 and were also told to expect a bank deposit of their prize in about 20 days. Subject to their acceptance to participate in our study (see scripted texts below), subjects were asked initial questions on the phone about their household status and how they were planning on using the lottery prize.

Winners were asked how they would dispose of their €1,000 prize. Non-winners were presented a hypothetical scenario of income windfall equivalent to €1,000 and asking them how they would react. Both winners and non-winners were asked a final hypothetical question, in which they had to answer how they would react in case of an unexpected one-time loss of €1,000 in their net income. Subjects were assured that full confidentiality would be maintained throughout this whole process and that they had the right to opt out of the survey and the study at any time without consequences, with their data deleted should they wish this. This option was provided to them during the telephone contact and it was also available to them through a link that was active for several months. Within a few weeks of the initial contact, 35 subjects asked for their data to be deleted. A total of 1,014 taxpayers responded positively to the CSC team answering the telephone questions and did not request for their data to be deleted. Of these, 481 were winners and 533 were non-winners. We refer to this as the **Telephone Sample**.

After answering this first set of questions, the taxpayers were asked to follow a link to a website (sent both by email and SMS text) and answer, at a later time and anonymously, a questionnaire. This link was forwarded to them via SMS and email immediately after the telephone contact. The main idea of the online questionnaire was to find out how subjects planned on distributing the amount they would receive shortly (in about 20 days) among consumption, savings, debt repayment, and financial aid to others, within the next 4 months from receiving it. As noted above, for the non-winners, the question regarding spending the additional income was asked hypothetically. This online questionnaire stage of the survey as well as following stages are not used in this paper and are for future research.

The survey we use in this study was conducted from 2 December 2019 to 13 December 2019 (with a limited number of phone calls also made on 19 and 20 December 2019). The approach was to attempt to contact by phone all 942 winners and as many as possible of the non-winners in the Donor Sample. Contact with non-winners was attempted repeatedly, giving up only after at least three tries had been made. For non-winners, the strategy was to go through the list of matches for each winner proceeding to the next person on the list after each failed attempt to reach a candidate non-winner.

To ensure overlap of propensity scores (PS) between the treated and control groups in the sample of 1,014 taxpayers, we excluded winners with PS greater than the maximum PS of non-winners, as well as non-winners with PS lower than the minimum PS of winners (see Imbens and Rubin (2015), pp. 292-293). PS is the individual's probability of winning one of the thousand prizes in the lottery, which is observed. The final sample used in estimation contains 440 winners and 491 non-winners.

A.2 Administrative data

The I.A.P.R. provided us with anonymous administrative data on the 1,014 individuals who agreed to participate and have their data disclosed. The data of interest were mainly drawn from the annual *Income Tax* Return (form E1) and the property statement (form E9). The related variables used in the regressions of this paper are:

Electronic Transactions: Data on monthly electronic transactions are employed when we estimate the MPCs based on revealed preferences. I.A.P.R. has provided us with monthly data on the totality of electronic transactions for each of the 1,014 taxpayers dis-aggregated by credit and debit card transactions and bank transfers, starting from January 2017 until July 2020. We define spending as the sum of credit- (CRD) and debit- (DDT) card transactions, that is we do not include bank transfers.

Arrears: The exact amount of participants' arrears to the State and the broader public sector at the end of 2019 was provided to us by I.A.P.R.

Income: Total tax and total income are officially reported in the tax returns. We deduct total taxes from total income to obtain net annual income. In this paper, we report results for gross income.

Liquid Wealth: Tax returns contain information regarding the annual interest earned by individuals on deposits. We calculate average annual deposits for the entire household employing the effective average interest rate on deposits provided by the Central Bank of Greece. We used the interest rate for deposits with agreed maturity of up to one year. See Bank of Greece - Bank Deposit and Loan Interest Rates, (Tables 1 and 1a).

We generate the variable "liquid wealth" using the total amount of bank deposits we calculated above plus a proxy for cash. Cash is estimated based on the following procedure. Firstly, we assume that households hold cash balances equal to 5 percent of their annual deposits. Additionally, we assume that each member of the household holds at least 10 euros in cash at any moment. Finally, we set an upper limit for cash at 150,000 euros.

Illiquid Wealth: Our measure of illiquid wealth consists of variables we took from the tax returns and the property statements of the participants. More specifically, the variable "illiquid wealth" represents the sum of the real property value, car value, and boat value. Regarding the value of the real property of each household, the I.A.P.R. has provided us with anonymous information about each household's property value. This is the value used for tax purposes (called "objective value"). Moreover, tax returns contain information regarding the characteristics of cars and boats the taxpayers own, which is used as presumptive criteria for taxable income. Since we do not know the exact market value of cars and boats, we make estimations based on the details reported in tax returns about the engine size (cars), length (boats), and age (both cars and boats). Our estimates are based on the prices of cars and boats that match the above characteristics in the most notable online sales platform in Greece through the online platform car.gr .

Position in the tax return: This category is comprised of the following levels: "HEAD", "SPOUSE", "GUEST", "GUEST MAIN RESIDENCY". "HEAD" is the head of the household for tax purposes, "SPOUSE" is the spouse of the head, "GUEST" and "GUEST MAIN RESIDENCY" are individuals who are being hosted and have not declared a main residence or were being hosted but declared a main residence part of the year, respectively.

Marital status: Comprises the following official categories according to I.A.P.R.: "UNMARRIED", "MARRIED", "DIVORCED", "WIDOWER", "SEPARATED". The category "UNMARRIED" is equivalently called in this study "NEVER MARRIED." In this study, we also use the term "SINGLE" to refer to the union of categories: "UNMARRIED", "DIVORCED", "WIDOWER", and "SEPARATED".

Household size: The number of individuals included in the tax return. This includes the head, the spouse, and all dependent members, but it does not include guests. If spouses file tax returns separately, then household size includes the dependent members of both tax returns. If an individual has been assigned the position "GUEST" or "GUEST MAIN RESIDENCY" this counts as a separate return, therefore household size is set to 1.

Greek Regions: This category provides the region of residence for each individual. The levels are "Attica2" (to distinguish it from 'Attica' the prefecture, which is different), "Eastern Macedonia and Thrace", "Epirus", "Central Macedonia", "Western Macedonia", "Thessaly", "Central Greece", "Western Greece", "Peloponnese", "Ionian Islands", "North Aegean", "South Aegean", and "Crete".

Propensity score: (PS) is defined as

$$P_i = \frac{N_i^{tickets}}{1,698,000,000/1000} = \frac{N_i^{tickets}}{1,698,000},$$

where $N_i^{tickets}$ is the number of tickets each individual was awarded for their electronic transactions. The maximum number of tickets awarded to any individual was 8,684, corresponding to electronic transactions of €50,000 or more in October 2019. Thus, the maximum PS (probability of winning) for any individual is 0.511%. Following Imbens and Rubin (2015), the linearized propensity score (LPS) is

$$\ell_i \equiv \ln\left(\frac{P_i}{1-P_i}\right).$$

Demographics: Since tax returns contain information regarding the sex, age, marital status, household size, and place of residence of the taxpayers, we were able to collect this kind of data as well and include them in regression analysis as controls. The demographic variables are categorized and used in regressions as dummies. Finally, we create dummies for the Prefectures of Greece where the household resides. Greece has a total of 54 prefectures; however, our sample of participants is distributed across 51 Prefectures for 2019.

B Methodology

B.1 Estimated Quantile Function

The quantile function we used is the inverse of an Empirical Weighted Cumulative Distribution Function (EWCDF). The EWCDF value 'y' is equal to the sum of weights of all entries of x that are less than or equal to y.

B.2 Observable predictors of treatment

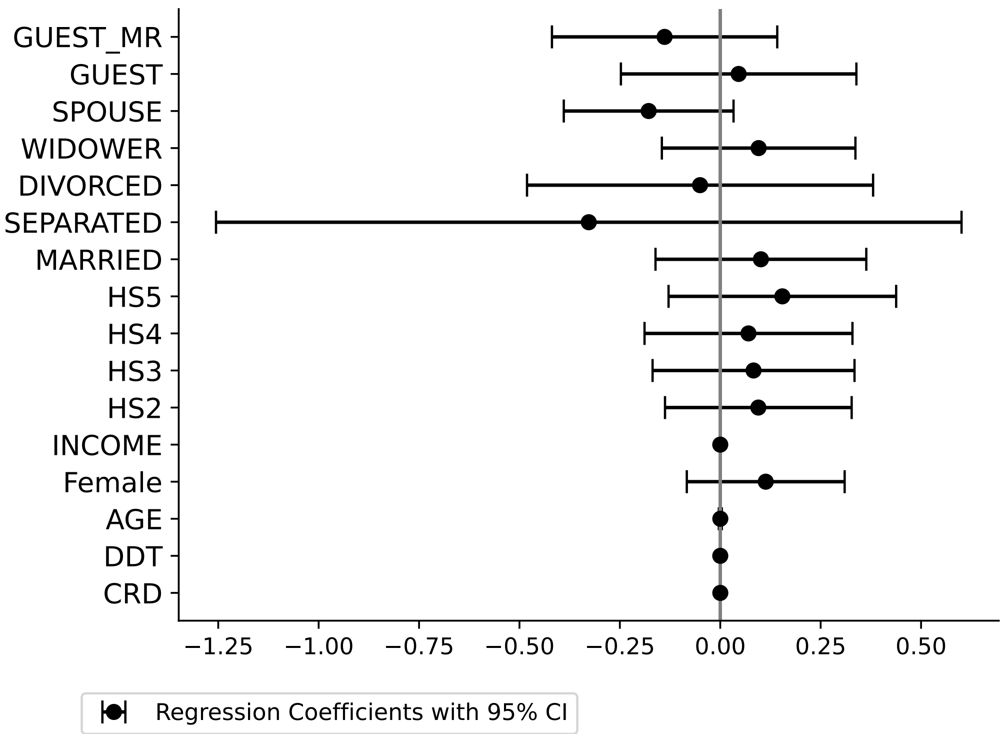


Figure B.1: Observable predictors of treatment

Note: We report the coefficient values and 95 percent Confidence intervals (HC) of a Weighted Least Squares regression, where the dependent variable is the treatment dummy (Winner) and we use the estimation sample (N=931). The covariates include indicator variables for household size (HS - baseline is the one-person household, i.e. HS1), Greek Regions (results not shown), position in the household's tax return (baseline is HEAD), marital status (baseline is UNMARRIED), income, sex, age and euro amount of credit- (CRD) and debit-card (DDT) transactions in October 2019. The definition of the covariates are found in Appendix A.2.

B.3 Bootstrap

In order to estimate the standard errors of our estimates, we opted to use a bootstrap method. We drew, with replacement, from the populations of the winners and the controls, creating two new "bootstrap sub-populations". The treated population comprised 1,000 individuals, while the control population consisted of 5,695,732. We then fitted a logistic regression on the two new populations. Any "bootstrap populations" on which the logistic regression could not converge were deleted. Also, if our new "population" resulted in perfect predictors, those regressions were dropped. This happened on some of the region of residence dummies, as the initial number of participants was relatively low. We then re-estimated the probability of being a participant of our study, conditionally on being treated or controls respectively. Since for each bootstrap sample we computed new weights, the standard errors we report incorporate the errors of the sampling weights. The results reported in the paper are based on 4,000 bootstrap samples of 5,696,732 individuals. For the confidence intervals we used the bias-corrected and accelerated (BCa) bootstrap interval (Efron and Tibshirani (1993), p 184-188).

During the estimation of heterogeneous treatment effects τ^w (Equation 1 in main text), for each observable characteristic we examine, we split the sample into terciles using the estimated Quantile function of the original population (see Appendix B.1). For some bootstrap samples this resulted in having groups with less than 5 control or treated individuals. In these cases, we do not use in calculations the bootstrap $\tau^w_{b_i}$ of that sample. For this reason, heterogeneous treatment effects may have a different number of bootstrap samples.

B.4 Normalized differences

The normalized differences of each bin are defined as (see Imbens and Rubin (2015) p.310)

$$\Delta_{ct} = \frac{\overline{x}_t - \overline{x}_c}{\sqrt{(\text{Var}_w(x_t) + (\text{Var}_w(x_c))/2}}. \tag{B.3.1}$$

Our estimates are weighted, hence $\overline{x}_t, \overline{x}_c$ are the weighted averages of the treated and controls respectively. Weighted averages are estimated by

$$\overline{x} = \frac{\sum_{i=1}^{n} \tilde{S}_i x_i}{\sum_{i=1}^{n} \tilde{S}_i}, \tag{B.3.2}$$

whereas the weighted variance is given by

$$Var_w(x) = \frac{\sum_{i=1}^{n} \tilde{S}_i (x_i - \overline{x})^2}{\sum_{i=1}^{n} \tilde{S}_i}. \tag{B.3.3}$$

The normalized differences of the sample is given by

$$\bar{\Delta}_{ct} = \sum_{j=1}^{K} \left[\Delta_{ct,j} \sum_{i:B_i=j} S_i \right] \cdot \left(\sum_{i=1}^{N} S_i \right)^{-1}. \tag{B.3.4}$$

B.5 Subclassification on the Propensity Score

The procedure we followed to determine the strata (blocks) used for the WATE is based on Imbens and Rubin (2015) sections 13.5 or 17.3.1. We set the minimum number of treated or control units in a stratum to 5, and the minimum number of units in a new stratum to 10. We set the maximum acceptable t-statistic on the linearized propensity score (LPS) to 1.96, unless the minimum count requirements in the block were not met. We opted to use Welch's t-test, with $\overline{x}$ and $Var_w(x)$ defined in Appendix B.4. This tends to give higher values in our sample than the one employed by Imbens and Rubin (2015) and is thus conservative. The algorithm, when applied to our sample, determined a subclassification into 10 blocks. Table B.1 provides some statistics for each block of the sample. Examining the LPS t-scores and normalized differences we find evidence of balance in the propensity score between treated and controls in all blocks with weaker evidence in blocks 2 and 5. Table B.2 provides some statistics relevant for the heterogeneity analysis of *revealed-preference* estimates and for each block of the estimation.

Table B.1: Statistics per block for the estimating sample

Block (j)	#C	#T	f(C)%	f(T)%	Wf(T)%	Wf(C)%	**q(j)**	**LPS t-score**	**LPS Norm. Diff.**
1	45	13	9.165	2.955	3.868	19.074	0.115	0.712	0.421
2	38	20	7.739	4.545	5.288	15.144	0.102	**5.013**	**0.560**
3	65	51	13.238	11.591	13.855	15.562	0.147	-0.403	-0.020
4	123	110	25.051	25	24.929	17.971	0.215	0.184	0.08
5	18	11	3.666	2.5	2.817	6.406	0.046	**2.580**	**1.71**
6	17	12	3.462	2.727	2.677	2.094	0.024	0.699	0.114
7	33	25	6.721	5.682	5.138	3.83	0.045	0.099	-0.023
8	58	59	11.813	13.409	12.157	5.08	0.086	-0.401	0.028
9	59	57	12.016	12.955	11.011	9.45	0.102	0.055	0.134
10	35	82	7.128	18.636	18.26	5.389	0.118	0.727	0.111

Note: #C, #T are the number of control and treated units in each block respectively. f(C)%, f(T)% refer to the frequency of the control and treated units in each block. Wf(T)=$\sum_{i:B_i=j;z=1} S_i / \sum_{i:z=1} S_i$%, and Wf(C)=$\sum_{i:B_i=j;z=0} S_i / \sum_{i:z=0} S_i$% are the weighted frequencies of treated and controls, respectively. $q(j)$ is the weighted frequency of observations in the entire block. "LPS t-score" and "LPS Norm. Diff" are measures of balance in terms of the propensity score between the treated and the controls. The t-score uses Welch's t-test, with $\overline{x}$ and $Var_w(x)$ defined in Appendix B.4.

The following refers to the heterogeneity groups by observable characteristic. The sample is split into terciles of household income, liquid and illiquid wealth, and individual age using the estimated population quantile function (see Appendix B.1). See Appendix A.2 for the description of the variables. Arrears to the State are split into those with zero arrears (Group 1), and two equal-sized groups with strictly positive arrears (split at the median of non-zero arrears). The amounts are in euros. Age is in years. See Table B.4 in the Appendix for the number of observations in each group. The groups for each column have a different membership as the terciles are defined separately for each distribution of observable characteristic.

Table B.2: Statistics per block for the heterogeneity groups

Group	Block (j)	#C	#T	f(C)%	f(T)%	Wf(T)%	Wf(C)%	**q(j)**	**LPS t-score**	**LPS Norm. Diff.**
Current Income										
1	1	47	14	32.414	13.861	14.849	59.004	0.374	1.111	0.077
	2	32	30	22.069	29.703	33.309	17.059	0.25	0.135	0.167
	3	21	9	14.483	8.911	7.09	8.822	0.08	1.088	0.343
	4	15	16	10.345	15.842	16.302	7.151	0.116	-2.182	-0.094
	5	30	32	20.69	31.683	28.45	7.963	0.18	0.655	-0.079
2	1	94	60	54.651	44.118	45.966	57.253	0.514	0.234	0.143
	2	44	33	25.581	24.265	23.174	31.78	0.273	-0.406	0.348
	3	18	20	10.465	14.706	12.822	4.7	0.089	-0.639	-0.063
	4	16	23	9.302	16.912	18.037	6.266	0.123	1.630	0.516
3	1	13	9	7.602	4.663	5.326	19.785	0.126	3.876	0.902
	2	12	11	7.018	5.699	6.245	6.251	0.062	1.495	0.498
	3	23	23	13.45	11.917	12.264	12.491	0.124	0.249	0.283
	4	43	48	25.146	24.87	24.776	17.113	0.209	-0.573	0.157
	5	80	102	46.784	52.85	51.389	44.36	0.479	1.161	0.196
Liquid Wealth										
1	1	49	21	29.697	17.797	22.044	38.492	0.299	2.176	0.623
	2	47	24	28.485	20.339	20.154	27.123	0.235	-1.290	0.042
	3	42	29	25.455	24.576	22.789	15.067	0.191	0.218	0.070
	4	16	19	9.697	16.102	14.598	7.049	0.11	0.954	-0.343

	5	11	25	6.667	21.186	20.415	12.269	0.165	-0.248	0.979
2	1	19	16	13.287	11.268	13.029	37.79	0.256	0.811	-0.002
	2	16	20	11.189	14.085	15.164	11.134	0.131	1.922	0.392
	3	37	34	25.874	23.944	24.66	14.058	0.193	1.302	0.273
	4	71	72	49.65	50.704	47.147	37.018	0.42	0.700	0.221
3	1	29	14	16.763	8.14	9.228	35.903	0.226	0.687	0.407
	2	19	24	10.983	13.953	16.276	11.169	0.137	2.433	0.247
	3	23	20	13.295	11.628	10.495	14.908	0.127	1.747	0.331
	4	25	18	14.451	10.465	9.794	10.56	0.102	0.231	0.221
	5	77	96	44.509	55.814	54.208	27.459	0.408	1.357	0.173
Illiquid Wealth										
1	1	113	101						1.595	0.044
2	1	31	9	15.897	7.2	7.743	28.441	0.181	-0.750	0.233
	2	26	14	13.333	11.2	13.7	27.509	0.206	-0.007	1.097
	3	24	16	12.308	12.8	12.445	12.165	0.123	4.986	0.897
	4	24	16	12.308	12.8	11.216	6.788	0.09	3.106	0.634
	5	46	34	23.59	27.2	25.563	14.602	0.201	-0.268	-0.034
	6	44	36	22.564	28.8	29.333	10.495	0.199	1.904	0.234
3	1	24	23	14.035	11.005	13.28	33.632	0.235	2.085	0.723
	2	18	30	10.526	14.354	14.866	10.247	0.126	-0.827	0.082
	3	55	40	32.164	19.139	19.748	29.098	0.244	-0.178	0.239
	4	19	28	11.111	13.397	12.135	6.763	0.094	-1.072	-0.243
	5	24	24	14.035	11.483	10.376	8.883	0.096	-0.763	-0.322
	6	16	31	9.357	14.833	14.509	6.285	0.104	2.566	0.417
	7	15	33	8.772	15.789	15.085	5.091	0.101	1.460	0.430
Arrears										
1	1	43	18	16.35	8	9.272	36.496	0.226	1.190	0.108
	2	35	26	13.308	11.556	14.02	12.582	0.133	-1.839	-0.260

	3	38	23	14.449	10.222	9.951	10.104	0.1	-2.539	-0.249
	4	29	32	11.027	14.222	15.133	7.537	0.114	-0.913	0.051
	5	118	126	44.867	56	51.624	33.282	0.427	0.870	0.178
2	1	17	11	15.044	9.821	13.553	28.241	0.209	-0.516	0.363
	2	15	13	13.274	11.607	13.1	17.806	0.155	-0.651	-0.060
	3	26	30	23.009	26.786	24.164	18.793	0.215	-0.903	-0.234
	4	32	24	28.319	21.429	20.936	23.181	0.221	0.029	-0.035
	5	23	34	20.354	30.357	28.246	11.98	0.201	0.479	0.265
3	1	17	8	16.346	8	9.793	25.247	0.173	4.874	0.925
	2	15	11	14.423	11	11.602	19.944	0.156	0.930	0.276
	3	29	22	27.885	22	20.606	20.072	0.203	-0.980	0.124
	4	13	12	12.5	12	10.719	6.565	0.087	1.225	0.144
	5	17	9	16.346	9	8.055	22.827	0.152	-1.417	-0.954
	6	13	38	12.5	38	39.224	5.345	0.229	1.584	0.413
Age										
1	1	35	20	24.823	15.385	20.837	52.479	0.353	2.249	0.419
	2	32	22	22.695	16.923	16.085	14.235	0.152	-1.895	-0.263
	3	30	24	21.277	18.462	21.755	14.342	0.184	-1.715	-0.170
	4	27	27	19.149	20.769	18.344	13.7	0.162	-0.614	-0.315
	5	17	37	12.057	28.462	22.979	5.245	0.149	1.750	0.526
2	1	42	25	23.333	16.34	18.808	27.947	0.234	-0.253	0.180
	2	36	30	20	19.608	19.373	19.046	0.192	-1.744	-0.390
	3	34	33	18.889	21.569	20.56	23.01	0.218	0.992	0.829
	4	36	30	20	19.608	17.273	7.996	0.126	3.067	0.562
	5	32	35	17.778	22.876	23.986	22.002	0.23	0.582	0.225
3	1	38	23	24.359	15.646	17.416	43.317	0.305	3.116	0.877
	2	32	28	20.513	19.048	20.063	23.024	0.216	1.701	0.346
	3	30	31	19.231	21.088	19.778	12.653	0.162	-0.394	0.073

	4	30	30	19.231	20.408	19.6	10.144	0.148	2.878	0.602
	5	26	35	16.667	23.81	23.144	10.862	0.169	2.719	0.564
Female										
1	1	48	20	16.054	8.032	10.152	22.646	0.163	1.891	0.518
	2	24	10	8.027	4.016	4.662	11.102	0.078	0.356	0.122
	3	18	17	6.02	6.827	7.216	7.363	0.073	-0.259	-0.223
	4	82	55	27.425	22.088	23.14	22.883	0.23	-0.011	0.138
	5	23	11	7.692	4.418	3.762	5.526	0.046	0.304	0.209
	6	15	19	5.017	7.631	7.137	3.397	0.053	2.688	0.397
	7	36	33	12.04	13.253	12.188	5.937	0.091	1.258	0.264
	8	18	16	6.02	6.426	5.473	9.602	0.075	1.844	0.590
	9	13	21	4.348	8.434	8.623	3.834	0.063	6.607	1.132
	10	22	47	7.358	18.876	17.646	7.71	0.128	0.998	0.218
2	1	33	13	17.742	6.952	7.644	29.046	0.185	0.375	0.429
	2	11	12	5.914	6.417	7.869	22.24	0.151	2.750	1.344
	3	10	14	5.376	7.487	8.594	5.11	0.068	2.816	0.433
	4	46	47	24.731	25.134	25.145	14.492	0.198	0.681	0.152
	5	43	50	23.118	26.738	25.294	19.286	0.223	0.509	0.353
	6	23	24	12.366	12.834	10.951	6.606	0.088	1.212	-0.140
	7	20	27	10.753	14.439	14.503	3.22	0.088	0.749	0.240

Note: #C, #T are the number of control and treated units in each block respectively. f(C)%, f(T)% refer to the frequency of the control and treated units in each block. Wf(T)=$\sum_{i:B_i=j;z=1} S_i/\sum_{i:z=1} S_i\%$, and Wf(C)=$\sum_{i:B_i=j;z=0} S_i/\sum_{i:z=0} S_i\%$ are the weighted frequencies of treated and controls, respectively. $q(j)$ is the weighted frequency of observations in the entire block. "LPS t-score" and "LPS Norm. Diff" are measures of balance in terms of the propensity score between the treated and the controls. The t-score uses Welch's t-test, with $\overline{x}$ and $Var_w(x)$ defined in Appendix B.4.

B.6 MPC Heterogeneity by Observable Characteristic

B.6.1 Supplementary tables for heterogeneous groups

Table B.3: Normalized Mean Differences in LPS

Group	**Current Income**	**Liquid Wealth**	**Illiquid Wealth**	**Arrears**	**Age**	**Sex**	**Single Female**
1	0.072	0.333	0.044	0.046	0.408	0.265	0.345
2	0.227	0.196	0.475	0.062	0.018	0.429	0.376
3	0.306	0.261	0.271	0.190	0.187	-	-

Note: In this table we report the normalized mean differences of LPS between treated and control individuals, $\bar{\Delta}_{ct}$ (see Appendix B.4), for each group of observable characteristic. Group 1 for "Sex" corresponds to "Male." Group 1 for "Single Female" corresponds to single Female (the complement set of married female) and Group 2 corresponds to married female. The dashes (-) indicate that Group 3 is not defined for that characteristic. Membership in a group is specific to each column of characteristic.

Table B.4: Range, Count and Total Count

	Current Income		**Liquid Wealth**		**Illiquid Wealth**		**Arrears**		**Age**	
Group	*Range*	*Count / Total Count*	*Range*	*Count / Total Count*	*Range*	*Count / Total Count*	*Range*	*Count / Total Count*	*Range*	*Count / Total Count*
1	0 - 12584.53	246 / 252	10 - 102.06	283 / 294	0 - 23367.45	214 / 227	0.00 - 0.00	488 / 498	22 – 42	271 / 282
2	12613.65 - 24417.83	308 / 315	102.65 - 995.59	285 / 292	23469.75 - 101456.77	320 / 324	0.01 - 615.77	225 / 226	43 – 57	333 / 334
3	24434.33 - 299733.31	364 / 364	1002.35 - 25151432	345 / 345	101499.46 - 2365509.25	380 / 380	615.90 - 142820.20	204 / 207	58 - 98	303 / 315

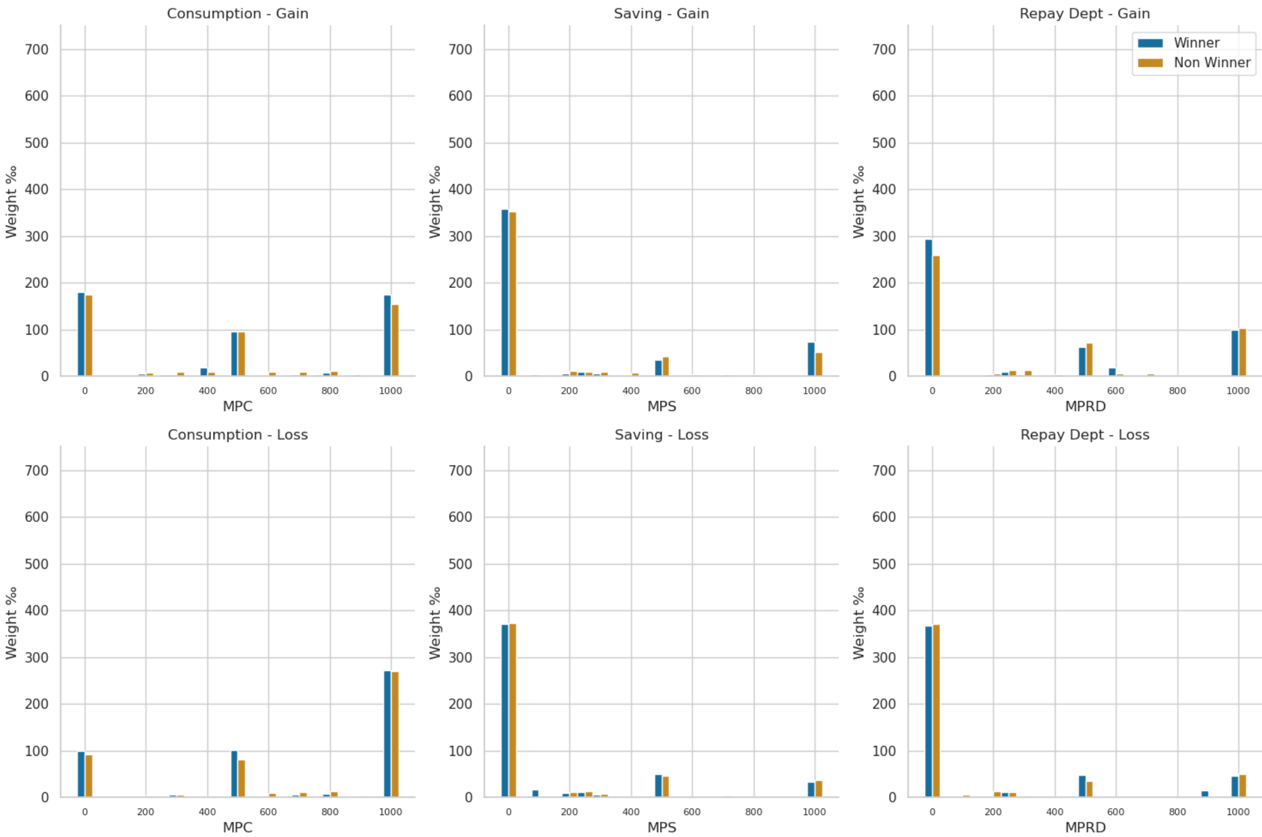
Note: In this table we report the range of values of the observable characteristic, and the count of individuals in each group. Count refers to the estimation sample, which is restricted to individuals with overlapping Propensity Scores (PS) in the group. Total Count refers to the total number of individuals in the group. For the variable "Female", the values of "Count/Total Count" are 548/554 and 373/377 for male and female respectively. For the variable "Single Female", "Count/Total Count" is 145/145 and 228/232 for single and married female respectively. Membership in a group is specific to each column of characteristic.

B.7 Inverse Probability Weights

For winners, the participation probability is the estimated probability from a participation logistic regression on the population of 1000 winners. The dependent variable $Y = 1$ if the winner was one of the 440 who participated in the estimation sample. For non-winners, the participation probability is the estimated probability from a participation logistic regression on the lottery population of non-winners. The dependent variable $Y = 1$ if the non-winner was one of the 491 that participated in the estimation sample. In both logistic regressions, the explanatory variables are the region of residence (13 dummies), household size, the position in the tax return [“HEAD”, “SPOUSE”, “GUEST”, “GUEST MAIN RESIDENCE”],[25] the marital status [”UNMARRIED”, “MARRIED”, “DIVORCED”, “WIDOWER”, “SEPARATED”], up to cubic terms of age, up to cubic terms of income, up to cubic terms of lottery tickets, up to quadratic terms of expenditures (separately for each of credit card, debit card, and transfers), and certain interaction terms. The estimated inverse probability weight (IPW), S, is the inverse of the above estimated probability.

B.8 Reported Heterogeneity: Winners versus Non Winners

Figure B.2: Distributions of MPC, MPS, and MPRD (*Reported Preference*)



Note: The figure contains the weighted distributions of responses on marginal propensities (in percent) to consume (MPC), save (MPS), or repay debt (MPRD) out of €1,000 unexpected, one-time tax-free transfer (GAIN) or €1,000 unexpected, one-time reduction on income (LOSS). The number of observations is 931 for GAIN and 929 for LOSS.

25. See Appendix A.2 for the definitions

Table B.5: Heterogeneity of Agent Types according to their Survey Answers
(LOSS Scenario)

Type	**Frequency**	**MPC**	**MPCND**	**MPCD**	**MPS**	**MPRD**
Spender	0.542	1.000	0.650	0.350	0.000	0.000
Saver	0.070	0.000	0.000	0.000	1.000	0.000
Debt Servicer	0.097	0.000	0.000	0.000	0.000	1.000
Mixed Saver/Servicer	0.024	0.000	0.000	0.000	0.254	0.746
Equal Splitters	0.184	0.500	0.288	0.212	0.271	0.229
Unequal Splitter	0.083	0.612	0.335	0.277	0.208	0.180

Note: The table describes six different types of consumers based on their reported preferences in the LOSS scenario. Frequency is weighted. The other columns contain the weighted averages of responses on marginal propensities (as a fraction of 1) to consume (MPC), consume non-durables (MPCND), consume durables (MPCD), save (MPS), or repay debt (MPRD) out of €1,000 unexpected, one-time tax-free income loss at the four-month horizon. The types are defined as follows. Spender: MPC=1, Saver: MPS=1, Debt Servicer: MPRD=1, Mixed Saver/Servicer: MPS+MPRD=1 and MPS≠1 and MPRD≠1, Equal Splitter: MPC=0.5, Unequal Splitter: MPC≠0 and MPC≠0.5 and MPC≠1. The number of observations is 929.

Table B.6: Heterogeneity of Agent Types according to their Survey Answers
(GAIN Scenario - Separated Winners and Non-Winners)

Type	**Frequency**	**MPC**	**MPCND**	**MPCD**	**MPS**	**MPRD**
Spender (W)	0.155	1.000	0.738	0.262	0.000	0.000
Spender (NW)	0.175	1.000	0.722	0.278	0.000	0.000
Saver (W)	0.051	0.000	0.000	0.000	1.000	0.000
Saver (NW)	0.075	0.000	0.000	0.000	1.000	0.000
Debt Servicer (W)	0.104	0.000	0.000	0.000	0.000	1.000
Debt Servicer (NW)	0.099	0.000	0.000	0.000	0.000	1.000
Mixed Saver/Servicer (W)	0.020	0.000	0.000	0.000	0.488	0.512
Mixed Saver/Servicer (NW)	0.006	0.000	0.000	0.000	0.402	0.598
Equal Splitter (W)	0.095	0.500	0.359	0.141	0.168	0.332
Equal Splitter (NW)	0.096	0.500	0.374	0.126	0.185	0.315
Non-modal (W)	0.075	0.486	0.383	0.104	0.220	0.293
Non-modal (NW)	0.050	0.492	0.413	0.079	0.132	0.376

Note: The table describes six different types of consumers based on their reported preferences. Frequency is weighted. The other columns contain the weighted averages of responses on marginal propensities (as a fraction of 1) to consume (MPC), consume non-durables (MPCND), consume durables (MPCD), save (MPS), or repay debt (MPRD) out of €1,000 unexpected, one-time tax-free transfer (GAIN scenario) at the four-month horizon. The types are defined as follows. Spender: MPC=1, Saver: MPS=1, Debt Servicer: MPRD=1, Mixed Saver/Servicer: MPS+MPRD=1 and MPS≠1 and MPRD≠1, Equal Splitter: MPC=0.5, Unequal Splitter: MPC≠0 and MPC≠0.5 and MPC≠1. The number of observations is 931. The sample is split into those who won the lottery (W) and those who did not(NW).

Table B.7: Heterogeneity of Agent Types according to their Survey Answers
(LOSS Scenario - Separated Winners and Non-Winners)

Type	**Frequency**	**MPC**	**MPCND**	**MPCD**	**MPS**	**MPRD**
Spender (W)	0.271	1.000	0.641	0.359	0.000	0.000
Spender (NW)	0.271	1.000	0.658	0.342	0.000	0.000
Saver (W)	0.037	0.000	0.000	0.000	1.000	0.000
Saver (NW)	0.033	0.000	0.000	0.000	1.000	0.000
Debt Servicer (W)	0.050	0.000	0.000	0.000	0.000	1.000
Debt Servicer (NW)	0.046	0.000	0.000	0.000	0.000	1.000
Mixed Saver/Servicer (W)	0.004	0.000	0.000	0.000	0.500	0.500
Mixed Saver/Servicer (NW)	0.020	0.000	0.000	0.000	0.201	0.799
Equal Splitter (W)	0.082	0.500	0.306	0.194	0.287	0.213
Equal Splitter (NW)	0.102	0.500	0.273	0.227	0.258	0.242
Unequal Splitter (W)	0.056	0.602	0.377	0.225	0.221	0.177
Unequal Splitter (NW)	0.028	0.632	0.251	0.381	0.181	0.187

Note: The table describes six different types of consumers based on their reported preferences. Frequency is weighted. The other columns contain the weighted averages of responses on marginal propensities (as a fraction of 1) to consume (MPC), consume non-durables (MPCND), consume durables (MPCD), save (MPS), or repay debt (MPRD) out of €1,000 unexpected, one-time income loss at the four-month horizon. The types are defined as follows. Spender: MPC=1, Saver: MPS=1, Debt Servicer: MPRD=1, Mixed Saver/Servicer: MPS+MPRD=1 and MPS≠1 and MPRD≠1, Equal Splitter: MPC=0.5, Unequal Splitter: MPC≠0 and MPC≠0.5 and MPC≠1. The number of observations is 929. The sample is split into those who won the lottery (W) and those who did not(NW).

Appendix C Survey Transcripts

1. **The telephone survey (December 2019) – First Stage**[26]

Good morning. Is this Mr./Mrs. (insert Full Name) with the following Tax Identification Number (insert Greek Tax ID Number)?

IF WE DO NOT FIND THE AFOREMENTIONED PERSON:

We are calling you from the I.A.P.R. We would like to talk with Mr./Mrs. (insert Full Name) [FOR WINNERS ONLY: with regard to his/her participation in the 34th Tax Lottery]. Can you provide us with a phone number so that we can reach out to him/her? What hours will he/she be available?

IF WE FIND THE AFOREMENTIONED PERSON:

We are calling you from the I.A.P.R.

[FOR WINNERS ONLY: We would like to inform you that you are one of the lucky winners in the 34th Tax Lottery which was conducted on the 28th of November 2019 with regards to the electronic transactions you carried out in October 2019. The lottery prize is €1,000 and is tax-free.]

Next, we would like to ask you whether you would be interested in participating in a scientific research conducted for a better understanding of household consumption behavior, which might assist in better economic and tax policy design. This call is being recorded.

Do you provide your consent so that we can continue with this call?

IF THE SUBJECT SAYS NO:

As you wish. Thank you.

[FOR WINNERS ONLY: Please check your inbox messages on TAXISnet to confirm that you are a winner and provide your bank account details by the 28th of February 2020. This will be the bank account to which the prize will be credited.]

Have a nice day.

IF THE SUBJECT SAYS YES:

[FOR WINNERS ONLY: First, we would like to thank you for helping the government in mitigating tax noncompliance and promoting tax morale by using electronic means of payment in your transactions.]

The survey in which you are currently participating is undertaken by the Tax Administration Research Centre (TARC) of the University of Exeter in the U.K and is being supported by the I.A.P.R.

The survey consists of two stages: We will ask you to answer a number of questions for the next 5 minutes. The answers you give, along with other information coming from your Tax Return Records (e.g. your birth year, gender, family status, reported asset, and tax information) will be forwarded anonymously to the Research Team of TARC. Confidentiality will be maintained throughout this whole process.

Next, we will send a link to your mobile phone and an e-mail that will direct you to an online questionnaire which we kindly ask you to complete. The completion of the questionnaire will take approximately 15 minutes, and it is very important that you answer the questions,

26. This is a translation of the original Greek version.

since they will be used to draw important policy conclusions.

The questionnaire is available on the Research Centre's website (www.tarc.exeter.ac.uk) and the answers will be collected anonymously by the researchers. You will be able to access the website with a 5-digit code that will be sent to you. You can opt out from the survey at any time without any consequences.

Shall we start with the questions?

Text for the lottery winners

1. Please provide us with your e-mail and your mobile phone number/confirm your e-mail and your mobile phone number so that we can later send you the questionnaire link and your 5-digit password.

2. How many people live in your household?

3. Are you listed as the Head, the Spouse, or a Dependent Member in your tax return?

4. Based on the current economic condition of your household, we would like you to tell us how you plan on using the tax-free prize of €1,000, which you will receive in about twenty (20) days from today. Consider a horizon of 4 months. Distribute the €1,000 into the following 4 possible uses:

A. Will you save so that you can spend after 4 months have passed? [0, 1,000]

B. Will you repay your debts? [0, 1,000]

C. Will you purchase durable goods and services within the next 4 months (e.g. car, motorcycle, jewellery, furniture, electronic devices, house equipment, house repairs or improvements, etc.) that you would not have initially bought or would have bought after 4 months have passed? [0, 1,000]

D. Will you purchase non-durable goods and services within the next 4 months (e.g. food, beverages, eat at restaurants, tobacco, clothes, shoes, traveling, vacation, etc.)? [0, 1,000]

5. Suppose that the government unexpectedly imposes an additional one-off tax of €1,000 on your income today. We want you to tell us how you would react to this unexpected reduction in your net income. Think in the depth of 4 months. What actions would you take? Distribute the €1,000 into the following 4 possible uses referring to the next 4 months:

A. Will you save less? [0, 1,000]

B. Will you borrow more or repay less of your debt? [0, 1,000]

C. Will you postpone or cancel purchases of durable goods and services that you had planned within the next 4 months (e.g. car, motorcycle, jewellery, furniture, electronic devices, house equipment, house repairs or improvements, etc.)? [0, 1,000]

D. Will you reduce your expenses for non-durable goods and services within the next 4 months (e.g., food, beverages, eat at restaurants, tobacco, clothes, shoes, traveling, vacation, etc.)? [0, 1,000]

Text for the non-winners

1. Please provide us with your e-mail and your mobile phone number/confirm your e-mail and your mobile phone number so that we can later send you the questionnaire link and your 5-digit password.

2. How many people live in your household?

3. Are you listed as the Head, the Spouse, or a Dependent Member in your tax return?

4. Suppose that today you receive an unexpected tax-free transfer of €1,000 from the government. We would like you to tell us how you would use the money coming from this unexpected transfer. Consider a horizon of 4 months. Distribute the €1,000 into the following 4 possible uses:

A. Will you save so that you can spend after the 4 months have passed? [0, 1,000]

B. Will you repay your debt? [0, 1,000]

C. Will you purchase durable goods and services within the next 4 months (e.g. car, motorcycle, jewellery, furniture, electronic devices, house equipment, house repairs or improvements, etc.) that you would not have initially bought or would have bought after 4 months? [0, 1,000]

D. Will you purchase non-durable goods and services within the next 4 months (e.g. food, beverages, eat at restaurants, tobacco, clothes, shoes, traveling, vacation, etc.)? [0, 1,000]

5. Suppose that the government unexpectedly imposes an additional one-off tax of €1,000 on your income today. We want you to tell us how you would react to this unexpected reduction in your net income. Consider a horizon of 4 months. What actions would you take? Distribute the 1,000 euros into the following 4 possible uses referring to the next 4 months:

A. Will you save less? [0, 1,000]

B. Will you borrow more or repay less of your debt? [0, 1,000]

C. Will you postpone or cancel purchases of durable goods and services that you had planned within the next 4 months (e.g., car, motorcycle, jewellery, furniture, electronic devices, house equipment, house repairs or improvements, etc.)? [0, 1,000]

D. Will you reduce your expenses for non-durable goods and services within the next 4 months (e.g. food, beverages, eat at restaurants, tobacco, clothes, shoes, traveling, vacation, etc.)? [0, 1,000]

[NOTE TO THE AGENTS CONDUCTING THE SURVEY TO INFORM THE SUBJECT IF NUMBERS DID NOT SUM TO 1,000]