Characteristics and Responses of Winners in the Greek Tax Lottery

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Abstract

The Greek tax lottery incentivises consumers to shift from cash to electronic payments by awarding €1,000 to 1,000 winners every month. Utilising administrative tax data, I analyse the income and occupation characteristics of winners, revealing that the lottery favours high-income taxpayers and the self-employed, who exhibit higher spending levels. Leveraging a unique event of retroactive draws in December 2017, I quantify the winners' responses after receiving a prize. Low-to-middle-income taxpayers increase their electronic consumption temporarily, indicating that those who are less likely to win respond the most. Self-employed taxpayers with high spending levels halve their electronic consumption, suggesting that winning leads to higher perceived visibility of transactions by the tax authority. Using lottery simulations, I explore ticket ceilings that reduce the concentration of prizes among high-consumption individuals.

JEL Classification: D13, D22, E21, H24, H25, H26, H31, H83

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1 Introduction

In business-to-business transactions, the value-added tax (VAT) exhibits a self-enforcing compliance mechanism through paper trail, where one firm's inputs become another's outputs (Pomeranz, 2015). However, in business-to-consumer transactions, consumers lack a similar motivation to obtain receipts.[1] Unrecorded transactions contribute to higher tax evasion and reduced public revenue. To address this issue, tax lotteries in retail transactions have been implemented by tax administrations to encourage consumers to request receipts in exchange for a chance to win a prize, thereby generating additional third-party information (Kleven *et al.*, 2011) that can enhance VAT compliance (Naritomi, 2019). Using administrative tax data from Greece, this paper studies the Greek tax lottery and examines (a) the income and occupation characteristics of winners and, (b) the winners' responses after receiving a prize.

The scheme automatically assigns lottery tickets to all Greek retail consumers who use credit and debit cards for everyday transactions. Its goal is to incentivise a shift from cash to electronic payments. Unlike cash, banks serve as third parties in electronic transactions, enabling them to transfer information to the tax authority and to enhance the oversight of retail firms.

Tax lottery tickets are allocated based on the total monthly electronic payments made by each individual, automatically entering them into a draw for €1 million in monthly prizes (€1,000 for 1,000 winners). I utilise data on income, electronic consumption, and occupation for 68,897 tax units in the Greek population: 18,897 winning units during 19 monthly draws in 2017 and 2018, alongside a random sample of 50,000 non-winning tax units. This data facilitates the reconstruction of a representative taxpayer population for analysing the characteristics and responses of lottery winners.

Focusing first on the characteristics of winners, the analysis reveals that the lottery's design favours high-income taxpayers and self-employed individuals, who record significantly higher volumes of electronic consumption. Compared to the reconstructed taxpayer population, winners have approximately seven times greater mean annual electronic consumption (€28,413 versus €3,931) and a higher mean annual income (€15,877 versus €9,403). Additionally, a 10% increase in income is associated with a 1.8% increase in electronic consumption and a 0.11% increase in the probability of winning the tax lottery. Self-employed winners display an exceptionally high mean annual electronic consumption of €181,520, compared to €14,626 for winners in other occupation categories (wage-earners, pensioners and, agricultural workers). Conditional on income, being self-employed increases the probability of winning by 0.18%. The scheme's design leads to both high-income individuals and the self-employed being selected more frequently as lottery winners.

Turning to how winners respond, I analyse the heterogeneity of responses based on income quintiles and occupation. The data allows for the separation of individuals in household income quintiles and in five occupation categories (wage-earners, pensioners, agriculture, self-employed, and zero income).

[1] The absence of a paper trail in retail VAT transactions is commonly referred to as VAT's "last mile" problem.

Estimating the responses relies on a natural experiment: the tax authority initially planned to launch monthly draws in January 2017, but due to a technical delay, the lottery was publicly announced in October 2017. Earmarked prizes of €9 million corresponding to the months of January to September could only be allocated to winners by the end of the 2017 budgetary year. An extraordinary superdraw took place on Christmas Eve 2017 for spending that occurred in the months leading up to the scheme's announcement.

Results from event studies indicate that winners experience a temporary increase in electronic consumption compared to non-winners. Responses are particularly pronounced among individuals in lower-to-middle income quintiles, while the highest income quintile shows no increase in electronic consumption compared to similar non-winners. Individuals in the lowest quintile exhibit statistically significant increases in electronic consumption of 16.6% in the first month, 20.9% in the second month, and 19.5% in the seventh month after winning. Those in the second quintile show significant increases of 23% and 20% in the first two months, while individuals in the third income quintile experience a significant increase of 16.9% only in the first month. Individuals in the fourth quintile increase their electronic consumption by 9.1% in the first month and 9.5% in the third month after winning. In contrast, the highest income quintile does not respond to winning. This pattern—where lower income quintiles show the greatest responses while the highest income quintile does not—runs counter to the scheme's design, which links higher spending to increased winning chances.

Similar effects are observed in an occupational comparison: wage-earners, pensioners, and individuals with zero income respond strongly, albeit temporarily. Wage-earners increase their electronic consumption by 11%, 7.5%, and 7.7% in the first three months. Pensioners show increases in consumption for six months, ranging from 5.9% to 13.3%. Individuals with zero income respond the most, with a 19.8% increase in the first month and 28.3% in the seventh month after winning. By contrast, self-employed individuals and those working in agriculture show no statistically significant difference in electronic consumption after winning, compared to that of non-winners in the same occupational categories.

An important finding is a significant permanent reduction of around 50%, in the electronic consumption of self-employed individuals with high levels of spending once a prize is received. As described above, these individuals have a higher probability of winning the lottery. One explanation for this sharp decline is the use of personal bank accounts for business expenses. Winning increases the salience of the lottery and the information-sharing system between banks and the tax authority, prompting a reduction in the volume of electronic consumption processed through their personal accounts.

On the other hand, the lack of response observed among high-income and high-consumption individuals reveals a fundamental issue in the scheme. Winning does not necessarily provide additional incentives to increase electronic payments. As a result, windfall gains are disproportionately allocated to the highest-income taxpayers, without generating additional third-party information.

To further examine the allocation of prizes, I conduct repeated simulations of the monthly draws generating 1.2 million winners. The findings indicate that tying lottery tickets to spending levels results in the top 5% of winners, ranked by electronic consumption, receiving three out of every four prizes. This occurs because these individuals generate a disproportionately large number of tickets compared to others. One possible solution to improve prize allocation in the population is to introduce a cap on the number of monthly tickets that can be allocated per individual, thereby limiting the advantage of high spenders. I simulate monthly draws under two different ceilings, set at €1,000 and €5,000. The results show that both ceilings reduce the concentration of prizes among individuals with particularly high spending levels; however, the stricter the ceiling, the more restrictive it becomes, potentially undermining the lottery's incentive structure.

Despite the introduction of tax lotteries in several countries in recent years, evidence on their effectiveness remains limited in the literature. While only very few studies have documented the policy's success in increasing tax revenue (Naritomi, 2019; Nicolaides, 2023), there is still a need for further evidence on how to improve their function. In the Brazilian tax lottery, Naritomi (2019) examines differences in wholesale versus retail sale of goods and services. The introduction of the lottery leads to a 21% increase in reported sales and a lower, yet significant, increase of 9.3% in reported revenue. The study points to whistle-blowing and collusion costs as potential mechanisms driving this increase. In the context of the Greek tax lottery, Nicolaides (2023) reports a rise in regional VAT by 0.01% for each additional winner. The primary mechanisms identified include idiosyncratic effects from winners, who increase their electronic payments after winning, as well as spillover effects in electronic consumption from winners to non-winners.

This paper contributes to the tax lottery literature by providing a detailed analysis of the characteristics of winners in terms of income, electronic consumption, and occupation, as well as evidence on how winners respond after winning. Understanding who wins and how they respond has important implications for the effectiveness of tax lotteries.

The paper is organised as follows. Section 2 provides the institutional information of the Greek tax lottery and Section 3 describes the data. The winners' characteristics are documented in Section 4, and their responses are presented in Section 5. Simulations of lottery draws and ticket ceilings are presented in Section 6. Lastly, Section 7 concludes.

2 Institutional Background

Tax lotteries have become a common tool to mobilise consumers as a source of third-party reporting, thereby expanding the tax base and ultimately increasing tax revenue (Naritomi, 2019). This trend was particularly visible in Europe, where several countries introduced tax lotteries during the European debt crisis (Fooken *et al.*, 2015). In 2017, when the Greek tax authority was granted institutional and financial independence, a tax lottery scheme gained traction. The design of the lottery was incorporated in a broader strategy that aimed at curbing tax evasion by encouraging the use of electronic payments over cash payments. For this reason, the Greek tax lottery focuses specifically on incentivising electronic transactions.

Electronic Transactions Cash has long been the dominant payment method in Greece. However, the imposition of capital controls in July 2015 marked a turn towards electronic payments, resulting in a significant surge in their usage.[2] From 2015 onward, Greece recorded a massive increase of debit cards issuance, while additional incentives to promote electronic payments were introduced in 2016 (Hondroyiannis and Papaoikonomou, 2017).[3] The acceptance of electronic payments and the introduction of Point-Of-Sale (POS) terminals became mandatory (in gradual roll-out phases starting 2017, depending on the profession). Overall, the legislative measures had a strong, positive impact on the use of cards of payments (Danchev *et al.*, 2020).

These reforms were complemented by the introduction of a comprehensive IT system. Starting in January 2017, banks were required to automatically report the total volume of electronic transactions per individual to the tax authority on a monthly basis. The reporting system serves as a key building block in the tax lottery: it links monthly electronic payments to lottery tickets.

Lottery Tickets At the end of each month, banks transmit the aggregate volume of electronic payments (but not single transactions) completed by each Greek tax resident.[4] All tax residents are included in the lottery by default, as long as they use payment cards.[5] The monthly volume of electronic transactions are converted into tax lottery tickets according to a given Ticket-Awarding Mechanism (TAM). The TAM has a slightly concave structure: at higher levels of electronic transaction volumes, an additional euro translates into fewer tickets.[6] This point is documented in Table 11 of Appendix C. While the first euro of monthly electronic consumption would translate into one ticket, the €1,001st would yield only 0.25 tickets. Note further that the TAM does not contain any upper bound. Figure 17 in Appendix C plots the resulting euro-to-ticket mapping.[7] Eligible payments that are converted into tickets are limited to everyday consumption expenses. Purchases of intangible or tangible assets, motor vehicles and payments of house rent, mortgages,

[2] Cash withdrawals were limited to €60 per day per individual in the summer of 2015, but electronic payments remained unlimited.

[3] This took place by Law 4446/2016.

[4] It is compulsory for all Greek tax residents above the age of 18 to acquire a tax ID, called AFM. This number acts as the main identifier of citizens by the state, much like an identity number. The matching of individuals between banks and the tax authority takes place through the tax ID. On one hand, when filing taxes individuals must declare their IBAN to complete the filing process. It is compulsory for all individuals to file, even if they had no income during the financial year. To improve tax compliance during the economic crisis the filing process became completely electronic and automated with pre-filled information (paper declarations were eliminated). Banks demand a tax ID when opening a bank account. This enables matching when banks send payment information to the tax authority.

[5] Individuals can opt out of the lottery by making a request to the tax authority. However, the request does not prevent banks from sending payment information.

[6] A concave structure must have reflected the legislator's concern that high income taxpayers would had been awarded more tickets.

[7] Note that the scale is public knowledge. At the introduction of the lottery it was rewarding 1 ticket per €1 for the first €100 spent; 1 ticket per €2 for the additional €400 (i.e. from €100 to €500); 1 ticket per €3 for the additional €500 (i.e. from €500 to €1,000); and 1 ticket per €4 for any payments above €1,000. For example, suppose that in a given month an individual spends €200 in electronic payments. The individual would receive 150 tickets (100 for the first €100 and 50 for the rest).

taxes and fines are excluded. All other purchases award tickets if they are completed with credit cards, debit cards and electronic payments.

Prizes Every month 1,000 winners win €1,000 each (€1 million in prizes per month). To ensure the fairness of the draws, the tax authority has implemented a double-blind draw system, where at first a research institute performs the draws and returns the winning numbers and then the tax authority applies a transformation to the numbers. In addition, individuals can only win once every month. For payments in a given month m, draws take place at the end of $m + 1$.[8] Winning tickets are announced to the public after the draw and winners are informed automatically via email and a text message to their mobile phones. They receive the prize in their bank accounts about a week after winning. A dedicate website allows the public to view their tickets for all lottery months, as well as, any winning tickets. The prizes are tax exempt and cannot be confiscated.

Superdraw in December 2017 On Christmas Eve in 2017, an unexpected superdraw took place, awarding prizes to 9,000 winners. Initially, the lottery was set to launch in January 2017, with the tax authority budgeting €12 million in prizes for the entire year, allocating €1 million for each month. The lottery was publicly announced on October 9 2017, revealing the TAM and the prize structure. The first draw occurred on November 30 2017, with payments completed in October, while a second lottery was scheduled for December 30, with payments finalised in November. A total of €9 million earmarked for lotteries from previous months remained unallocated and had to be distributed before the end of the budgetary year.[9] On December 24 2017, the tax authority decided to conduct nine consecutive draws, each corresponding to monthly payments made from January 2017 to September 2017.[10] I utilize the superdraw as an identification strategy to evaluate taxpayers' responses to winning.

The Greek tax lottery differs from other tax lotteries in that it is hardly based on self-selection. Typically, consumers must register in a system and collect receipts in order to participate. Instead, the Greek lottery automatically includes the vast majority of taxpayers provided that complete electronic transaction in a given month.[11] While the intention of the tax authority was to include only the private consumption by individuals to the draws, the lottery included a non-trivial volume

[8] For example, for all payments completed in October, banks collect payment information from October 1st to 31st, aggregate them and send them to the tax authority early November. Payments are converted to eligible tickets and the draw take place at the end of November. Winning numbers are announced immediately after the draw. The same procedure applies for the rest of the months.

[9] This was due to budgetary constraints. Accrual amounts to individual winners could only be made until December 31st, even if payments were processed a few days into the new fiscal year. As with any public organization, the budget is annual, and earmarked amounts cannot be transferred to the following year.

[10] A visual illustration of the lottery's timeline in 2017 is shown in Figure 18 in Appendix C. Search volumes in Google search engine recorded in Greece at the time for the word "Lottery" in Greek are shown in Figure 19 in Appendix C. While the search volume was close to zero in the months prior to the first lottery, it spiked at the end of November (1st lottery), with the highest volume recorded at the end of December, indicating increasing public awareness. The search volume index continued to rise at the end of each month thereafter, in line with the timing of the monthly draws.

[11] According to the World Bank's Global Findex database, 85% of individuals in Greece above the age of 15 had a bank account in 2017. As some of these are joint 'family' accounts, the formal banking system includes almost the entire population.

of business transactions because of this automatic inclusion.[12] The distinction between business and personal transactions can become particularly blurred for self-employed individuals, as they often conduct business transactions through their personal bank accounts. This group may also have a greater incentive to mix transactions, as work-related expenses can help lower their tax liability, including costs like office rent, phone bills, and travel expenses. Since 2014, legislation has mandated that only expenditures exceeding €500 qualify for tax deductions, and these must be made through electronic payments.

3 Data

Tax Filings The data include (a) anonymised taxpayer information on monthly electronic consumption from January 2017 to July 2018, and (b) corresponding tax filings.[13] I examine the annual pre-tax income of tax units, which can consist of either single or joint filings (the latter comprising income from both the primary taxpayer and their spouse) from economic activities in 2017. For joint filings, the monthly level of electronic consumption corresponds to only one of the individuals in the tax unit. Monthly electronic consumption is rounded to the nearest €10, while information in tax filings is rounded to the nearest €5.[14] For joint filings, I observe income values for both partners, enabling the calculation of the tax unit's total income.[15] For single filings, I observe the income of the individual, which represents the total income of the single-person household.[16] Filing tax returns is compulsory, even for individuals with zero income.[17]

Occupation Categories In addition to the income amount, the data indicate the source(s) of income in broad categories: from wages (WG); from pensions (PE); self-employed income or small business (SB); and agricultural income (AG).[18] WG includes income received from salaried activities, which is the tax unit's reported annual gross salary. PE includes all individuals who receive pensionable income. SB includes sole proprietorships, such as the self-employed and sole traders. AG contains declared annual income from agricultural activities, such as for farm owners, agricultural workers and small cultivation. An additional category contains individuals who have

[12]This peculiarity covers the entire time horizon of our data. It was solved only in 2019, by obliging individuals to hold separate bank accounts for business transactions. The data in this study cover the period prior to this change.

[13]The last day of tax filings for the tax year of 2017 was July 30, 2018. The tax returns underwent a basic plausibility check and tax payment statements were issued by the tax authority in August 2018. The data in this paper were received in October 2018.

[14]Income information does not include any income received from the government, such as social welfare transfers for poor households or tax credits.

[15]For tax filings in 2017, joint filing was mandatory for married couples. Law no. 4172/2013 provided that the main taxpayer of the household is the husband, responsible for submitting the tax return, while the wife must sign-in before finalising the submission and give consent to the declared amounts.

[16]However, I cannot distinguish individuals and households in the case were the main taxpayer has declared some level of income, and the spouse has declared 0 income.

[17]As a result, the data encompass many students over the age of 18 (in tertiary education) as well as unemployed individuals. With an unemployment rate of 21.5% in 2017, the latter group represented a substantial portion of the working population. However, the zero-income group may also include tax units that conceal all of their income.

[18]These income categories in Greece corresponded to different pension insurance funds contributions that existed in the past.

reported zero income in 2017 (NO). The breakdown of these categories for single-filing and joint-filing households is shown as percentages in Table 3. It is important to note that a tax unit may report income from multiple sources. Below, I will use indicators to identify the primary source of reported income. These binary variables also act as proxies for each tax unit's main occupational activity.

As a result of between-category variation in third-party reporting, there are major differences in the opportunities to under-report income. For WG and PE income, the income values (as reported by employers or pension funds) appear automatically in the individuals' tax returns. SB and AG incomes, on the contrary, are self-reported. Hence, as noted above, some individuals with non-zero incomes from these sources might not report any income and thus end up in the NO category.

Samples I use data from two different samples. First, the universe of tax lottery winners. This includes 18,897 individuals from tax units that have won the lottery during the first 19 lottery draws, from January 2017 to July 2018. Second, a randomly-drawn sample of 50,000 tax units that did not win the lottery. For the winners' sample, the monthly volume of electronic consumption for each winning individual is observed across all 19 months covered. In the randomly drawn sample, electronic consumption is tracked for one individual within each tax unit. Additionally, the annual income for both samples is recorded during tax filing. Table 3 presents basic summary statistics for the two samples.

Construction of Taxpayer Population To allow for a meaningful comparison of the winners' characteristics, one has to account for the different sampling for winners and non-winners. The winners sample was pre-selected from the taxpayer population. The non-winners sample was drawn randomly from the population of taxpayers conditional on not having won. To arrive at a sample that represents the population of taxpayers, I expand (or re-weight) the non-winner population such that they match the overall number of lottery tickets observed in 2017.

The following procedure is used to obtain the sample weights. Firstly, I observe the total number of lottery tickets issued in each calendar month, $\bar{T}_m$. Secondly, given that lottery tickets are derived from monthly electronic consumption, one can compute $T_{i,m,s}$, which is the number of tickets from individual i in month m in sample s, where $s \in \{1, 2\}$ indicates the winner and non-winner sample, respectively. As a final step, non-winners in 2017, who were winners in 2018 must be added in the expansion. To avoid a different subscript for the year, I utilise $\hat{T}_{i,m,1}$.

Given this, the following identity must hold:

$$\sum_{m=1}^{12} \bar{T}_m = \sum_{m=1}^{12} \sum_{i=1}^{N_1} T_{i,m,1} + \sum_{m=1}^{12} \sum_{i=1}^{N_1} \hat{T}_{i,m,1} + \omega \sum_{m=1}^{12} \sum_{i=1}^{N_2} T_{i,m,2} \tag{1}$$

where N_s indicates the size of the samples s (with $N_1 = 18,897$ and $N_2 = 50,000$).

From this identity, the final step is to derive ω, the weight or expansion factor for the non-winners sample that matches the population in terms of lottery tickets, which is the sole unknown. One can observe the total number of tickets in 2017, $\sum_{m=1}^{12} \bar{T}_m$ and the total number of tickets in the samples. The calculation derives ω to be 129.

A further plausibility check is that $N_1 + \omega N_2 \cong N$. Expanding the random sample gives a total tax unit population of 6.45 million (50,000×129), to which 18,897 winners are added. This is very close to official statistics from the tax authority, indicating 6.37 million tax returns being filed for 2017.[19] Considering that the winning sample represents only a small fraction of the overall population, the non-random selection of winners does not lead to any significant distortions in the characteristics of the taxpayers.

Basic summary statistics are presented in Table 4. The table compares the baseline tax unit population with the winners from 2017, revealing several noteworthy characteristics. Firstly, the mean electronic consumption and average income of winners are significantly higher than those of the general taxpayer population. Secondly, the self-employed are overrepresented among the winners, exhibiting exceptionally high levels and variance in electronic consumption. These insights are crucial for understanding the characteristics of winners.

4 Characteristics of Lottery Winners

This section examines the income, consumption and occupation characteristics of winners. Descriptive evidence show that (a) winners exhibit higher income and electronic consumption compared to the representative taxpayer population (b) self-employed winners generate a particularly large volume of electronic consumption. The evidence suggests that the lottery selects specific subgroups of the population as winners, influenced by income and occupational characteristics. In a second step, I parametrically estimate the effect of income and occupation on the probability of winning.

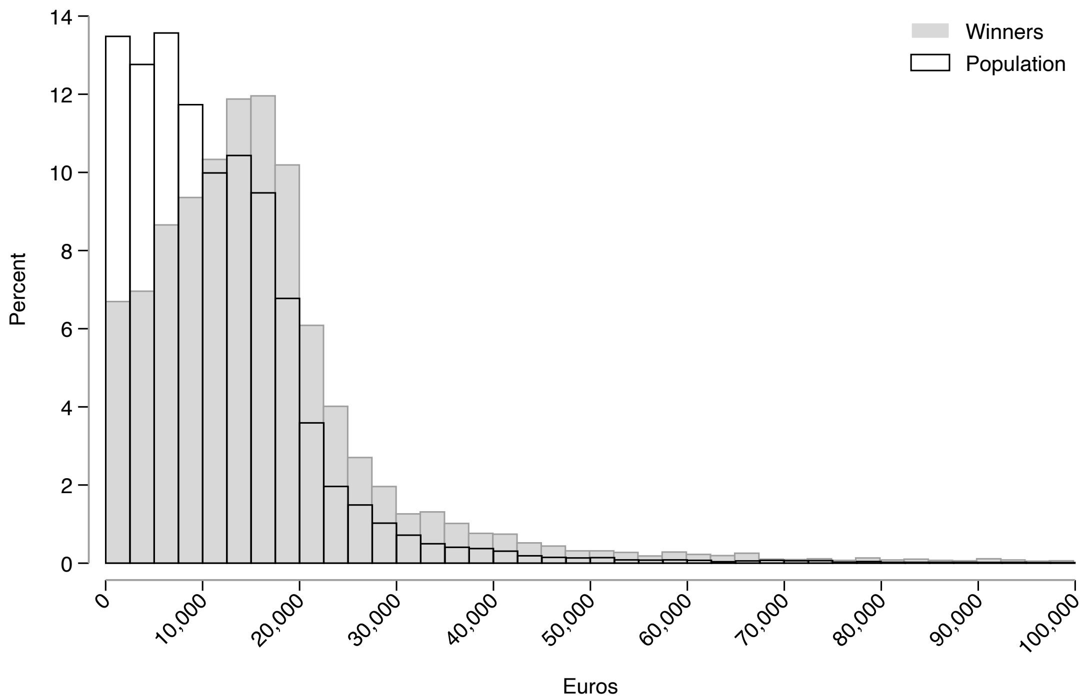
4.1 Income and Consumption Characteristics

Winners exhibit a higher level of income compared to the taxpayer population. Their mean income is €15,877, as opposed to €9,403 (median values are €12,113 and €6,850, respectively). This observation is illustrated in Table 4 and graphically represented in Figure 1, which compares their income distributions. For the taxpayer population, a high visual mass can be observed below the €10,000 level, after which the distribution tails-off fast as income increases. By contrast, the distribution of winners exhibits lower mass below the €10,000 level, after which the mass increases substantially with income. Tailing off takes place after about €16,000. Overall, Figure 1 clearly

[19] Annual statistics for the 2017 filing are published by the Tax Authority at `https://www.aade.gr/menoy/statistika-deiktes/eisodima/etisia-statistika-deltia`.

illustrates that lottery winners are higher-income taxpayers when compared to the broader taxpayer population.[20]

Fig. 1 Income Distribution in 2017



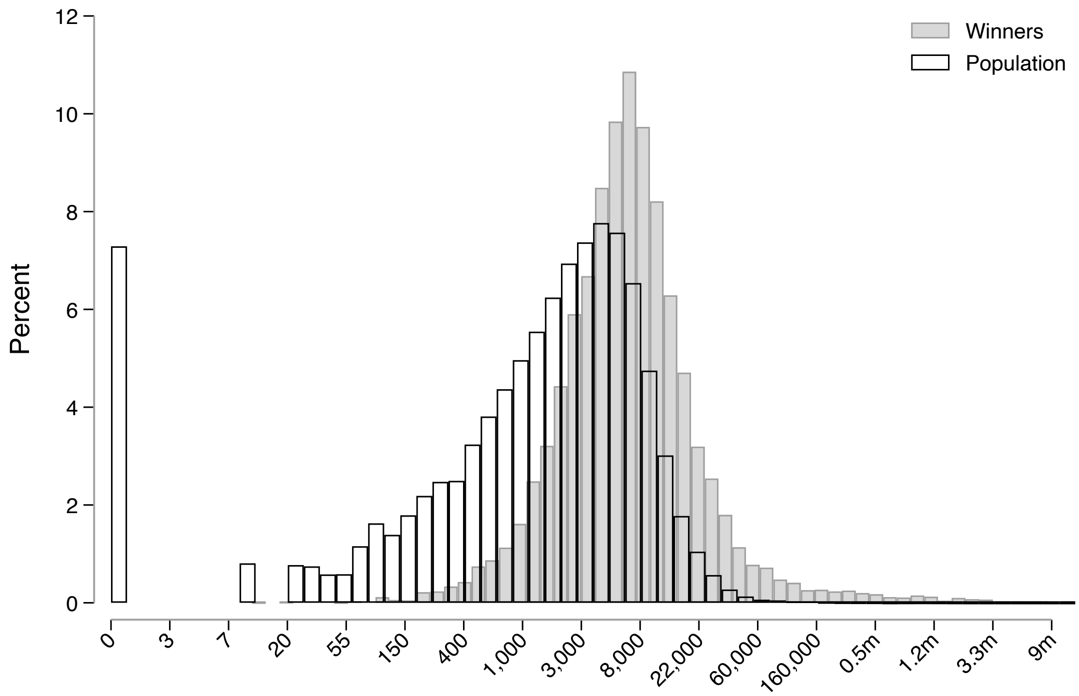
Notes: The figure compares the distribution of declared income in the 2017 tax filings for lottery winners against the corresponding distribution of income for the taxpayer population. The latter has been reconstructed from a random sample of 50,000 tax units as described in Section 2. The graph is truncated at €100,000, as right-tails diminish quickly in the distribution.

Income characteristics are presented in Table 4, showing that winners exhibit roughly seven times as high mean annual electronic consumption compared to the taxpayer population, at €28,413 versus €3,931 (with median values at €6,400 and €1,940, respectively). This highlights a fundamental characteristic of the lottery's design: the chances of winning increase proportionally to the level of electronic consumption. Since the TAM contains no upper bound (there is no maximum number of assigned tickets in a given month), the probability of winning *cet.par.* approaches unity if $z_{i,m} \to \infty$. While this holds for a given month m, as electronic consumption fluctuates between months, the annual level Z_i is only an indirect indicator for the selection implied by the TAM.[21]

[20] Note that for illustration purposes, Figure 1 is truncated at €100,000. The winners distribution exhibits a longer tail as income increases, with a number of observations with high incomes well above €100,000.

[21] The difference between mean electronic consumption for winners relative to the population is even more evident in a monthly comparison. The taxpayer population's monthly mean electronic consumption followed an upward trend in 2017, fluctuating between €278 (in the beginning of the year) to €445 (at the end of the year). The mean electronic consumption of those who have won in a particular month fluctuated around €4,000 (without observing any upward trend).

Fig. 2 Distribution of Annual Electronic Consumption

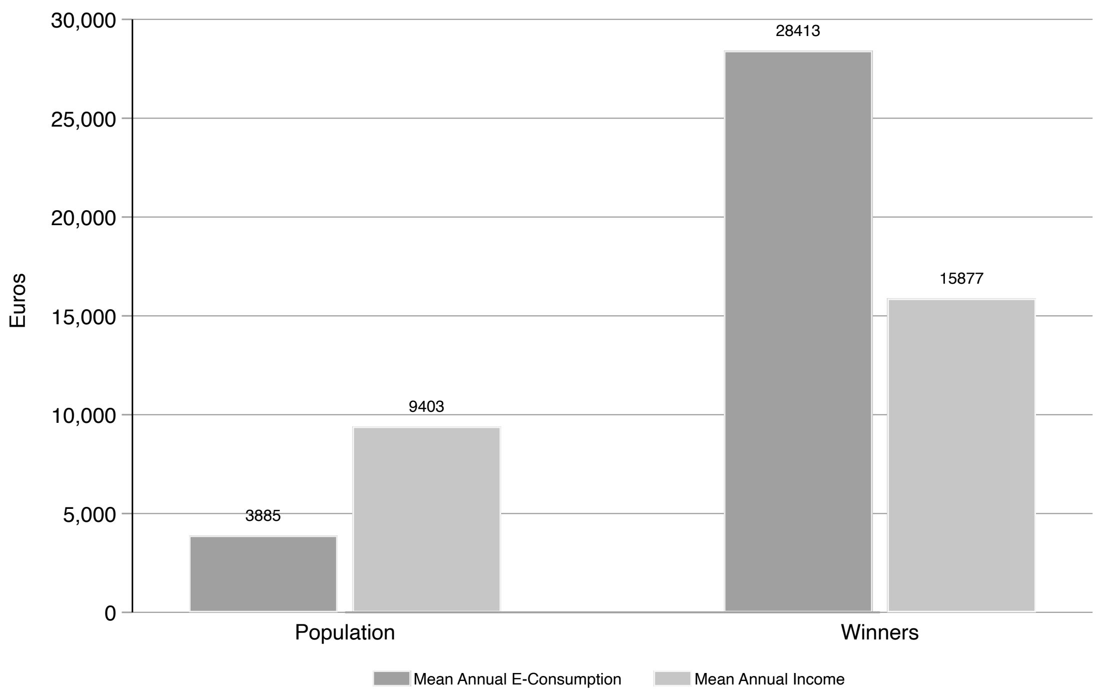


Notes: The figures presents distributions of the log of annual electronic consumption in 2017 for individuals in the taxpayer population and for lottery winners. The x-axis is a log scale representing the equivalent values in €. Tickers are rounded to the nearest thousand in €. The population distribution includes the individuals from 6.4 million tax units in the reconstructed taxpayer population. The winners distribution includes 11,960 winners in tax lotteries that took place in 2017. The monthly electronic consumption of individuals was summed up over the 12 months to create the annual electronic consumption. Monthly values in the data were rounded to the nearest €10 by the tax authority.

The distributional difference in electronic consumption (more specifically, in $\log(Z_i)$) is shown in Figure 2. For the taxpayer population, the distribution is bi-modal: a large visual mass of taxpayers (about 7%) exhibit zero electronic consumption for the entire year. The remaining taxpayers are concentrated around the €3,931 mean value. By contrast, the winners' distribution is symmetrical and normally-distributed, with more taxpayer mass as income increases. There is a heavier right-hand tail, with a non-trivial share of electronic consumption volumes well above €60,000. For 2017, there were 334 winners with more than €1 million annual electronic consumption, 34 with more than €2 million and one extreme value of more than €9 million e-consumption (who has won twice in 2017). The taxpayer population distribution, exhibits hardly any mass in the range of $Z_i >$€$22,000$.

A peculiar characteristic for winners is that their electronic consumption is significantly higher than their income. This is shown in the winners' column of Figure 3, while the corresponding comparison for the taxpayer population is shown in the population column. The e-consumption-over-income ratio is 1.79 for winners and 0.42 for the taxpayer population. This indicates that winners spent almost twice as much as their income using electronic payments, while the taxpayer population spent less than half. While this peculiarity in the winners' consumption pattern is largely driven by some outliers with very high electronic consumption values, it does hold for a significant number of winners. Specifically, for every third winner (33.5%) I observe an e-consumption-over-income ratio above unity, i.e., their annual electronic consumption volume exceeds their income.

Fig. 3 Electronic Consumption and Income



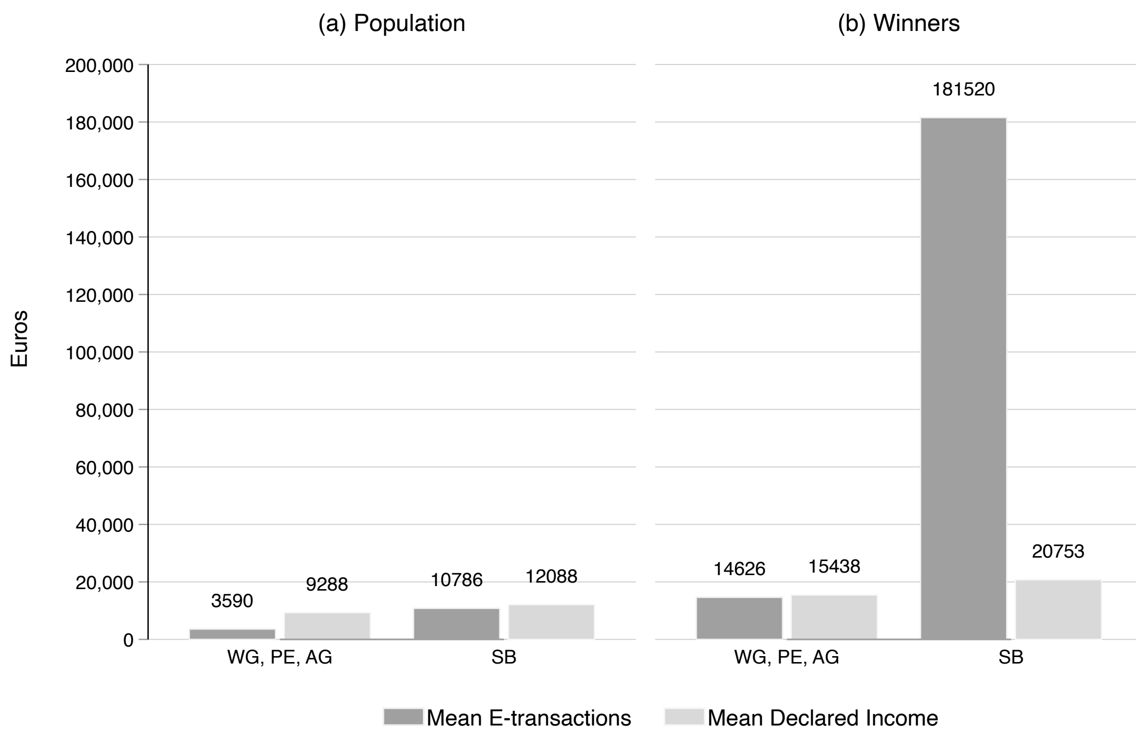
Notes: The figure compares the annual mean electronic consumption against the mean annual income for winners and for the taxpayer population. Only winners from lotteries in 2017 are included in the winners' sample. Non-parametric estimates of the differences are provided in Table 5.

4.2 Occupational Characteristics

In addition to the income and consumption characteristics described above, the income source of taxpayers is a determining factor in winning the tax lottery, and in particular being self-employed. Table 4 documents significant within-occupational-category differences in mean income between winners and the taxpayer population. SB taxpayers are over-represented among lottery winners. Relative to a population share of 4.1%, this group accounts for 8.3% of all winners. WG, PE and AG taxpayers have roughly similar representation in the winners as in the taxpayer population. Taxpayers in the zero income (NO) group are under-represented compared to their population percentage.

Comparing winners against the taxpayer population per occupation category, reveals that income differences are statistically significant for all WG, PE, SB and AG categories. Regardless of the income category, winners exhibit higher income, as shown in non-parametric estimations in Table 5. A larger income variance for these categories is also observed. The median income differences per occupation category, for winners and the population respectively are: for SB €11,073 and €6,260; for WG €14,325 and €9,145; for PE €14,858 and €11,275; and for AG €17,090 and €7,575.

Fig. 4 Annual Income and Electronic Consumption, by Income Category



Notes: The figure compares mean electronic consumption and mean income for groups with different primary income sources: self-employed (SB) vs other non-zero incomes from wages, pensions and agricultural activities (WG, PE, and AG). Individuals who declare zero income (NO) are excluded from this comparison. Figure (a) is based on taxpayer population and figure (b) presents the lottery winners from 2017.

A similar comparison for electronic consumption reveals an extremely large difference between winners and taxpayer population in the SB category. As documented in Table 4, the mean electronic consumption for winners is €181,520 (median of €17,565). Among the taxpayer population, the corresponding value €11,420 (median of €4,410). Hence, in addition to the fact SB taxpayers win the lottery more frequently than others, the lottery also selects (within the SB group) winners with unusually high electronic consumption volumes.

This discrepancy in SB individuals is depicted in Figure 4, where income and electronic consumption are compared for winners (on the right) and for the taxpayer population (on the left). To aid the comparison, the corresponding graphs for pooled groups of WG, PE and AG are also plotted.[22] Firstly, note that the mean electronic consumption represents about one-third of income if the taxpayer is not SB and about as much as their income if the taxpayer is SB. Hence, these income categories display a different pattern: the self-employed exhibit high volumes of electronic consumption, which interestingly is as high as their income. Importantly, as shown in Figure 4 (b), these differences are extremely large among winners: for SB winners, electronic consumption is ten times as high as their income. For winners in other income categories, electronic consumption is about as high as their income.[23]

Additional evidence examining the relationship of electronic consumption and income for the categories examined above are presented in scatter plots in Figure 8. As can be seen, in the Winners - SB scatter plot at the bottom right-hand corner, a proportionally larger number of SB winners exhibit high volumes of electronic consumption, than winners from other categories. When the SB winners are compared to the SB population, one can observe that SB winners exhibit high consumption volumes, as well as, higher income.

The extreme divergence between electronic consumption and income for SB lottery winners suggests that they (a) use private bank accounts when completing business transactions and/or (b) income is under-reported. Regarding the former, the flow of business transactions through personal bank accounts can result in particularly high electronic consumption levels, which then generates a large number of tax lottery tickets. Regarding the latter, the observed pattern might also originate from illegal under-reporting of income: since the SB group has (relative to third-party reported income) more opportunities to conceal (Kleven *et al.*, 2011), the vast electronic consumption/income gap may therefore – at least in part – reflect income tax evasion.[24] These two reasons rationalise the disproportionate representation of SB among tax lottery winners.

4.3 Intra-Household Characteristics

Examination of intra-household income sharing and household income source composition, provides corroborating evidence of the income and occupational characteristics of winners. As long as some couples share their bank account, and if partners with SB income use the accounts for business transactions, one should expect to observe higher electronic consumption in individuals who file jointly with an SB (rather than a non-SB) spouse. To assess this case, I focus on individuals who filed jointly in 2017. Overall, I observe that 37% tax units in the data file jointly, which is very close to the official percentage of 40% for 2017.[25]

[22]To allow for a meaningful comparison, the NO category individuals are excluded because they declare zero income.

[23]Out of 988 winners from the SB category, 64% exhibit e-consumption higher than their income. Among the SB group in the taxpayer population, the equivalent percentage is 39% – which is still much higher compared to taxpayers with other income sources. For example, in the WG group, about 9% of the population (16% of winners) have electronic consumption levels higher than their income.

[24]Note that the data do not allow quantification of this channel.

[25]This information is included in the annual statistics published by the tax authority in `https://www.aade.gr/menoy/statistika-deiktes/eisodima/etisia-statistika-deltia`.

Figure 9 compares electronic consumption and income levels of individuals who file jointly and who have an SB spouse against those who have a WG/PE/AG spouse.[26] (To facilitate interpretation, the sample underlying this graph excludes individuals from the SB and the NO income categories). Having an SB spouse is associated with higher levels of electronic consumption. This holds for the taxpayer population (Panel (a) of Figure 9) but, more strongly among the group of winners (Panel b).[27] At the same time, the partner's income source does not make a difference for the reported income. Overall, the data indicates that (many) jointly filing couples seem to share private bank accounts and that the spouses of SB individuals seem to use these accounts for business transactions.[28]

4.4 Estimating the Probability of Winning

This section examines the relationship between the characteristics of winners and their probability of winning. Specifically, I analyse how individual and spousal income, as well as occupation categories, influence (i) the level of electronic consumption and (ii) the probability of winning the lottery, using models of the following structure:

$$\log(Z_i) = \beta_0 + \beta_1 \log\left(Y_i\right) + \beta_2 \log\left(Y_{j|i}\right) + \beta_3\, SB_i + \beta_4\, SB_{j|i} + \beta_5\, Joint_i + \varepsilon_i \tag{2}$$

where Z_i is the annual electronic consumption, Y_i indicates the annual income and SB_i is a binary variable indicating self-employed income. The sub-index $j|i$ measures these variables for i's spouse j. $Joint_i$ is a binary variable indicating an individual who has filed jointly with a spouse. Note that β_1 and β_2 capture taxpayer i's elasticity of electronic consumption with respect to their own and their spouse's income, respectively.[29]

Columns (1)–(3) in Table 1 report ordinary least squares estimates. The estimated β_1 suggests that a 10% increase in income correlates with a 1.8% increase in electronic consumption. This measure is similar to a marginal propensity to consume estimate for electronic consumption. The aggregate marginal propensity to consume in Greece is estimated to range between 0.10, based on a net wealth distribution, and 0.35, based on a liquid assets distribution (Carroll *et al.*, 2014). The estimate presented in Table 1 falls within this range. The coefficient remains largely unchanged in Column (2), which controls for spousal income. However, the correlation is significantly lower: a 10% increase in spousal income is associated with only a 0.7% increase in the electronic consumption

[26] Figures that compare the same type of sample split for individuals with WG, PE and AG spouses are included in an online appendix.

[27] The differences are even greater if the spouse receives any part of income from SB activities, instead of having SB as a primary income source as shown in column (1). Table 6, column (2), documents that this difference in annual electronic consumption is economically and statistically highly significant. The difference is hardly affected by controlling for income in 2017, as shown in column (3).

[28] The pattern might also be shaped by individuals who record certain private, household expenses (such as the purchase of a personal computer) as business input costs in order to exempt these costs from VAT.

[29] Perfect income sharing within a household (plus equal propensities to spend money electronically) would imply $\beta_1 = \beta_2$.

of individual i. An F-test rejects the null $\beta_1 = \beta_2$, indicating imperfect income sharing within the household (Browning *et al.*, 1994; Lundberg *et al.*, 1997) or differential propensities to engage in electronic consumption. The results are quantitatively similar in Column (3), where only taxpayers who filed jointly are considered.

Table 1 Estimation Results

	Log(e-consumption)			P(winning)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			joint-filers			joint-filers	
Log-Income	0.181***	0.179***	0.205***	0.011***	0.011***	0.016***	0.002
(β_1)	(0.003)	(0.003)	(0.008)	(0.000)	(0.001)	(0.001)	(0.002)
Log-Income Spouse		0.073***	0.076***		0.006***	0.008***	0.001
(β_2)		(0.005)	(0.006)		(0.001)	(0.001)	(0.001)
Self-employed	0.773***	0.745***	0.519***	0.179***	0.177***	0.186***	0.021
(β_3)	(0.050)	(0.050)	(0.074)	(0.014)	(0.014)	(0.022)	(0.025)
Self-employed Spouse		0.445***	0.466***		0.036**	0.035**	-0.005
(β_4)		(0.063)	(0.063)		(0.017)	(0.017)	(0.021)
Joint Filing		-0.130***			-0.010		-0.008
		(0.044)			(0.007)		(0.008)
Tickets in 2017							0.000***
							(0.000)
Constant	5.582***	5.371***	5.002***	0.098***	0.080***	0.009	0.019
	(0.026)	(0.028)	(0.090)	(0.003)	(0.004)	(0.014)	(0.012)
F-Tests (p-values):							
$\beta_1 = \beta_2$		0.000	0.000		0.000	0.000	0.461
$\beta_3 = \beta_4$		0.000	0.594		0.000	0.000	0.338

Notes: The table presents estimation results from Equation (2). The dependent variable in columns (1)–(3) are the logarithm of annual electronic consumption ($\log(Z_i)$) and, in columns (4)–(7), the probability of winning the lottery. Coefficients and standard errors in columns (4) – (7) are multiplied by 100. The sample is $N = 6,468,609$ observations, except for columns (3) and (6), where the sample is constrained to $2,406,683$ joint-filing taxpayers. Robust standard errors (clustered at the level of 50,000 non-winning tax units + 11,960 winners from 2017) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The estimates further document that, consistent with the descriptive evidence from above, being an SB is associated with significantly higher levels of electronic consumption. The estimated semi-elasticities imply that someone with SB income has approximately 75% higher level electronic consumption compared to other income categories. An SB spouse increases electronic consumption by 45%. It is worth stressing that this holds while controlling for the taxpayer's own, as well as, for spousal income. Hence, the pattern reflects an occupational rather than a mere income correlation.

In a second step, I estimate how these income and occupational characteristics affect the probability of winning the tax lottery. The dependent variable from Equation (2) is replaced with a binary variable W_i which indicates that the taxpayer has won in the lottery in 2017. The results from a linear probability model are presented in Columns (4)–(7) in Table 1. Note that for presentation reasons, the estimates have been multiplied by 100 (since the probabilities of winning are rather small). The results document a positive correlation vis-à-vis a taxpayer's income and spousal income with the probability of winning the tax lottery. A 10% increase in taxpayer (spousal) income raises the probability of winning by 0.11% (0.06%).

It is notable that self-employed taxpayers, as well as jointly filing taxpayers with a self-employed spouse, have a significantly higher likelihood of winning the tax lottery. Controlling for income, the semi-elasticity presented in Column (5) shows that being self-employed increases the probability of winning by 0.177% compared to other income categories. Additionally, having a self-employed spouse is associated with a 0.036% increase in the probability of winning the lottery. The results remain qualitatively unchanged when considering estimates from the sample of jointly filing taxpayers alone, as shown in Column (6).

Finally, it is important to highlight the specification in Column (7) of Table 1, which incorporates into the regression the annual number of tickets assigned to an individual in 2017. It is reassuring to find that, when controlling for the total number of tickets, all other variables become statistically insignificant. This indicates that the lottery is not rigged. The correlations between the probability of winning, income level, and income category are primarily influenced by their association with the amount of electronic consumption. This consumption ultimately translates into tickets and determines the probability of winning.

5 Winner Responses in Electronic Consumption

The income and occupation characteristics documented above imply that certain subgroups are selected more frequently as winners. This section examines how winners respond in electronic consumption after they win. The comparison takes place by matching winners and non-winners by (a) household income quintile and by (b) occupational category. Since the data include information on electronic consumption per month from January 2017 to July 2018, one can compare how winners respond before and after winning.

A program evaluation of the lottery would have considered the impact of its introduction on consumer behaviour more broadly. Such an evaluation is constrained by data availability and by the lottery's automatic inclusion of the entire population in the monthly draws. Firstly, monthly electronic consumption data that count towards lottery tickets began to be sent by banks to the tax authority after the lottery's introduction and not before, thus, preventing a before-after comparison to identify any electronic consumption increase. Secondly, since taxpayers are included in the lottery automatically, conditional on paying by electronic payments, the lottery treats the majority of the population by default. Hence, it is impossible to identifying a comparable group that is not included in the announcement. An alternative approach to assessing the lottery's efficiency is to compare the electronic consumption responses of winners with those of non-winners. This comparison is feasible with the available dataset, and it serves as the basis for the analysis in this section.

5.1 Identification Strategy

The identification strategy utilises the superdraw that took place on Christmas Eve in December 2017 (see Section 2) to compare responses of winners against those of non-winners. The superdraw created conditions that resemble a natural experiment. Firstly, it was impossible for taxpayers to self-select in the lottery: eligible electronic payments, which were converted into lottery tickets, were completed before the tax lottery's announcement. This ensured that any attitudes that would favour lottery participation by some individuals or information frictions about the lottery's existence for others, were not factors affecting their participation. Secondly, as the draws were retroactive (for payments that took place during the months of 2017 before the lottery's announcement), taxpayers could not affect their winning chances. Thirdly, the allocation of prizes (which determines the treatment and control groups in our setting) was random conditional on electronic consumption. Lastly, the setup is simple since it involves a common treatment level (€1,000) and single timing (information on winning arriving on Christmas 2017 and prize money in early January 2018 by bank transfer in the taxpayers' bank accounts).

To ensure that winners and non-winners come from the same income or occupational category and, that they have a similar electronic consumption pattern in the months leading the the superdraw, I follow a two-step matching procedure. Matching is particularly important in ensuring that winners and non-winners have similar chances of winning and similar habits in debit/credit card payments.

The first step is to implement coarsened exact matching based on income quintiles and occupation categories.[30] This ensures that the comparison between winners and non-winners accounts for similar household income levels and occupation categories, both of which can influence spending habits and electronic consumption patterns. As a second step, for each coarsened exact matched subsample (5 quintile groups and 5 occupation categories), I obtain a propensity score of being treated using the following procedure. The propensity score produces a metric for the probability of an individual being a winner. Recall that when assessing the probability of winning in Column(7) of Table 1, the number of tickets was the most important variable, rendering any other variable statistically insignificant. Let W_i be a binary variable for individual i with the value of 1 if winning occurs and 0 otherwise. Let $T_{i,m}$ represent tickets received in months $m \in [1, 9]$ (January to September 2017, which were the months of the Superdraw – see Section 2). The following logit model calculates the probabilities of winning:

$$P\left(W_i = 1\right) = \frac{1}{1 + \exp\left(-\left(\beta_0 + \sum_{m=1}^{9} \beta_m T_{i,m}\right)\right)} \tag{3}$$

Logistic regressions are fitted for the 5 quintile income groups and for 5 occupation groups (WG, PE, SB, AG and NO), using maximum likelihood with Firth's bias reduction (Firth, 1993; Heinze

[30] Note that matching on cross-categories of income quintiles and occupation is not considered in this study, since some occupational categories are small (SB and AG in particular), which does not provide enough statistical power after matching, propensity scoring and event study regressions are implemented.

and Schemper, 2002).[31] Regression results and predicted values, plotted in Kernel density functions are available in an online appendix.[32] The estimates are used to produce inverse probability weights from the propensity score, to re-weight the probability of being a winner. This procedure generates comparable groups of winners and non-winners, factoring in their spending patterns as well as their income and occupation characteristics.

5.2 Estimation

Estimation takes place by utilising the superdraw as an event to investigate the electronic consumption responses for 7 months post-winning. Recall that monthly electronic consumption is denoted by $z_{i,m}$ for individual i, while the binary indicator for winning is denoted by W_i. Variables χ_i and λ_m represent individual and time fixed effects, respectively. Robust standard errors, clustered at the individual level, are used in all specifications. The following regression captures differences in electronic consumption between winners and non-winners:

$$\underbrace{z_{i,m}}_{E-Consumption} = \alpha + \overbrace{\beta W_i \times Post_m}^{Winner's\ \ Indicator} + \chi_i + \lambda_m + \epsilon_{i,m} \tag{4}$$

Note that income quintiles exclude self-employed individuals because of the high volumes of electronic consumption documented in Section 4. Since their electronic consumption is multiple times their income, inclusion in the income quintiles would have massively distorted the results. Secondly, NO category individuals are excluded since they declare zero income (allocation in income quintiles cannot take place). Therefore, income quintiles include WG, PE and AG individuals, who exhibited positive income and positive electronic consumption in 2017.

The main estimator used for Regression 4 is a Poisson pseudo maximum likelihood that quantifies the monthly semi-elasticity of electronic consumption with respect to winning.[33] Log-point estimates can be transformed into percentages; a comparable measure of responsiveness in electronic consumption across income quintiles and occupation categories. Additional results from a within-estimator in logarithmic form are presented in Appendix A.2.

5.3 Responses by Income Quintile

The responses of winners by income quintile are presented in Figure 5, with estimates in Table 8. The propensity score matching produces comparable samples with no statistically significant differences

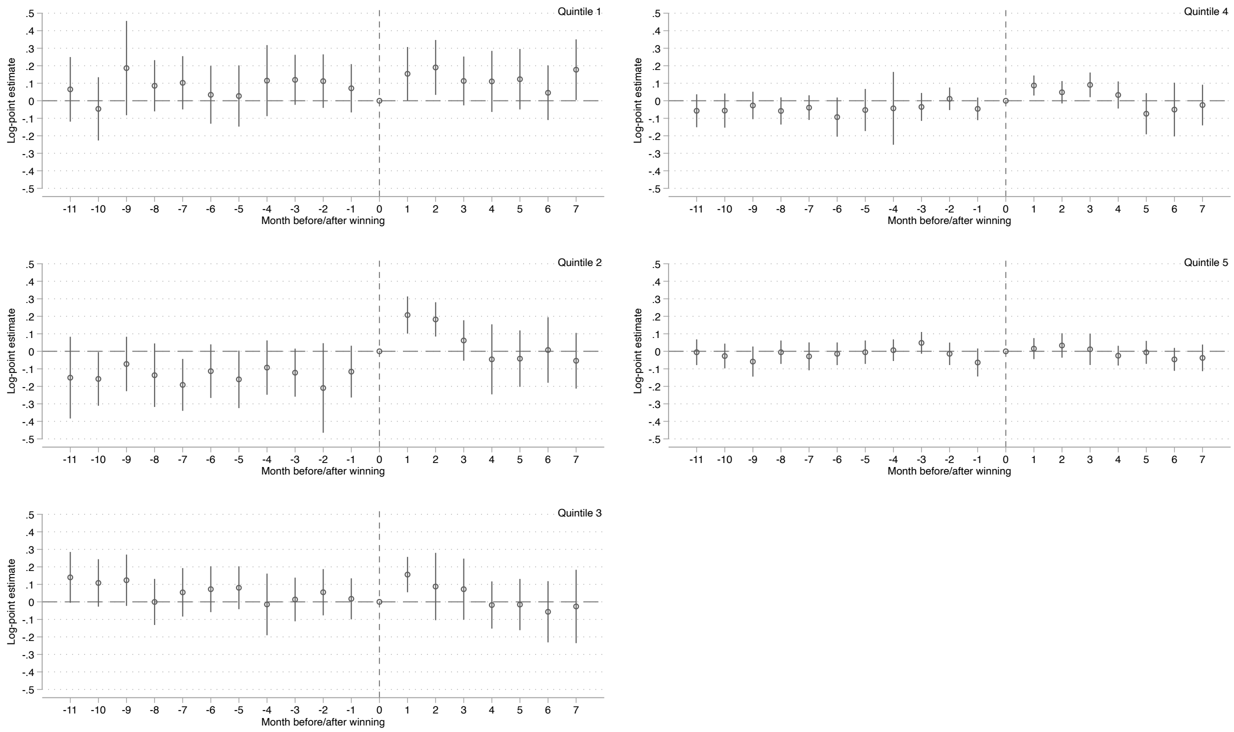
[31] There are 1,000 winning tickets every month and roughly €10 billion in electronic consumption monthly, which makes winning a rare event. Firth's bias reduction ensures convergence of the maximum likelihood estimator.

[32] These show the increase in probability of winning for every ticket obtained in the months of January to September 2017, which are relatively small indicating that one extra ticket does not increase the probability significantly (given a high aggregate volume of transactions in the economy). Most of the values are positive and statistically significant.

[33] This approach is preferred to logarithmic transformation of electronic consumption values since some months may contain zero values for some individuals.

in all quintiles but the 2nd, which exhibits a small (parallel) level difference. Matched winners and non-winners have similar spending patterns before the superdraw in December 2017.

Fig. 5 Winners' Responses by Income Quintile



Notes: The figures present log-point differences between winners and non-winners, for each income quintile. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from a Poisson pseudo maximum likelihood estimation after propensity score matching on the level of tickets for each income quintile. Results are shown in Table 8. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

The estimates show that winners respond temporarily before converging back to the non-winners' spending level. This result is not surprising because of the relatively small prize and the extremely low probability of winning again. It is likely that both winners and non-winners increased their electronic consumption due to the lottery's introduction. This fact can be observed from the monthly trends of both winners and non-winners in Figure 11, which show electronic consumption increase over time for all income quintiles. Winners appear to have used part of their prize money to further boost their spending for a few months after winning.

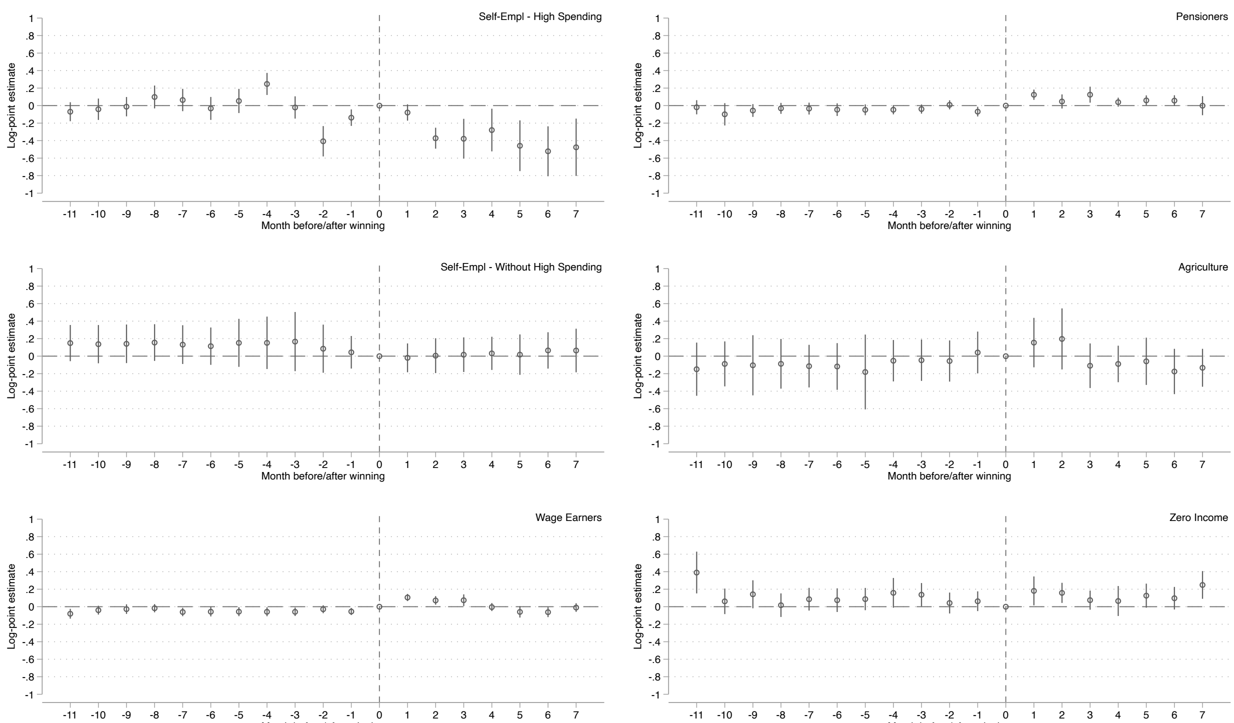
Secondly, individuals with lower income tend to have a stronger response. Individuals in the lowest quintile (top-left panel) of Figure 5 exhibit statistically significant increases in electronic consumption by 16.6% in the first month, 20.9% in the second month and 19.5% in the seven month following winning. Those in the 2nd quintile exhibit statistically significant increases by 23% and 20% in the first two months. Individuals in the 3rd income quintile have a statistically significant increase only in the first month by 16.9%, while those in the 4th quintile increase their electronic consumption by 9.1% in the first month and by 9.5% in the third month following winning. Log-point differences are statistically insignificant between winners and non-winners in the 5th quintile.

Overall, findings from income quintile event studies indicate that winners display only a temporary change in behaviour compared to non-winners, suggesting that winning does not result in a sustained increase of electronic payments. Notably, the response is stronger among winners with low-to-middle income, while those in the highest income quintile exhibit no greater response than non-winners.

5.4 Responses by Occupation Category

The winners' responses yield significant insights when analysed by occupational category. Figure 6 plots the regression results for matched winners and non-winners across six panels: wage-earners, pensioners, individuals in agriculture, and those with zero income, while the self-employed are split into two groups; those in the top 20% of electronic spending and all others. The corresponding log-point estimates for these graphs are provided in Table 9 in Appendix A.2.

Fig. 6 Winners' Responses by Occupation Category



Notes: The figures present log-point differences between winners and non-winners, for each occupational category. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from a Poisson pseudo maximum likelihood estimation after propensity score matching on the level of tickets for each occupational category. Self-employed individuals are separated in those with high-consumption (top 20% ranked by electronic consumption) and all the rest. Results are shown in Table 10. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

An important finding is the significant reduction, around 50%, in the responses of self-employed individuals with high electronic spending. This result is shown in the top-left panel and could stem from a perceived increase in visibility of their transactions as the tax lottery is introduced. As highlighted in Section 4, self-employed winners displayed electronic consumption levels ten times higher than their reported income, suggesting potential income concealment or the channeling of business transactions through personal accounts. This substantial reduction suggests that the tax lottery is effective in curbing tax evasion among these taxpayers through winning.

By contrast self-employed winners who exhibit lower levels of electronic transactions (middle-left panel) do not respond to winning. Their electronic consumption remains the same as that of non-winners. For both groups the use of electronic consumption is trending strongly upwards after the introduction of the lottery, as can be observed in the top-left and middle-left panels of Figure 13. Comparing the responses of high-spending and lower-spending self-employed individuals suggests that winning may serve as a signaling mechanism regarding the existence of the lottery and the increased visibility of transactions to the tax authority. In response, high-spending winners reduce their electronic consumption to avoid drawing attention.

Similar to income categories, wage-earners, pensioners and zero income individuals respond strongly but temporarily. Wage-earners increase their electronic consumption by 11%, 7.5% and 7.7% in the first three months. Pensioners increase consumption for 6 months ranging from 5.9% to 13.3%. And individuals with zero income respond the most by 19.8% in the first month and up to 28.3% in the seventh month after winning. Responses by winners in agriculture are not statistically significant compared to non-winners.

5.5 Explaining Differences in Responses

Several factors may account for the observed differences across the subsamples. One explanation is information frictions. Individuals in higher income quintiles may be better informed about the lottery's existence, leading to an increase in electronic payments for both winners and non-winners after the lottery's introduction. This could result in a smaller response among winners, either because they react to the lottery's informational impact or because the comparable group of non-winners also increases electronic consumption. Conversely, lower income quintiles may be less informed, leading to a stronger effect once a win occurs. In this way, the general awareness of the lottery's existence may crowd out the effect of the winning signal for higher income groups.

Another explanation lies in habitual differences in electronic payment usage, which may vary widely across income groups and occupations. Lower income individuals may be spending less on electronic payments on average, allowing more scope for increasing such payments, while higher income groups may already rely heavily on electronic methods. This could rationalise the more sustained response we observe among pensioners and wage-earners, who may have weaker habits for electronic payments, compared to the self-employed, who may use them for business purposes. Additionally, access to card payment options, such as living in rural areas, is a related issue that might help explain the lack of response among agricultural workers.

Lastly, lottery participation might vary due to the prize structure. First, the €1,000 prize may represent a more substantial amount for low-income individuals than for higher-income individuals, leading to a diminishing impact of a win with rising income. This could explain the temporary responses observed, stemming from a short-term income effect that is stronger for lower-income individuals. Secondly, in terms of incentives, people often participate in lotteries for the prospect of winning larger sums. The relatively small prize may appeal less to taxpayers in higher income quintiles, leading to a smaller response. In a recent reform, the tax authority revised the prize structure to include one €50,000 prize and five €20,000 prizes, indicating the legislator's concern about the effect of small prizes on lottery participation.

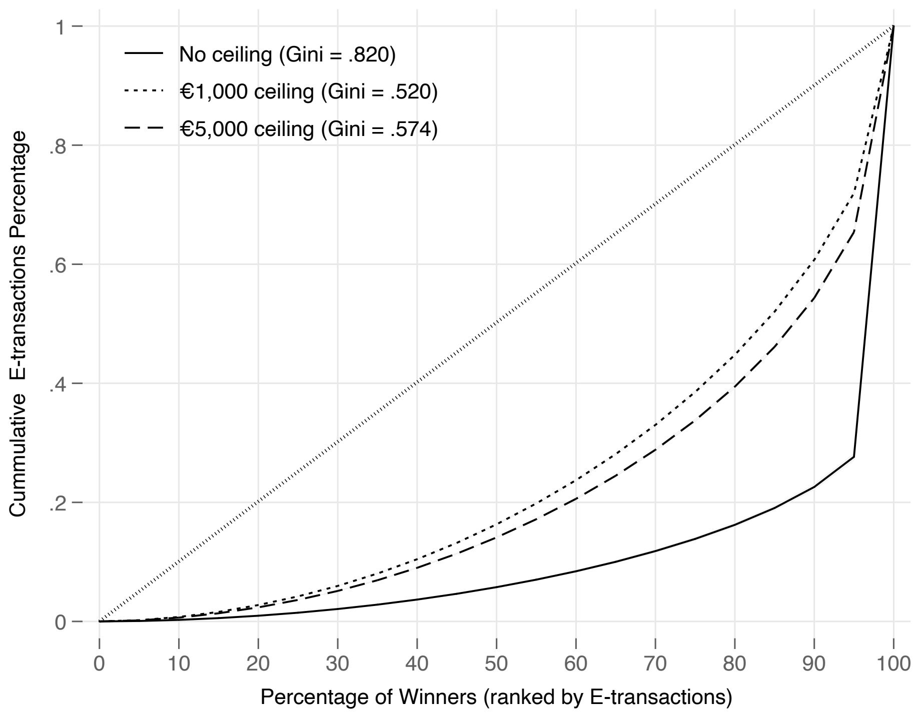
6 Lottery Simulations

This final section presents simulations of the lottery draws to investigate the distributional properties of ticket allocation. The analysis considers whether introducing a ticket ceiling could improve this allocation. Simulations convert the monthly electronic consumption of the population into lottery tickets, followed by 100 iterations of the draw for each month in 2017. Each iteration yields 1,000 winners, resulting in a total of 1.2 million winners (12 months $\times$ 100 iterations $\times$ 1,000 winners). Note that these simulations are conducted within a static framework. Behavioural responses could influence the results, especially in cases where high-consumption, self-employed winners reduce their electronic spending. As demonstrated in Section 5.2, this subgroup reduces their electronic consumption by half once they win.

Results are illustrated by the solid line in Figure 7. The dotted 45-degree line represents an equal allocation benchmark, where the percentage of the population aligns with the percentage of winners ranked by electronic consumption. High electronic consumption produces an extremely high concentration of winners: the top 5% secure three in every four prizes. When ranking winners by annual income, however, the top 5% claim roughly one out of every four prizes, as shown by the solid line in Figure 16. This contrast between annual income and electronic consumption aligns with the finding that winners typically exhibit higher electronic consumption relative to their annual income.

To address this effect, I evaluate two monthly ticket ceilings, at €1,000 and €5,000. These ceilings cap the maximum tickets an individual can obtain at 467 and 1,467, respectively, based on the TAM. Figures 14 and 15 illustrate the resulting ticket distributions, showing the levels at which the ceilings become binding. As can be observed, the €1,000 ceiling impacts a larger group of individuals, limiting their ticket counts once the threshold is reached, whereas the €5,000 ceiling applies to a far smaller subset of high spenders. Since lottery tickets are awarded based on everyday transactions (and not large payments), the €5,000 ceiling primarily affects individuals with exceptionally high monthly electronic consumption.

Fig. 7 Electronic Consumption Distributions after Lottery Simulations



Notes: The figure plots of cumulative electronic consumption distribution curves for 1.2 million winners in simulations of the lottery. The x-axis represents the population percentiles of winners, ranked by electronic consumption in 2017. The y-axis shows the percentage of individuals who have won the lottery in the simulations. The dotted line is a 45-degree line, at which the population percentage equals the winners percentage in the distribution. The "no ceiling" curve is a simulation of the lottery assigning tickets using the ticket-awarding mechanism in Table 11. The €1,000 ceiling introduces a maximum ceiling in monthly tickets. For electronic consumption beyond €1,000 per month no more tickets are awarded to individuals. Similarly, the €5,000 curve introduces a ceiling at the €5,000 monthly electronic consumption level.

Simulation results are presented in Table 2, showing that both ceilings effectively reduce the winning probabilities associated with very high monthly electronic consumption. At the highest decile, average electronic consumption declines to €15,350 under the €5,000 ceiling and to €13,550 under the €1,000 ceiling. These effects are illustrated in the dashed and dotted lines of 7, where the ceiling reduces the prizes allocated to the top 5% roughly to one in every four prizes, down from three out of four. This prize allocation more closely aligns with the prize allocation based on income rankings in Figures 16. While the ceilings have only a marginal effect on the income distribution of winners, they significantly constrain ticket allocations to individuals with very high levels of electronic consumption.

Table 2 Simulation Results with Ticket Ceilings

	Ceiling €1,000				*Ceiling €5,000*			
	Mean	p10	p50	p90	Mean	p10	p50	p90
Annual E-Consumption	6,994	970	4,630	13,550	8,316	990	4,800	15,350
	(24,783)				(33,949)			
Annual Income	13,088	0	11,210	24,160	13,553	0	11,225	24,950
	(19,307)				(21,259)			

Notes: The table presents the main statistics from lottery simulations using a €1,000 monthly ticket ceiling per individual (left-hand side) and a corresponding €5,000 ceiling (right-hand side). Each simulation aggregates 1,200,000 observations of winners (100 lottery iterations, drawing 1,000 winners in each iteration, for each of the 12 months in 2017). The first column presents the mean values and standard deviation in parentheses. The median values are presented in the "p50" columns, together with the lowest and highest deciles in "p10" and "p90" respectively.

7 Conclusion

This paper examined the income and occupational characteristics of winners in the Greek tax lottery and their responses after receiving a prize. By linking electronic consumption to ticket allocations, the lottery structure assigns higher winning probabilities to subgroups with higher income and higher consumption. A 10% increase in income correlates with a 0.11% increase in the probability of winning, while self-employed individuals are selected more frequently due to their particularly high levels of electronic consumption. Compared to wage-earners, pensioners, and agricultural workers, being self-employed raises the probability of winning by 0.18%, even when controlling for income.

Leveraging an unanticipated superdraw in 2017, this paper conducted event studies comparing the electronic consumption patterns of winners and non-winners across income quintiles and occupational categories. Winners temporarily increased their electronic consumption for a few months following the win, with low-to-middle-income individuals showing a stronger response, while high-income winners displayed no statistically significant differences. Variations in response across income and occupational categories might be explained through information frictions about the lottery's introduction, differing habits around electronic payments, or the influence of the prize structure on participation.

A key finding is that self-employed winners display unusually high levels of electronic consumption, potentially indicating either income concealment or the use of personal accounts for business transactions. However, after winning, they reduce their electronic payments by half relative to comparable non-winners. This substantial reduction suggests that winning the tax lottery increases the perceptions of transaction visibility by the tax authority, thereby leading to greater tax compliance.

While winning can enhance tax compliance among high-consumption self-employed individuals, the allocation of tickets and prizes remains skewed toward high-income earners and the self-employed. These groups do not increase their electronic consumption after winning compared to similar non-winners. Consequently, certain subgroups may benefit from windfall gains without any added third-party reporting being generated to aid the lottery's objective. To address this, simulations in this paper explored the effect of monthly ticket ceilings on prize allocations. Results indicate that these ceilings can limit excessive electronic consumption, therefore, reducing the concentration of prizes among individuals with particularly high spending levels.

Declarations

Competing interests

Partial financial support for field work in Greece was received from the Hertie School, Berlin through the German Academic Exchange Service (DAAD) funds. The author has no other known competing interests.

Data availability statement

The data used in this study consist of (i) 50,000 randomly-drawn tax units from the 2017-2018 taxpayer population in Greece and, (ii) 18,897 winning tax units. Both samples were anonymised and are non-identifiable. These were provided by the Independent Authority of Public Revenue in collaboration with the Greek Ministry of Finance in October 2018. The data were drawn and anonymised at the tax authority premises, to ensure confidentiality. However, the anonymised data are still considered confidential and cannot be shared publicly. Access to the data for replication purposes or use in future projects can be granted in a safe computer at the Paris School of Economics upon reasonable request to the author.

References

Browning, M., Bourguignon, F., Chiappori, P.-A. and Lechene, V. (1994). Income and Outcomes: A Structural Model of Intrahousehold Allocation. *Journal of Political Economy*, **102** (6), 1067–1096.

Carroll, C. D., Slacalek, J. and Tokuoka, K. (2014). The Distribution of Wealth and the MPC: Implications of New European Data. *The American Economic Review*, **104** (5), 107–111.

Danchev, S., Gatopoulos, G. and Vettas, N. (2020). Penetration of Digital Payments in Greece after Capital Controls: Determinants and Impact on VAT Revenues. *CESifo Economic Studies*, **66** (3), 198–220.

Firth, D. (1993). Bias Reduction of Maximum Likelihood Estimates. *Biometrika*, **80** (1), 27–38.

Fooken, J., Hemmelgarn, T. and Herrmann, B. (2015). Improving VAT Compliance – Random Awards for Tax Compliance, Directorate General Taxation and Customs Union, European Commission, Taxation Paper No. 51.

Heinze, G. and Schemper, M. (2002). A solution to the problem of separation in logistic regression. *Statistics in Medicine*, **21** (16), 2409–2419.

Hondroyiannis, G. and Papaoikonomou, D. (2017). The effect of card payments on VAT revenue: New evidence from Greece. *Economics Letters*, **157**, 17 – 20.

Kleven, H. J., Knudsen, M., Kreiner, C., Pedersen, S. and Saez, E. (2011). Unwilling or Unable to Cheat? Evidence From a Tax Audit Experiment in Denmark. *Econometrica*, **79** (3), 651–692.

Lundberg, S., Pollak, R. and Wales, T. (1997). Do Husbands and Wives Pool Their Resources? Evidence from the United Kingdom Child Benefit. *Journal of Human Resources*, **32** (3), 463–480.

Naritomi, J. (2019). Consumers as Tax Auditors. *American Economic Review*, **109** (9), 3031–3072.

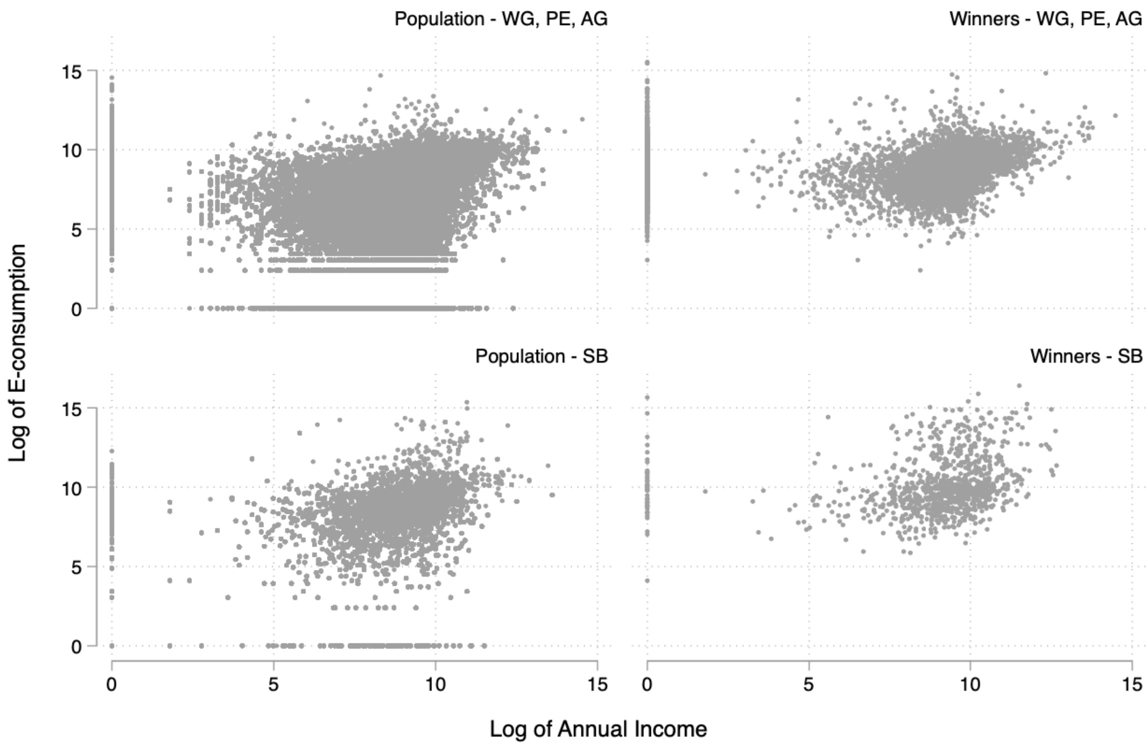
Nicolaides, P. (2023). Winning the Tax Lottery: Evidence from a Superdraw on Christmas Eve, Working Paper.

Pomeranz, D. (2015). No Taxation without Information: Deterrence and Self-Enforcement in the Value Added Tax. *American Economic Review*, **105** (8), 2539–69.

A Figures

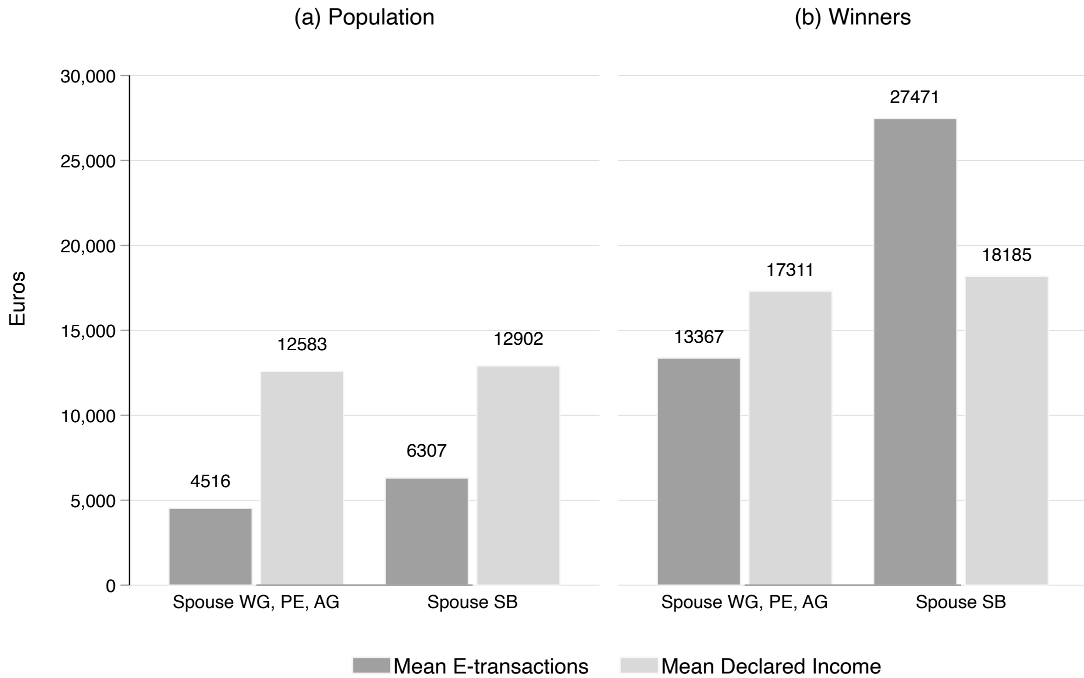
A.1 Descriptives

Fig. 8 Scatter Plots of Annual Income and Electronic Consumption by Occupational Category



Notes: The figures plots the relationship between the logarithm of annual electronic consumption (y-axis) against the logarithm of annual income (x-axis) for groups with different primary income sources: self-employed (SB) vs other non-zero incomes from wages, pensions and agricultural activities (WG, PE, and AG). Individuals who declare zero income (NO) are excluded from these plots. Right-hand side scatter plots contain only winners. Left-hand side plots contain taxpayer units who have not won in the lottery.

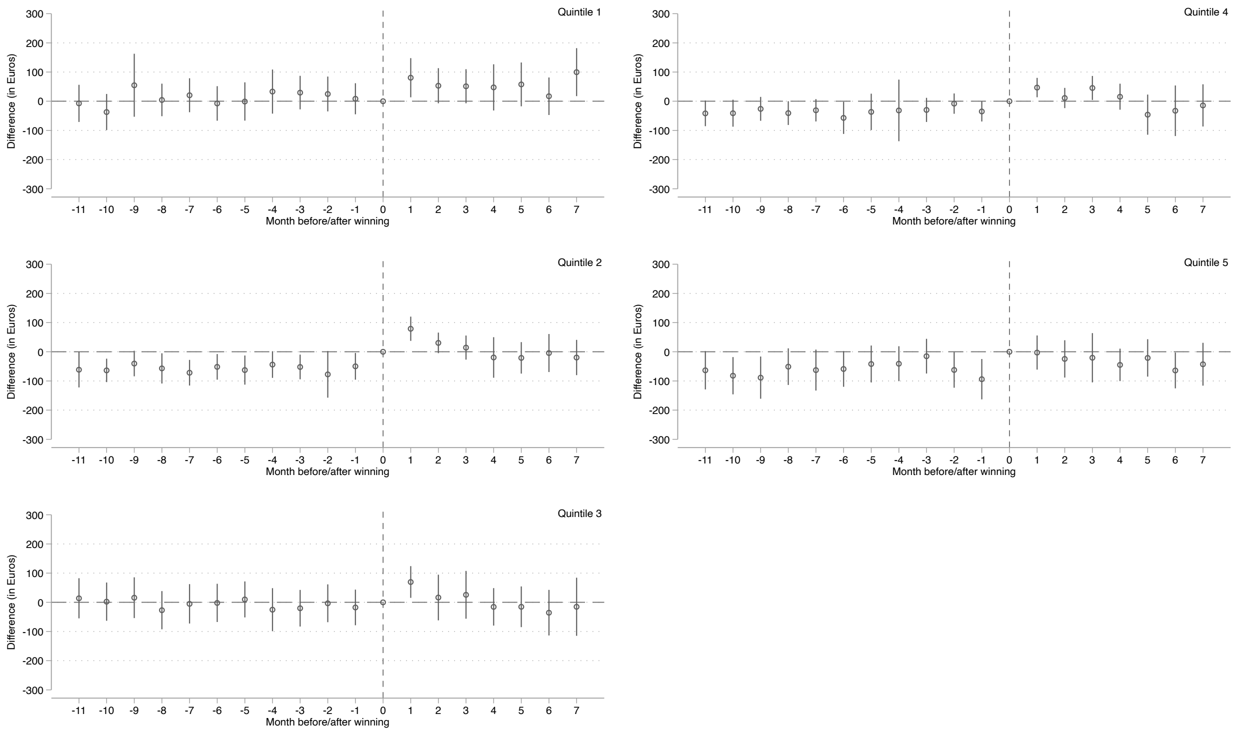
Fig. 9 Annual Income and Electronic Consumption - Taxpayers with SB spouses



Notes: The figure compares the mean annual income and mean annual electronic consumption of the taxpayer population, figure (a) on the left-hand side and for winners, figure (b) on the right-hand side. The left-hand side columns of each figure include individuals who have a spouse with primary income from WG, PE and AG, against individuals who have a spouse with primary income from SB. Individuals with primary SB income and NO income are excluded from the sample.

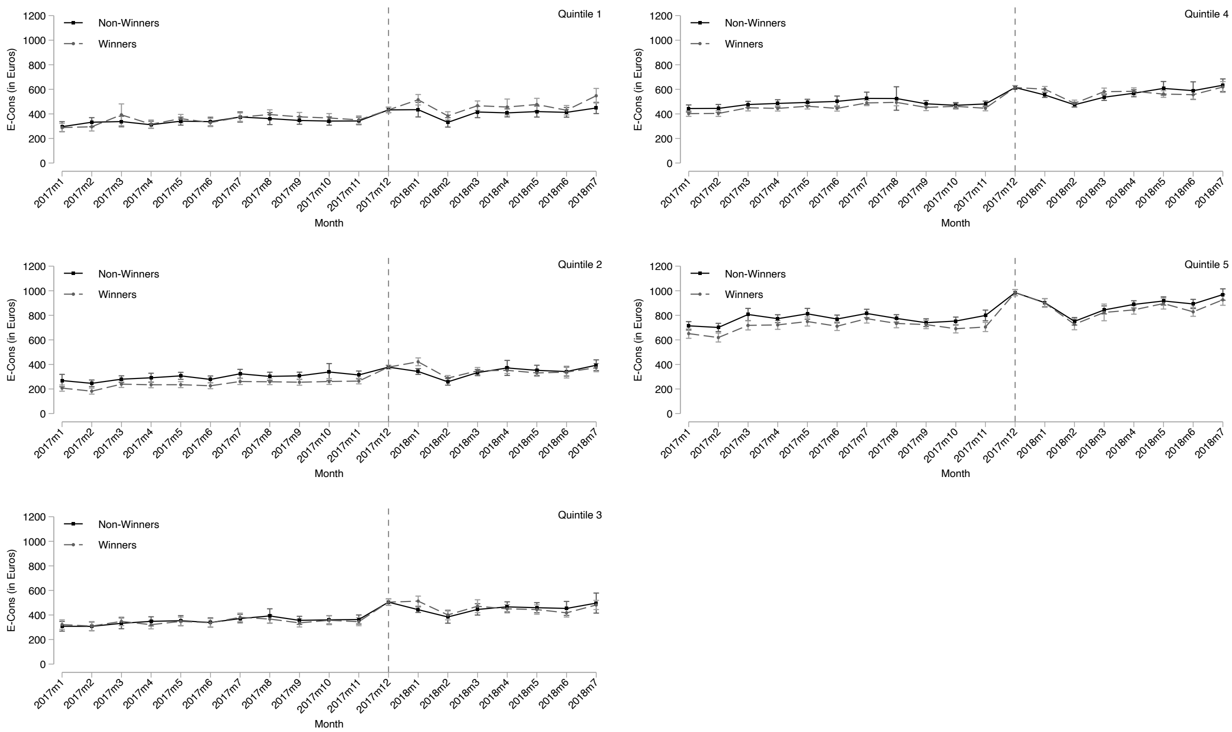
A.2 Event Studies

Fig. 10 Winners' Responses by Income Quintile (Monthly Differences)



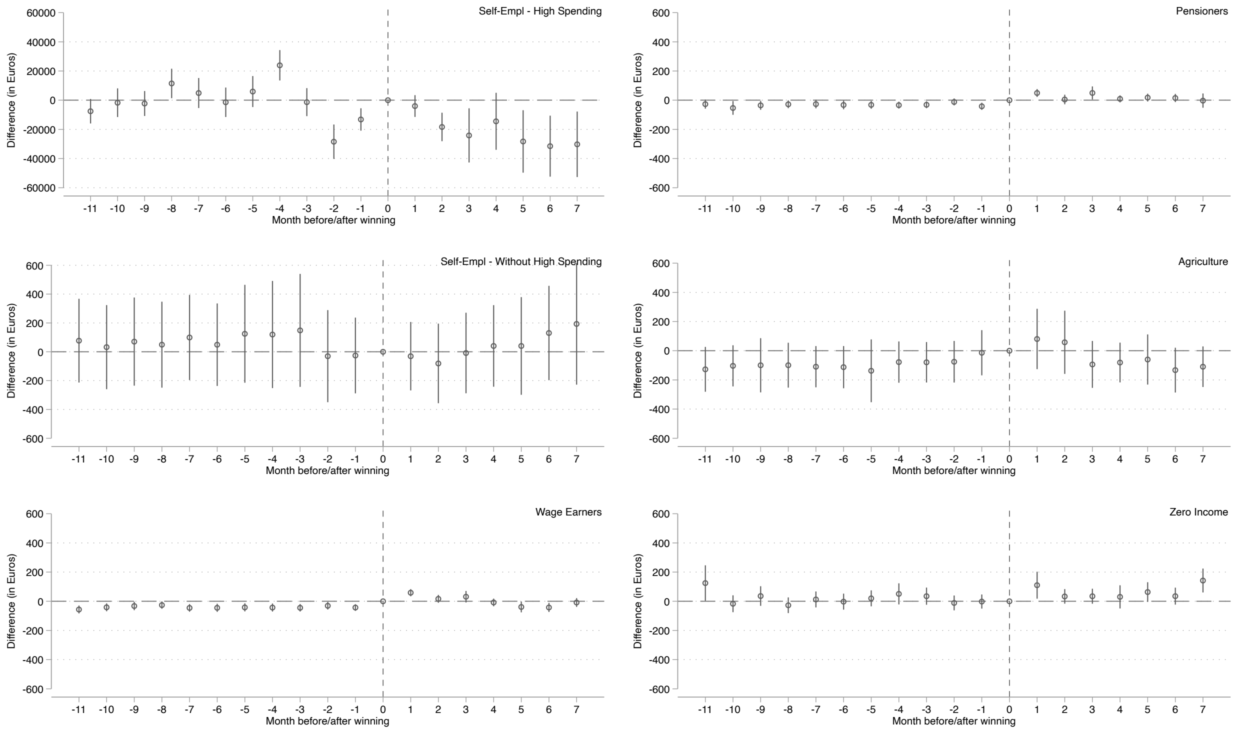
Notes: The figures present monthly differences in euros between winners and non-winners for each income quintile. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from a linear estimation after propensity score matching on the level of tickets for each income quintile. Results are shown in Table 7. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 11 Winners' Responses by Income Quintile (Monthly Trend)



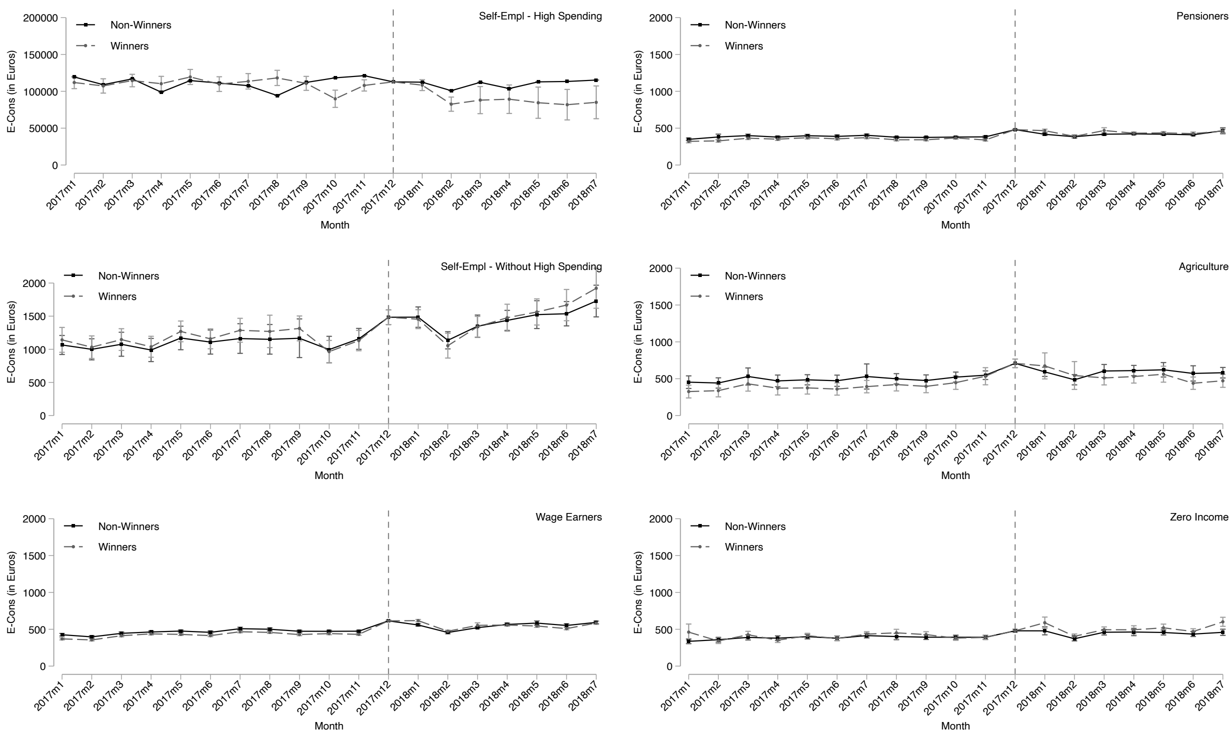
Notes: The figures present the evolution of electronic consumption between winners and non-winners for each income quintile. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from a linear estimation after propensity score matching on the level of tickets for each income quintile. Results are shown in Table 7. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 12 Winners' Responses by Occupational Category (Monthly Differences)



Notes: The figures present monthly differences in euros between winners and non-winners for each occupational category. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from a linear estimation after propensity score matching on the level of tickets for each occupational category. Self-employed individuals are separated in those with high-consumption (top 20% ranked by electronic consumption) and all the rest. Results are shown in Table 9. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

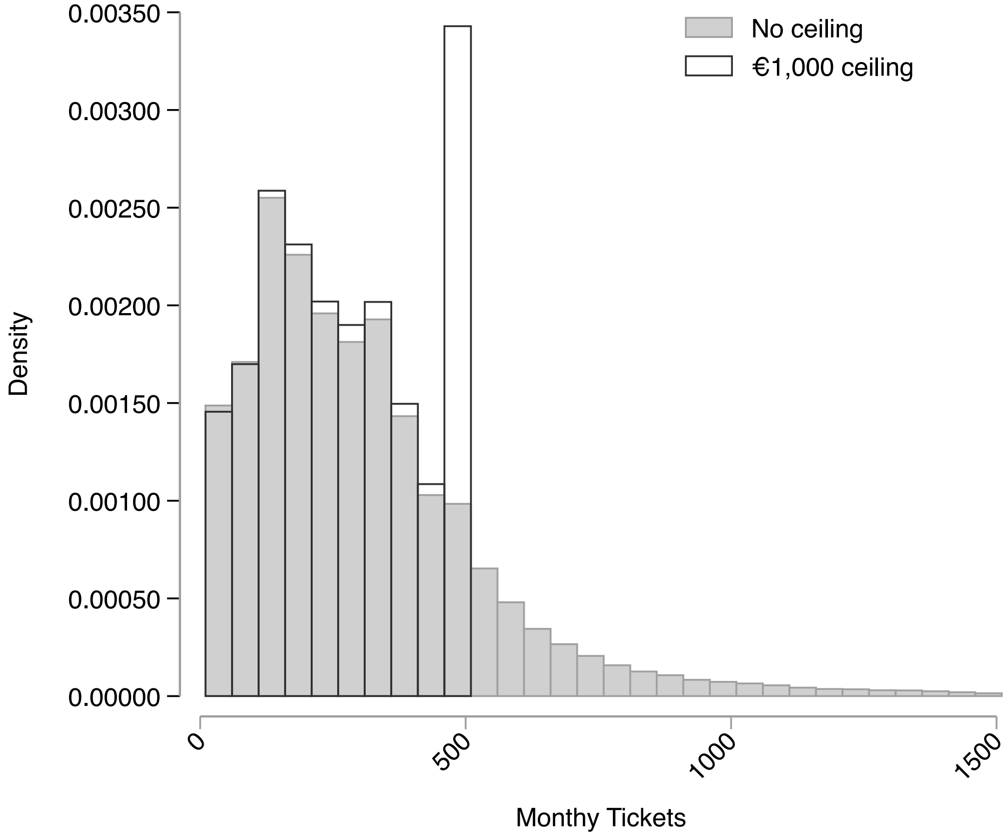
Fig. 13 Winners' Responses by Occupational Category (Monthly Trend)



Notes: The figures present monthly differences in euros between winners and non-winners for each occupational category. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from a linear estimation after propensity score matching on the level of tickets for each occupational category. Self-employed individuals are separated in those with high-consumption (top 20% ranked by electronic consumption) and all the rest. Results are shown in Table 9. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

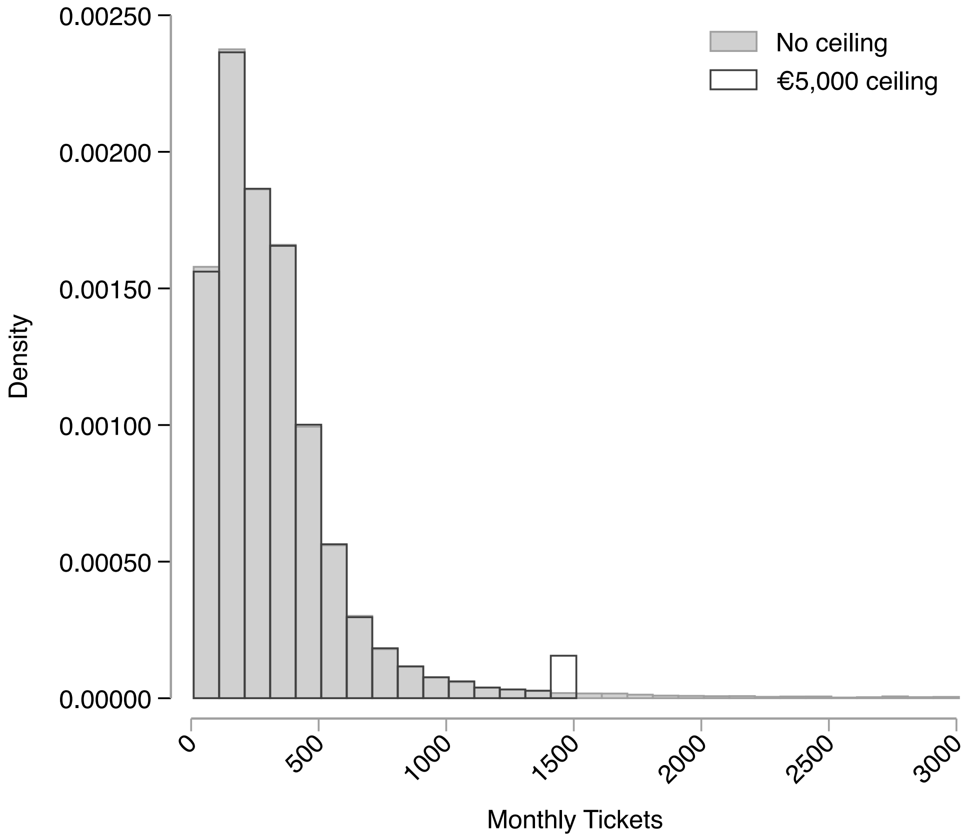
A.3 Simulations

Fig. 14 Winners' Distribution of Tickets in Simulations



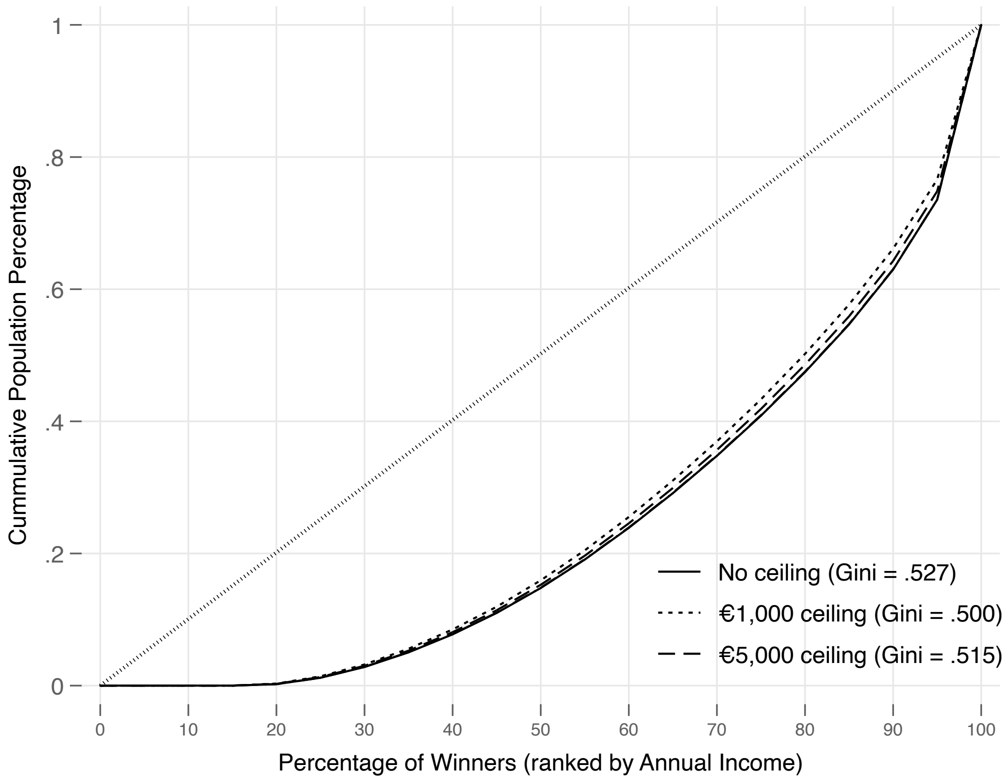
Notes: The figure compares the distribution of winners' tickets in simulations with and without the €1,000 ceiling. The ceiling translates to a maximum number of 467 monthly tickets per individual. Both simulations contain 1,200 iterations of the lottery (100 for each month in 2017), drawing 1,000 winners in each iteration. Both distributions contain 1.2 million winners. The "no ceiling" distribution is a simulation of the lottery assigning tickets using the ticket-awarding mechanism in Table 11. The "€1,000 ceiling" distribution retains introduces a maximum ceiling in monthly tickets. For electronic consumption beyond €1,000 per month no more tickets are awarded to individuals. The distributions is truncated at 1,500 tickets, as right-tails diminish quickly in the distribution beyond this point.

Fig. 15 Winners' Distribution of Tickets in Simulations



Notes: The figure compares the distribution of winners' tickets in simulations with and without the €5,000 ceiling. The ceiling translates to a maximum number of 1,467 monthly tickets per individual. Both simulations contain 1,200 iterations of the lottery (100 for each month in 2017), drawing 1,000 winners in each iteration. Both distributions contain 1.2 million winners. The "no ceiling" distribution is a simulation of the lottery assigning tickets using the ticket-awarding mechanism in Table 11. The "€5,000 ceiling" distribution retains introduces a maximum ceiling in monthly tickets. For electronic consumption beyond €5,000 per month no more tickets are awarded to individuals. The distributions are truncated at 3,000 tickets, as right-tails diminish quickly in the distribution beyond this point.

Fig. 16 Income Distributions after Lottery Simulations



Notes: The figure plots of cumulative income distribution curves for 1.2 million winners in simulations of the lottery. The x-axis represents the population percentiles of winners, ranked by their declared annual income in 2017. The y-axis shows the percentage of individuals who have won the lottery in the simulations. The dotted line is a 45-degree line, at which the population percentage equals the winners percentage in the distribution. The "no ceiling" curve is a simulation of the lottery assigning tickets using the ticket-awarding mechanism in Table 11. The €1,000 ceiling introduces a maximum ceiling in monthly tickets. For electronic consumption beyond €1,000 per month no more tickets are awarded to individuals. Similarly, the €5,000 curve introduces a ceiling at the €5,000 monthly electronic consumption level.

B Tables

B.1 Summary Statistics and Regressions

Table 3 Sample Statistics

	Samples		*Single/Joint Filing*	
	Non-Winners Freq (Percent)	Winners Freq (Percent)	Single Filers Freq (Percent)	Joint Filers Freq (Percent)
By Primary Income Source:				
SB : Self-Employed	2,052	1,609	1,855	1,806
	(4.10)	(8.52)	(4.46)	(6.61)
WG : Wage-Earner	22,335	9,107	17,205	14,237
	(44.67)	(48.19)	(41.38)	(52.11)
PE : Pensions	12,163	4,201	8,979	7,385
	(24.33)	(22.23)	(21.60)	(27.03)
AG : Agriculture	2,635	831	1,463	2,003
	(5.27)	(4.40)	(3.52)	(7.33)
NO : Zero-declared Income	10,815	2,861	12,072	1,604
	(21.63)	(15.14)	(29.04)	(5.87)
No Filing : Tax return not submitted	-	288	-	288
	-	(1.52)	-	(1.05)
Total	50000	18897	41574	27323

Notes: The table presents basic summary statistics for the winners and non-winners samples, per income source category. The left-hand side columns present the number of observations and percentages (in parentheses), of the non-winners and winners samples in the tax lottery. The winners sample includes winners in 19 consecutive months, from January 2017 to July 2018. The non-winners sample has been randomly drawn. The right-hand side columns present the frequencies and percentages of single and joint-filing tax units in each primary income source category. Joint-filing units can be indirectly deduced from the sample, based on annual declared income from both spouses in a household. The case where the main taxpayer declares positive income and the spouse zero income cannot be identified in the sample.

Table 4 Summary Statistics - Winners and Reconstructed Taxpayer Population

	Winners			*Population*		
	Obs.	Income	E-Cons	Obs.	Income	E-Cons
by Primary Income Category:						
SB	988	20,753	181,520	266,317	12,120	11,420
Self-Employed income	8.3%	(32,955)	(695,170)	4.1%	(25,891)	(60,163)
WG	5,773	18,357	10,857	2,890,322	11,418	4,064
Wage income	48.3%	(38,738)	(45,598)	44.7%	(13,941)	(6,138)
PE	2,704	14,631	10,964	1,573,228	11,875	3,322
Pension income	22.6%	(6,347)	(67,821)	24.3%	(6,046)	(5,350)
AG	503	47,423	15,532	340,746	17,582	3,817
Agriculture income	4.2%	(106,648)	(33,355)	5.27%	(38,113)	(6,627)
NO	1,818	0	27,618	1,397,996	0	2,935
Zero income declared	15.2%	(0)	(197,309)	21.6%	(0)	(15,109)
No Filing	174	-	37,119	-	-	-
(Tax return not submitted)	1.45%	-	(342,630)	-	-	-
Total	11,960	15,877	28,413	6,468,897	9,403	3,931
	100%	(37,277)	(229,919)	100%	(15,036)	(15,243)

Notes: The table presents the number of observations, the mean income and the mean electronic consumption Z_i in 2017 (nominal € values) winners and the reconstructed taxpayer population. They are presented by primary income source as has been declared in their tax returns: from wages (WG), self-employed (SB), agricultural income (AG), pensions (PE). Additional categories indicates zero-declared income (NO) and no filing. Standard deviations are in parenthesis. The 'Winners' sample includes all individual winners from 2017 draws. The 'Population' sample is a reconstructed sample of the taxpayer population (see Section 3).

Table 5 Non-parametric Estimates, by Income Category

	(1)	(2)	(3)	(4)	(5)	(6)
Annual Income	SB	WG	PE	AG	NO	No Filing
Winner in 2017	8,665***	6,952***	2,760***	29,884***	0	0
	(1,192)	(518)	(134)	(4,807)	(0)	(0)
Constant	12,088***	11,404***	11,870***	17,538***	0	0
	(568)	(92)	(55)	(733)	(0)	(0)
Annual E-consumption						
Winner in 2017	170,733***	6,807***	7,655***	11,732***	24,715***	53,286
	(22,125)	(601)	(1,305)	(1,491)	(4,628)	(33,389)
Constant	10,786***	4,050***	3,309***	3,800***	2,903***	4,925***
	(860)	(37)	(41)	(126)	(125)	(1,137)
Observations	266,317	2,890,322	1,573,228	340,746	1,397,996	288

Notes: The table presents estimation results per income category. Results on the top table use annual income as independent variable and at the bottom, annual electronic consumption. The NO and No Filing categories in columns (5) and (6) do not record results for annual income regressions, since no income was declared. Robust standard errors (clustered at the individual level, depending on the number in each income category) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6 Estimates - Spouse's Income Source

	(1) E-Cons	(2) E-Cons	(3) E-Cons	(4) E-Cons	(5) E-Cons	(6) E-Cons
SB Spouse (primary source)	2,006***		1,778***	1,781***	1,791***	1,747***
	(317)		(320)	(256)	(268)	(256)
SB Spouse (any SB income)		2,321***				
		(357)				
Annual Income in 2017			0.153***	0.139***		0.138***
			(0.027)	(0.021)		(0.021)
Winner in 2017					8,851***	8,196***
					(1,369)	(1,374)
Winner in 2017 & Spouse SB					12,313**	12,236**
					(6,088)	(6,081)
Constant	4,970***	4,943***	3,049***	2,788***	4,516***	2,774***
	(119)	(119)	(328)	(266)	(79)	(265)

Notes: The table presents estimation results for taxpayers with SB spouses. The sample is restricted to 2,406,971 individuals in the population who filed jointly, shown in regressions (1) - (3). Observations are restricted to 2,279,469 in (4) - (6), which include joint-filers, but exclude individuals who declared SB as their primary income source. Robust standard errors (clustered at the level of 27,323 and 25,517 unique taxpayers for regressions (1) - (3) and (4) - (6) respectively) in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

B.2 Event Study Estimates

Table 7 Event Studies by Income Quintile (Linear Fixed Effects Estimation)

	1st Quintile (1) E-cons	2nd Quintile (2) E-cons	3rd Quintile (3) E-cons	4th Quintile (4) E-cons	5th Quintile (5) E-cons
Winners Interaction ×					
January 2017	-7.381	-61.46**	13.79	-41.55*	-63.45*
	(32.47)	(31.00)	(35.08)	(22.43)	(33.47)
February 2017	-36.97	-63.79***	2.256	-41.05*	-82.02**
	(31.58)	(20.45)	(33.43)	(23.55)	(32.58)
March 2017	54.74	-40.35*	15.81	-26.13	-88.64**
	(55.04)	(22.30)	(35.62)	(20.88)	(36.87)
April 2017	4.401	-56.95**	-27.00	-40.63*	-51.01
	(28.44)	(26.40)	(33.38)	(20.75)	(31.99)
May 2017	20.53	-71.82***	-5.216	-31.05	-62.76*
	(29.69)	(22.42)	(34.43)	(19.53)	(35.79)
June 2017	-7.578	-51.69**	-1.961	-57.02**	-58.89*
	(30.19)	(22.37)	(33.41)	(28.10)	(31.20)
July 2017	-0.902	-62.70**	9.870	-36.52	-41.87
	(33.46)	(25.47)	(31.44)	(31.80)	(32.29)
August 2017	33.09	-43.83*	-25.26	-31.57	-40.87
	(38.53)	(23.28)	(37.61)	(53.84)	(30.55)
September 2017	29.56	-52.01**	-20.28	-29.76	-15.12
	(29.30)	(21.55)	(31.97)	(21.09)	(30.30)
October 2017	24.83	-77.39*	-3.307	-8.225	-62.29**
	(30.42)	(40.77)	(33.07)	(17.75)	(31.10)
November 2017	8.454	-49.84**	-17.55	-35.08**	-93.95***
	(27.13)	(23.34)	(31.13)	(17.50)	(35.26)
January 2018	80.56**	78.86***	69.68**	46.78***	-2.676
	(34.20)	(21.16)	(27.71)	(16.95)	(29.84)
February 2018	53.09*	30.45*	16.44	11.07	-24.39
	(30.69)	(17.99)	(39.91)	(17.65)	(32.60)
March 2018	51.26*	14.35	25.80	45.50**	-20.45
	(29.78)	(21.07)	(41.79)	(20.97)	(43.03)
April 2018	47.46	-19.50	-15.55	15.48	-44.89
	(40.37)	(35.43)	(32.73)	(22.73)	(28.35)
May 2018	57.69	-20.90	-15.31	-46.03	-21.07
	(38.30)	(27.53)	(35.55)	(35.07)	(32.66)
June 2018	17.15	-4.339	-35.54	-32.65	-64.07**
	(32.79)	(33.24)	(39.83)	(44.23)	(31.30)
July 2018	99.66**	-19.70	-15.25	-14.32	-42.75
	(41.91)	(30.80)	(50.79)	(36.90)	(37.43)
Constant	432.5***	378.0***	504.5***	615.1***	985.1***
	(11.38)	(7.522)	(13.47)	(7.691)	(12.57)
Individual FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Number of obs.	195373	194974	203277	212024	229192
Number of Individuals	10284	10263	10700	11160	12065

Notes: The table presents monthly event study estimates from Regression 4 for each of the income quintiles. A linear regression is used. Estimates present differences in monthly electronic consumption between winners and non-winners. Results are plotted in Figure 10 for each quintile. The regressions use inverse probability weights generated from the propensity scores as shown in and online appendix. Robust standard errors are clustered at the individual level.

Table 8 Event Studies by Income Quintile (Poisson Maximum Likelihood Estimation)

	1st Quintile (1) E-cons	2nd Quintile (2) E-cons	3rd Quintile (3) E-cons	4th Quintile (4) E-cons	5th Quintile (5) E-cons
Winners Interaction ×					
January 2017	0.0652	-0.150	0.140*	-0.0572	-0.00521
	(0.0941)	(0.119)	(0.0741)	(0.0480)	(0.0374)
February 2017	-0.0462	-0.158**	0.108	-0.0562	-0.0268
	(0.0922)	(0.0781)	(0.0692)	(0.0498)	(0.0361)
March 2017	0.187	-0.0724	0.124*	-0.0268	-0.0587
	(0.137)	(0.0793)	(0.0747)	(0.0400)	(0.0438)
April 2017	0.0856	-0.136	-0.000520	-0.0582	-0.00520
	(0.0746)	(0.0925)	(0.0671)	(0.0396)	(0.0340)
May 2017	0.103	-0.192**	0.0544	-0.0391	-0.0288
	(0.0776)	(0.0757)	(0.0706)	(0.0360)	(0.0407)
June 2017	0.0341	-0.113	0.0724	-0.0933	-0.0142
	(0.0843)	(0.0780)	(0.0669)	(0.0571)	(0.0330)
July 2017	0.0272	-0.160*	0.0807	-0.0528	-0.00512
	(0.0893)	(0.0837)	(0.0624)	(0.0613)	(0.0341)
August 2017	0.115	-0.0929	-0.0146	-0.0433	0.00643
	(0.103)	(0.0792)	(0.0898)	(0.106)	(0.0316)
September 2017	0.120	-0.122*	0.0137	-0.0352	0.0482
	(0.0729)	(0.0700)	(0.0636)	(0.0407)	(0.0317)
October 2017	0.112	-0.210	0.0550	0.0113	-0.0142
	(0.0780)	(0.131)	(0.0674)	(0.0329)	(0.0328)
November 2017	0.0712	-0.116	0.0173	-0.0462	-0.0637
	(0.0703)	(0.0755)	(0.0598)	(0.0329)	(0.0408)
January 2018	0.154**	0.207***	0.156***	0.0871***	0.0154
	(0.0779)	(0.0541)	(0.0515)	(0.0292)	(0.0306)
February 2018	0.190**	0.182***	0.0876	0.0485	0.0333
	(0.0799)	(0.0499)	(0.0981)	(0.0326)	(0.0356)
March 2018	0.113	0.0619	0.0725	0.0908**	0.0115
	(0.0711)	(0.0589)	(0.0891)	(0.0359)	(0.0457)
April 2018	0.111	-0.0459	-0.0180	0.0330	-0.0248
	(0.0890)	(0.102)	(0.0688)	(0.0395)	(0.0288)
May 2018	0.123	-0.0418	-0.0155	-0.0740	-0.00605
	(0.0880)	(0.0822)	(0.0747)	(0.0599)	(0.0335)
June 2018	0.0459	0.00750	-0.0566	-0.0503	-0.0460
	(0.0796)	(0.0955)	(0.0891)	(0.0782)	(0.0334)
July 2018	0.178**	-0.0540	-0.0263	-0.0245	-0.0375
	(0.0884)	(0.0812)	(0.107)	(0.0592)	(0.0388)
Constant	6.934***	6.631***	6.720***	6.841***	7.243***
	(0.0259)	(0.0224)	(0.0265)	(0.0137)	(0.0124)
Individual FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Number of obs.	195373	194974	203277	212024	229192
Number of Individuals	10284	10263	10700	11160	12065

Notes: The table presents monthly event study estimates from Regression 4 for each of the income quintiles. A Poisson pseudo maximum likelihood regression is used. Estimates present log-point differences in monthly electronic consumption between winners and non-winners. Results are plotted in Figure 5 for each quintile. The regressions use inverse probability weights generated from the propensity scores as shown in an online appendix. Robust standard errors are clustered at the individual level.

Table 9 Event Studies by Occupation Category (Linear Fixed Effects Estimation)

	WG	PE	AG	NO	SB w/o high cons	SB high cons
	(1)	(2)	(3)	(4)	(5)	(6)
	E-cons	E-cons	E-cons	E-cons	E-cons	E-cons
Winners Interaction ×						
January 2017	-56.25***	-27.24*	-127.5	124.7**	76.96	-7569.1*
	(13.71)	(15.79)	(78.38)	(62.09)	(148.1)	(4244.0)
February 2017	-41.46***	-53.34**	-103.5	-16.89	32.20	-1733.3
	(13.66)	(23.97)	(71.93)	(29.49)	(148.7)	(4968.4)
March 2017	-32.50**	-35.52**	-99.61	35.85	70.65	-2282.1
	(14.59)	(15.49)	(94.67)	(34.31)	(155.9)	(4315.4)
April 2017	-26.09**	-28.07**	-99.23	-27.26	49.25	11472.6**
	(12.82)	(13.63)	(78.38)	(27.35)	(152.1)	(5095.2)
May 2017	-45.48***	-26.92*	-109.5	12.57	99.27	4911.6
	(13.27)	(14.70)	(72.02)	(27.84)	(150.6)	(5204.6)
June 2017	-44.87***	-32.82**	-112.6	-2.478	49.06	-1427.8
	(14.19)	(15.13)	(73.80)	(27.91)	(145.9)	(5099.7)
July 2017	-41.79***	-31.83**	-137.5	20.14	124.7	5916.3
	(14.13)	(13.61)	(109.7)	(27.84)	(173.2)	(5366.0)
August 2017	-42.95***	-34.22***	-77.85	50.69	119.7	23914.2***
	(14.09)	(11.98)	(72.24)	(36.91)	(189.5)	(5260.8)
September 2017	-44.59***	-31.53***	-79.24	34.93	148.4	-1338.3
	(13.12)	(11.90)	(70.67)	(30.00)	(199.8)	(4847.1)
October 2017	-30.83**	-12.03	-75.47	-11.38	-30.36	-28453.1***
	(13.12)	(12.03)	(72.67)	(25.94)	(162.8)	(5956.7)
November 2017	-42.84***	-41.94***	-13.85	-1.893	-25.79	-13213.5***
	(11.56)	(12.38)	(78.91)	(24.65)	(133.9)	(3880.7)
January 2018	58.74***	49.23***	80.59	110.2**	-30.67	-4019.5
	(12.33)	(13.63)	(105.5)	(47.04)	(121.0)	(3769.0)
February 2018	16.64	4.753	57.88	33.37	-80.87	-18346.7***
	(13.80)	(16.72)	(110.4)	(25.45)	(140.8)	(4929.7)
March 2018	31.25	49.69**	-93.83	34.60	-8.540	-24142.8**
	(20.11)	(22.73)	(81.99)	(26.17)	(142.5)	(9382.0)
April 2018	-8.158	8.977	-80.76	30.26	40.48	-14480.0
	(13.33)	(12.14)	(69.44)	(40.53)	(144.3)	(9870.8)
May 2018	-38.91**	17.70	-60.16	63.17*	40.38	-28282.3***
	(18.85)	(13.58)	(87.61)	(34.37)	(172.7)	(10816.3)
June 2018	-42.35***	15.01	-132.9*	35.10	130.2	-31509.0***
	(15.88)	(14.28)	(78.26)	(29.64)	(166.9)	(10559.9)
July 2018	-8.456	-2.901	-109.5	142.3***	193.2	-30240.4***
	(15.31)	(24.89)	(70.95)	(41.74)	(214.9)	(11344.9)
Constant	614.3***	480.5***	709.0***	479.4***	1483.5***	112850.0***
	(4.642)	(4.774)	(29.71)	(10.11)	(56.60)	(0.00126)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	479763	252658	52649	201206	48640	2359
Number of Individuals	25255	13299	2771	10591	2560	129

Notes: The table presents monthly event study estimates from Regression 4 for each of the occupation categories. A linear regression is used. Estimates present differences in monthly electronic consumption between winners and non-winners. Results are plotted in Figure 12 for each occupational category. The regressions use inverse probability weights generated from the propensity scores as shown in an online appendix. Robust standard errors are clustered at the individual level.

Table 10 Event Studies by Occupation Category (Poisson Maximum Likelihood Estimation)

	WG	PE	AG	NO	SB w/o high cons	SB high cons
	(1)	(2)	(3)	(4)	(5)	(6)
	E-cons	E-cons	E-cons	E-cons	E-cons	E-cons
Winners Interaction ×						
January 2017	-0.0802***	-0.0189	-0.149	0.390***	0.150	-0.0694
	(0.0285)	(0.0412)	(0.155)	(0.122)	(0.105)	(0.0552)
February 2017	-0.0393	-0.0990	-0.0881	0.0615	0.137	-0.0413
	(0.0256)	(0.0650)	(0.131)	(0.0745)	(0.111)	(0.0623)
March 2017	-0.0273	-0.0558	-0.104	0.142*	0.141	-0.0122
	(0.0279)	(0.0372)	(0.175)	(0.0816)	(0.112)	(0.0563)
April 2017	-0.0171	-0.0312	-0.0873	0.0174	0.155	0.0987
	(0.0238)	(0.0318)	(0.145)	(0.0687)	(0.107)	(0.0666)
May 2017	-0.0604**	-0.0341	-0.114	0.0856	0.132	0.0642
	(0.0243)	(0.0345)	(0.124)	(0.0661)	(0.113)	(0.0650)
June 2017	-0.0570**	-0.0461	-0.118	0.0747	0.114	-0.0320
	(0.0275)	(0.0369)	(0.136)	(0.0689)	(0.109)	(0.0668)
July 2017	-0.0565**	-0.0477	-0.181	0.0874	0.152	0.0533
	(0.0262)	(0.0314)	(0.218)	(0.0648)	(0.140)	(0.0704)
August 2017	-0.0579**	-0.0468*	-0.0520	0.159*	0.152	0.248***
	(0.0259)	(0.0269)	(0.121)	(0.0867)	(0.153)	(0.0642)
September 2017	-0.0582**	-0.0390	-0.0462	0.137**	0.167	-0.0211
	(0.0242)	(0.0267)	(0.121)	(0.0679)	(0.172)	(0.0648)
October 2017	-0.0288	0.00913	-0.0553	0.0423	0.0853	-0.407***
	(0.0230)	(0.0265)	(0.120)	(0.0610)	(0.140)	(0.0884)
November 2017	-0.0546***	-0.0685**	0.0419	0.0627	0.0444	-0.137***
	(0.0207)	(0.0281)	(0.122)	(0.0574)	(0.0949)	(0.0480)
January 2018	0.105***	0.125***	0.155	0.181**	-0.0190	-0.0786*
	(0.0207)	(0.0298)	(0.144)	(0.0841)	(0.0840)	(0.0475)
February 2018	0.0720***	0.0476	0.197	0.158***	0.00579	-0.372***
	(0.0249)	(0.0411)	(0.178)	(0.0586)	(0.101)	(0.0610)
March 2018	0.0744**	0.125***	-0.109	0.0753	0.0171	-0.378***
	(0.0340)	(0.0466)	(0.130)	(0.0557)	(0.101)	(0.116)
April 2018	-0.00394	0.0392	-0.0888	0.0652	0.0323	-0.279**
	(0.0233)	(0.0261)	(0.106)	(0.0872)	(0.0966)	(0.124)
May 2018	-0.0590*	0.0597**	-0.0586	0.126*	0.0177	-0.458***
	(0.0331)	(0.0291)	(0.138)	(0.0700)	(0.118)	(0.148)
June 2018	-0.0621**	0.0574*	-0.175	0.0971	0.0655	-0.521***
	(0.0288)	(0.0311)	(0.132)	(0.0657)	(0.106)	(0.146)
July 2018	-0.00964	-0.000902	-0.132	0.249***	0.0648	-0.476***
	(0.0252)	(0.0554)	(0.110)	(0.0807)	(0.127)	(0.167)
Constant	6.848***	6.591***	7.190***	6.955***	7.991***	11.63***
	(0.00731)	(0.0100)	(0.0456)	(0.0205)	(0.0363)	(1.10e-08)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	479763	252658	52649	201206	48640	2359
Number of Individuals	25255	13299	2771	10591	2560	129

Notes: The table presents monthly event study estimates from Regression 4 for each of the occupation categories. A Poisson pseudo maximum likelihood regression is used. Estimates present log-point differences in monthly electronic consumption between winners and non-winners. Results are plotted in Figure 6 for each occupational category. The regressions use inverse probability weights generated from the propensity scores as shown in an online appendix. Robust standard errors are clustered at the individual level.

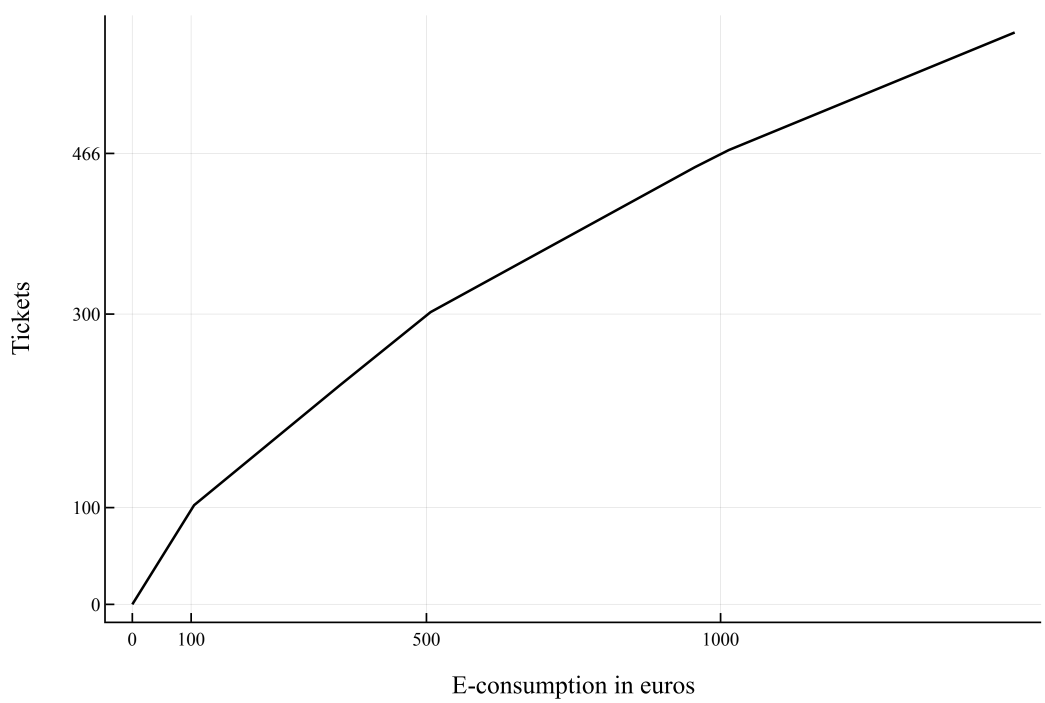
C Tax Lottery Information

Table 11 Ticket-Awarding Mechanism

Monthly E-Consumption	Ticket Conversion	Maximum number of tickets
€1 – 100	1 ticket per €1	100
€101 – 500	1 ticket per €2	300
€501 – 1,000	1 ticket per €3	466
> €1,000	1 ticket per €4	No limit

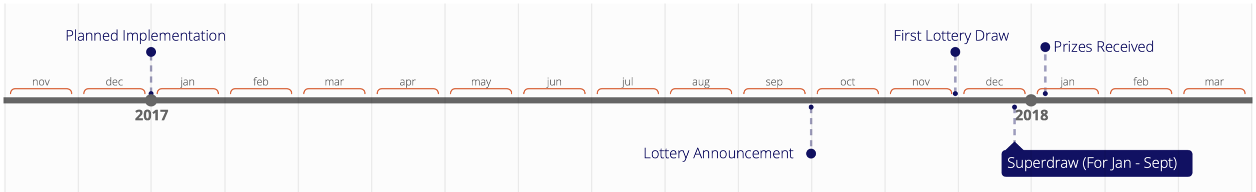
Notes: The table shows the ticket-awarding mechanism (TAM) used to convert the monthly electronic consumption of individuals into lottery tickets. At €1-100, tickets correspond at 1 for every €1. At €101-500, tickets correspond at 1 for every €2. At €501-1,000, tickets correspond at 1 for every €3. For over 1,000, tickets correspond at 1 for every €4. There was no upper limit in tickets.

Fig. 17 Euro-to-Ticket Scale



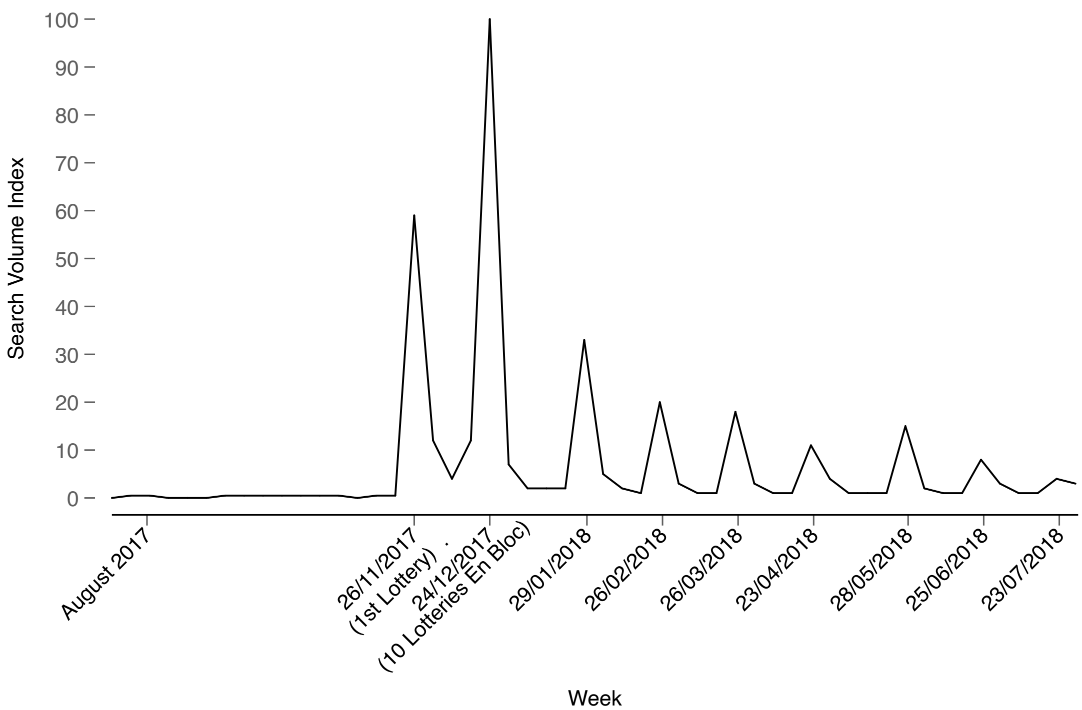
Notes: The graph illustrates the scale used to convert the aggregate level of monthly electronic consumption to eligible tickets in the lottery. Banks send the aggregate level of electronic consumption completed by each individual and this is converted to ticket using the following scale. At €1-100, tickets correspond at 1 for every €1. At €101-500, tickets correspond at 1 for every €2. At €501-1,000, tickets correspond at 1 for every €3. For over 1,000, tickets correspond at 1 for every €4. There was no upper limit in tickets. Details about eligible payments and additional information on the institutional structure are explained in Section 2.

Fig. 18 Superdraw Timeline



Notes: The figure shows an indicative timeline of the superdraw that took place on Christmas Eve 2017. The planned implementation was in January 2017. The lottery announcement took place in October 2017 with the first draw taking place at the end of November 2017 for payments completed in October. The superdraw took place on the 24th of December 2017, for payments corresponding to months of January to September 2017. Prizes were handed out directly to the individuals' bank accounts in early January 2017.

Fig. 19 "Lottery" Google Trends in Greece

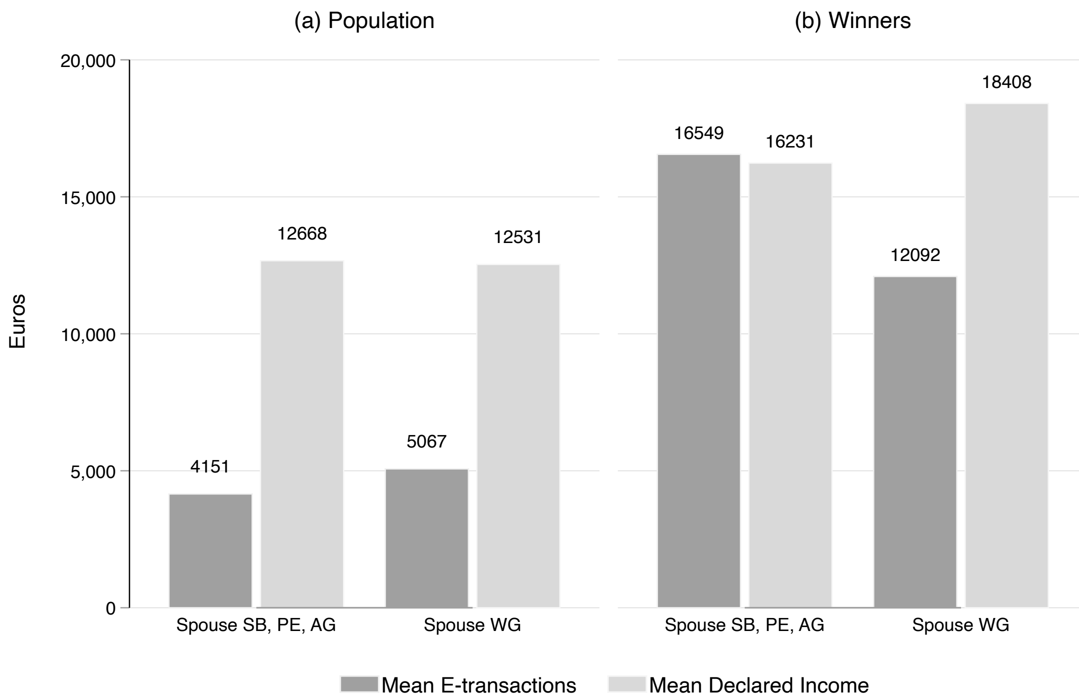


Notes: The figure plots the Google search volumes (indexed from 0-100 on the y-axis) for the word "lottery" in Greek. The geographical area is constraint to Greece alone. The timeline is shown on the x-axis, containing weekly trends for every week starting with the first week of August 2017 and ending in the last week of July 2018.

Online Appendix - Not for publication

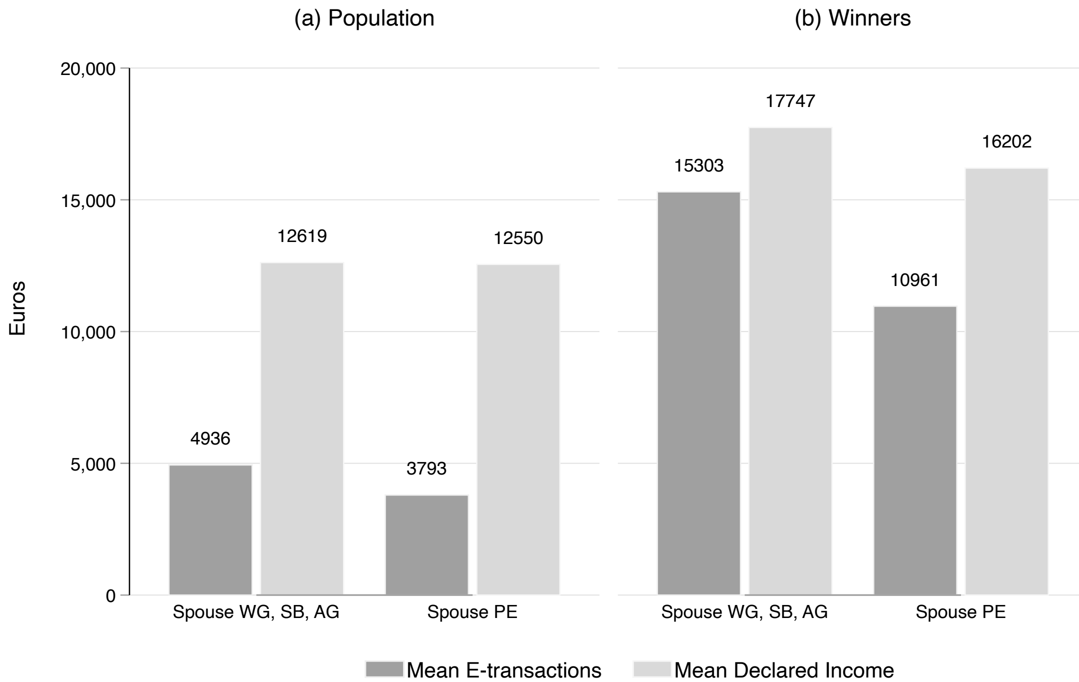
Descriptives

Fig. 20 Annual Income and Electronic Consumption - Taxpayers with WG spouses



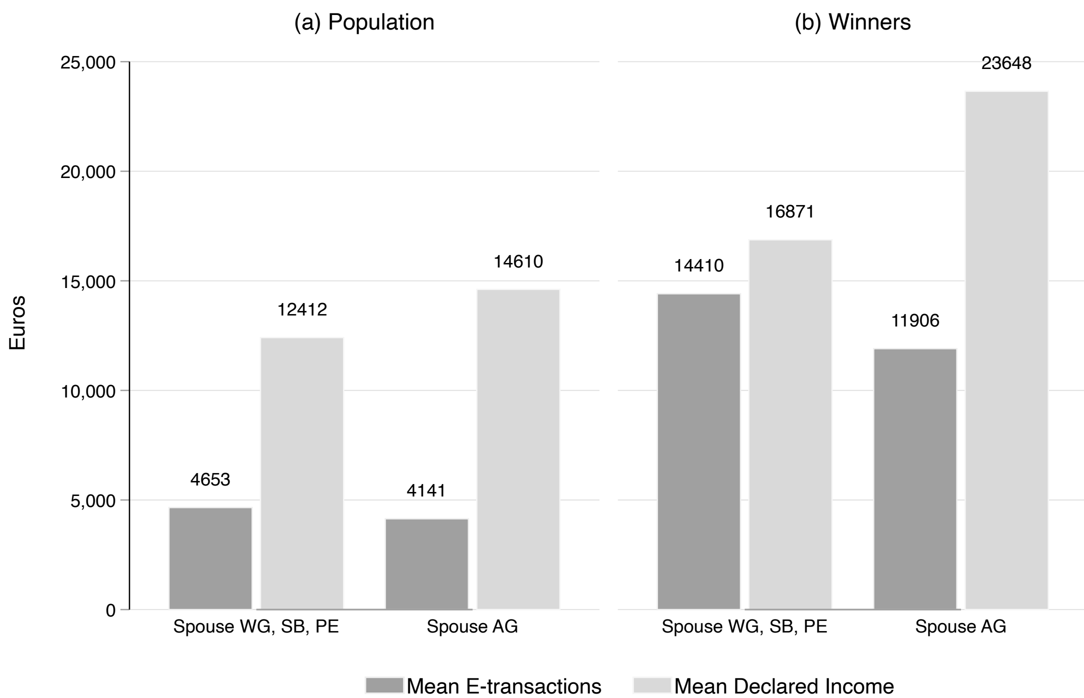
Notes: The figure compares the mean annual income and mean annual electronic consumption of the taxpayer population, figure (a) on the left-hand side and for winners, figure (b) on the right-hand side. The left-hand side columns of each figure include individuals who have a spouse with primary income from SB, PE and AG, against individuals who have a spouse with primary income from WG. Individuals with primary SB income and NO income are excluded from the sample.

Fig. 21 Annual Income and Electronic Consumption - Taxpayers with PE spouses



Notes: The figure compares the mean annual income and mean annual electronic consumption of the taxpayer population, figure (a) on the left-hand side and for winners, figure (b) on the right-hand side. The left-hand side columns of each figure include individuals who have a spouse with primary income from WG, SB and AG, against individuals who have a spouse with primary income from PE. Individuals with primary SB income and NO income are excluded from the sample.

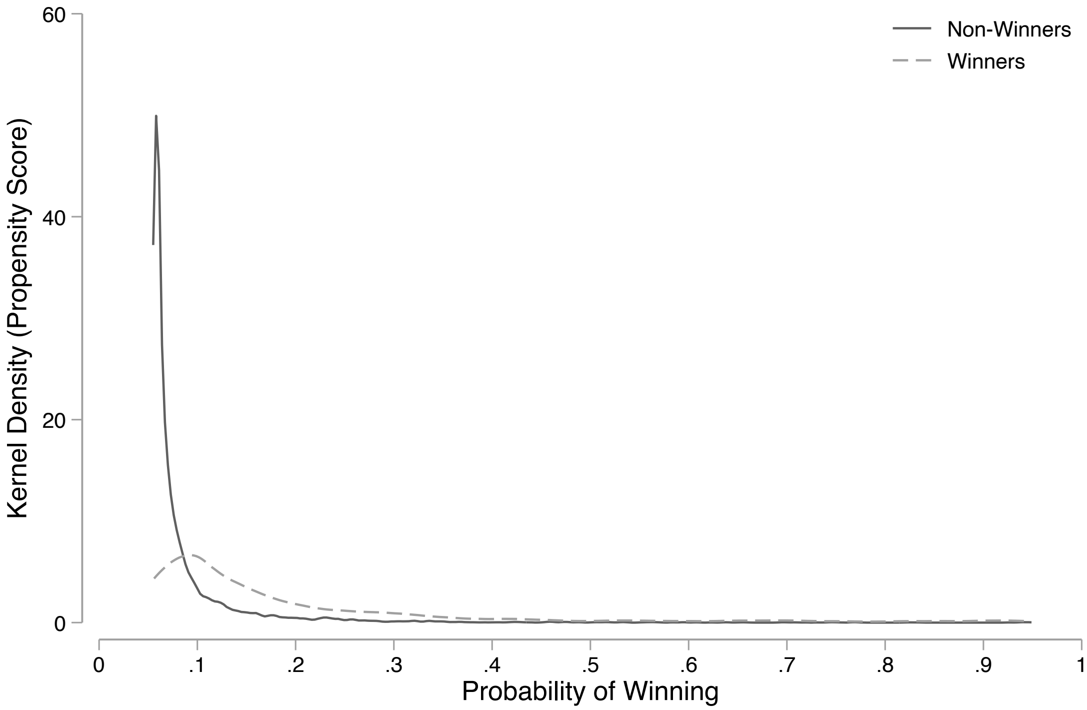
Fig. 22 Annual Income and Electronic Consumption - Taxpayers with AG spouses



Notes: The figure compares the mean annual income and mean annual electronic consumption of the taxpayer population, figure (a) on the left-hand side and for winners, figure (b) on the right-hand side. The left-hand side columns of each figure include individuals who have a spouse with primary income from SB, PE and WG, against individuals who have a spouse with primary income from AG. To allow for a meaningful comparison, SB individuals are excluded from the sample since these have exhibited a very high volume of e-consumption as shown in Fig. 4. NO income category and single filings are excluded from the sample.

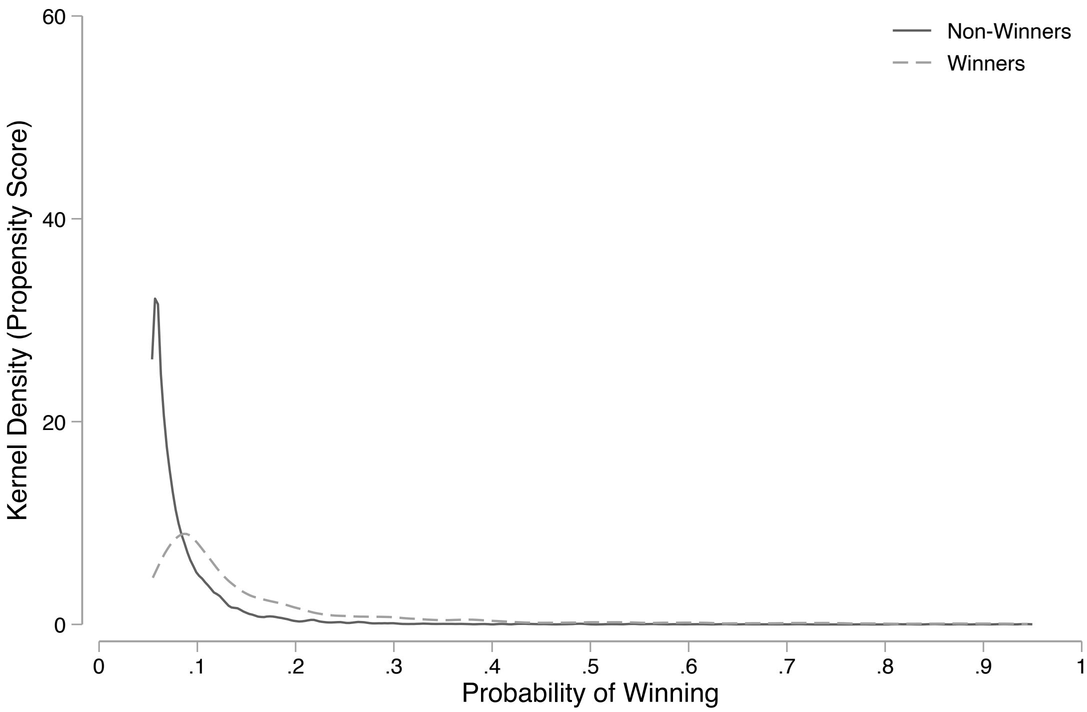
Propensity Score Matching Figures

Fig. 23 Propensity Score - First Quintile



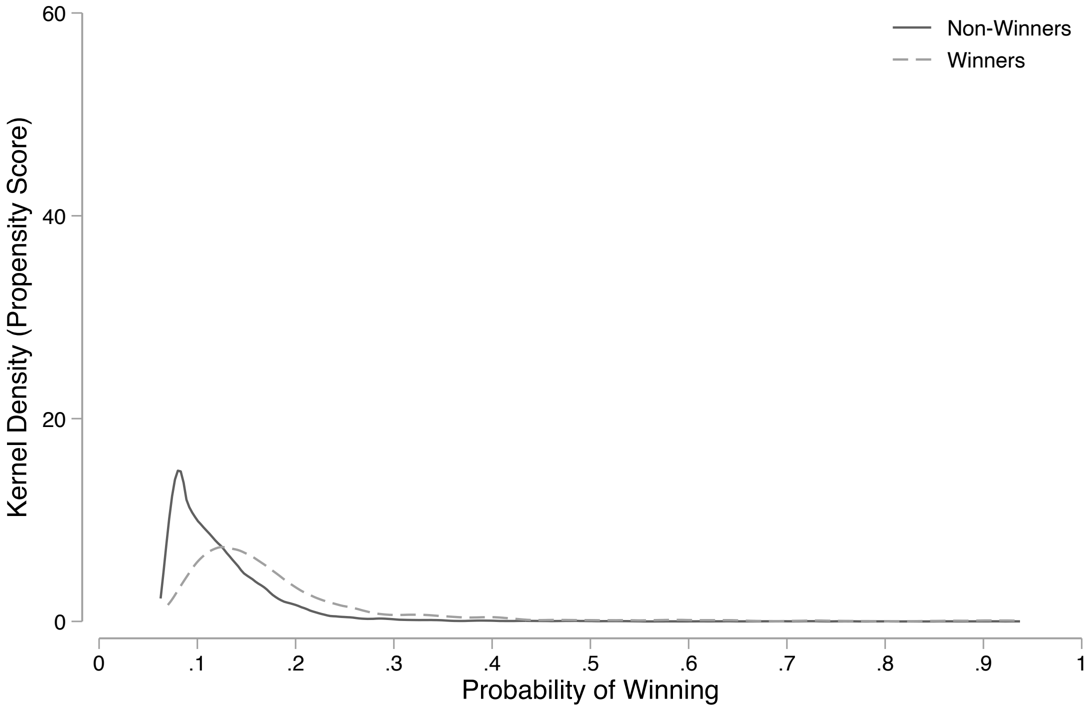
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Taxpayers in the first quintile ranked by household income are included. The samples exclude SB and NO income categories. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws). Both winners and non-winners are winsorised at 5%.

Fig. 24 Propensity Score - Second Quintile



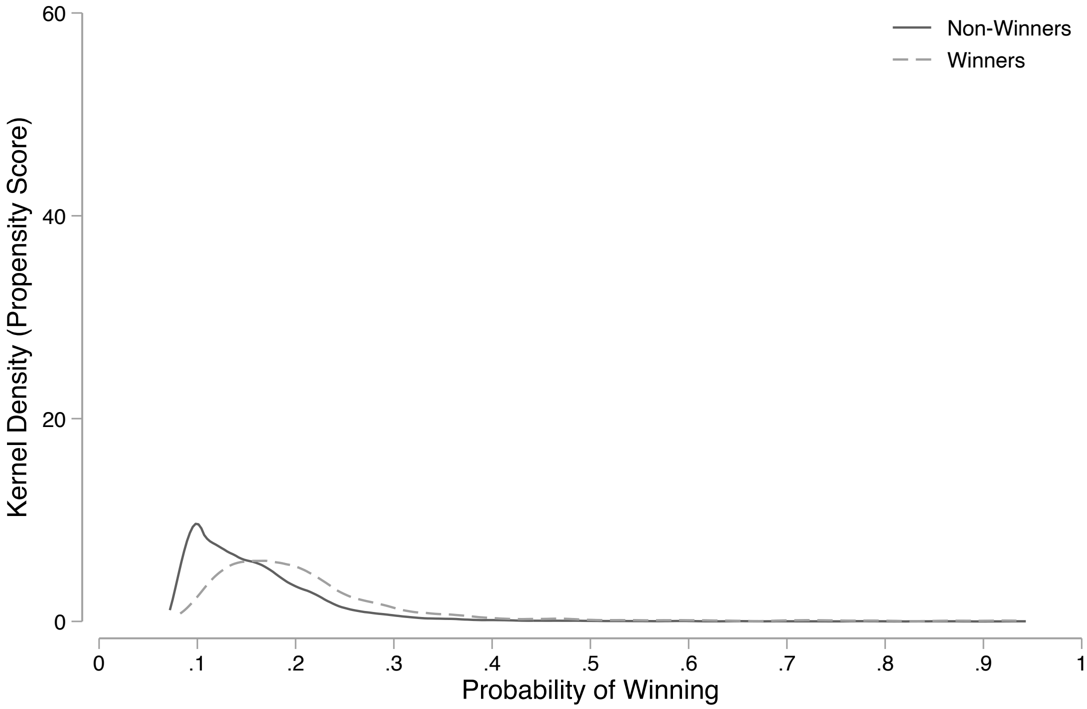
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Taxpayers in the second quintile ranked by household income are included. The samples exclude SB and NO income categories. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws). Both winners and non-winners are winsorised at 5%.

Fig. 25 Propensity Score - Third Quintile



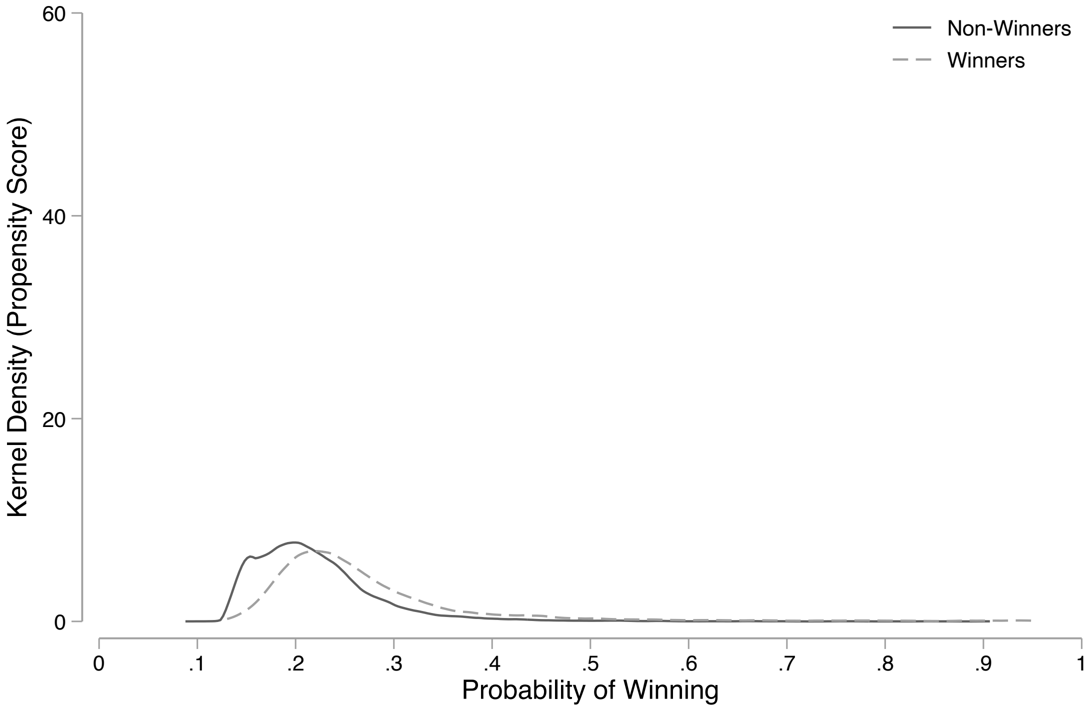
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Taxpayers in the third quintile ranked by household income are included. The samples exclude SB and NO income categories. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws). Both winners and non-winners are winsorised at 5%.

Fig. 26 Propensity Score - Fourth Quintile



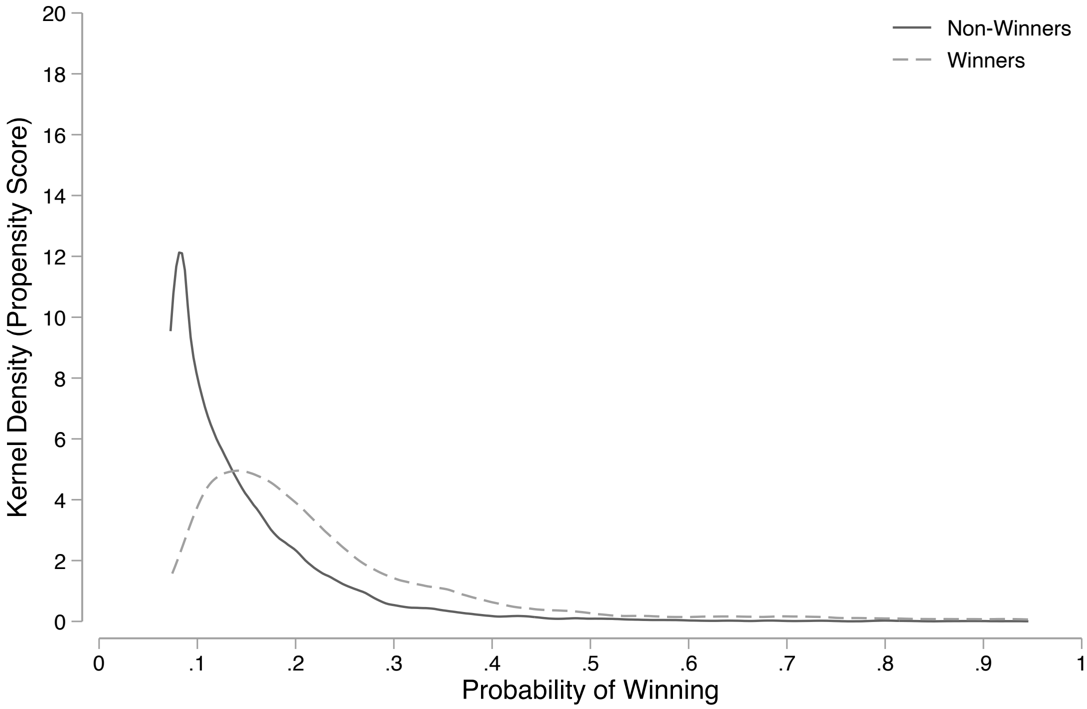
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Taxpayers in the fourth quintile ranked by household income are included. The samples exclude SB and NO income categories. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws). Both winners and non-winners are winsorised at 5%.

Fig. 27 Propensity Score - Fifth Quintile



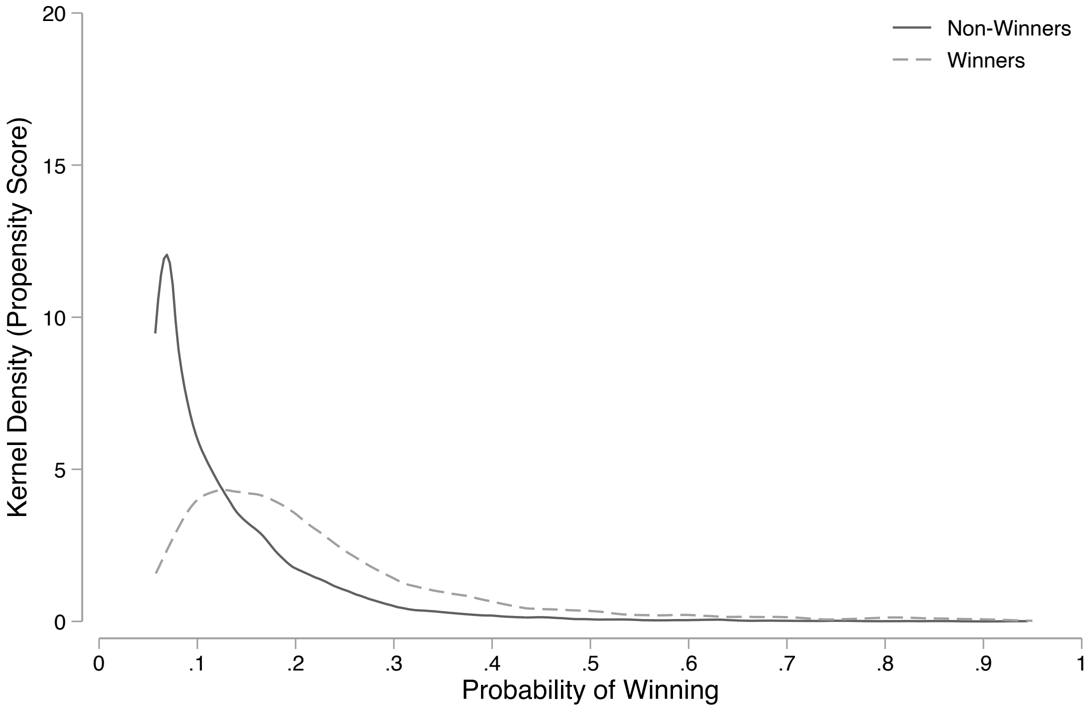
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Taxpayers in the fifth quintile ranked by household income are included. The samples exclude SB and NO income categories. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws). Both winners and non-winners are winsorised at 5%.

Fig. 28 Propensity Score - Wage-Earners



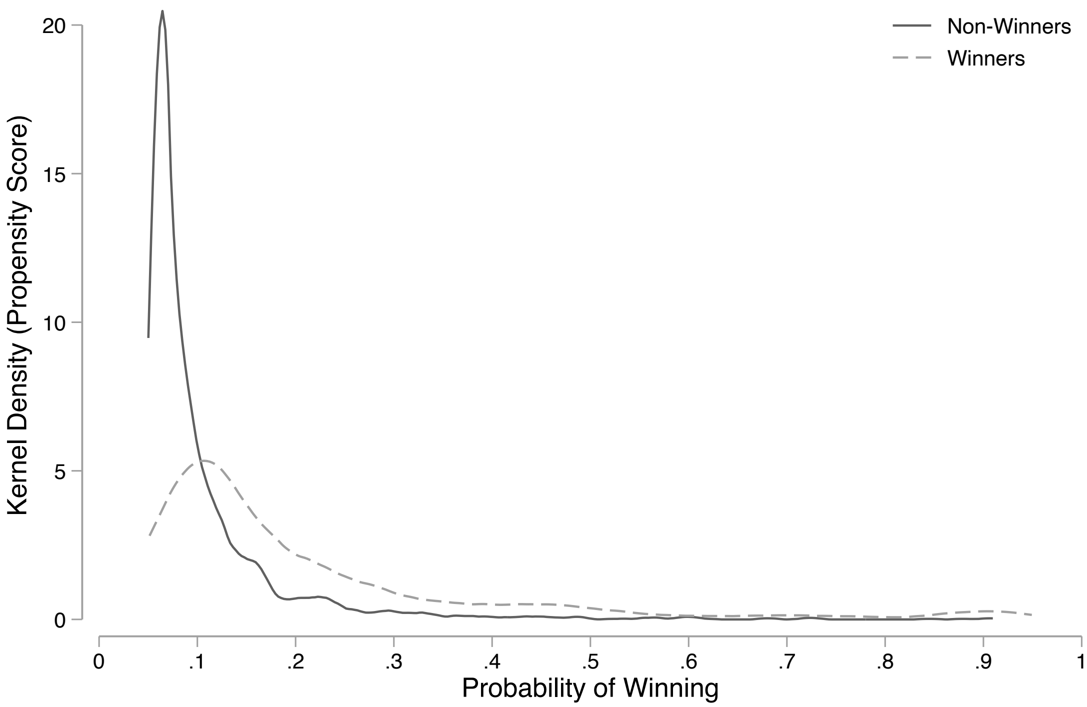
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Wage-earners only are matched. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws). Both winners and non-winners are winsorised at 5%.

Fig. 29 Propensity Score - Pensioners



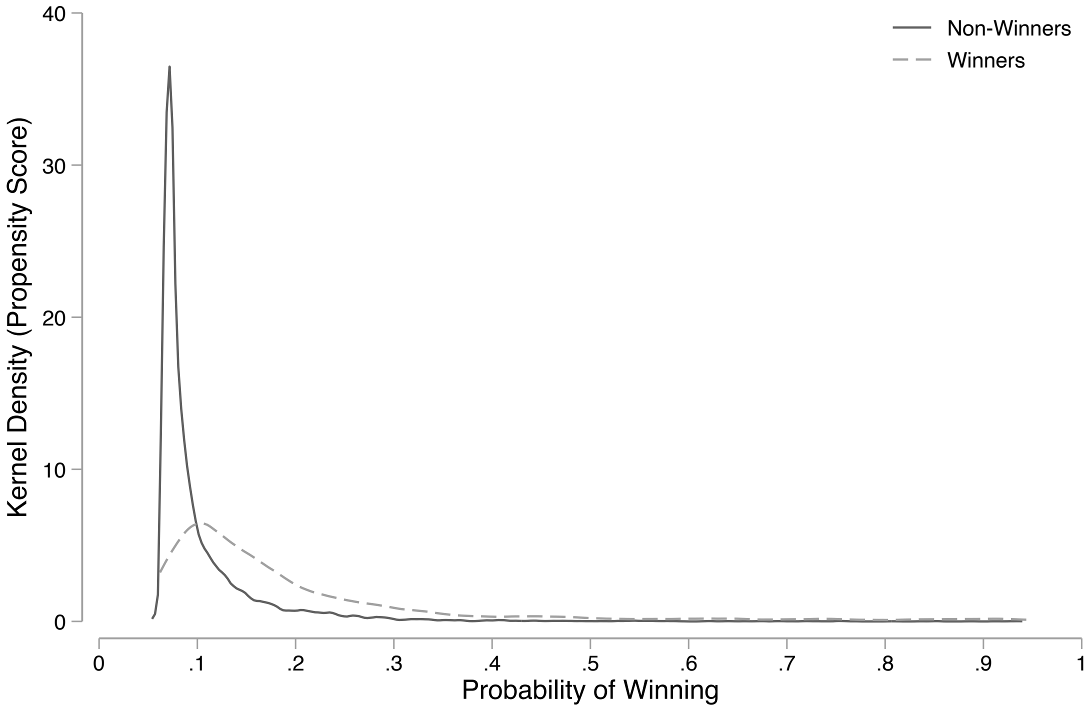
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Pensioners only are matched. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws). Both winners and non-winners are winsorised at 5%.

Fig. 30 Propensity Score - Agriculture



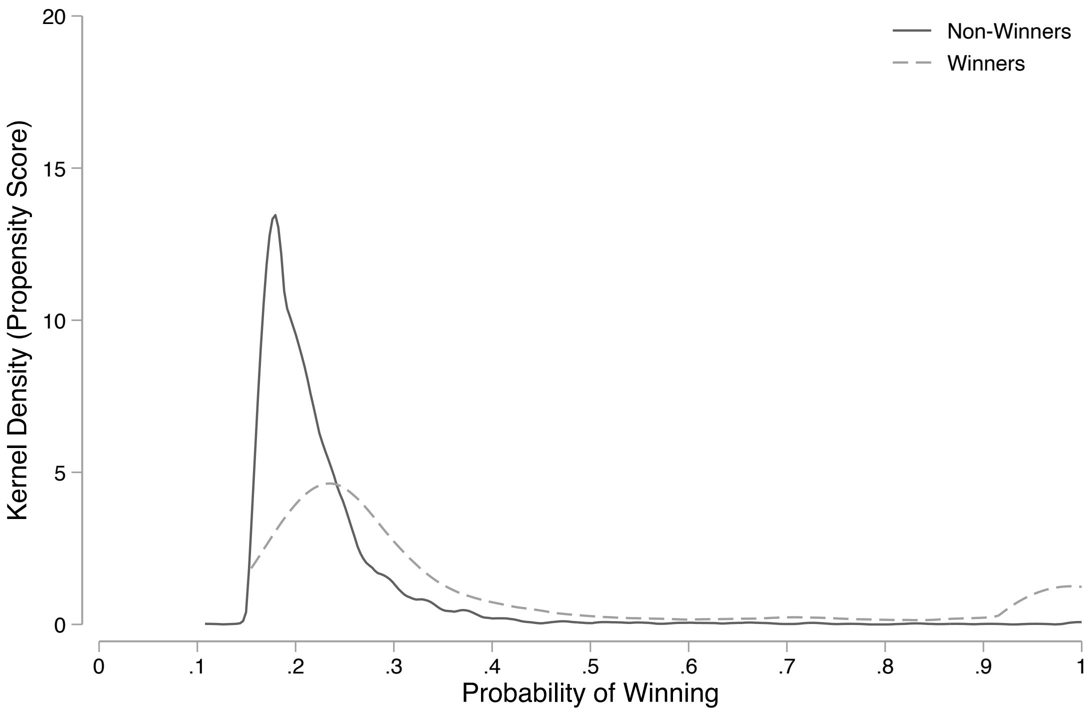
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Agriculture income only are matched. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws). Both winners and non-winners are winsorised at 5%.

Fig. 31 Propensity Score - Zero income



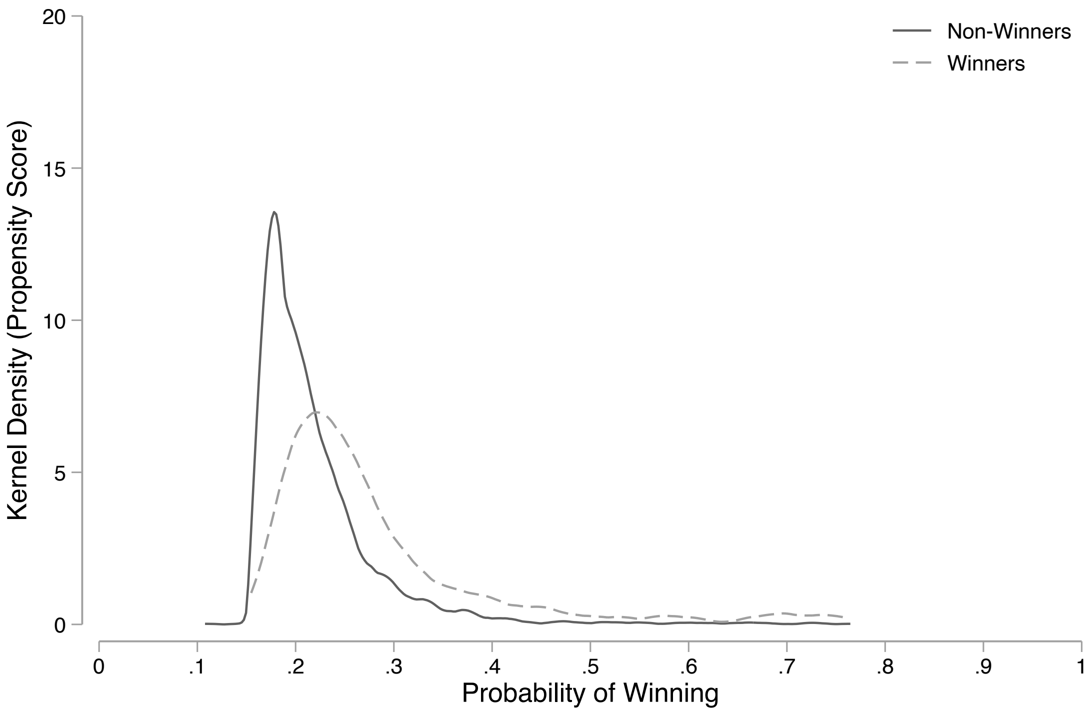
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Zero income (NO category) only are matched. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws). Both winners and non-winners are winsorised at 5%.

Fig. 32 Propensity Score - Self-Employed (All)



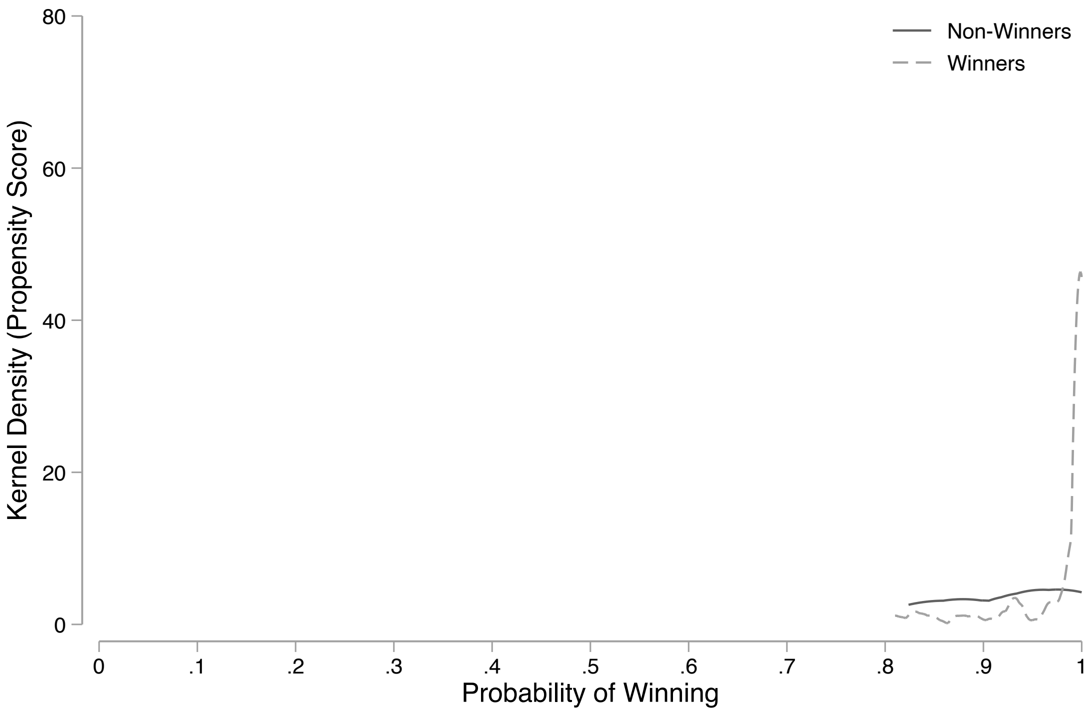
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Self-employed only are matched (entire sample). The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws).

Fig. 33 Propensity Score - Self-Employed (without High E-Consumption)



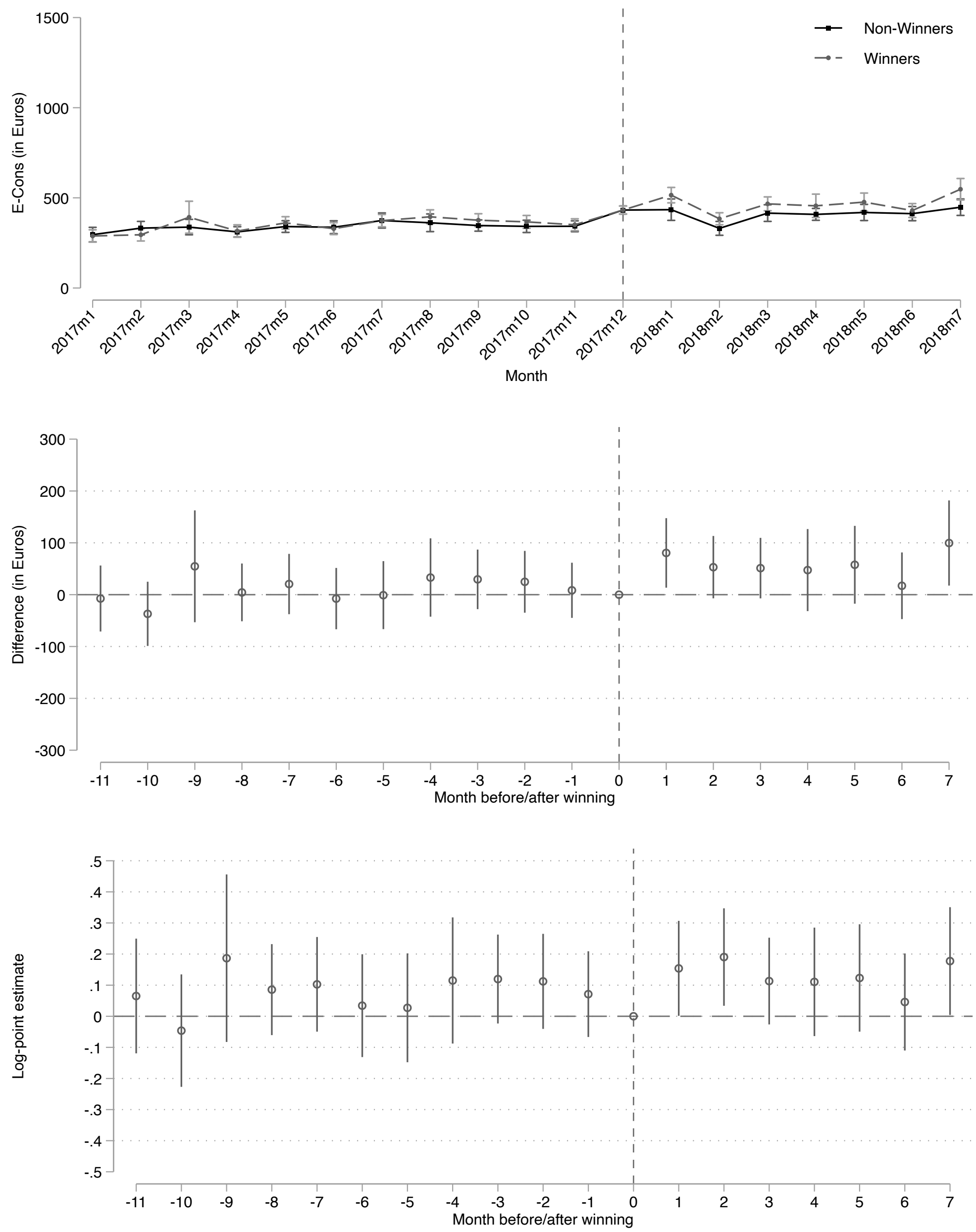
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Self-employed only are matched (from 0.8 propensity score matching and lower). This excludes the highest 20% of self-employed individuals, both for winners and non-winners. The sample is truncated on the lower side at 5%. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws).

Fig. 34 Propensity Score - Self-Employed (High E-Consumption)



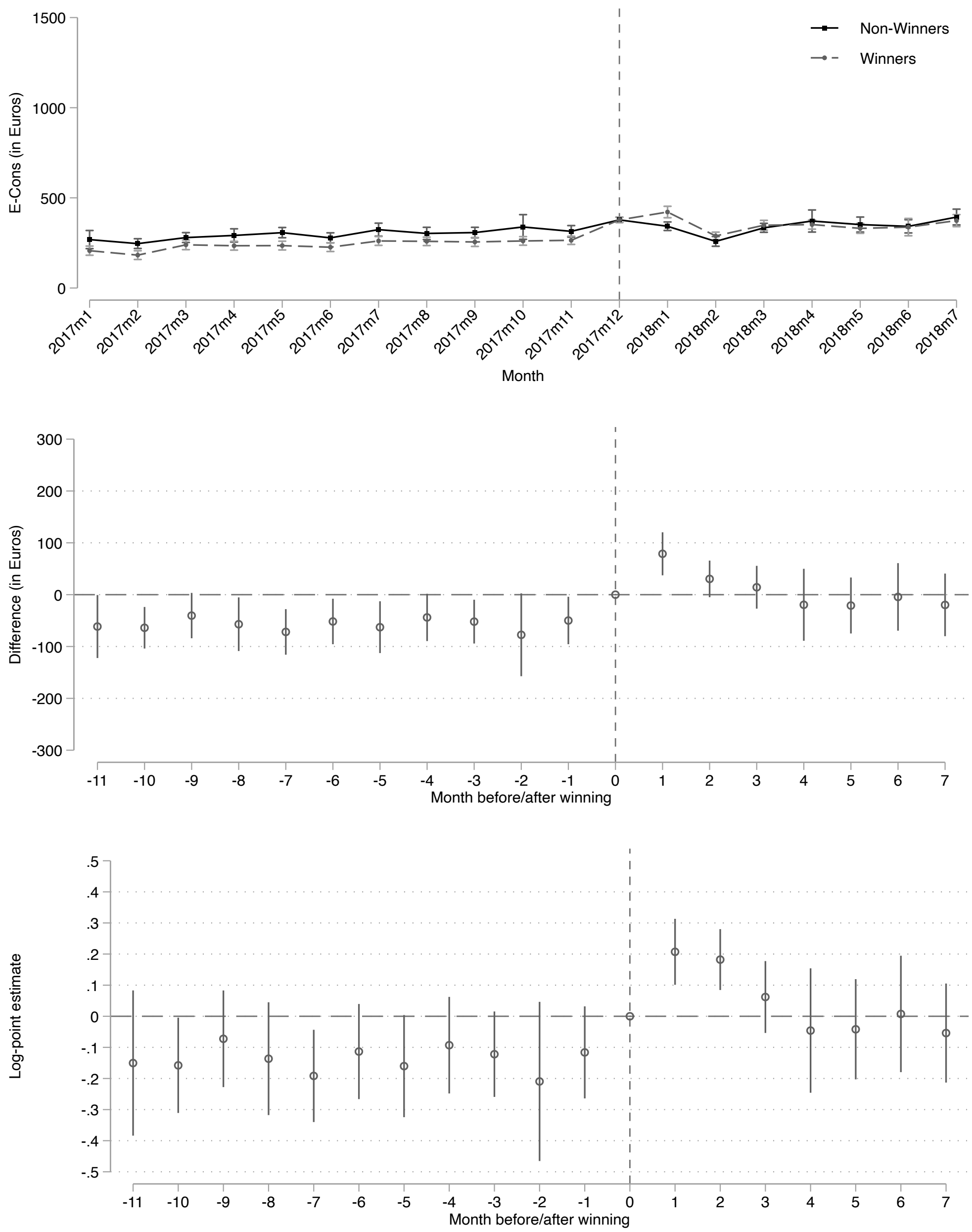
Notes: The graph plots kernel density functions of the propensity scores generated by Equation 3 for winners (dashed line) and non-winners (solid line). Self-employed only are matched (from 0.8 propensity score matching and higher), corresponding to SB taxpayers with high consumption both for winners and non-winners. The propensity scores indicate the probability of individuals in winning in the superdraw based on the tickets generated in the months of January to September 2017 (which corresponded to the lottery draws).

Fig. 35 First Income Quintile



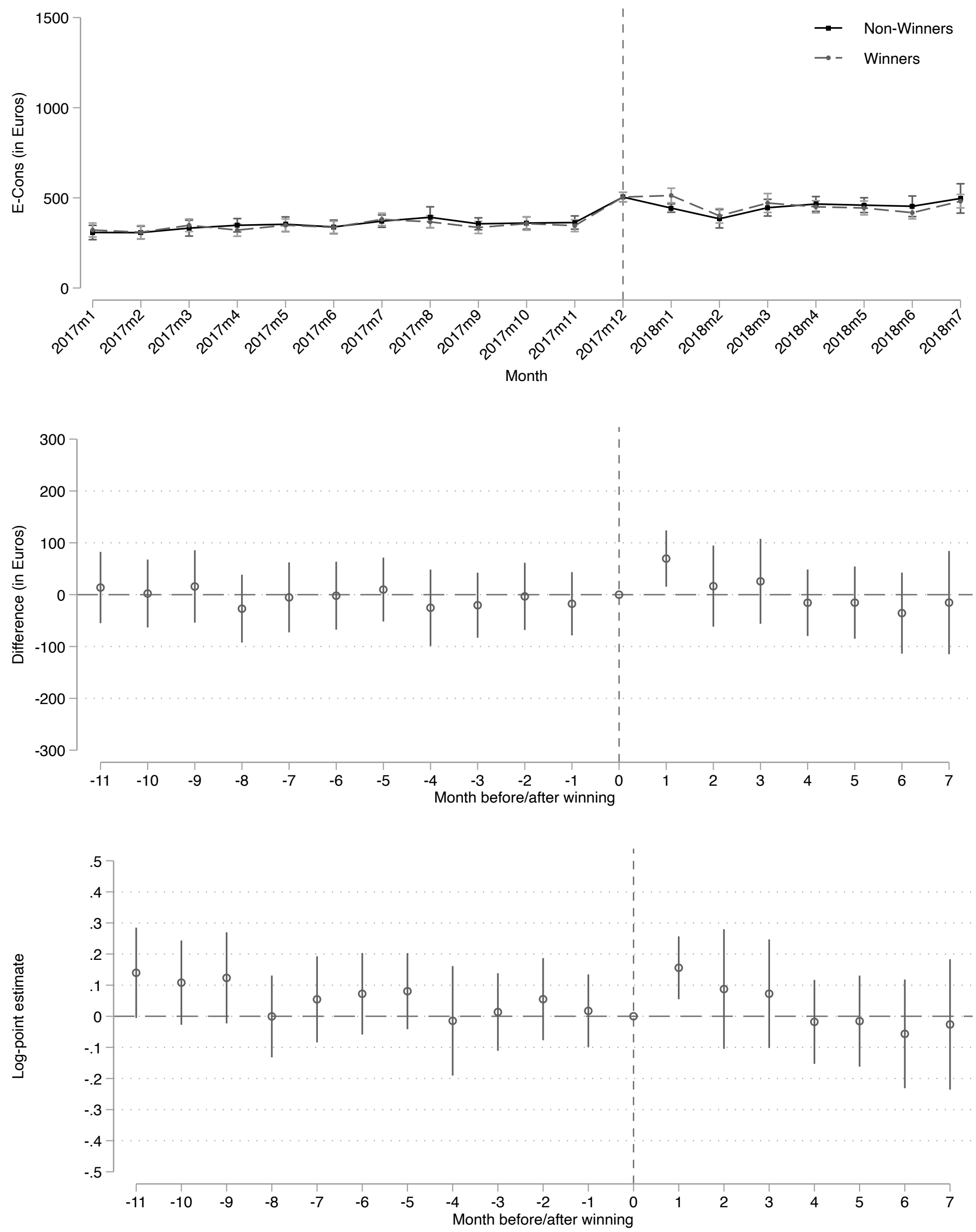
Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who belong in the first income quintile. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (1) of Table 7 for the former and in Table 8 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 36 Second Income Quintile



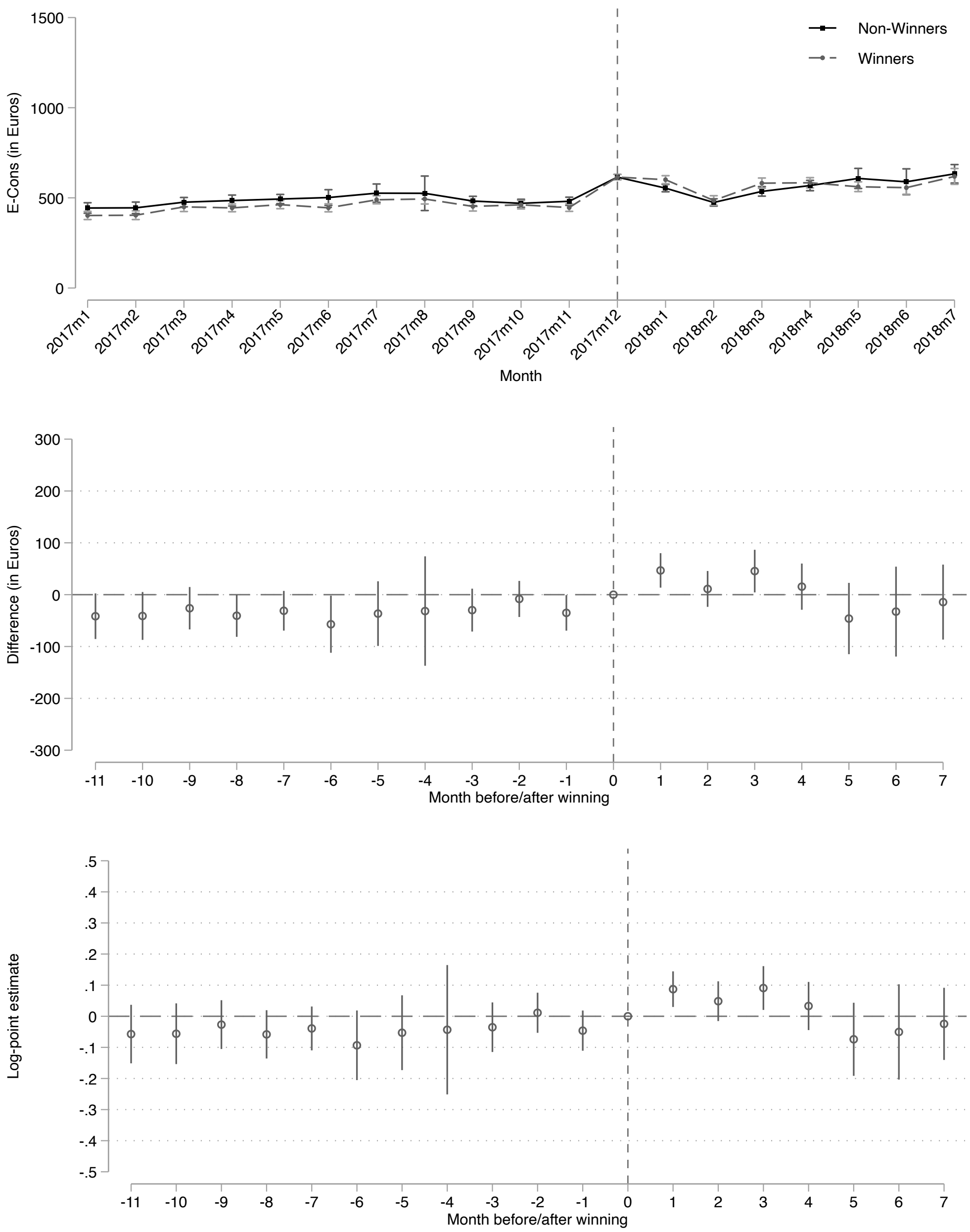
Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who belong in the second income quintile. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (2) of Table 7 for the former and in Table 8 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 37 Third Income Quintile



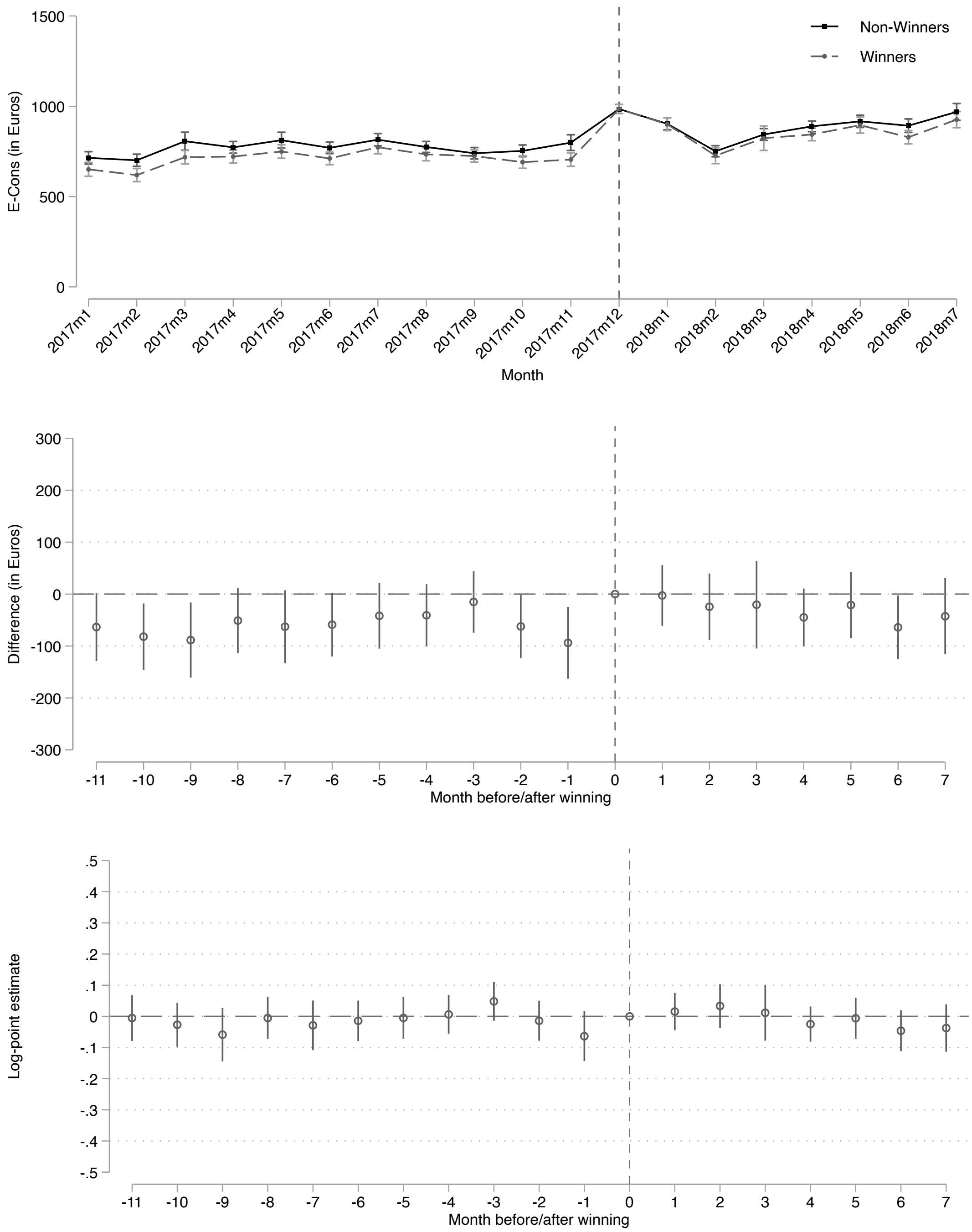
Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who belong in the third income quintile. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (3) of Table 7 for the former and in Table 8 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 38 Fourth Income Quintile



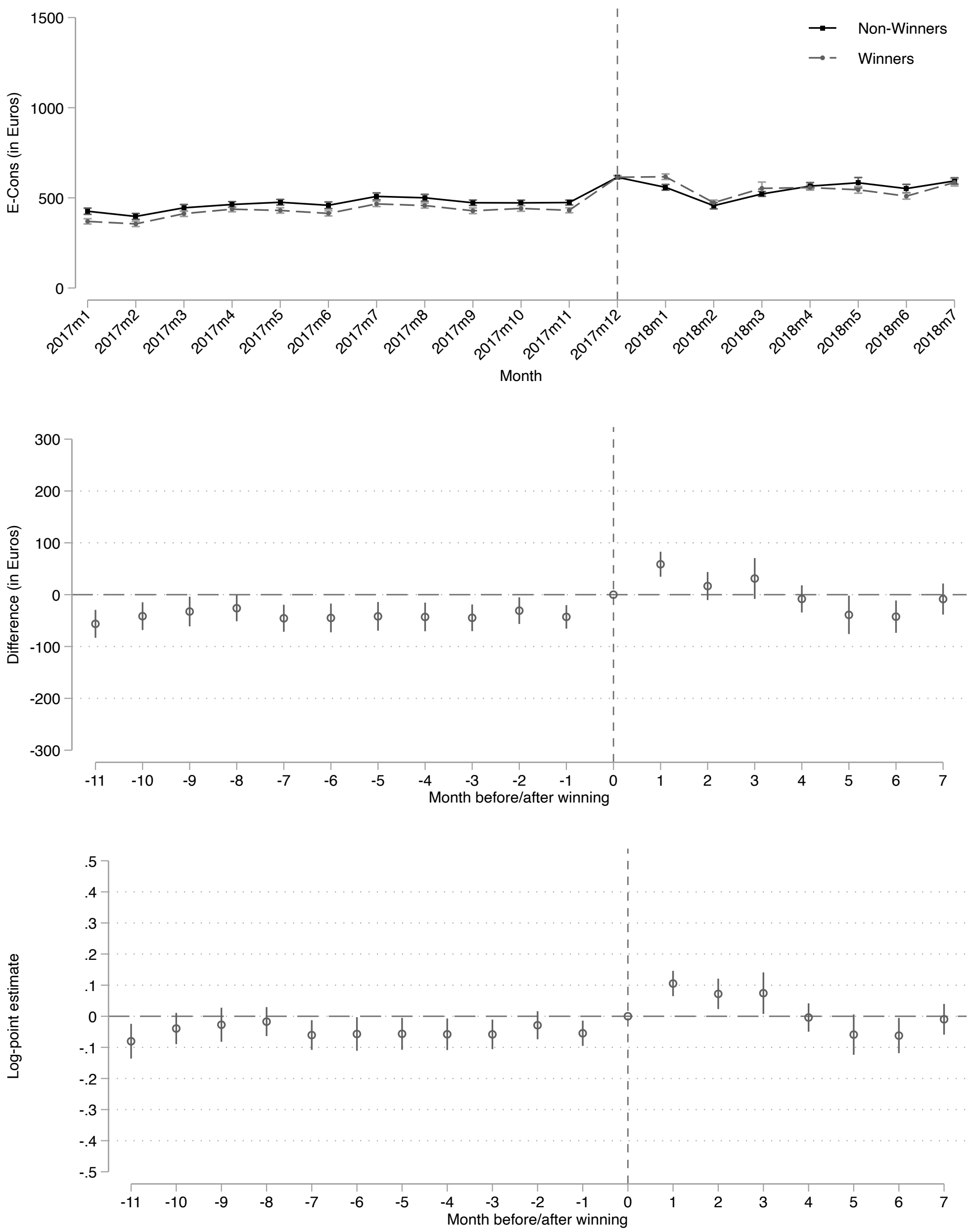
Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who belong in the fourth income quintile. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (4) of Table 7 for the former and in Table 8 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 39 Fifth Income Quintile



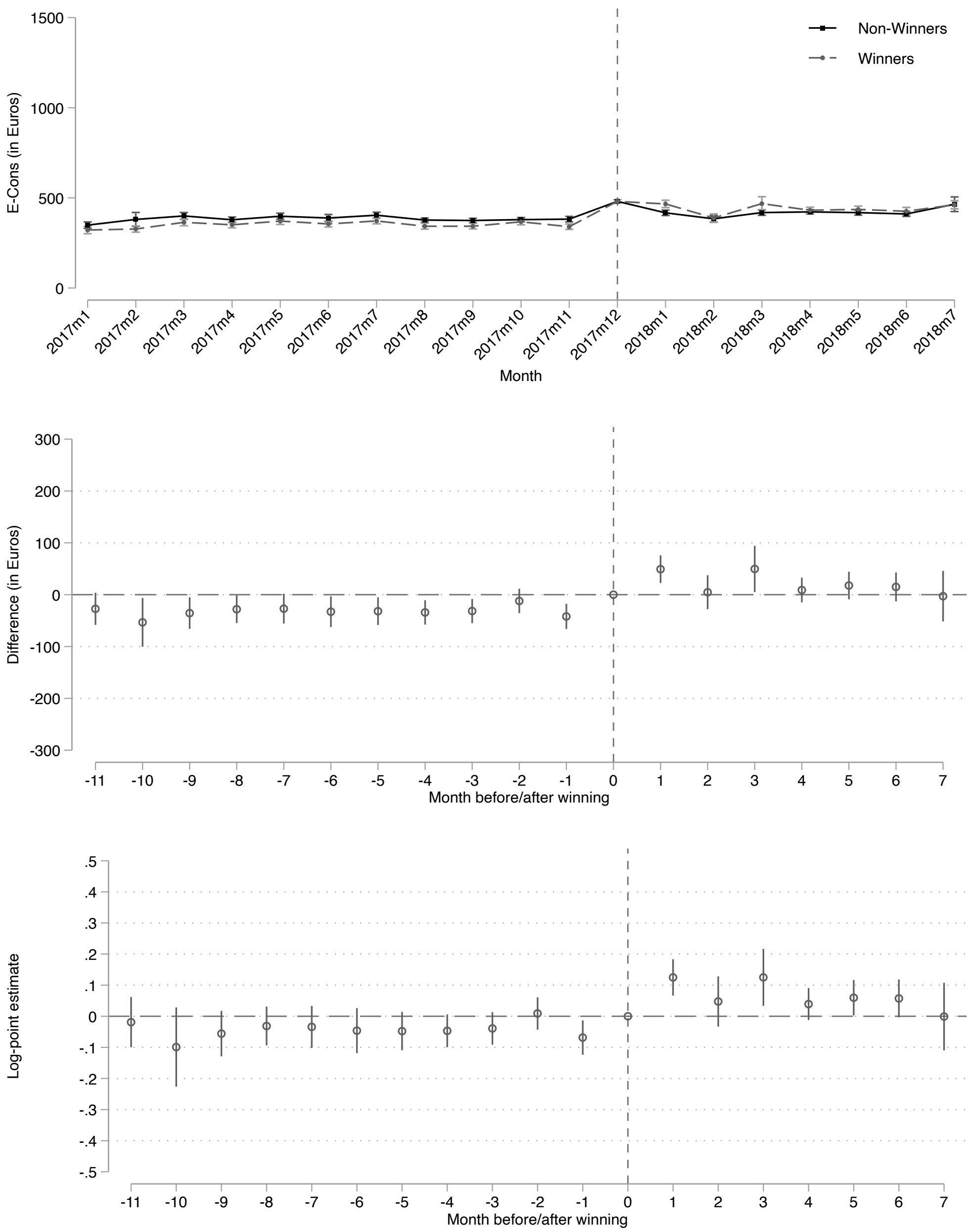
Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who belong in the fifth income quintile. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (5) of Table 7 for the former and in Table 8 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 40 Wage-earners



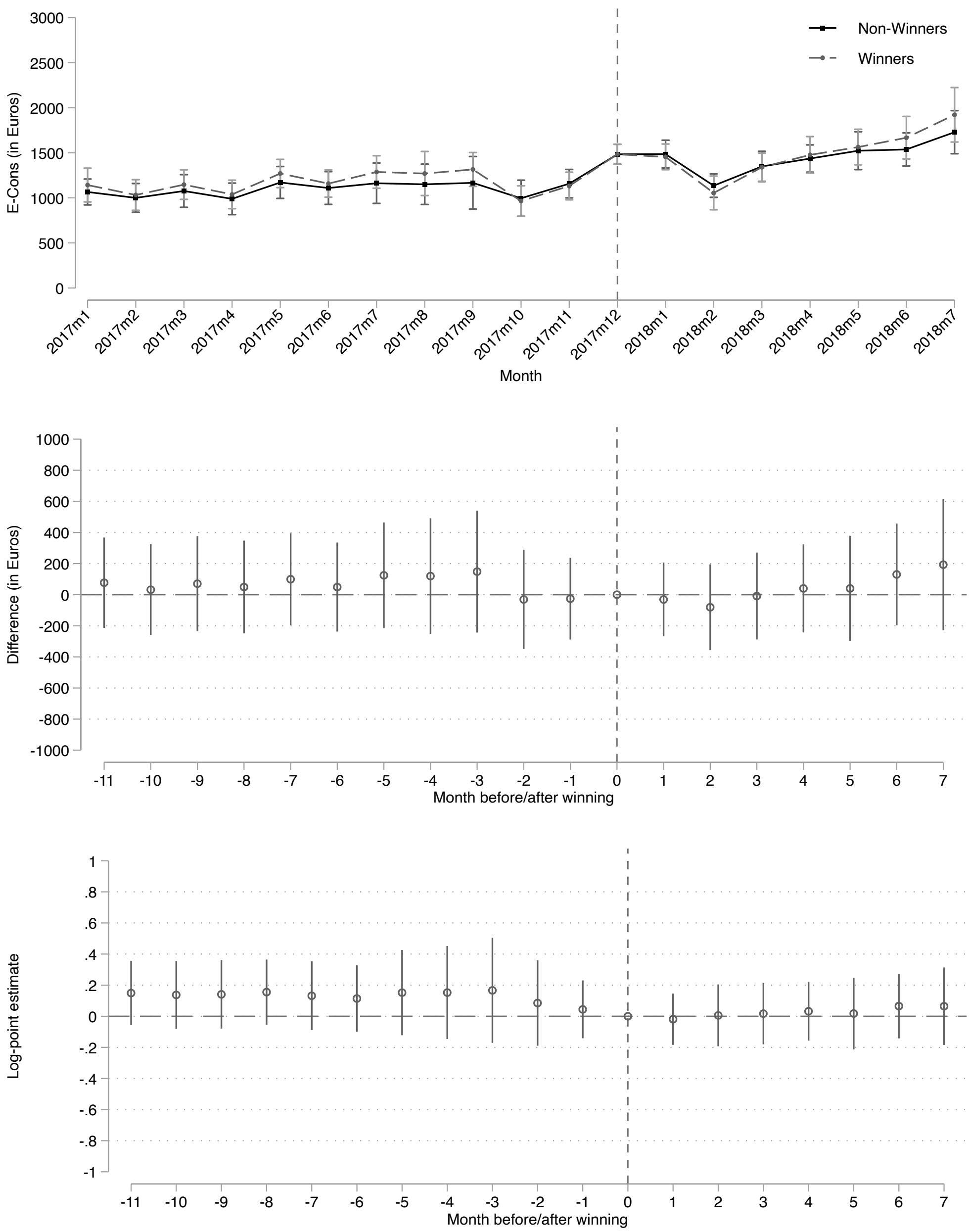
Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who are wage-earners (WG). The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (1) of Table 9 for the former and in Table 10 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 41 Pensioners



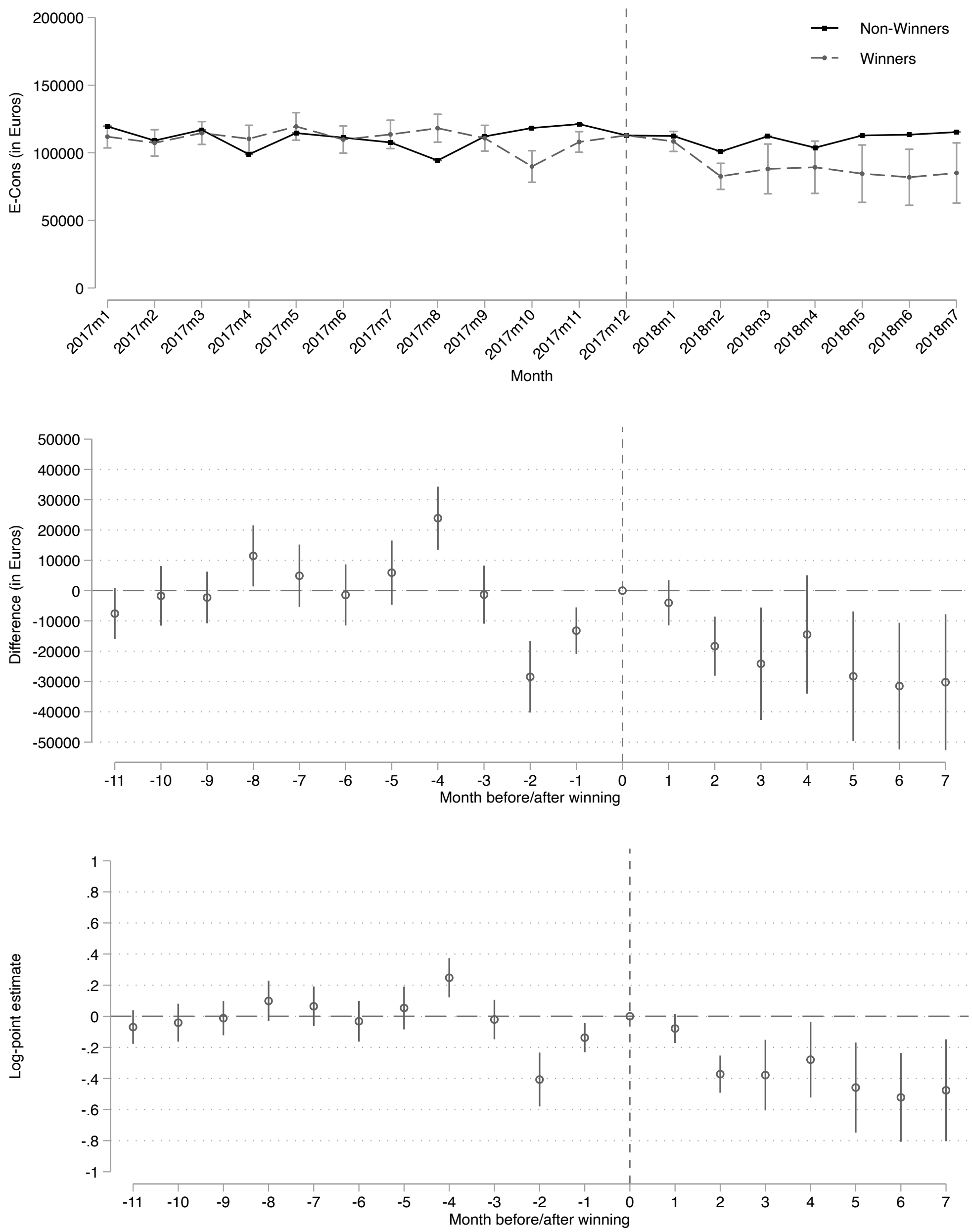
Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who are pensioners (PE). The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (2) of Table 9 for the former and in Table 10 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 42 Self-Employed (without High Electronic Consumption)



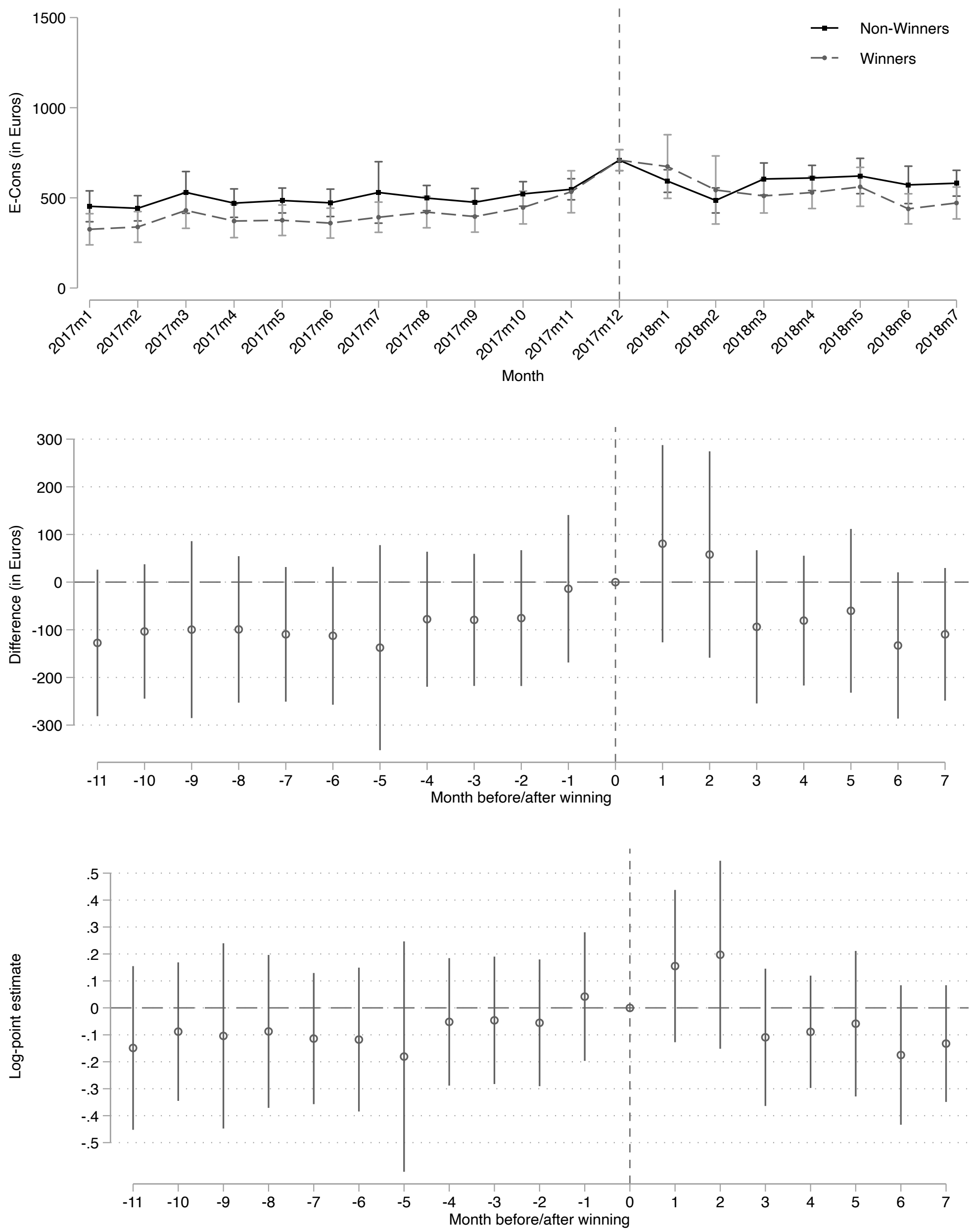
Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who are self-employed (SB), but excluding high consumption individuals as explained in Section 5. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (5) of Table 9 for the former and in Table 10 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 43 Self-Employed (with High Electronic Consumption)



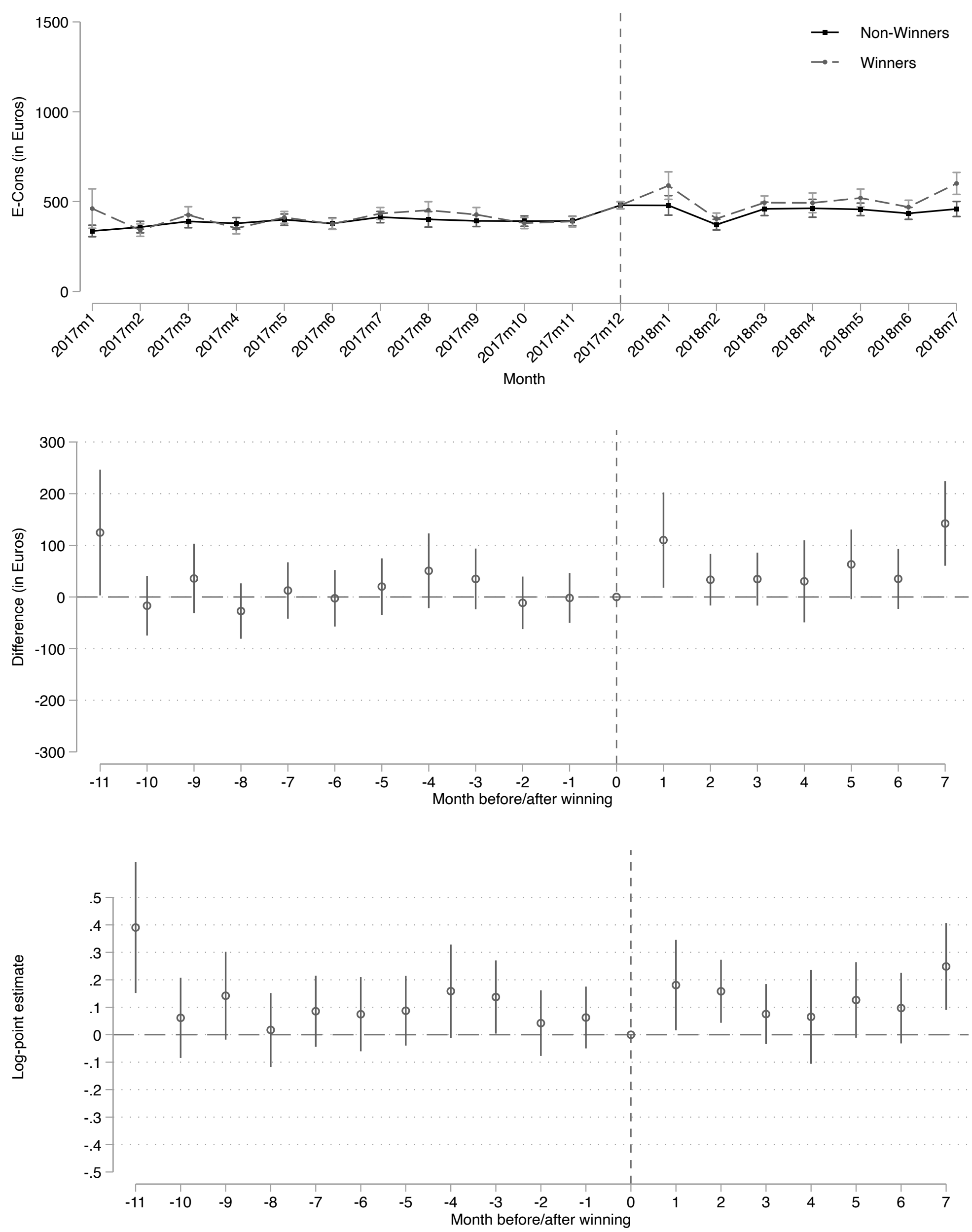
Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who are self-employed (SB) with high consumption, as explained in Section 5. The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (6) of Table 9 for the former and in Table 10 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 44 Agriculture Income



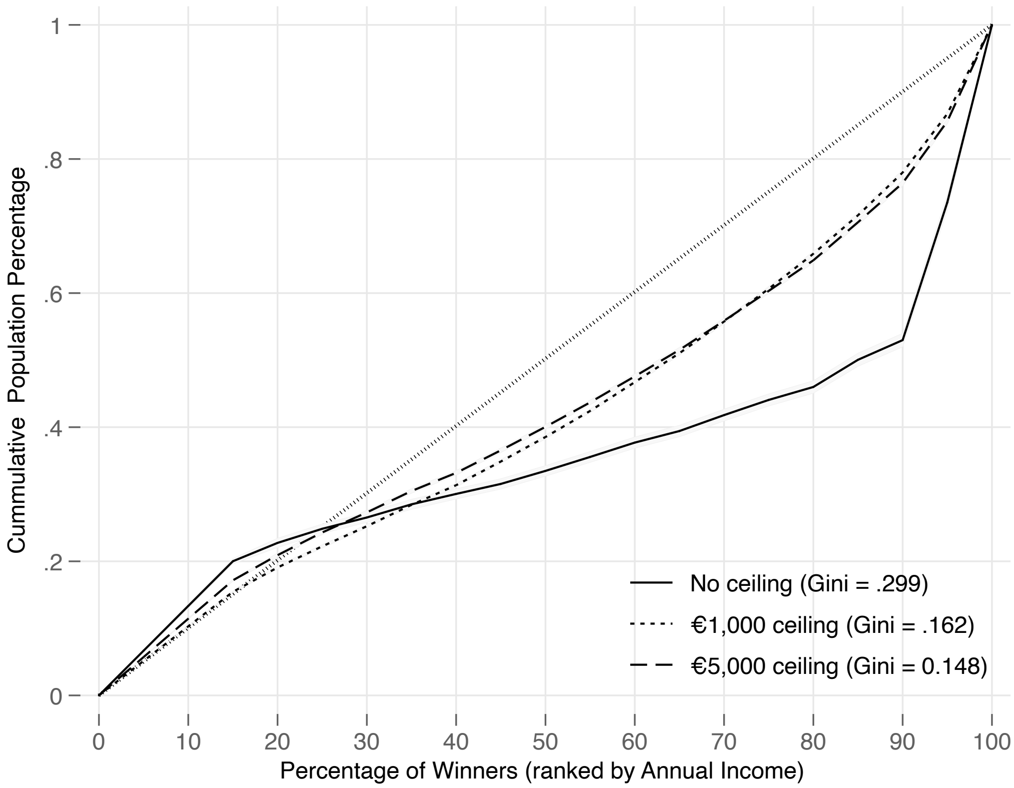
Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who have agricultural income (AG). The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (3) of Table 9 for the former and in Table 10 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 45 Zero Income



Notes: The figure presents the evolution of electronic consumption from January 2017 to July 2018 (top graph), monthly differences in euros (middle graph), and log-point differences (bottom graph) between winners and non-winners, who declare zero income (NO). The line at time 0 indicates December 2017, when the superdraw took place. The estimates are obtained from fitted values in a linear regression (for the top and middle graphs) and with Poisson pseudo maximum likelihood (bottom graph). Estimates are shown in Column (4) of Table 9 for the former and in Table 10 for the latter. Confidence intervals are drawn at the 99% level. Robust standard errors are clustered at the individual level.

Fig. 46 Electronic Consumption Distributions (Ranked by Income) after Lottery Simulations



Notes: The figure plots electronic consumption distribution curves for 1.2 million winners in simulations of the lottery. The x-axis represents the population percentiles of winners, ranked by annual income in 2017. The y-axis shows the percentage of individuals who have won the lottery in the simulations. The dotted line is a 45-degree line, at which the winners' income percentage equals the winners' e-consumption percentage. The "no ceiling" curve is a simulation of the lottery assigning tickets using the ticket-awarding mechanism in Table 11. The €1,000 ceiling introduces a maximum ceiling in monthly tickets. For electronic consumption beyond €1,000 per month no more tickets are awarded to individuals. Similarly, the €5,000 curve introduces a ceiling at the €5,000 monthly electronic consumption level.

Propensity Score Matching Tables

Table 12 Logistic Regression - Probability of Winning by Income Quintile

	1st Quintile (1) P(W=1)	2nd Quintile (2) P(W=1)	3rd Quintile (3) P(W=1)	4th Quintile (4) P(W=1)	5th Quintile (5) P(W=1)
January 2017	0.0008074***	0.0005565***	-0.0001914	0.0003780**	0.0001560
	(0.0002046)	(0.0001767)	(0.0002104)	(0.0001535)	(0.0001011)
February 2017	0.0003480*	0.0008430***	0.0001972	0.0004650***	0.0002808**
	(0.0002023)	(0.0002378)	(0.0001958)	(0.0001363)	(0.0001179)
March 2017	-0.0000238	0.0004860**	0.0003292*	0.0003185***	0.0003122***
	(0.0001914)	(0.0002380)	(0.0001903)	(0.0001212)	(0.0000928)
April 2017	0.0006890***	0.0003445*	0.0011533***	0.0008519***	0.0003169***
	(0.0002109)	(0.0002085)	(0.0002208)	(0.0001596)	(0.0001146)
May 2017	0.0005256***	0.0002735	0.0005250**	0.0001659	0.0003100***
	(0.0001710)	(0.0002430)	(0.0002159)	(0.0001268)	(0.0000933)
June 2017	0.0005256**	0.0003677	0.0000300	0.0005593***	0.0002866***
	(0.0002128)	(0.0002497)	(0.0002307)	(0.0001608)	(0.0001069)
July 2017	0.0004123**	0.0006417**	0.0001613	0.0001907	0.0002787***
	(0.0001903)	(0.0002576)	(0.0002175)	(0.0001479)	(0.0000963)
August 2017	0.0000332	0.0004797**	0.0006224***	-0.0001677*	0.0000547
	(0.0001820)	(0.0002128)	(0.0001904)	(0.0000983)	(0.0001121)
September 2017	0.0002983**	0.0004078***	0.0005707***	0.0004412***	-0.0001664
	(0.0001504)	(0.0001562)	(0.0002031)	(0.0001441)	(0.0001155)
Constant	-2.8221821***	-2.8642454***	-2.5310466***	-2.3491349***	-1.8079439***
	(0.0459354)	(0.0482135)	(0.0465215)	(0.0453989)	(0.0391753)
Number of Individuals	10359	10315	10747	11213	12191

Notes: The table presents estimates from the logistic regression in Equation 3 for each household income quintile. Taxpayers from SB and NO categories are excluded, as well as, taxpayers from other income categories who exhibited zero consumption in 2017 (no lottery participation). The results are used to generate the propensity scores of winning the lottery. The months used correspond to the months that generated the tickets for the superdraw, from January to September 2017. Winning was a rare event, hence to ensure convergence of the maximum-likelihood function, a Firth logistic regression is used for these estimates. The positive values indicate the percentage increase in the probability of winning of one extra ticket in each of the months. The regression produces propensity scores, which are plotted for each quintile in Figures 23 to 27.

Table 13 Logistic Regression - Probability of Winning by Occupation Category

	WG (1) $P(W=1)$	PE (2) $P(W=1)$	AG (3) $P(W=1)$	NO (4) $P(W=1)$	SB (5) $P(W=1)$
January 2017	0.0006191***	0.0002919**	0.0002418	0.0000446*	-0.0000634
	(0.0001258)	(0.0001442)	(0.0002684)	(0.0000264)	(0.0001179)
February 2017	0.0003792***	0.0008837***	0.0008282***	0.0004129***	0.0001008
	(0.0001218)	(0.0001718)	(0.0002963)	(0.0001564)	(0.0001070)
March 2017	0.0006011***	0.0003440**	-0.0002930	-0.0002520	0.0002909**
	(0.0001106)	(0.0001408)	(0.0002174)	(0.0001689)	(0.0001179)
April 2017	0.0002238*	0.0005810***	0.0003674*	0.0010939***	0.0005584***
	(0.0001189)	(0.0001744)	(0.0002099)	(0.0001785)	(0.0001405)
May 2017	0.0004430***	0.0003082**	0.0004271*	0.0005056***	0.0001264
	(0.0001144)	(0.0001402)	(0.0002522)	(0.0001520)	(0.0000808)
June 2017	0.0002798**	0.0003965**	0.0003959	0.0007636***	0.0000199
	(0.0001222)	(0.0001768)	(0.0002541)	(0.0001842)	(0.0000893)
July 2017	0.0005468***	0.0008127***	0.0002938	0.0003013*	-0.0000076
	(0.0001208)	(0.0002052)	(0.0002159)	(0.0001611)	(0.0000913)
August 2017	0.0004917***	0.0007107***	0.0006596**	-0.0003071***	0.0000830
	(0.0001167)	(0.0001992)	(0.0002648)	(0.0000949)	(0.0000662)
September 2017	0.0002109*	0.0005264***	0.0006502**	0.0004137***	-0.0000895
	(0.0001094)	(0.0001796)	(0.0002610)	(0.0001309)	(0.0000883)
Constant	-2.5455238***	-2.8028727***	-2.8012180***	-2.6084126***	-1.5915826***
	(0.0307634)	(0.0462220)	(0.0916161)	(0.0424092)	(0.0630651)
Number of Individuals	25334	13330	2793	10674	2694

Notes: The table presents estimates from the logistic regression in Equation 3 for each income category. Taxpayers with zero consumption in 2017 were excluded (no lottery participation). The results are used to generate the propensity scores of winning the lottery. The months used correspond to the months that generated the tickets for the superdraw, from January to September 2017. Winning was a rare event, hence to ensure convergence of the maximum-likelihood function, a Firth logistic regression is used for these estimates. The positive values indicate the percentage increase in the probability of winning of one extra ticket in each of the months. The regression produces propensity scores, which are plotted for each occupation category in Figures 31 to 34.