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 by analyzing administrative and survey data from the same households. Leveraging the randomized assignment of a tax lottery in November 2019, we identify large causal effects of the income windfall and track iMPCs over eight months. The spending response is front-loaded, though notable spending continues in later months as well. *Revealed-preference* estimates based on expenditure data align closely with *reported-preference* results from a survey of the same households conducted at the announcement of the unexpected transfer. This underscores the validity of our data and methods. Furthermore, survey responses from participants facing a hypothetical transfer align with those of participants facing an actual windfall, supporting the reliability of survey-based approaches using hypothetical scenarios. We document significant variation in MPCs across households and link this heterogeneity to observable household characteristics. Households report a higher MPC for unexpected income losses compared to gains and exhibit a strong preference for using windfalls to repay debt.

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. 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) 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. Jappelli and Pistaferri (2014), 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 (iMPCs) from an unexpected fiscal transfer using two methods: *revealed preferences*, derived from administrative data on household spending, and *ex-ante reported preferences* collected through a customized survey of the same households. Our study leverages a unique setting—a tax lottery with randomized and simultaneous assignment—to identify the causal effects of an unexpected fiscal transfer of €1,000. These effects are estimated by comparing the behavior of lottery winners (treated group) and non-winners (control group). Our first key finding is that the *revealed-preference* estimates, based on actual monthly expenditures, align with the *reported-preference* estimates from a survey of the same individuals conducted at the time of the income shock announcement. Moreover, survey responses are consistent regardless of whether individuals were responding to a hypothetical or imminent windfall. These novel findings reinforce the widely used approach of employing surveys with well-designed instruments to capture households' behavioral responses to different economic shocks, such as fiscal stimulus. We then provide causal estimates of key moments that can help discipline consumption and macroeconomic models. By tracking spending changes and estimating iMPCs on a monthly basis for up to eight months after the income shock, we find strong consumption responses in the first two months, followed by smaller but still significant effects in later months. Next, we explore factors associated with heterogeneity in iMPC across households and find that certain observable characteristics significantly differentiate spending behavior. Our analysis further incorporates *reported-preference* estimates of consumption, saving, and debt repayment responses to both unexpected income gain and loss scenarios, offering insights into how these shocks influence household financial decisions.

A major challenge in providing *revealed-preference* estimates of iMPCs 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, while others, who

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, Carroll et al. (2023) on the effectiveness of fiscal stimulus policies , 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.

did not win, were matched with the winners according to their true propensity scores and observable characteristics.[2] 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 entered into the lottery automatically. This allows us to use randomized 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. This enhances the external validity of our setup.

Second, to ensure that our estimates are representative of the broader Greek population, and to correct for any participation and selection biases, we applied inverse probability weights derived from selection logits on the population of lottery ticket holders, which included about 5.7 million individuals. This is another feature that enhances 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, both winners and non-winners, collecting detailed data on their consumption, saving, and debt behavior, as well as their expectations about future activity and other behavioral traits. The survey was conducted in early December 2019, shortly after the announcement of the prize to the winners and before the arrival of the funds. 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. For the control group, the situation was hypothetical. Fourth, we obtained access to anonymized administrative tax, income, spending, 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. 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 using the Imbens and Rubin (2015) estimand that stratifies the sample according to true propensity scores, and compares outcomes of the treated group of winners to the control group of non-winners within each stratum. A key distinction from previous studies is that in our study, identification is not based on the assumption of random variation in prize size or timing of its distribution.

To estimate *reported-preference* MPC, 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

2. We observe the true propensity score; the probability of winning the lottery. The lottery took place on 28 November 2019. The winners were notified by email the following day and the prize was deposited in their accounts on 20 December 2019. Sample participants, winners and non-winners, were contacted by telephone in the beginning of December 2019. An extensive description of the lottery and the empirical setup is given in Section 2.

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.[3] The average reported MPC for the GAIN scenario is €487, very close to the *revealed-preference* estimate of €448 at the four-month horizon. This result 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 and respond truthfully. In addition, the results provide general confidence in the use of survey instruments to elicit marginal propensities to consume, to save and to repay debt.

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 is uniquely designed to include both lottery winners, who were about to receive an actual income transfer, and non-winners, who were presented with a hypothetical transfer scenario. This setup functions similarly to a Randomized Control Trial (RCT). We find that both groups report similar planned responses to the income windfall in terms of consumption, saving, and debt repayment. To our knowledge, this is the first direct comparison of its kind in the literature. The consistency in responses between these two groups, carefully balanced in the distributions of observable characteristics, suggests that survey-based hypothetical scenarios can reliably capture real-world spending and saving behaviors. This finding reinforces the validity of using survey responses to inform real-world applications, such as fiscal policy decisions, and to inform and refine economic models.

Our *revealed-preference* estimates portray the dynamics of the consumption response to the income shock, tracking the path of iMPCs (as discussed in Auclert, Rognlie, and Straub (2024, forthcoming)) over the following 8 months (see Table 3). They show that a significant portion of the spending response occurs in the first two months after treatment (front-loading), though notable spending continues later as well. The estimated MPC is €157 (out of €1,000) within the first month after the treatment, rising to €406 in the first two months.[4] By the eight-month mark, the cumulative 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)).

Analyzing the *reported-preference* estimates of MPC, we find significant heterogeneity in consumption, saving and debt management behavior among the individuals in our sample. Beyond MPC, we also asked respondents how they would divide their windfall between savings and debt repayment, allowing us to estimate their marginal propensity to save (MPS) and marginal propensity to repay debt (MPRD). Based on these responses, we identify roughly six distinct household types. Focusing on the GAIN scenario and at the 4-month horizon, we find that the distribution of MPCs is heavily concentrated on three values: 0, 0.5 and 1. The first household type, *Spenders* (MPC = 1), are hand-to-mouth consumers who spend their entire windfall. This group makes up 33 percent of the population and allocates its spending between non-durable and durable goods at a 3-to-1 ratio. The second major group follows behavior consistent with the Permanent Income Hypothesis, with MPC = 0. These households, comprising 35 percent of the population, do not increase their consumption but instead save their windfall, repay debt, or do both. Within this group, we identify three subtypes: *Savers*, who allocate all their windfall to savings (MPS = 1); *Debt Servicers*, who use the

3. We did not include in the survey instrument questions about consumption, saving and debt repayment behavior at horizons other than four months.

4. Our estimates include announcement and imbursement effects as lottery winners were informed about the windfall on November 29th, 2019, whereas the funds were deposited in their accounts on December 20th, 2019.

entire amount to repay debt (MPRD = 1); and *Mixed Saver/Servicers*, who divide their windfall between saving and debt repayment (MPS + MPRD = 1), typically splitting it evenly. Notably, nearly two-thirds of households with MPC = 0 prioritize debt repayment, indicating a strong focus on deleveraging. The remaining households, with MPC values strictly between 0 and 1, fall into two categories: *Equal Splitters* (19 percent of the population), who divide their windfall evenly between consumption and net savings; and *Unequal Splitters* (13 percent of the population), who also allocate their windfall between consumption and net savings but in a less balanced way. Both *Splitter* groups prioritize non-durable goods over durables in their consumption choices. These key moments are useful in disciplining macroeconomic models.

We next examine how MPC varies across different observable characteristics. To do this, we analyze *revealed-preference* estimates, which allow us to assess iMPC heterogeneity across multiple time horizons—an aspect that sets our study apart from previous research. Specifically, we consider household income, liquid wealth, and illiquid wealth, as well as individuals' age, sex, and outstanding arrears to the State in 2019. While the first three financial characteristics have been extensively studied, our inclusion of arrears to the extended public sector is a novel contribution. To explore heterogeneity, we segment our sample into terciles, separately for each characteristic, and estimate iMPCs for each group over multiple time horizons.

For current income, we find that the highest-income households consistently exhibit the highest MPCs across all time horizons. Two months after learning about their prize, their MPC is estimated at €747, rising to €1,855 by the eight-month mark. In contrast, the two lower-income groups have significantly lower MPCs at all observed horizons.

For liquid wealth, households with greater liquidity display the highest and statistically significant MPCs at every time horizon. Those in the lowest liquidity tercile have an MPC of €478 within the first two months, increasing slightly to €510 by the eight-month mark, with most of the response occurring early on. While these figures are substantial, they remain far below those of the highest-liquidity group, whose MPC reaches €1,376 by the eight-month mark.

When examining illiquid wealth, we observe a non-monotonic relationship with cumulative MPC. Households in the middle tercile of illiquid wealth exhibit the highest and most precisely estimated MPCs across all time horizons. The lowest tercile also shows substantial, albeit lower, MPCs, though the estimates become less precise beyond the two-month mark. In contrast, households in the highest illiquid wealth tercile have MPCs that are not statistically different from zero at any horizon—a sharp contrast to the findings for liquid wealth. This underscores the need to distinguish between liquid and illiquid assets when analyzing consumption behavior.

Next, we analyze individuals' arrears to the extended public sector as of the end of 2019, which serves as a key indicator of financial health or distress. Since individuals are likely to default on State obligations only after exhausting other options, arrears provide insight into their financial vulnerability. We find a clear negative relationship between arrears and MPC. Households with no arrears—accounting for over half of the sample—show a strong consumption response, with an MPC of €547 at two months and €1,062 at eight months, suggesting that financially healthier households increase spending significantly when receiving a windfall.

In contrast, households with the highest arrears have MPCs that are statistically insignificant at all horizons, indicating that financially distressed individuals are more likely to use their windfall to repay obligations rather than increase consumption. Meanwhile, individuals with low arrears initially show a strong consumption response, but their cumulative MPC approaches zero by the end of the observation period. This pattern suggests intertemporal substitution, where early spending is offset

by later reductions in consumption.

We also explore how MPC varies by age and sex. Our findings reveal a clear negative relationship between age and MPC, with younger individuals exhibiting higher MPCs than older ones. Regarding sex, men generally have higher MPCs than women. However, this difference appears to be driven by marital status. Married women display strong and statistically significant MPCs, while single women's MPCs are not significantly different from zero. This suggests that marital status may be an important factor in shaping consumption responses among women.

Our survey instrument provides additional insights into two key aspects of household behavior. First, we estimate how households allocate their additional spending between durables and non-durables. We find that the average increase in spending on non-durables (€360) is significantly larger than that on durables (€127), a pattern that differs from previous studies, which are primarily based on U.S. data. As reviewed by Laibson, Maxted, and Moll (2022) and Di Maggio, Kermani, and Majlesi (2020), prior research generally finds that the marginal propensity to expend (MPX) on non-durables accounts for about one-quarter to one-third of total MPX. In contrast, our estimates suggest that non-durable MPX comprises roughly three-quarters of the total expenditure. As a result, the implied notional MPC for a model of the Greek economy is close to our total MPX estimates (using the terminology of Laibson, Maxted, and Moll (2022)). This contrasts with the rule of thumb advocated for the U.S. economy by Laibson, Maxted, and Moll (2022), which states that "MPC times 3 equals MPX."

Second, our survey includes an unexpected one-time income LOSS scenario of €1,000, for which we lack corresponding revealed-preference estimates. The average reported MPC in this scenario is €685, divided into €433 for non-durables and €252 for durables. Consistent with the literature, we find that reported responses to losses are significantly larger than to gains (where the MPC was €487). Survey respondents were also asked how they would allocate their savings from the windfall income in the GAIN scenario. On average, they reported allocating €194 to gross savings and €319 to debt repayment, highlighting their strong focus on servicing debt. In the LOSS scenario, households significantly adjusted their savings allocation. They reduced gross savings by a similar amount as in the GAIN scenario (€143) but made only a small reduction in debt repayment (€172). These responses reinforce the idea that households prioritize debt servicing, which contributes to the higher MPC in the LOSS scenario. This suggests that debt overhang in the Greek economy plays a crucial role in shaping households' reported MPC.

Relation to the Literature. A substantial body of research now examines consumption and saving behavior using surveys to generate what we term *reported-preference* estimates of the MPC and other key moments. These surveys ask individuals to directly report the causal effects of hypothetical scenarios on their behavior. Several studies employing this approach have been referenced in the opening paragraph of this paper. Naturally, concerns arise regarding whether respondents fully comprehend the presented scenarios, possess the cognitive ability to accurately predict their hypothetical behavior, and provide truthful answers. These concerns are critical when using reported causal effects to assess economic policies or calibrate economic models.

Our study is the first in the literature to directly address these issues by comparing *ex ante* reported preferences with *ex post* revealed preferences for the same households' consumption behavior. We link individuals' *ex ante* survey responses to their actual consumption data from administrative sources and find consistent results.[5] Furthermore, individuals who were about to receive an actual

5. Parker and Souleles (2019) run a different consistency exercise. They evaluate the consistency of *ex ante* reported intentions and *ex post* recall of behavior within the same households. Another strategy to test

transfer (lottery winners) reported *ex ante* preferences similar to those in a purely hypothetical scenario (non-winners). Given that surveys typically present hypothetical situations, these findings are reassuring, as they suggest that survey responses can be meaningfully applied to real-world contexts, such as fiscal transfers, and to inform and refine economic models.

This paper also contributes to the literature that provides *revealed-preference* estimates of the 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. Imbens, Rubin, and Sacerdote (2001) studied winners of large lottery prizes in Massachusetts (ranging from USD 22,000 to USD 9.7 million) in the mid-1980s and found that they saved approximately 16 percent of their payment stream. Several subsequent studies examined household consumption responses to U.S. tax rebates and fiscal stimulus payments, such as those in 2001 and 2008 (examples of such studies are given in the opening paragraph of the paper). Agarwal, Liu, and Souleles (2007) used credit card data to show that consumers initially saved their 2001 tax rebates but increased spending over time.

These innovative studies primarily leveraged near-random variation in the timing of payment receipt or payment size, capturing only the spending caused by the arrival of funds. Our approach differs in that we exploit randomized simultaneous assignment between winners (treated) and non-winners (control) in a tax lottery, allowing us to capture not only post-receipt spending but also any additional spending that may have occurred between the prize announcement and payout. This design is similar to those of Aydin (2022) and Boehm, Fize, and Jaravel (2024), though their setups are fully experimental. Furthermore, unlike Agarwal, Liu, and Souleles (2007), Boehm, Fize, and Jaravel (2024), and Aydin (2022), we analyze comprehensive monthly credit and debit card transactions and ATM withdrawals, covering the entire financial system servicing these individuals.

A key contribution of our paper is the provision of *revealed-preference* estimates of iMPCs, which track the aggregate consumption response at each date following the income shock. A pivotal study in this area is Fagereng, Holm, and Natvik (2021), which examined how Norwegian lottery winners responded to transitory income shocks. They found that more than 50 percent of winnings were spent within the first year and about 90 percent within five years. Compared to this study, our design and data offer several advantages. First, Fagereng, Holm, and Natvik (2021) imputed consumption at an annual frequency from income and wealth data, without precise timing for the arrival of news or funds. In contrast, our study directly measures consumption monthly using financial transaction data from the entire Greek financial system, improving precision and enabling calibration of economic models at monthly or quarterly frequencies.[6]

Second, in Fagereng, Holm, and Natvik (2021), lottery winnings were linked to active behavioral decisions (betting), and the probability of winning (propensity score) was not explicitly controlled as it was unknown. In our study, lottery participation was automatic, requiring only one electronic transaction in October 2019. Additionally, we observe and control for the propensity score when comparing treated and control individuals.

Third, our estimation methods also diverge. Fagereng, Holm, and Natvik (2021) estimated MPCs by comparing winners' consumption before and after the prize using OLS with two-way fixed effects in a staggered event-study design, assuming exogeneity of prize size and timing. In contrast, we leverage randomized and contemporaneous assignment in the tax lottery and apply the Imbens and Rubin (2015) causal estimand to identify causal effects by comparing winners' post-lottery con-

consistency 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.

6. We note, however, that we are unable to provide iMPC estimates beyond the eight-month horizon.

sumption to that of non-winners with similar propensity scores.

Fourth, our study features a uniform income shock of €1,000 for all treated individuals, allowing us to estimate iMPCs specific to this magnitude. In contrast, Fagereng, Holm, and Natvik (2021) examined prize sizes ranging from USD 1,100 to USD 150,000, with their OLS estimates reflecting a weighted average moment influenced by larger prizes.

Boehm, Fize, and Jaravel (2024), written contemporaneous with our study, presents experimental evidence on MPC using randomized assignment to distribute prepaid debit cards with varying features. Our study differs in that it examines unanticipated, transitory transfers directly from the public revenues authority, analyzes the complete financial accounts of individuals rather than a subset from a single banking group, and extends the observation period to eight months post-treatment. This allows us to estimate iMPCs over a longer horizon and provide evidence of continued additional spending until the end of the eight-month horizon. Another key distinction is that our study compares both *revealed-preference* and *reported-preference* estimates for the same households, finding consistency between them. This supports the robustness of our dataset, methodology, and results.

The literature on survey-based *reported-preference* estimates of MPC includes Shapiro and Slemrod (1995), Shapiro and Slemrod (2003), and other studies referenced in the opening paragraph of the paper. Two studies closely parallel ours in survey design: Christelis et al. (2019) estimated an MPC of 40 percent for a one-month income gain scenario, while Fuster, Kaplan, and Zafar (2021) reported a much lower MPC of 7 percent for a $500 GAIN scenario over three months. Our estimate, at 49 percent over four months, is higher, likely reflecting differences in timeframe and economic conditions. 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.

This paper contributes to the recent literature examining the Greek Depression, a crisis of unprecedented scale and duration among advanced economies. Previous studies, such as Gourinchas, Philippon, and Vayanos (2017), Ioannides and Pissarides (2015), Chodorow-Reich, Karabarbounis, and Kekre (2023), focus on macroeconomic analyses, 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. We offer new insights into austerity policies and fiscal stimulus effectiveness during a deep contraction, rather than during typical recessions. Specifically, we show that a significant portion of the population was financially fragile and burdened with high arrears to the State, forcing them to allocate a large share of their resources to debt servicing instead of consumption.

The remainder of the paper is structured as follows. Section 2 details the tax lottery setup, the data and our methodology. Section 3 presents *revealed-preference* iMPC estimates. Section 4 presents the *reported-preference* estimates from our survey. Section 5 presents evidence of heterogeneity in marginal propensities to consume, save, and repay debt. Section 6 concludes with implications for policy and future research.

2 The Tax Lottery, Data, and Methodology

2.1 The Tax Lottery

Our dataset is based on a tax lottery in Greece conducted on November 28, 2019, which awarded a tax-free prize of €1,000 to 1,000 taxpayers. Since 2017, the Independent Authority for Public Revenue (I.A.P.R.) of the Hellenic Republic has held monthly lotteries to encourage the use of electronic payments. The prize cannot be seized for unpaid tax debts, even if the recipient is not enrolled in a

payment arrangement with the Revenue Authority. Additionally, it is protected from legal claims by private-sector creditors. The lottery population includes all individuals with a Greek Tax Identification Number who made at least one electronic transaction during the previous month (the reference month was October 2019, in our setup). The number of lottery tickets allocated to each participant is determined by a step function based on their total electronic transactions in euros during the reference month. The number of tickets per euro decreases as spending increases. Eligible transactions include credit and debit card purchases as well as bank transfers. Individuals under 18 years old are not eligible to participate. Eligible spending is capped at €50,000, and each participant can win a maximum of twice per calendar year, but not in consecutive months. Lottery winners receive the prize directly into their bank accounts, and nearly all taxpayers in Greece have a registered bank account with the tax authorities for receiving tax refunds.

The lottery held on November 28, 2019, included a total of 5,695,732 participants, representing approximately 85 percent of the Greek population within the relevant age group.[7] At the time, the minimum gross monthly salary in Greece was €650 (€546 net), making the €1,000 prize a significant amount—equivalent to nearly two months' wages for minimum-wage earners. All winners were notified by email about their prize on November 29, 2019. For most winners, the prize was deposited into their bank accounts on December 20, 2019, although a small number (12 out of 1,000 individuals) received it in January or February 2020.

2.2 Sample construction and weights used

With the support of the I.A.P.R., we attempted to contact 942 of the 1,000 tax-lottery winners (W) by telephone. The remaining 58 individuals were excluded because they either had not filed taxes or were listed as dependents on tax returns. Among the 702 winners that were contacted, 481 individuals consented to share their data and answered the survey questions. At the same time, we contacted and surveyed 533 non-winners (NW) by telephone. This process took place in the first half of December 2019.[8] Anticipating non-response or opt-out and aiming for a final sample with well-balanced covariate distributions, we created a donor pool of non-winners pre-matched to the 942 winners based on propensity score (the probability of winning) and other observable characteristics.[9]

To enhance internal validity, we followed the recommendations of Imbens and Rubin (2015) and trimmed the sample to ensure overlap in propensity scores (PS) between the treatment and control groups. Specifically, we excluded winners whose PS exceeded the highest PS observed among non-winners, as well as non-winners with PS values lower than the minimum PS of winners (see Imbens and Rubin (2015), pp. 292-293). After trimming, the final estimation sample consisted of 440 winners (W) and 491 non-winners (NW). To maintain external validity and correct for potential biases due to non-response, participation, and trimming, we apply inverse probability weights (IPW) throughout our analysis. For winners, participation probabilities were estimated using logistic regression based on the full population of 1,000 winners. For non-winners, participation probabilities were estimated from

7. In 2021, the latest Census year, Greece's total resident population was 10,432,481, with 6,773,700 individuals aged between 20 and 70.

8. Participants were informed that the survey was anonymous, that they could withdraw at any time, and that if they chose to do so, their data would be deleted. They were also told that their responses, along with relevant anonymized tax return information (such as birth year, gender, family status, reported assets, income, and arrears), would be securely forwarded to the research team while maintaining confidentiality.

9. Our setup is rare among empirical studies as the propensity score is known with certainty. Balance refers to the similarity of the marginal covariate distributions between the two treatment groups. Details of the matching process are provided in Appendix A.1.

a logistic regression model applied to the entire lottery population of non-winners (approximately 5.7 million individuals).[10] The complete sample construction process, which resulted in a final dataset of 931 individuals, is detailed in Appendix A.1.

2.3 Administrative Expenditures and Tax Data

The anonymous administrative data were obtained from the I.A.P.R. and include monthly non-cash expenditures recorded across the entire Greek financial system. These expenditures are categorized into credit card, debit card, and bank transfer transactions, covering the period from January 2017 to July 2020. We do not have data on detailed expenditure categories. For the *revealed-preference* estimates presented in Section 3, we define expenditures as the sum of credit and debit card transactions, excluding bank transfers, as the latter may include debt repayments. This exclusion could potentially result in a downward bias in our MPC estimates if some bank transfers were actually used for consumption. Additionally, we obtained comprehensive household-level data from individual income tax filings (Form E1), including information on real estate holdings (Form E9) and automobile and boat assets, dating back to 2006 for individuals who had filed during those years. The I.A.P.R. provided anonymous data on the exact amount of arrears owed by the individuals to the extended public sector as of the end of 2019.

2.4 The Survey

To supplement the administrative data, we developed a survey instrument administered to the entire (pre-trimmed) sample of subjects who agreed to participate. The survey was conducted by telephone through the Customer Support Center of I.A.P.R. between December 2 and December 13, 2019.[11] Survey participants were asked to consider their household's current economic condition and allocate a tax-free, one-time income windfall of €1,000 among four categories: saving, debt repayment, non-durable consumption, and durable consumption. The time horizon for this decision was set at four months.[12] We refer to this as the GAIN scenario. A key innovation in our survey design is that lottery winners faced an imminent, real income windfall, whereas non-winners considered a purely hypothetical scenario. Additionally, participants were presented with a hypothetical LOSS scenario in which the government unexpectedly imposed a one-time tax of €1,000, effective immediately. This scenario was hypothetical for all respondents. A detailed description of the survey methodology is provided in Appendix A.1, and the full transcript of the questionnaires is available in Appendix C.

2.5 Summary statistics

To assess the external validity of our empirical design and results, we present in Table 1 key characteristics of the population that participated in the November 2019 lottery. We compare these characteristics with those of our estimation sample of 931 individuals, using the inverse probability weights (IPW) described earlier.[13] Examining moments of the weighted sample distribution, we find that it closely matches the population distribution in terms of income, age, sex, household size, and marital status.

10. A detailed description of the construction of inverse probability weights used throughout the analysis is provided in Appendix B.7.
11. A very limited number of calls were also made on December 19 and 20, 2019.
12. This design is similar to that used in Fuster, Kaplan, and Zafar (2021).
13. A more comprehensive table on the distribution of the same characteristics is given in Appendix Table A.1.

Our sample participants had more electronic transactions in October 2019 than the general lottery population, resulting in a higher number of lottery tickets and a greater average propensity score.[14]

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. Electronic transactions refer to the month of October 2019. Single Female include females that are never married, widowed, separated or divorced.

To assess internal validity, we compare in Table 2 the observable characteristics of our sample across the two groups, 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). Using the threshold of one-half standard deviation as a rule of thumb, we conclude that the standardized mean differences indicate that the two groups are generally well-balanced in terms of observable characteristics.[15]

2.6 The Causal Estimand

Our tax lottery setup is an instance of a "Classical Randomized Experiment," where $e(X_i) = Pr(Z_i = 1 \mid X_i)$ is the propensity score (PS), Z_i=0 or 1 indicates whether an individual belongs to the control or treated group, and X_i is individual i's electronic transactions in October 2019. For the *revealed-preference* estimates of MPC, we compute the Weighted Average Treatment Effect (WATE) of the income windfall using the method of subclassification on the propensity score (PS) proposed by Imbens and Rubin (2015). Since the probability of winning the lottery (PS) is known with certainty, we stratify the sample of $N = 931$ observations into K blocks (strata) in ascending order of PS so that within the strata, the PS are approximately constant. We denote stratum membership with the indicator variable B. By construction, covariate distributions between treated and control units within each stratum exhibit minimal differences. A detailed description of this procedure is provided in Appendix B.5.

14. Unreported results indicate that, without weighting, our sample consists of individuals with higher income, expenditures, and lottery tickets on average compared to the overall population.

15. While Imbens and Rubin (2015) (Section 14.4) argue that assessing differences in the distribution of the true propensity score is theoretically sufficient to evaluate overlap in the full joint distribution of covariates, we also report comparisons for individual covariates for completeness.

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 contains 440 winners and 491 non-winners. Sample moments refer to the weighted distribution. Norm. Diff. denotes normalized mean differences between treated and control observations. 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.

To estimate WATE, we use the following framework, where Y represents the outcome variable (expenditures), and S denotes 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 estimate IPW as described in Appendix B.7. We normalize the weights, S_i, by the sum of weights within each treatment group and use the adjusted weights, $\tilde{S}_i$, in our estimation.

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

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

3 *Revealed-preference* results

We start our empirical analysis by providing *revealed-preference* estimates of iMPC. For this purpose, we use administrative data on total monthly credit- and debit-card spending by the individuals in our sample.

3.1 iMPC Estimates

We apply the 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 within each block. The causal effects of winning the lottery on expenditures are presented in Table 3 and Figure 1. These correspond to iMPCs out of €1,000 at different horizons.

The MPC for December is estimated at a high value of €157, with a standard error of €62. This estimate should be interpreted with caution, as it includes only 11 days after the receipt of funds, since the prize was paid on December 20th. We consider the treatment period as beginning with the receipt of information about the lottery win, which was communicated to winners on November 29th. Therefore, we consider December a full treatment month. Additionally, December includes Christmas and New Year's Eve holiday expenditures.[16]

In January 2020, the MPC is even higher, estimated at €249 (s.e. €71). In contrast, the MPCs for February and March are significantly lower, despite February being a key month for biannual retail sales in Greece. The cumulative MPC at the three-month horizon is €440. The MPC continues to rise over longer horizons. At four months, the cumulative MPC reaches €448. At six months, it increases further to €568. By July 2020 (eight months post-treatment), the cumulative causal effect of winning the lottery is even more pronounced, reaching €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 withdrawals used for cash expenditures. If individuals took on new debt to finance additional spending through debit or credit cards, 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 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 two months. The estimated MPC for the month of July 2020 is €89, and statistically significant. This is consistent with continued increases in expenditure

16. In Greece, it is traditional to exchange gifts on New Year's Eve rather than on Christmas Day or Christmas Eve. Consequently, major shopping days fall in the second half of December.

Table 3: **Revealed-preference iMPC Estimates**

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) of a €1,000 income windfall, 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).

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.[17] 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 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.

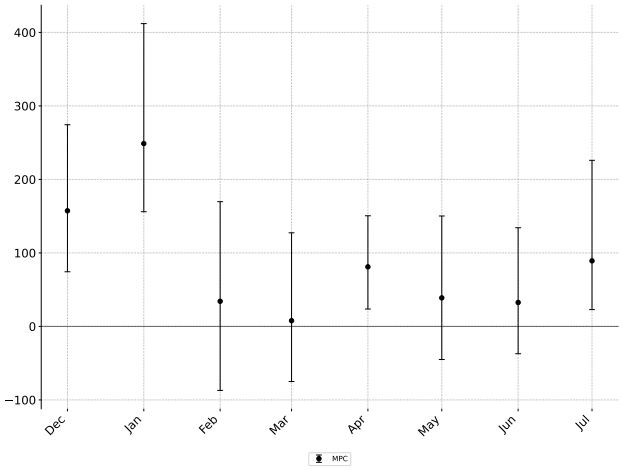
The above estimates of MPC are higher than those found in much of the literature at similar horizons.[18] Johnson, Parker, and Souleles (2006) and Parker et al. (2013) examine the response of U.S

17. 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.

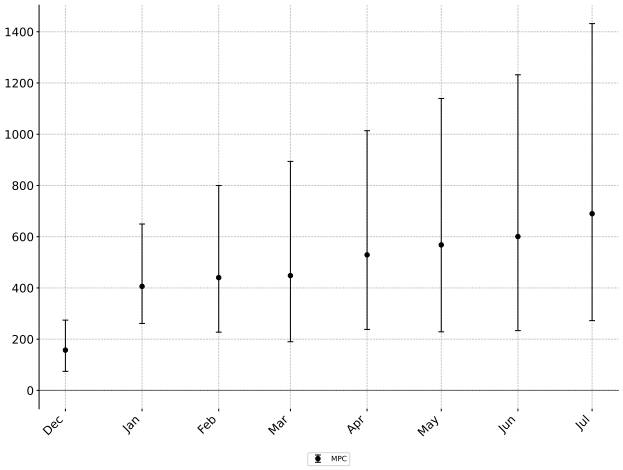
18. See Browning and Lusardi (1996), Jappelli and Pistaferri (2010) and Krueger, Mitman, and Perri (2016)

Figure 1: **Revealed-preference iMPC Estimates**

(a) Monthly MPC



(b) Cumulative MPC



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 estimates are in euros and the treatment was €1,000. The announcement of the prize to the winners was on November 29, 2019. The vertical lines report the 95 percent bias-corrected and accelerated bootstrap confidence intervals (calculated as described in Appendix B.3).

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 at an average horizon of six months following the windfall.[19] 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.

4 *Reported-preference* results

Do people follow through on what they say they will or would do in surveys? Are individuals' financial responses to unexpected income gains the same as their responses to unexpected income losses? To explore these questions—as well as other related issues—we present *reported-preference* estimates for the same sample of individuals previously used to calculate *revealed-preference* estimates

for surveys and Havranek and Sokolova (2020) for a meta-analysis.

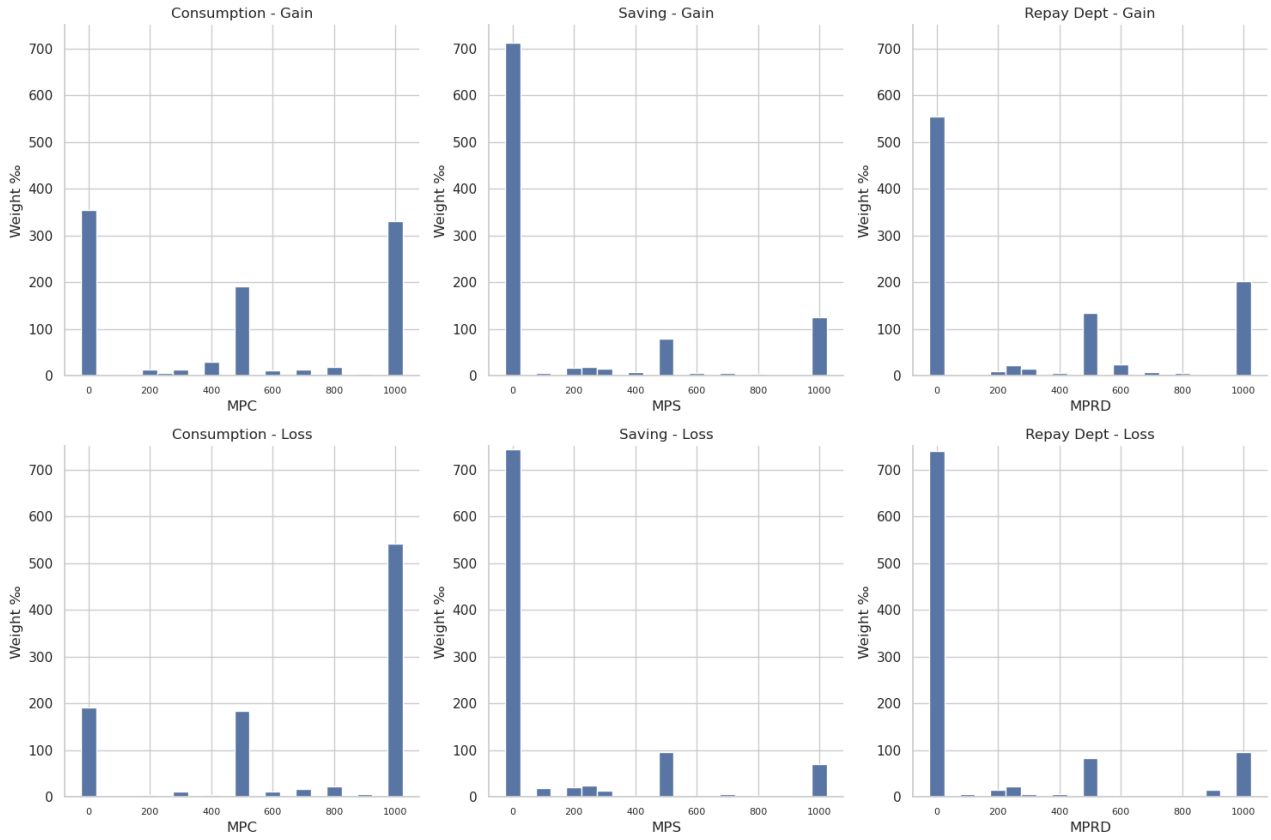
19. In their setup the timing of treatment within the year is unknown, so six months is an average estimate of the time horizon.

of iMPCs.

We conducted a survey similar to that of Christelis et al. (2019), using telephone interviews in early December 2019. Following Fuster, Kaplan, and Zafar (2021), we introduced key modifications. Specifically, we standardized the income change to €1,000, considering both a gain (GAIN scenario) and a loss (LOSS scenario), and set a four-month time horizon for observed behavior.[20]

The sample is identical to that used for the revealed-preference estimates and includes 931 participants who consented to provide their household administrative data.[21] Figure 2 shows substantial variation in reported MPC across individuals in both scenarios. In the next section, we will analyze this heterogeneity in detail. Tables 4 and 5 present the results for the GAIN and LOSS scenarios, respectively. These findings are best visualized in Figure 3.

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

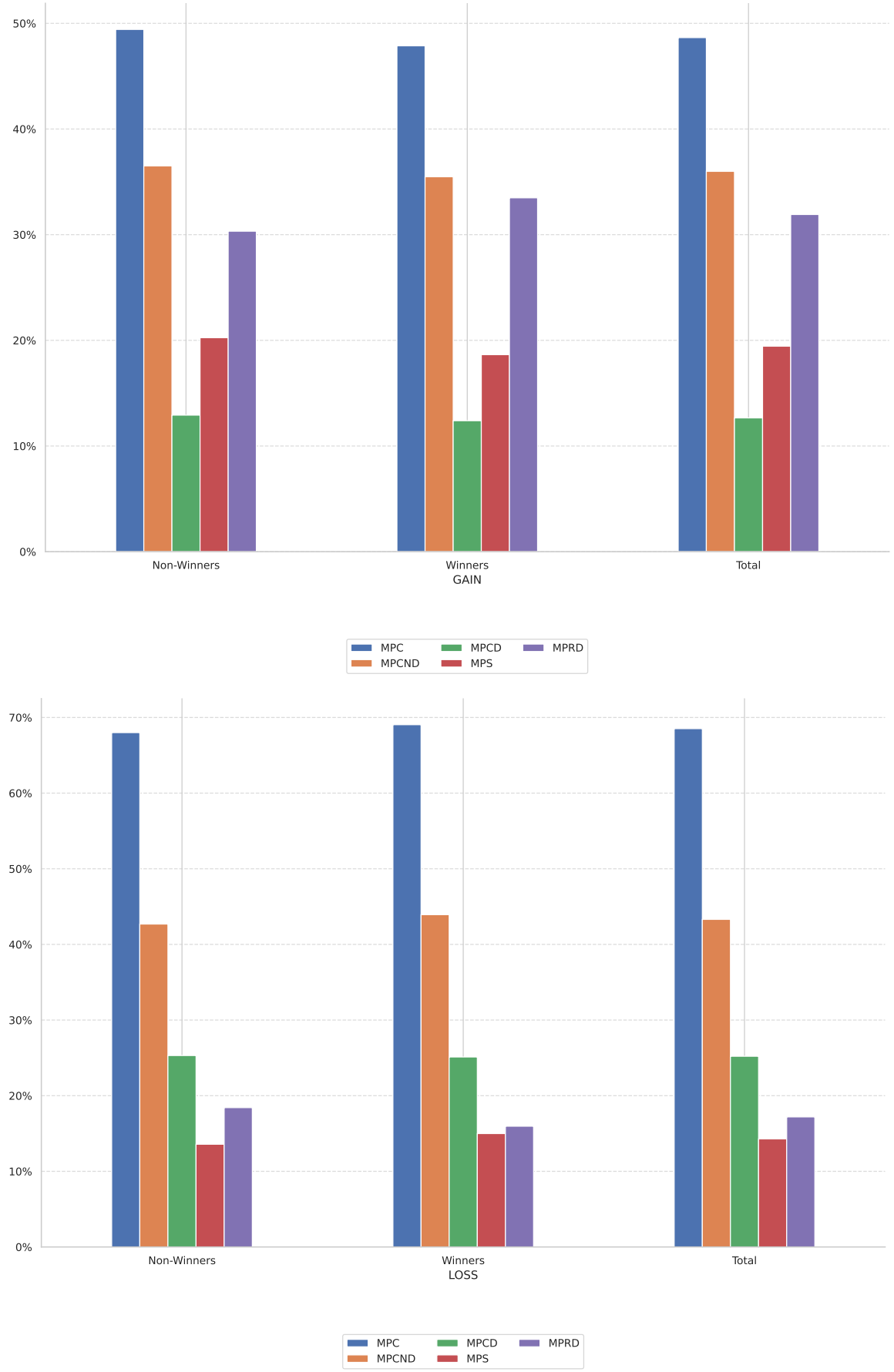


Note: The figure contains the weighted distributions of responses on marginal propensities (in percent) to consume (MPC), save (MPS), or repay debt (MPRD) out of €1,000 unexpected, one-time tax-free transfer (GAIN) or €1,000 unexpected, one-time reduction on income (LOSS). The number of observations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

The average reported MPC for the GAIN scenario is €487 very close to the *revealed-preference* effect estimate of €448 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. Our study is the first in the literature to directly compare *ex ante* reported preferences with *ex post* revealed preferences for the same households' consumption behavior.

20. Appendix A.1 provides a detailed description of the survey methodology, while Appendix Appendix C contains the questionnaire transcript.
21. Two participants did not respond to the LOSS scenario.

Figure 3: **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 in income (LOSS). The number of observations is 931 for GAIN and 929 for LOSS.

Table 4: **Reported preferences - GAIN Scenario**

	MPC	MPCND	MPCD	MPS	MPRD
Mean	486.5	359.9	126.6	194.4	319.1
Std. Dev.	23.4	21.4	14.2	19.4	22.4
Mean (Winners)	478.7	354.8	123.9	186.4	334.9
Std. Dev. (Winners)	21.2	19.7	13.0	17.0	20.6
Mean (Non-Winners)	494.2	365.0	129.2	202.5	303.3
Std. Dev. (Non-Winners)	42.3	38.1	25.4	36.1	39.8

Note: The table contains reported Marginal Propensities in euros, at the four-month horizon, for 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 5: **Reported preferences - LOSS Scenario**

	MPC	MPCND	MPCD	MPS	MPRD
Mean	685.2	433.1	252.1	142.8	171.9
Std. Dev.	21.8	21.1	17.3	16.1	18.3
Mean (Winners)	690.4	439.3	251.2	149.9	159.6
Std. Dev. (Winners)	19.9	19.9	16.9	15.2	16.3
Mean (Non-Winners)	680.0	426.9	253.1	135.8	184.2
Std. Dev. (Non-Winners)	39.2	36.6	28.8	27.7	33.5

Note: The table contains reported Marginal Propensities in euros, at the four-month horizon, for 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.

The second key finding from our survey is that individuals who were about to receive an actual transfer (lottery winners) reported *ex ante* preferences similar to those in a purely hypothetical scenario (non-winners). This is evident in Tables 4 and 5. Moreover, Figure B.2 in Appendix B.8 demonstrates that the entire distribution of responses regarding marginal propensities–not just the average–is remarkably 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 closely aligned 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. It suggests that such responses can be informative for real-world applications, such as fiscal transfers, and for informing and refining economic models.

We now compare our MPC estimate for the GAIN scenario with findings from previous studies. This is not intended as a strict consistency check, as these studies rely on different datasets, and MPC can vary due to economic conditions and survey design, including question wording. Our MPC estimate is somewhat higher but still close to the 40% estimate found in the one-month income GAIN

scenario of Christelis et al. (2019). However, since our study uses a longer time horizon, the comparison is not entirely direct. Jappelli and Pistaferri (2014) report an average MPC of 48%, noting that this is at the high end of reported-preference estimates derived from survey data.[22]

In contrast, Fuster, Kaplan, and Zafar (2021) estimate a much lower MPC of 7% for a $500 GAIN over a three-month period. One possible explanation for this difference is the economic environment at the time of each study. In 2019, Greek GDP per capita was still 20% below its 2008 peak, while in the U.S. economy, where the Fuster, Kaplan, and Zafar (2021) sample was drawn, GDP per capita had risen by 35% compared to 2008. Additionally, in our study the €1,000 treatment represents a larger proportion of the average monthly salary compared to the U.S. study. Similarly, Crossley et al. (2021) find an MPC of 11% for UK households during the COVID-19 pandemic. They attribute this relatively low estimate to a strong preference for deleveraging, driven by economic uncertainty. However, as we show below, in our sample, a strong desire to deleverage coexists with a high MPC.

Our survey respondents indicated in the GAIN scenario that they would split their consumption response to €360 spending on non-durables and €127 spending on durables. This is a pattern that differs from previous studies, which are primarily based on U.S. data. As reviewed by Laibson, Maxted, and Moll (2022) and Di Maggio, Kermani, and Majlesi (2020), prior research generally finds that the marginal propensity to expend (MPX) on nondurables accounts for about one-quarter to one-third of total MPX. In contrast, our estimates suggest that nondurable MPX comprises roughly three-quarters of the total expenditure. As a result, the implied notional MPC for a model of the Greek economy is close to our total MPX estimates (using the terminology of Laibson, Maxted, and Moll (2022)). This contrasts with the rule of thumb advocated for the U.S. economy by Laibson, Maxted, and Moll (2022), which states that "MPC times 3 equals MPX."

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

22. Jappelli and Pistaferri (2014) base their estimates on responses from the 2010 Italian Survey of Household Income and Wealth, which does not specify an action horizon. It is plausible that respondents assumed a longer period than our four-month horizon.

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 key finding that highlights the impact of financial distress on consumption and saving decisions emerges when we categorize individuals based on their arrears to the State. Arrears refer to past-due debts owed to the Greek State and public-sector entities as of December 2019. We divide the sample into three groups: (1) individuals with no arrears, comprising just over half the sample, and (2) those with arrears, further split at the median into *Low Arrears* and *High Arrears* groups.

In the GAIN scenario, individuals with no arrears report nearly equal marginal propensities to save (MPS) and to repay debt (MPRD), at €245 and €247, respectively. In contrast, individuals with high arrears allocate significantly more of their windfall to debt repayment (€472) than to savings (€117). This stark contrast indicates that those facing greater financial distress prioritize reducing their outstanding debts at the expense of both consumption and gross savings. A similar pattern emerges in the LOSS scenario. Individuals without arrears report an MPS of €166 and an MPRD of €129, while those in the high-arrears group allocate just €88 to savings but €284 to debt repayment. These figures further underscore the financial strain on individuals with high arrears, who plan to allocate a substantial portion of their resources to servicing their debt obligations.

5 MPC Heterogeneity

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.[23] In this section, we will explore the heterogeneity of MPC in our sample, first using the survey and then the transactions data.

5.1 Heterogeneity of Reported MPC

Following Campbell and Mankiw (1989), the two-agent model–combining hand-to-mouth and permanent-income households–has become a widely used framework for incorporating heterogeneity into macroeconomic models. However, as shown in Figure 2, which presents the distribution of reported preferences from our survey, the heterogeneity in consumption responses is much richer.[24]

Figure 2 reveals a trimodal distribution of MPCs, with peaks at 0, 0.5, and 1. We classify this heterogeneity into six distinct consumer types, with summary statistics for the GAIN scenario provided in Table 6. *Spenders* (MPC=1), account for 33% of the population and exhibit hand-to-mouth behavior, immediately consuming their entire windfall. Their spending is allocated between non-durables and durables in a 3-to-1 ratio. A second modal group, with MPC = 0, makes up 35% of the population and adheres to the Permanent Income Hypothesis. They either save the windfall, repay debt, or do both. This group is further divided into three types. *Savers*, who allocate their entire windfall to savings (with a marginal propensity to save, MPS, equal to 1); *Debt Servicers*, who use the full amount to pay down debt (with a marginal propensity to repay debt, MPRD, of 1); and

23. 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)).

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

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* (MPC=0.5) represent 19 percent of the population and split their windfall equally between consumption and net saving. *Unequal Splitters* (13 percent of the population) allocate on average roughly equally between consumption and net savings. Both of these groups prioritize non-durable goods over durable goods 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 6: **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.

5.2 Heterogeneity of MPC by observable characteristics

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 past-due 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.[25] Table 7 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. Appendix Table B.4 provides the range of values in each group, along with the count of observations used in each group estimation.

Table 7: **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.

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 4 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 8 for the January '20, March '20 and July '20 horizons only.[26]

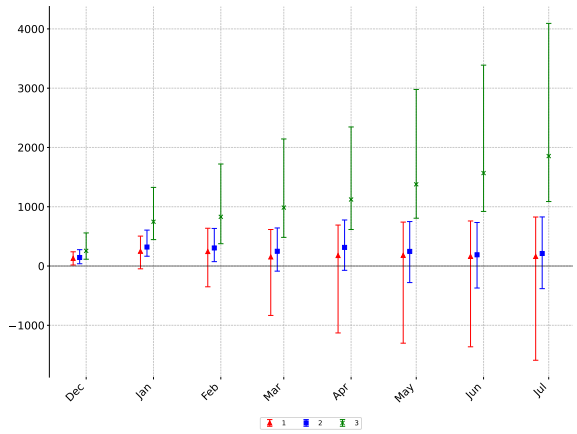
Income. The estimates (Panel a of Figure 4) show that the highest-income households exhibit the largest MPCs among the three groups across all time horizons. At the end of January 2020, 42 days after receiving the €1,000 prize, the MPC is estimated at €747 (s.e. €269). By the end of March 2020, the MPC rises to €986 (s.e. 459). Even more strikingly, at the end of July '20, eight 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 difference is largest (and significant) at the eight-month mark.

25. Ideally, we would have chosen a finer classification, but we are constrained by sample size when groups become too small.

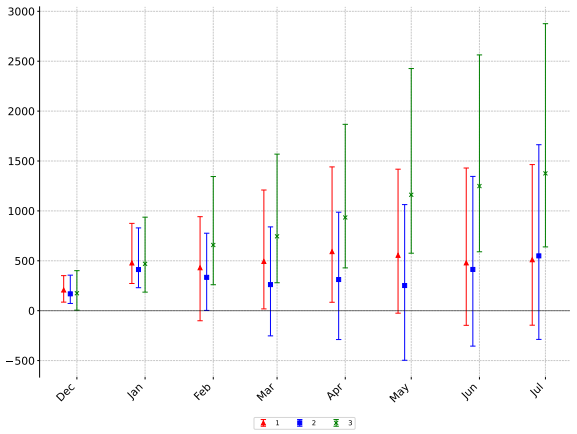
26. In Table B.3 we report the normalized mean differences of LPS between treated and control individuals within each group of observable characteristic. These indicate balance of covariate distributions within each group. In Appendix B.5 we provide some statistics and evidence of balance in the propensity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

Figure 4: **Cumulative MPC by Observable Characteristic**

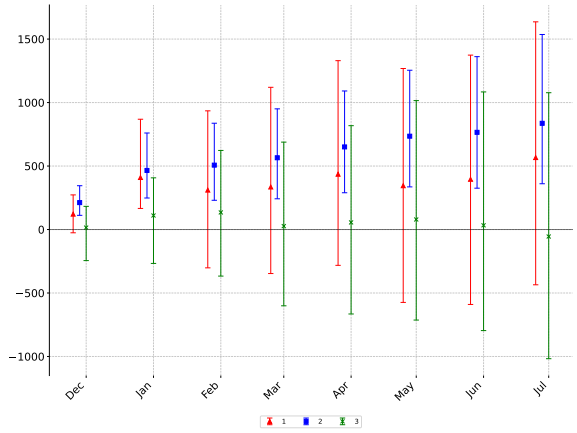
(a) Household Income



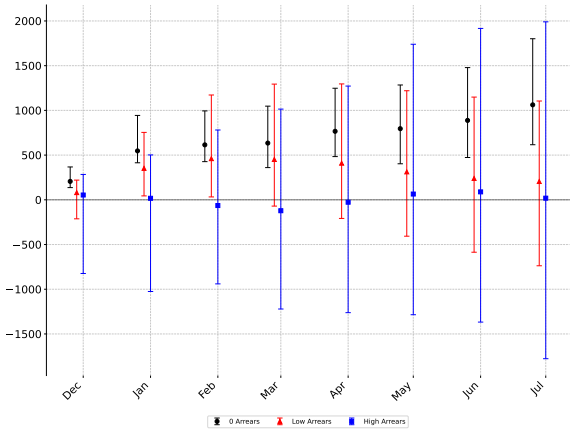
(b) Household Liquid Wealth



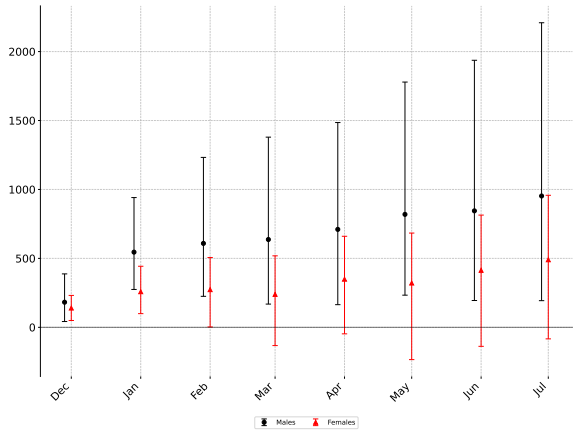
(c) Household Illiquid Wealth



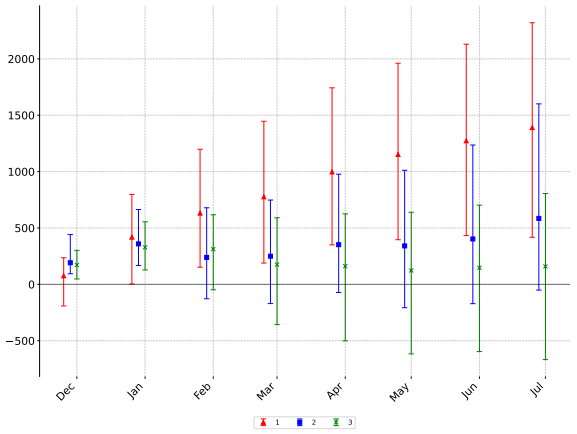
(d) Individual Arrears to the State



(e) Males vs Females



(f) Age



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 8: **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).

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 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 8 and Figure 4 (Panel b), we find that households with high liquid wealth have the highest MPCs and these 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)).[27] 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 balances.

Illiquid Wealth. The picture that emerges for illiquid wealth is a non-monotonic relationship to cumulative MPC (Table 8 and Figure 4, 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

27. 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.

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 on 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.[28] 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 8, married 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, their cumulative MPC was estimated at €827 (s.e. €413). In contrast, single females' MPCs at the same horizons are statistically insignificantly different than zero.[29] 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).

6 Concluding remarks

This paper utilizes randomized 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 of 45% over the four-month period following unexpected income windfalls. These *revealed-preference* estimates

28. In Section 4, we analyzed *reported-preference* estimates and provided 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 two groups.

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

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). Since we provide iMPC estimates at a monthly frequency, these results can help guide the design of theories of consumer behavior and inform the calibration of macroeconomic models to yield policy-relevant outcomes. Furthermore, 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 identified moments we present in this paper can be used to calibrate such models.

This paper highlights the robustness of our approach by assessing consistency between two empirical methods—*revealed-preference* and *reported-preference* estimates—and in identifying the causal effects of one-time income shocks. The consistency check 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.[30] 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.

30. 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 held on November 28, 2019. The lottery population included 5,695,732 individuals who had conducted transactions in October 2019 and possessed a Tax Identification Number (TIN), which is required to open a Greek bank account or obtain a credit card issued by a Greek bank. The I.A.P.R. notified the 1,000 winners via email and SMS the following day. The €1,000 prize was deposited into winners' bank accounts on December 20, 2019, except in a few cases where the transfer was delayed to January 17, 2020, or February 21, 2020, due to late submission of bank account details. Two winners failed to provide their details by February 28, 2020, and were thus disqualified from receiving the prize, excluding them from our sample. A key aspect to consider in interpreting the empirical results is that winners received their prizes 20 days after being informed of their lottery win.

Out of the 1,000 winners, 58 were excluded from contact attempts because they had never filed a tax return (16), were listed as dependents in a household (35), or had filed a separate tax return from their spouse/partner (7). This left 942 winners eligible for contact. For each of these 942 winners, we created a *match list* of up to 10 matched non-winners. The procedure used to populate each of the 942 *match lists* was the following. 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. This step always generated more than ten matches per winner. 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 more than 10 matches remained, the algorithm prioritized 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, resulting in a donor pool of 3,026 non-winners.

The survey began on Monday, December 2, 2019. A team of 15 specialized employees from the Customer Support Center (CSC) of the I.A.P.R. was assigned to work on the study. The CSC, whose regular mandate is all contact with taxpayers regarding I.A.P.R. matters, ensured that all team members were properly briefed to maintain consistency in responses to any inquiries. A Q&A document was prepared by the CSC and the research team and distributed among team members. The survey concluded on December 13, 2019, with a limited number of follow-up phone calls made on December 19 and 20. The strategy was to attempt telephone contact with all 942 winners and as many non-winners as possible from the donor pool but not necessarily all. Non-winners were contacted repeatedly, with at least three attempts per individual before moving to the next person on the match list of each winner.

At the start of each call, winners were reminded that they had won in the 34th tax lottery, held on November 28, 2019, and informed that they should expect their €1,000 prize to be deposited approximately 20 days from the announcement of the lottery results, i.e. around the 20th of December. Participants who agreed to take part in the study were asked initial questions about their household status and intended use of the lottery winnings. Winners were asked how they planned to use their tax-free prize of €1,000. Non-winners were presented with a hypothetical scenario in which they received a tax-free windfall of €1,000 and were asked how they would respond. Both groups were then given a hypothetical question about how they would react to an unexpected one-time loss of €1,000 in net income.

Participants were assured that their responses would remain fully confidential and that they had the right to withdraw from the survey and study at any time without consequences. If they chose to withdraw, their data would be deleted upon request. This option was provided both during the telephone contact and through a dedicated online link that remained active for several months. Within a few weeks of initial contact, 35 subjects requested data deletion. From the pool of 942 winners, the CSC team successfully contacted 701 individuals. From the donor pool of 3,026 non-winners, they managed to reach 1,577 individuals. In total, 1,014 taxpayers both agreed to participate in the telephone survey and did not request data deletion. Of these, 481 were winners and 533 were non-winners. We refer to this group as the **Telephone Sample**.

To enhance internal validity, we followed the recommendations of Imbens and Rubin (2015) (pp. 292-293) and trimmed the **Telephone Sample** to ensure overlap in propensity scores (PS) between the treatment and control groups. Specifically, we excluded winners whose PS exceeded the highest PS observed among non-winners, as well as non-winners with PS values lower than the minimum PS of winners The final sample used in estimation contains 440 winners and 491 non-winners (931 individuals).

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. We do not have data on different expenditure categories.

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

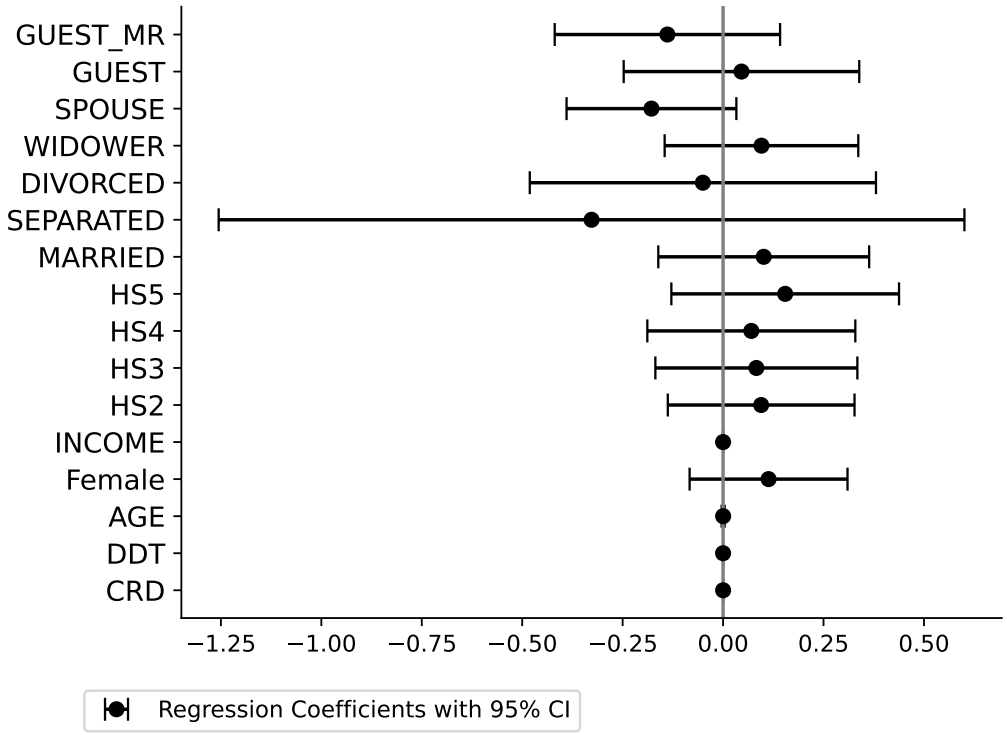


Figure B.1: Observable predictors of treatment

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 mean 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

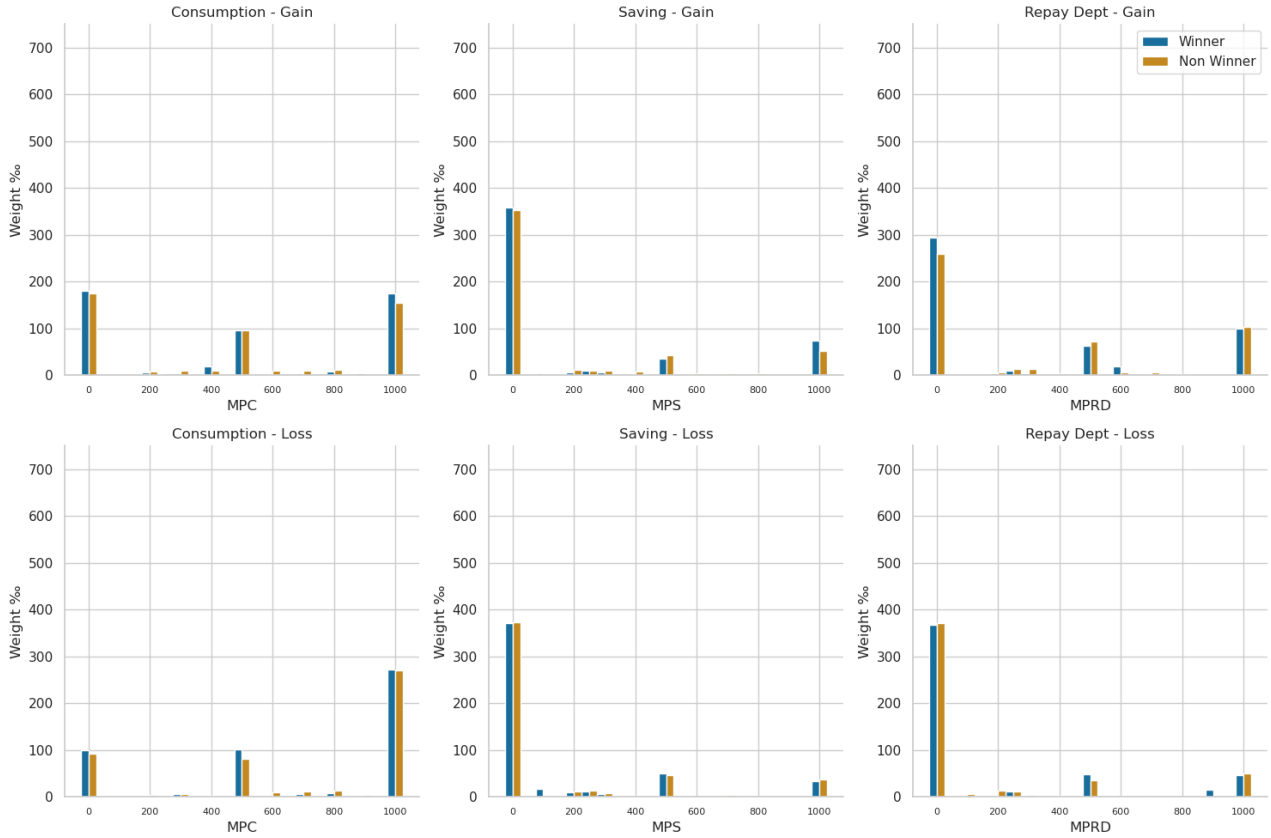
Note: In this table we report the range of values of the observable characteristic, and the count of individuals in each group. Count refers to the estimation sample, which is restricted to individuals with overlapping Propensity Scores (PS) in the group. Total Count refers to the total number of individuals 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"],[31] 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.

31. 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
Unequal Splitter (W)	0.075	0.486	0.383	0.104	0.220	0.293
Unequal Splitter (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**[32]

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,

32. 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 the lottery date. 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]