For Online Publication

Appendix to "Five Facts about MPCs"

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Contents

A A Survey of Recent Time-Limited Consumption Vouchers Policies

In the wake of the Covid pandemic, several countries both in Europe and in Asia have implemented time-limited consumption vouchers policies.

In Europe, the British Isle of Jersey implemented a program that delivered a £100 prepaid credit card, which could be used in all national retail stores, to all of its citizens. The cards were issued in the beginning of September 2020 and expired on October 31st of the same year. In total 105,964 prepaid cards were distributed, at a total cost of around 11.7 million pounds. 97.5% of cards were delivered and activated. 98 % of the amount of all activated cards was spent. The spending was concentrated in the first weeks as the majority of spending was achieved in the first month. Northern Ireland implemented a very similar scheme in 2021. The government of Northern Ireland also distributed £100 prepaid cards to its entire adult population (1.4 million residents). The card was restricted to work only as a means of payment for in-store purchases, thereby excluding online transactions. The first cards were sent on October 3rd 2021, and cards were usable until December 19th. The take-up was very high: 99.6% card were activated and on average 97.94 pounds were spent (see Youth Training Statistics and Research Branch (2022)). In Italy, the city of Milan also experimented with time-limited pre-paid credit cards, which were sent to vulnerable citizens in 2020.

Similar programs were implemented in Asia. The city of Seoul, for instance, offered households below median income a choice of either a consumption voucher ("coupon") or a prepaid card, both with a 5-month expiry date. 80 % of households opted for the coupons, which had geographic retrictions but carried a 10 % higher value than the cards. The take up rate for this program was also high, at 99 %. Woo et al. (2021) and Kim and Lee (2021) find a significant effect on direct spending, and Ku et al. (2023) estimate a MPC of at least 59%. Baek et al. (2023) look at a similar policy in Gyeonggi, another Korean province, and find MPCs ranging from 36 to 58%.

China implemented a digital coupon program where the government would subsidize additional consumption for targeted categories and a very limited time period. if consumers spent a least X yuan electronically on a particular product category (e.g. food delivery), they would receive a government subsidy of $Y < X$. Recents studies (Ding et al. (2024); Xing et al. (2023); Liu et al. (2021); Wu et al. (2020)) analyzed this policy and documented large and persistent responses of consumption. According to these studies, for every yuan of subsidiy, around 3 additional yuan were spent.

B Data Appendix

In this appendix, we discuss the representativeness of the data, the data structure, and the exact definition of our variables for replication purposes.

B.1 Sampling and Representativeness

We build on a sample of households that the bank drew in June 2020, using the following steps. First, in order to be eligible for inclusion in the sample, the bank had to be the main bank used by the households

(i.e., households could be using multiple banks but must have located their main assets, credits and income at the bank). Second, households had to be client of the bank in January 2019. Third, French overseas territory and employees of the bank were excluded of the sampling process. Finally, the sampling procedure drew clients from cells at the local area ("*département*") × age bin level. Specifically, 94 different *départements* and six age bins were used: 18-25, 26-35, 36-45, 46-55, 56-65 and 66+ years. For the largest 31 départements 1,000 households per cell were selected, then 500 for the next 26 départements and finally 100 for the least populated département. The initial sample size was around 300,000 households. The sample was never renewed and, because of attrition, the sample size decreased over time. We received remote access to anonymized versions of the data that start in January 2019.

This dataset is by design representative of the population of clients at the bank. Bounie et al. (2020) and Bonnet et al. (2023) find that the sample is also broadly representative of the French population along several characteristics, with some slight differences. Specifically, compared to the French population, the bank sample is younger, with fewer retired people, features a higher share of individuals out of the labor force,[1] and a higher share of single households. The distribution of spending (and the ratio of spending over income) by income deciles in the bank sample are in line with the French consumption survey ("*Budget des Familles*"). The trends in card spending and liquid bank account balances also match macro aggregates from the French national accounts (see Bounie et al., 2020 and Bonnet et al., 2021). Bonnet et al. (2023) also show, using the 2017 French Wealth Survey, that the customer base of the bank is representative of the French population in terms of financial wealth and disposable income. This survey shows that 75% of households in France have a checking account in one bank only. Moreover, more than 80% of all financial assets of French household is held in their main or only bank. Finally, Bonnet et al. (2023) document that the distribution of monthly fuel spending with respect to income in the bank data looks close to the one obtained from the French consumption survey ("*Budget des Familles*").

Our paper focuses on a sub-sample of this panel. In order for an individual to be eligible in our experimental draw, a number of conditions have to be satisfied:

1. Age above 26 and below 75 years at the time of draw, and be in legal capacity, i.e. not having a legal guardian ("*majeur non protégé*")
2. Resident at the address registered with the bank
3. Account is a personal account, not a professional account. According to the records of the bank, the household is either entirely or mostly banking with them.
4. The checking account is active and the account holder is in good standing with the bank ("*compte courant ouvert et sain*"), and there were movements on the checking account within the last 10 days.
5. At least one transfer received every month over the course of the last six months; at least 10 transfers received in 2020, and at least 10 transfers received in 2019.
6. At least one payment made every month in the last six months, in 2020, and in 2019.
7. Has an active bank card that it has used at least once within the prior 20 days.

[1] The "inactive" category includes students, the unemployed, and any other person with no professional activity.

8. Is using internet/distance banking (*"détenteur d'un contrat banque à distance"*) with at least one connection within the prior 20 days. Has an email address registered on file.

Constraints 1, 2, and 8 are imposed for operational and ethical reasons. Constraints 3, 4, 5, 6, and 7 are imposed to exclude people whose consumption expenditure patterns are poorly captured through the data available to us.

B.2 Data Structure

The data is divided in six different tables:

- The first table is at the individual×month level, it contains socio-demographic information for all individuals in the household at month t.
- The second table is at the household×month level. It contains information on the balance of all different bank accounts of the household (current account, liquid savings account, life insurance and illiquid savings). The table also provides information on household debt (total debt, and by subcategories such as mortgage debt or consumption debt), and on the sum of incoming and outgoing banking movement for some categories of banking operations (checks, cash withdrawal, card purchases). Finally, it includes information on payment or other financial difficulties faced by the household, such as overdraft.
- The third table is at the household×operation level. This dataset provides information (time, amount) on all banking operations, i.e. all inflows and outflows. These flows cover a vast range of transactions, including card purchases, wire transfers, checks, and direct debit. The bank also provides information on incoming wire transfers. The bank classifies the incoming wire transfers into distinct categories: pensions, unemployment insurance, government subsidies, and salaries.
- The fourth table is at the household×operation level. This dataset gives information on all card transactions.[2] Compared to the previous table, this table gives more information for the card transactions (e.g., the Merchant Category Code (MCC) for the purchase). Moreover, while the previous table records the date at which there is a banking movement, this table records the date at which the transaction occurs (i.e., when the card is actually used). The two dates may differ for several reasons. For instance, some household choose to have a deferred debit, where the banking movements comes at the end of each month for all card transactions. The difference can also comes from delays from either the bank (in case the purchase is made on a bank holiday, or on a Sunday) or from the merchant (for instance, for fuel and gas purchases).
- The fifth table is at the household×operation level and provide provides a classification of all direct debit operations (phone bill, water bill...).
- The sixth table is at the household×period level. This table is a snapshot of all real estate wealth owned by the household, according to the bank's records. The information was collected twice, in September of 2020 and in November of 2021.

[2]Our dataset covers both debit and credit cards. About 2% of households have a credit card. French households use credit cards primarily as a way to access a line of credit: contrary to the United States, credit card history is not used to build credit scores and there are rarely features such as cash back, reward points, or frequent-flyer miles.

All of these tables can be joined thanks to an anonymized household identifier.

B.3 Variable Definitions

Our main variables are defined as follows:

- Consumption expenditure, per week: sum of card purchases and cash withdrawals of the household within the week (according to the third table described in Appendix B.2). We construct our winsorized weekly consumption spending by winsorizing regular client transactions at the 99th percentile (1940 euros in a week) and add up treatment card expenses in a week at the household level.
- Consumption expenditure on non-durable / durable / semi-durable goods or services: sum of card purchases and cash withdrawals of the household within the week linked to Merchant Category Codes classification to include only expenditure on specific categories of consumption expenditure (following the classification of Ganong and Noel (2019)).
- Treatment card expenditure: sum of household treatment card purchases within a week. Treated household who have effectively used the treatment card will have at least one week with positive value during the treatment period. Control group households have a value of zero for this variable.
- Regular card expenditure: sum of card purchases and cash withdrawals of the household within the week (according to the third table described in Appendix B.2) that are not identified as treatment card expenditure for treated households.
- Withdrawals: sum of cash withdrawals of the household within the week (according to the third table described in Appendix B.2).
- Weekly consumption expenditure, broad measure: sum of card purchases and cash withdrawals of the household within the week (according the third table described in Appendix B.2) plus all other outflows (direct debits, wire transfers, etc).
- Take-up dummy: Time-invariant dummy variable, equal to one for treated households who have used the treatment card at some point during the treatment period.
- Number of eligible individuals in the household: number of individuals in the household that would have been eligible to receive the treatment, at the time of randomization.
- Unemployed: time-invariant dummy, equal to one for households that receive at least one transfer from the unemployment benefits agency ("Pôle emploi") within the 6 months prior to treatment.
- Aggregation of individual characteristics to the household level: We aggregate individual characteristics to the household level by using the characteristic of the eligible household member. For control group households composed of two eligible people, we randomly choose one person's characteristic to represent the entire household. For treatment group households with two eligible members, we use the characteristic of the individual that has been chosen (at random) as treated. The relevant individual characteristics are as follows:

  - Age: time invariant variable that corresponds to the age of the individual.
  - Location: capture the département where the household lives.
  - Location type: this variable measures whether the household lives in rural, periphery or urban areas.
  - Occupation: this variable measures whether the individual works in one of the following occupations: farmers, artisans, executives, intermediate professions, employee, worker, retired, unemployed/students.

- Number of household members: this variable is used to correct time invariant characteristics like income and wealth. We account for the presence of children to compute a unit of consumption (UC) for each household. Following the OECD scale, we attribute 1 UC to a first adult in a household, 0.5 UC to the following one and 0.3 UC for every child below 14 years old.

- Variables for time-invariant heterogeneity analysis: all of these variables are divided by the sum of the unit of consumption in the household (see above):

  - Household monthly mean expenditure: average of monthly card expenditures in a week for 1 year before treatment.
  - Household monthly income: average monthly inflows to the household's bank account within the six months prior to treatment. Individual transactions value above 15,000 euros are trimmed.
  - Household wealth: we build two versions of the variables listed below over different time horizons, taking averages over either one month or six months prior to treatment.
    * Household bank current account: current account balance prior to treatment. This variable captures the bank account funds that the household can use at any point in time.
    * Household liquid saving accounts: liquid saving balance prior to treatment. This variable capture the funds available on liquid, tax-free savings accounts with instant access: *Livret A*, *Livret d'épargne populaire*, *Livret Jeune*, and philanthropic savings accounts, etc.
    * Household life insurance accounts: life insurance balance prior to treatment.
    * Household illiquid savings: illiquid saving accounts balance prior to treatment, including the "share savings plan" (*Plan d'épargne en action*).
    * Net liquid wealth: sum of the balances of the household's current account and liquid saving accounts at the end of the month, net of consumer debt.
    * Net illiquid wealth: sum of the balances of the household's illiquid saving accounts, share dealing accounts, and brokerage accounts at the end of the month, net of mortgage debt.
    * Household real estate wealth: real estate wealth reported by the household during a survey conducted in November 2021.

C Experimental Design Appendix

In this appendix, we describe the letter sent to the participants, as well as the survey administered in June 2022.

C.1 Letter Sent to the Participants

The letter sent to participants is printed on the bank's letterhead and is personally addressed to the selected participant:

Vous avez été sélectionné pour participer à une étude et ainsi bénéficier d'une enveloppe d'un montant de 300 EUR, qui vous est offerte.*

En effet, afin de contribuer au débat économique, le CIC participe à une étude scientifique menée par le Conseil d'Analyse Economique (CAE) et financée par l'Agence Nationale de la Recherche (ANR). L'objectif de cette initiative est d'étudier, dans le cadre d'une politique destinée à favoriser la relance économique, les comportements de dépenses des personnes lorsqu'une somme d'argent leur est distribuée gratuitement.

Le CIC veille à la protection des données de ses clients. Toutes les analyses réalisées dans le cadre de cette étude seront effectuées sur des données strictement anonymisées sur les seuls systèmes d'information sécurisés du CIC. Il s'agit des mouvements bancaires, de la situation financière et de données socio-économiques.

Ce montant de 300 EUR sera utilisable au moyen d'une carte de paiement spécifique. Cette carte vous sera adressée gratuitement par courrier postal dans les prochains jours.

- *Le code confidentiel de cette carte est identique à celui de la carte que vous possédez déjà. Vous pouvez le retrouver dans votre espace personnel en ligne, sur l'application mobile ou le site internet www.cic.fr.*
- *Cette carte peut être utilisée auprès des établissements affichant les logos CB ou Mastercard, ainsi que pour des achats en ligne, dans la limite du solde disponible.*
- *Il n'est pas possible de retirer des espèces, ni d'effectuer des dépôts.*
- *Le suivi des opérations et le solde disponible sur cette carte sont consultables dans votre espace personnel en ligne, sur l'application mobile ou sur le site internet www.cic.fr.*
- *Les conditions générales d'utilisation qui régissent votre carte actuelle, s'appliquent également à cette carte (CG.03.20).*

Translation:

You have been selected to participate in a study and, as a result, benefit from an amount of 300 EUR, which is offered to you.*

Indeed, in order to contribute to the economic debate, CIC is participating in a scientific study conducted by the Council of Economic Analysis (CAE) and funded by the National Research Agency (ANR). The objective of this initiative is to study, within the framework of a policy

aimed at promoting economic recovery, people's spending behaviors when a sum of money is distributed to them for free.

CIC ensures the protection of its clients' data. All analyses carried out as part of this study will be performed on strictly anonymized data on CIC's secure information systems. This includes banking transactions, financial situation, and socio-economic data.

This amount of 300 EUR will be available for use through a specific payment card. This card will be sent to you free of charge by postal mail in the coming days.

- *The confidential code for this card is the same as the one for the card you already possess. You can find it in your personal online space, on the mobile application, or on the website www.cic.fr.*
- *This card can be used at establishments displaying the CB or Mastercard logos, as well as for online purchases, up to the available balance.*
- *It is not possible to withdraw cash or make deposits. The operations and available balance on this card can be checked in your personal online space, on the mobile application, or on the website www.cic.fr.*
- *The general terms of use that govern your current card also apply to this card (CG.03.20).*

The next paragraph contains information that is specific to the treatment group.

For treatment group 1:

La carte fonctionne jusqu'au 03/10/2022. Si vous ne dépensez pas l'intégralité du montant de 300 EUR avant cette date, le solde restant sera automatiquement transféré sur votre compte courant habituel du CIC.

Transl.: *The card is valid until 10/03/2022. If you do not spend the entire amount of 300 EUR before this date, the remaining balance will be automatically transferred to your regular current account at CIC.*

For treatment group 2:

L'objectif de cette expérience est d'encourager une hausse de la consommation à court terme, dans le cadre d'une politique économique de relance. Pour cette raison, la carte fonctionne jusqu'au 23/05/2022 à 23 heures 59. Il ne sera plus possible d'utiliser les fonds après cette date limite; les fonds inutilisés seront perdus.

Transl.: *The objective of this experiment is to encourage an increase in short-term consumption, as part of an economic policy for recovery. For this reason, the card is valid until 05/23/2022 at 11:59 PM. It will no longer be possible to use the funds after this deadline, and any unused funds will be lost.*

For treatment group 3:

L'objectif de cette expérience est d'encourager une hausse de la consommation à court terme, dans le cadre d'une politique économique de relance. Pour cette raison, le montant disponible de la carte est débité automatiquement d'un certain montant chaque lundi à 23 heures 59 (à partir du lundi 09/05/2022). Le montant débité dépend du solde restant à ce moment, avec un montant débité plus élevé lorsque le solde restant est plus élevé afin d'encourager une consommation rapide. Ainsi, le solde disponible sera diminué :

- *de 30 EUR si le solde restant est supérieur à 200 EUR ;*
- *de 20 EUR si le solde restant est entre 100 EUR et 200 EUR ;*
- *de 10 EUR si le solde est inférieur à 100 EUR (le débit correspond au solde restant si celui-ci est inférieur à 10 EUR).*

Par exemple, si vous dépensez le montant de 300 EUR avant le lundi 09/05/2022 à 23 heures 59, le solde restant est nul et aucun montant ne sera débité. Si vous dépensez seulement 50 EUR avant le lundi 09/05/2022 à 23 heures 59, le solde disponible sera diminué de 30 EUR et le solde disponible le mardi 10/05/2022 à 00h00 sera de 220 EUR (= 300 – 50 – 30).

Transl.: *The goal of this experiment is to promote an increase in short-term consumption as part of an economic policy for recovery. For this reason, the available amount on the card is automatically debited by a certain amount every Monday at 11:59 PM (starting from Monday, 05/09/2022). The debited amount depends on the remaining balance at that moment, with a higher amount debited when the remaining balance is higher, to encourage rapid consumption. As a result, the available balance will be reduced as follows:*

- *by 30 EUR if the remaining balance is above 200 EUR;*
- *by 20 EUR if the remaining balance is between 100 EUR and 200 EUR;*
- *by 10 EUR if the remaining balance is below 100 EUR (the debit amount will be equal to the remaining balance if it is below 10 EUR). For example, if you spend the full amount of 300 EUR before Monday, 05/09/2022, at 11:59 PM, the remaining balance will be zero, and no amount will be debited. If you only spend 50 EUR before Monday, 05/09/2022, at 11:59 PM, the available balance will be reduced by 30 EUR, and the available balance on Tuesday, 05/10/2022, at 12:00 AM will be 220 EUR (= 300 – 50 – 30).*

Next, a paragraph that depends on whether the partipant is part of a framing group. Participants that are not in the framing group receive the following message:

Vous êtes totalement libre d'utiliser le montant de 300 EUR comme vous le souhaitez.

Transl.: *You are completely free to use the amount of 300 EUR as you wish.*

Participants that are in the framing group receive instead:

Bien que vous soyez libre d'utiliser le montant de 300 euros comme vous le souhaitez, nous vous invitons à:

- *dépenser l'argent aussi rapidement que possible;*

- *acheter des produits fabriqués en France et des services qui soutiennent l'emploi local, car l'objectif de ce transfert est la relance de l'économie française, en encourageant la consommation de produits made in France;*
- *acheter des produits ou services que vous n'achèteriez pas habituellement (autres que vos dépenses courantes) afin d'augmenter vos dépenses totales, et ainsi de contribuer à la relance économique, plutôt que de couvrir des dépenses déjà prévues.*

Transl.: *Although you are free to use the amount of 300 euros as you wish, we invite you to:*

- *spend the money as quickly as possible;*
- *buy products made in France and services that support local employment, as the objective of this transfer is to stimulate the French economy by encouraging the consumption of "made in France" products;*
- *purchase products or services that you wouldn't normally buy (other than your regular expenses) to increase your total spending and thereby contribute to the economic recovery, rather than covering expenses that were already planned.*

All groups conclude with the following:

L'utilisation de cette carte n'entraine aucun frais pour vous. Si vous ne souhaitez pas participer à cette étude, n'utilisez pas la carte et détruisez la. En utilisant la carte, vous acceptez de participer à l'étude. En vous remerciant pour votre confiance, votre conseiller CIC se tient à disposition pour répondre à toutes vos questions.

Transl.: *The use of this card does not incur any fees for you. If you do not wish to participate in this study, do not use the card and destroy it. By using the card, you agree to participate in the study. Thank you for your trust; your CIC advisor is available to answer any questions you may have.*

The footnote is as follows:

** L'étude est menée et a été définie par une équipe scientifique du CAE et financée par l'Agence Nationale de la Recherche. Les critères de sélection des participants, l'utilisation des cartes, les données étudiées et la durée de l'étude qui s'étend du 01/10/2021 au 03/10/2022 ont été définis par le CAE. Les 1 000 participants qui bénéficient de la somme de 300 EUR ont été tirés au sort sous contrôle d'huissier.*

Transl.: *The study is conducted and has been defined by a scientific team from the CAE and funded by the National Research Agency. The criteria for selecting participants, the use of the cards, the data studied, and the duration of the study, which extends from 10/01/2021 to 10/03/2022, have been determined by the CAE. The 1,000 participants who are receiving the sum of 300 EUR have been randomly selected under the supervision of a bailiff.*

C.2 Survey Questions

Participants were contacted by email with the following message:

Bonjour,

Vous avez récemment fait appel au service Etudes, Satisfaction et Qualité pour vous accompagner dans le cadre du projet : Enquête de satisfaction CAE / CARTE DE PAIEMENT 300 euros. Afin d'améliorer la qualité de nos prestations, nous sollicitons votre retour d'expérience. Nous vous proposons donc une courte enquête composée de quelques questions. Cela vous prendra moins de 5 minutes pour y répondre.

[Hyperlink: Répondre à l'enquête]

Nous vous remercions par avance.

Notre équipe reste bien évidemment à votre disposition.

Bonne journée.

Le service Etudes, Satisfaction et Qualité

Translation:

Hello,

You recently used the Studies, Satisfaction, and Quality service to assist you in the context of the project: Satisfaction Survey CAE / 300 Euro Payment Card. In order to improve the quality of our services, we would appreciate your feedback. We invite you to participate in a short survey consisting of a few questions. It will take you less than 5 minutes to complete.

[Hyperlink: Respond to the survey]

Thank you in advance.

Our team remains at your disposal.

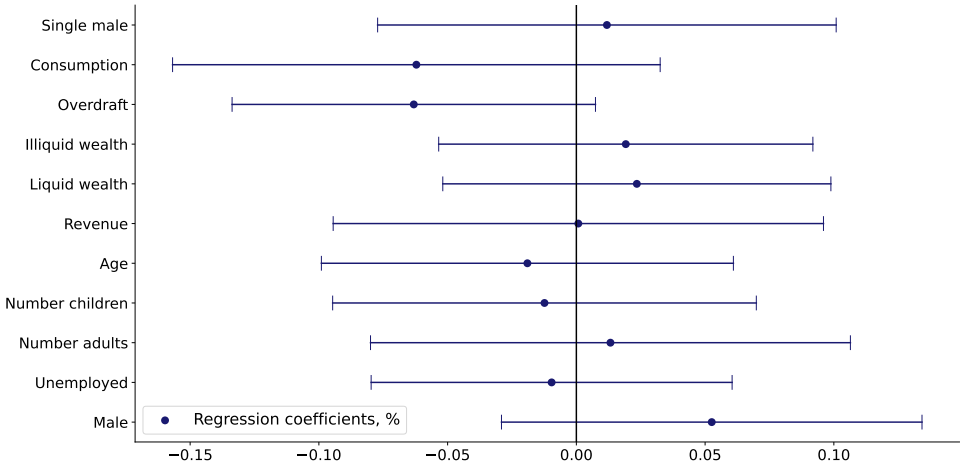
Have a great day.

The Studies, Satisfaction, and Quality service

The full text of the questionnaire is available from the authors upon request.

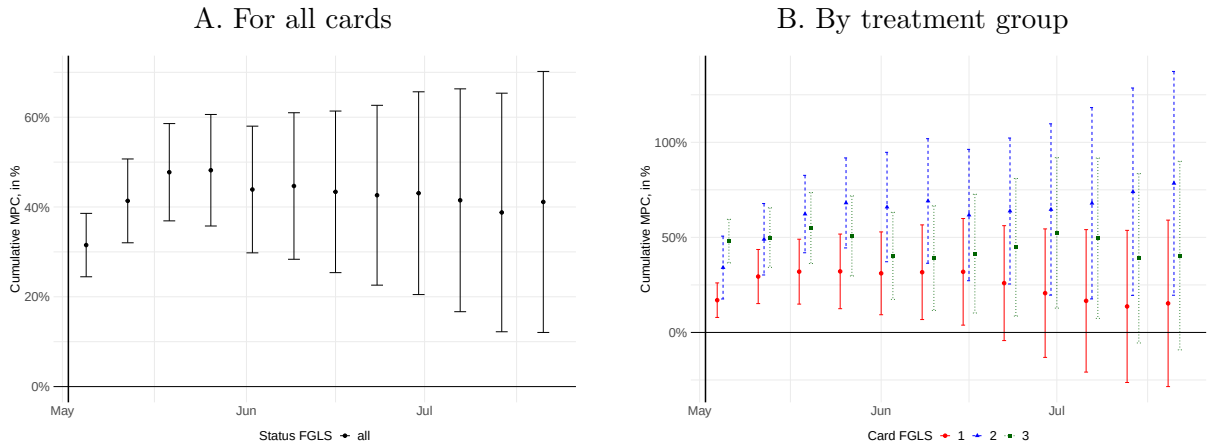
D Main Additional Figures and Tables

Figure D1 Randomization Tests



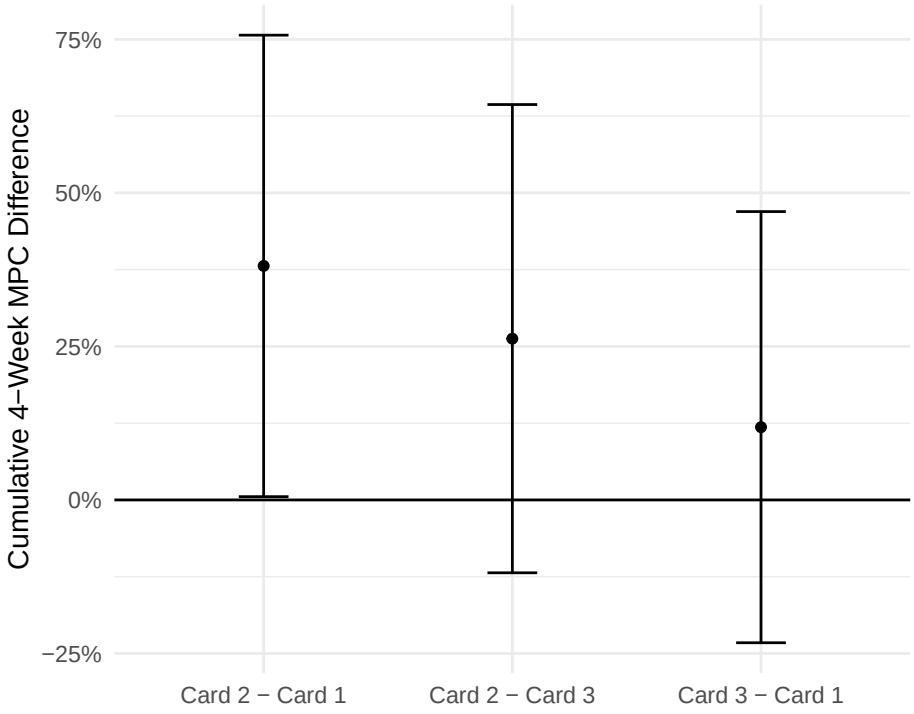
Notes: This figure reports the randomization tests for participation in the experiment, regressing a dummy for participation status on several household characteristics. We control for the number of eligible members in the households. The probability of being treated in the sample is 1%.

Figure D2 FGLS estimates of the MPC



Notes: This figure shows the estimated MPC using a feasible generalized least square (FGLS) procedure, where standard errors of each household's error term are parameterized to be able to vary with each bin of time-invariant characteristics calculated from pre-period data (10 age bins, 10 income bins, gender dummy, 10 liquid wealth bins, 10 average consumption expenditure bins, 95 local area dummies), i.e. in each iteration we calculate weights from $1/\hat{\sigma}_i^2$, where $\hat{\sigma}_i$ is the predicted standard error from a regression of the household-level standard error in the previous iteration on characteristic bin dummies. While Panel A considers all cards, Panel B presents the estimates by treatment group. Both panels report 95% confidence intervals, clustered at the household level.

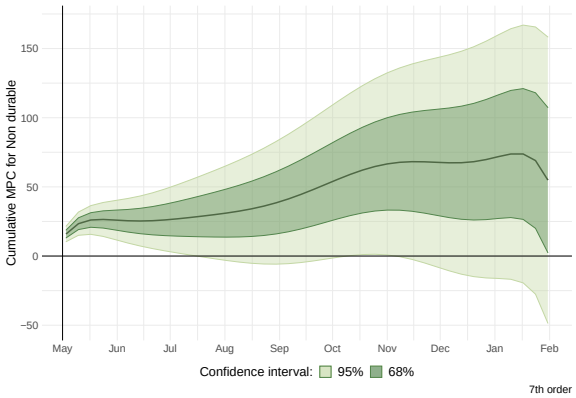
Figure D3 4-week MPC Differences between Card Types



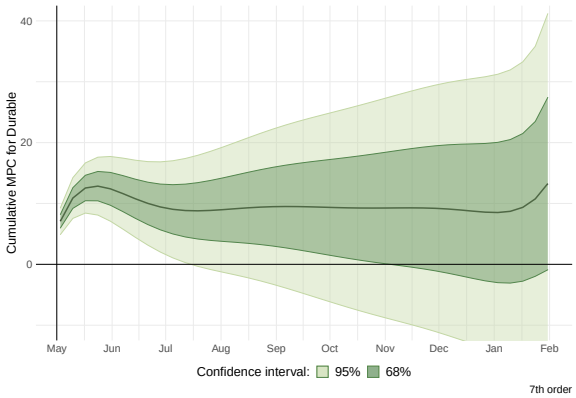
Notes: This figure reports the 4-week MPC difference between card types, with 95% confidence intervals.

Figure D4 Long-term MPC Estimates for Durables and Nondurables

A. Non durable MPC



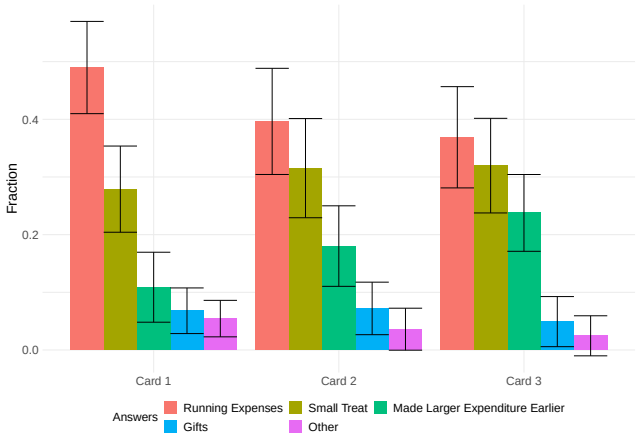
B. Durable MPC



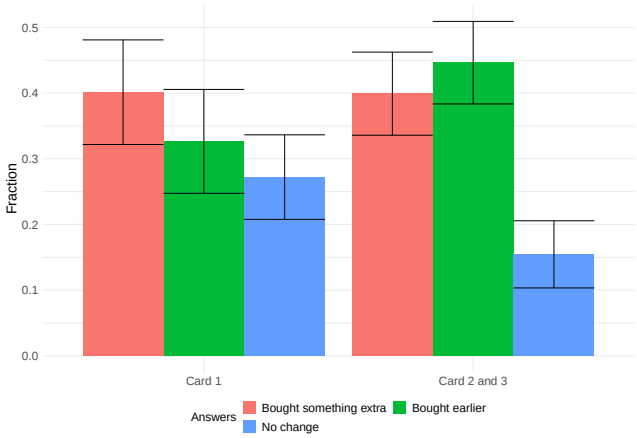
Notes: This figure reports the cumulative MPC estimates for nondurables and durables, considering all cards together. To reduce noise we use a seventh-order polynomial to model the weekly outcome response after treatment: $Y_{it} = \sum_{k=1}^{8} \beta_{\tau}^{k-1} \cdot \tau_{it}^{k-1} + \alpha_i + \alpha_{tE} + \varepsilon_{it}$, which we estimate with the same FGLS procedure as in Figure D2. The figure reports the cumulative change in the outcome and the 95% confidence intervals, clustered at the household level.

Figure D5 Understanding Participants' Spending Behavior by Card Type

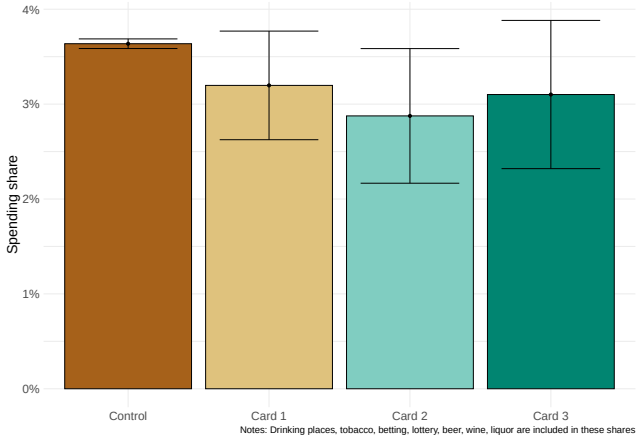
A. What did you buy with the prepaid card?



B. Were the purchases on the card already planned?

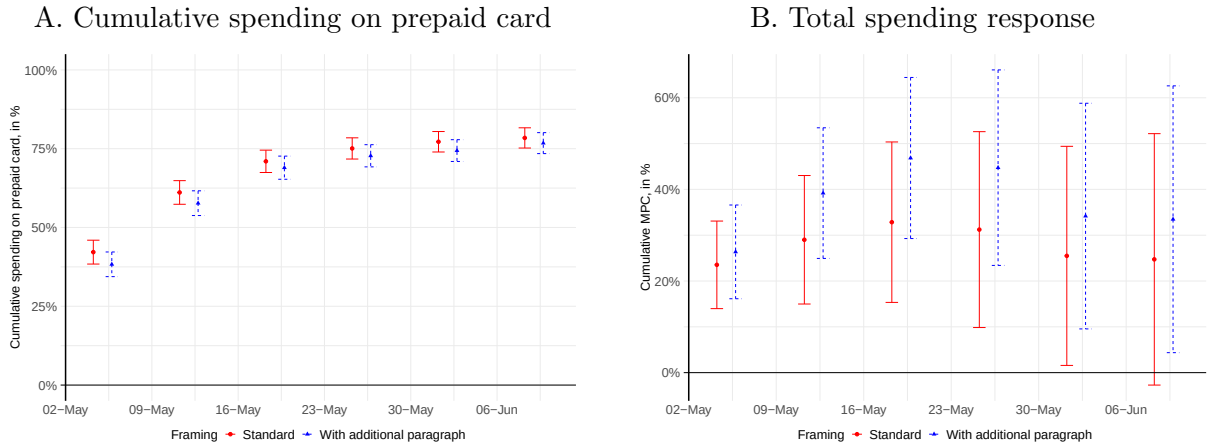


C. Spending share on goods with "negative externalities"



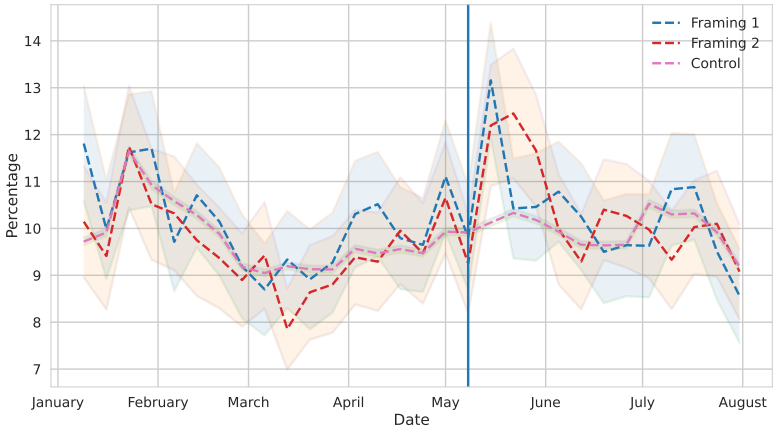
Notes: Panels A and B of this figure report the answers of participants to survey questions. The other panels use the bank data to document the expenditure patterns of the treatment and control groups depending on the prepaid card type. Panel C reports the spending share on treatment cards for the treatment groups, considering products that may have negative externalities (drinking, tobacco, betting, lottery).

Figure D6 MPC Estimates by Framing Group



Notes: This figure reports MPC estimates depending on the framing of the intervention. We compare the consumption behavior of participants in who received the standard letter to those of participants who received a letter with an additional paragraph encouraging them to spend the money quickly and on local goods or services. Panel A reports spending patterns on the prepaid card, while panel B report the overall MPC. In panel B, 95% confidence intervals are reported, clustering the data at the household level.

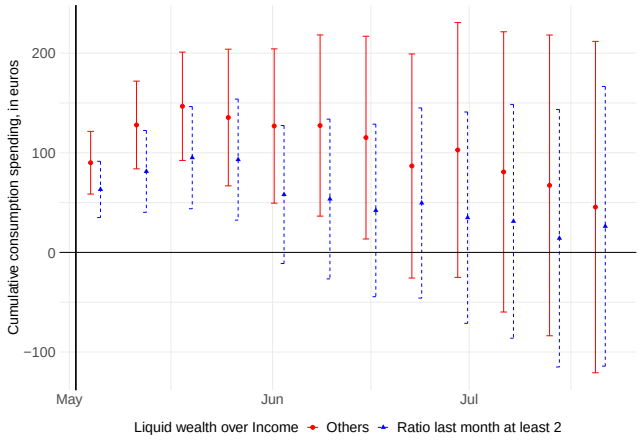
Figure D7 Spending on Imports, by Framing Group



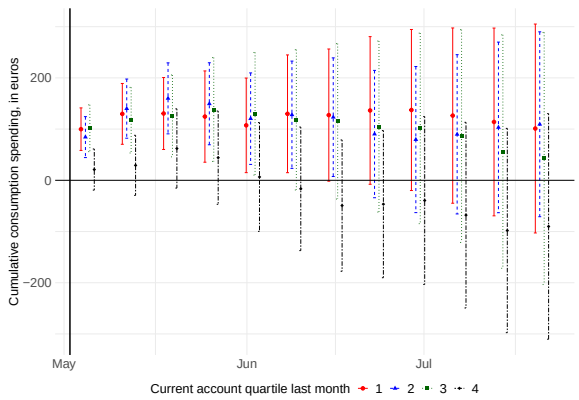
Notes: This figure shows the average expenditure share on imports for households in the two framing groups and the control group. Imports are calculated as the fraction of each product category that is directly imported from abroad, using the Input-Output table provided by the French statistical institute INSEE, and linked to MCC codes using our crosswalk.

Figure D8 Total spending response, weekly, for households with high liquid wealth

A. Liquid wealth ¿ 2 × monthly income



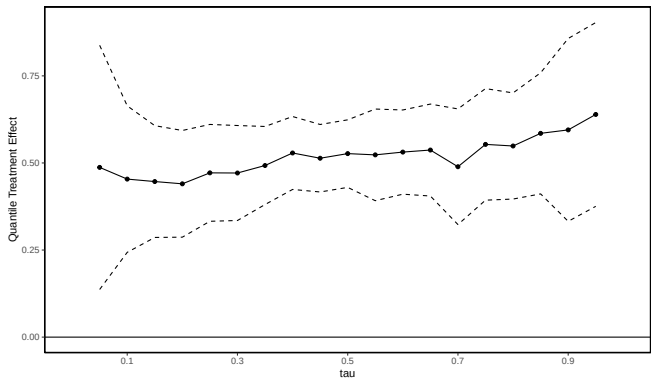
B. By quartile of current account wealth



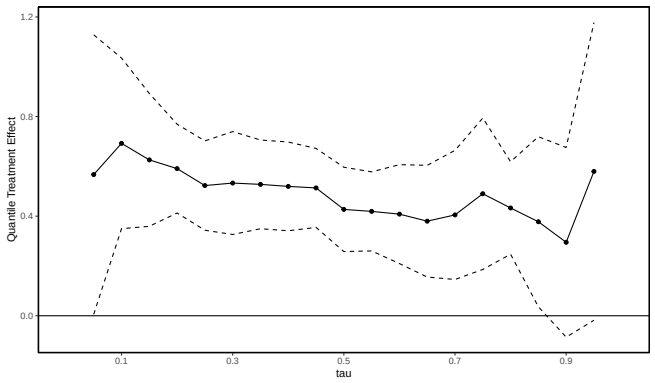
Notes: The panels of this figure shows the results of estimating equation 1 in a subsample of households whose liquid wealth is larger than twice their monthly income, and by quartiles of current account wealth. The figure plots the estimates for the cumulative MPC at different time horizons.

Figure D9 Quantile treatment effects: de-meaned cumulative consumption, treated vs. control

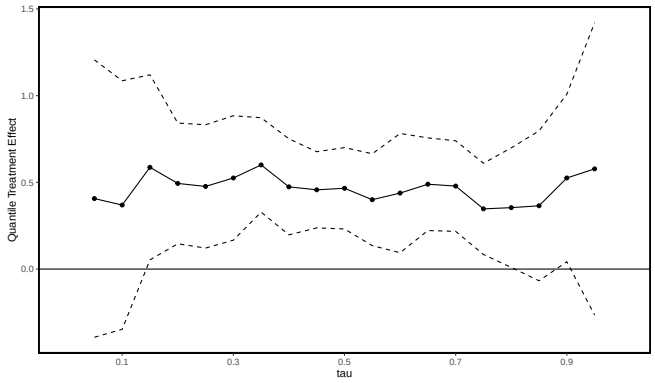
A. 4-week horizon



B. 8-week horizon

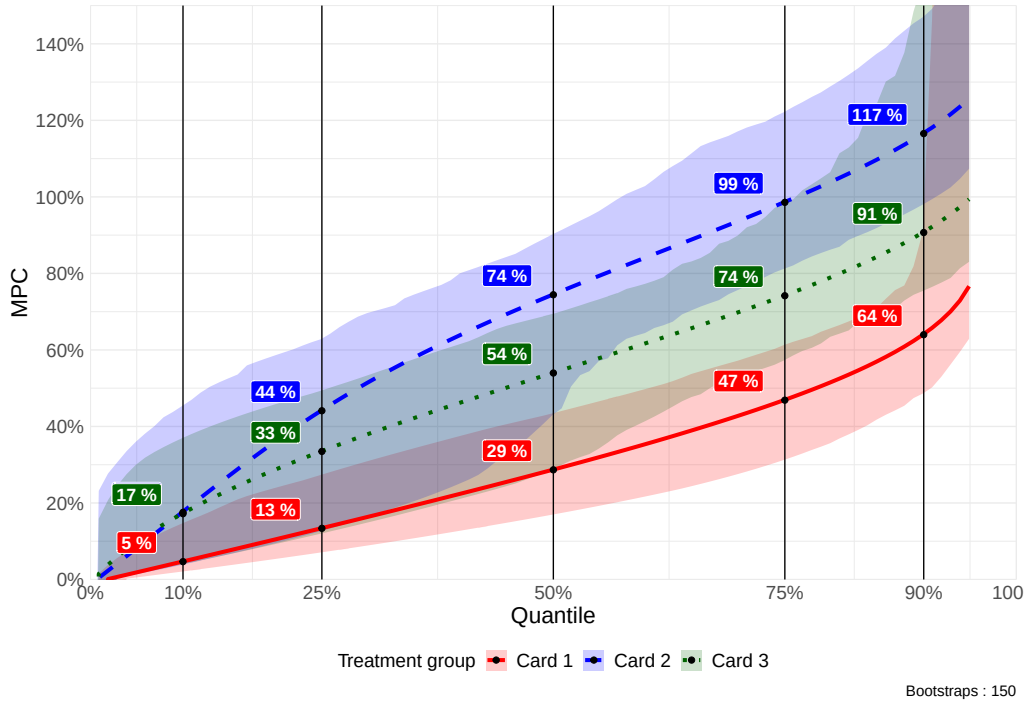


C. 12-week horizon



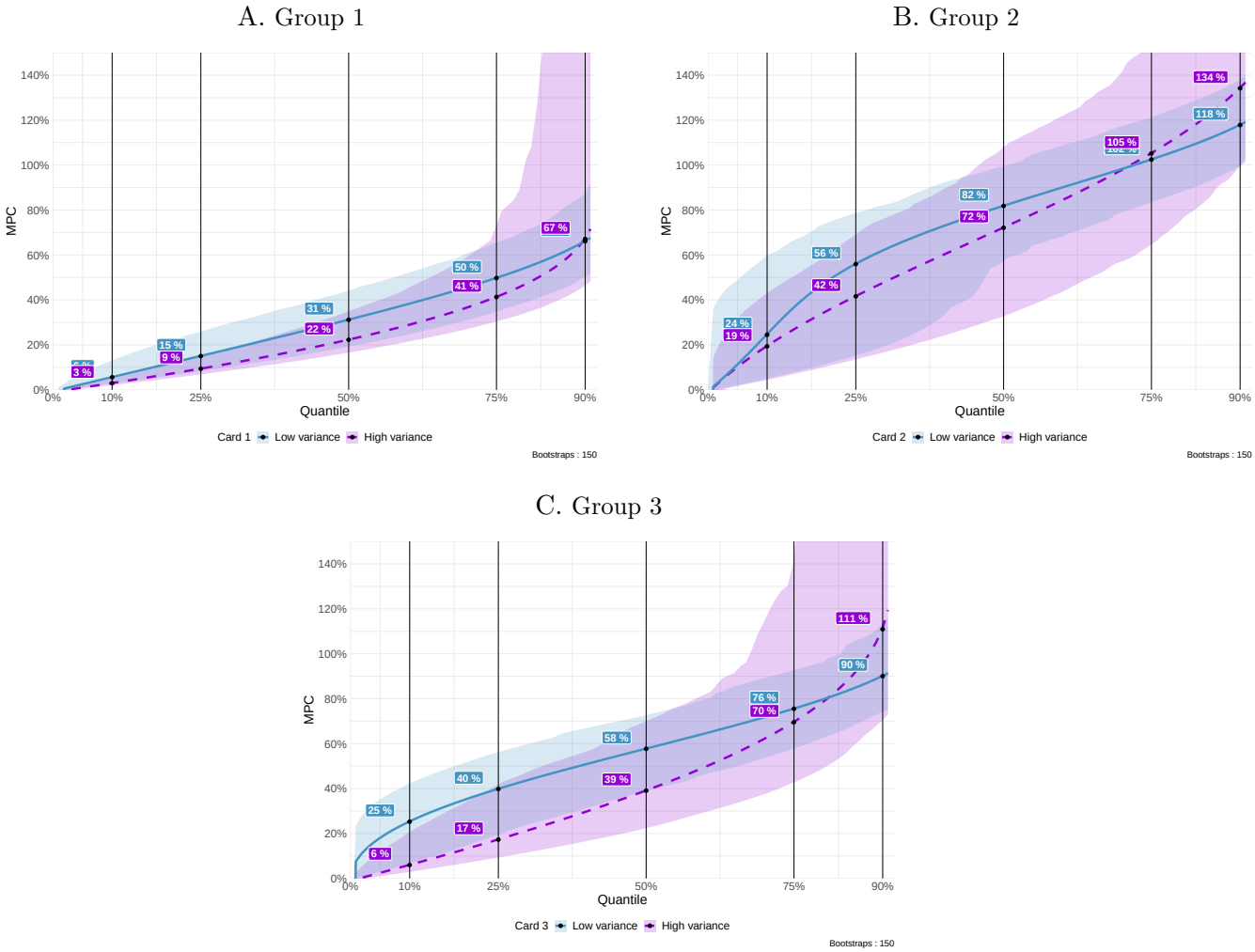
Notes: This figure shows quantile treatment effects—the difference between the quantiles of the distribution of treated and control groups—for cumulative de-meaned consumption expenditures. Standard errors are estimated using the bootstrap.

Figure D10 Household-level Quantiles of the 4-week MPC Distribution: Robustness to inclusion of observed characteristics bins



Notes: This figure reports the quantiles of the distribution of 4-week treatment effects by treatment group in a two-stage procedure with controls. In the first stage of our estimation procedure we project weekly consumption expenditures on household and week fixed effects interacted with (a, i, c, l, g) fixed effects, where a, i, c, and l are age, income, consumption, and liquid assets quartile bins, and g is a gender dummy. In the second state we deconvolve, as before, the outcome distribution for the treated by the empirical distribution of the error term of the control group. Constraints on the estimated distribution (mass on positive part of real line, and penalization) are as in the specification of the benchmark estimate. The figure shows the resulting treatment distribution estimates, which are similar to those reported using the baseline procedure. Shaded regions are delineated by the 10th and 90th percent quantile of the bootstrapped simulated distribution of the corresponding moment.

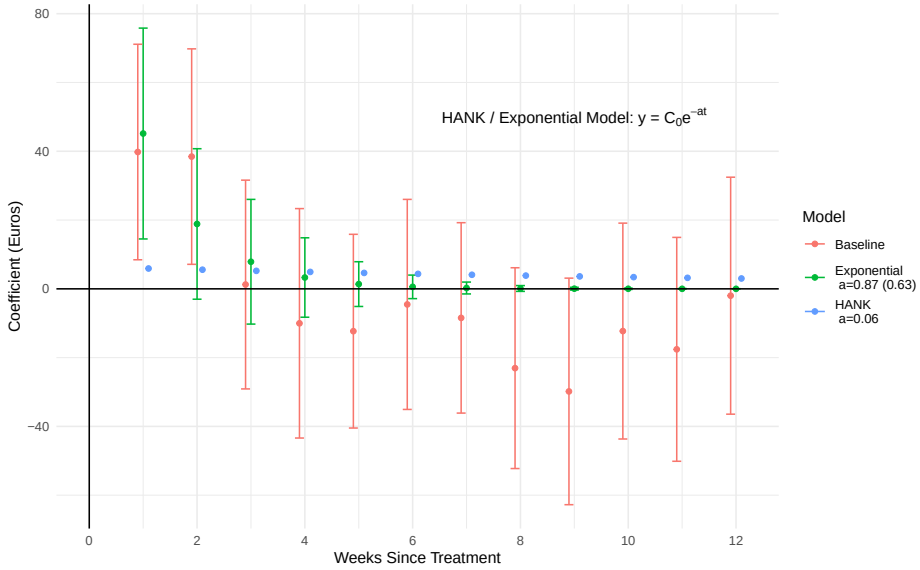
Figure D11 Unconditional MPC distribution estimates, high-variance vs low-variance households



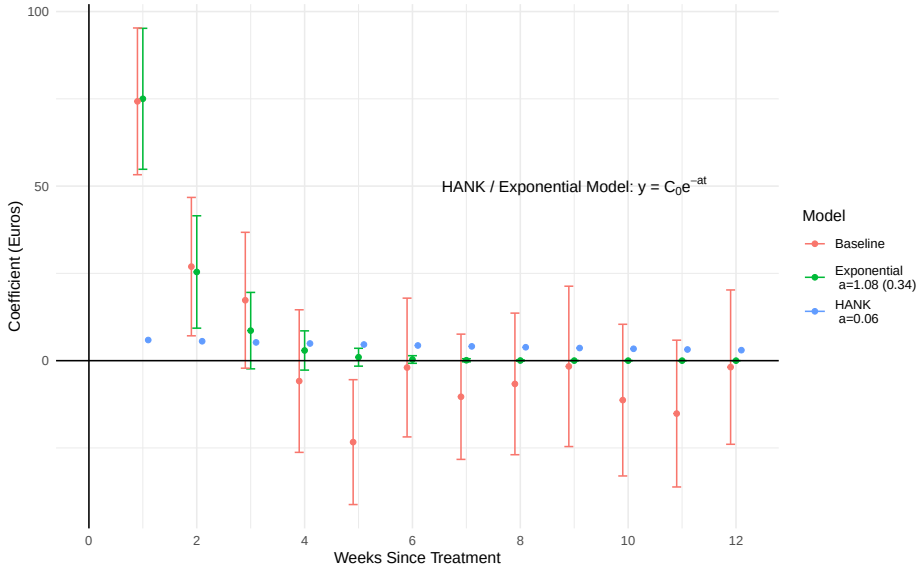
Notes: The panels of this figure show estimates of the 4-week MPC distribution for each treatment group, where the sample is split into households that have a below-median variance of pre-period weekly consumption expenditures (green) and above-median variance of pre-period weekly consumption expenditures (purple). For each treatment card, the estimated distributions for both variance groups are very similar (indeed, no quantile is significantly different from each other), giving support to the view that treatment effect distributions are similar even for households that have different higher moments of consumption. Shaded regions are delineated by the 10th and 90th percent quantile of the bootstrapped simulated distribution of the corresponding moment.

Figure D12 Comparison of Dynamic MPC Estimates to Standard HANK Model

A. Comparison to Card 1 MPC Estimates

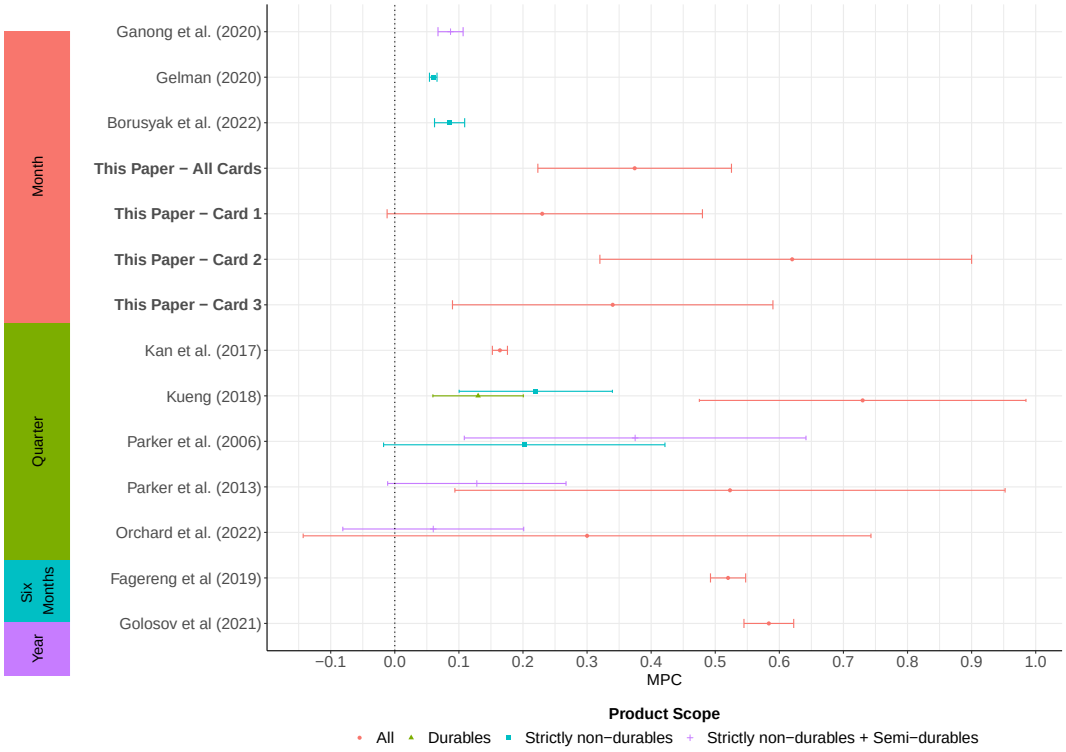


B. Comparison to Pooled MPC Estimates



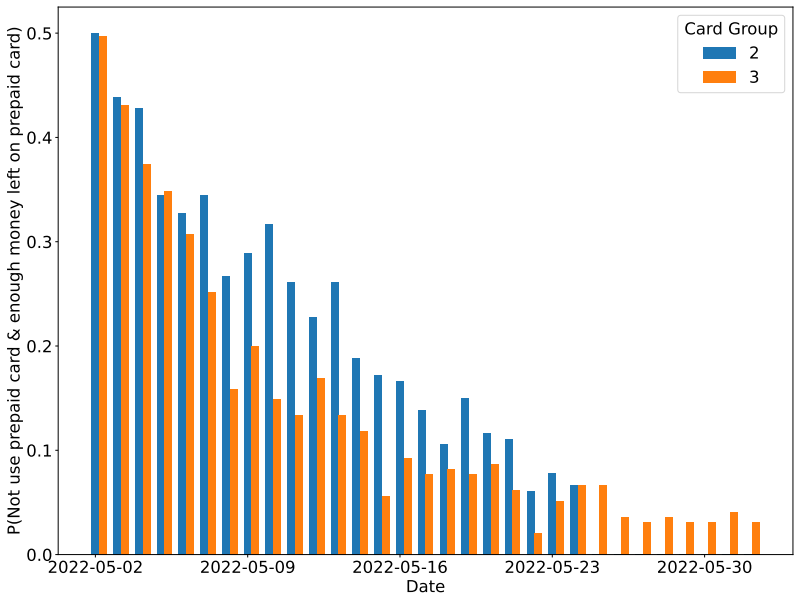
Notes: This figures compare the dynamics of the spending response in our experiment and in the calibrated HANK model of Kaplan et al. (2018). Panel A draws this comparison using Group 1 participants. The red line reports our baseline weekly MPC estimates for Card 1. The green line reports the estimates obtained by fitting an exponential model such that the MPC t weeks after treatment is given by $C_0 \cdot e^{-a \cdot t}$. Finally, the blue line reports the path of MPCs according to the calibrated HANK model of Kaplan et al. (2018); while their model is quarterly, we fit by nonlinear least squares an exponential model of weekly MPCs to match the calibrated quarterly MPCs reported in Figure 2 of Kaplan et al. (2018), which gives a cumulative MPC out of a \$300 transfer of 17%, 25%, and 36% at 13, 26 and 52 weeks respectively. Panel A shows that the estimated decay parameter a is one order of magnitude larger in our data than in HANK. We reject that the baseline weekly MPC model with Card 1 is the same as the MPC path from HANK with a p-value of 0.038. In contrast, when comparing our baseline weekly MPC estimates to our estimated exponential model, we cannot reject the exponential model (p-value = 0.63). Panel B repeats the analysis using all treatment groups, rather than Group 1 alone. We estimate an even larger decay parameter and reject the HANK model with a p-value close to zero (p-value = $5 \cdot 10^{-11}$). In contrast, we cannot reject our estimated exponential model (p-value = 0.38).

Figure D13 Summary of MPCs estimates



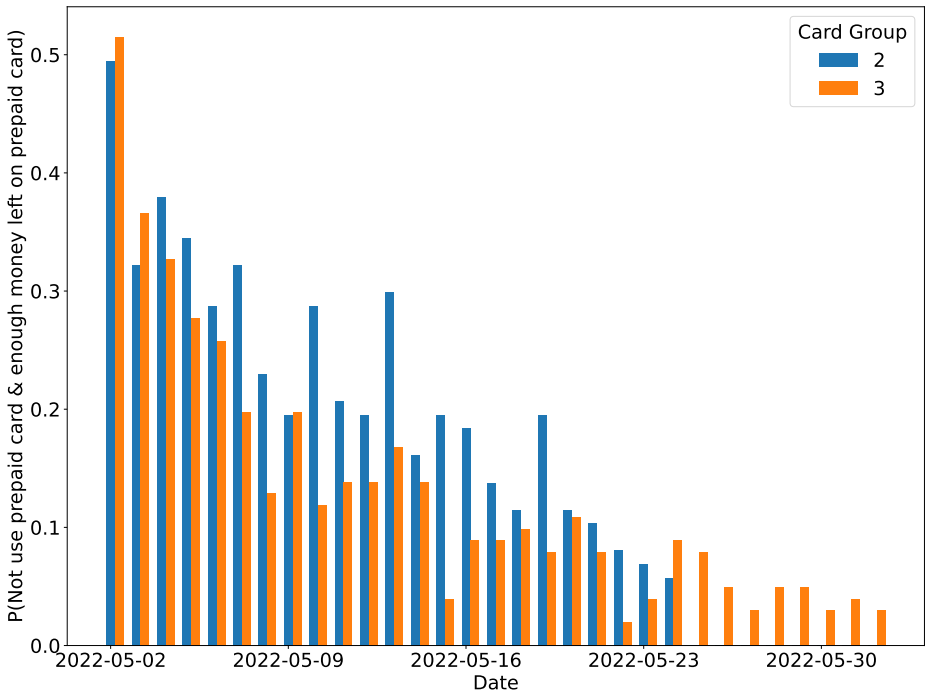
Notes: This figure reports the estimates of MPCs in the literature (typically from their baseline specifications), coded by time horizon and expenditure categories; 95% confidence intervals are also reported.

Figure D14 A Simple Test of the Fungibility of Money



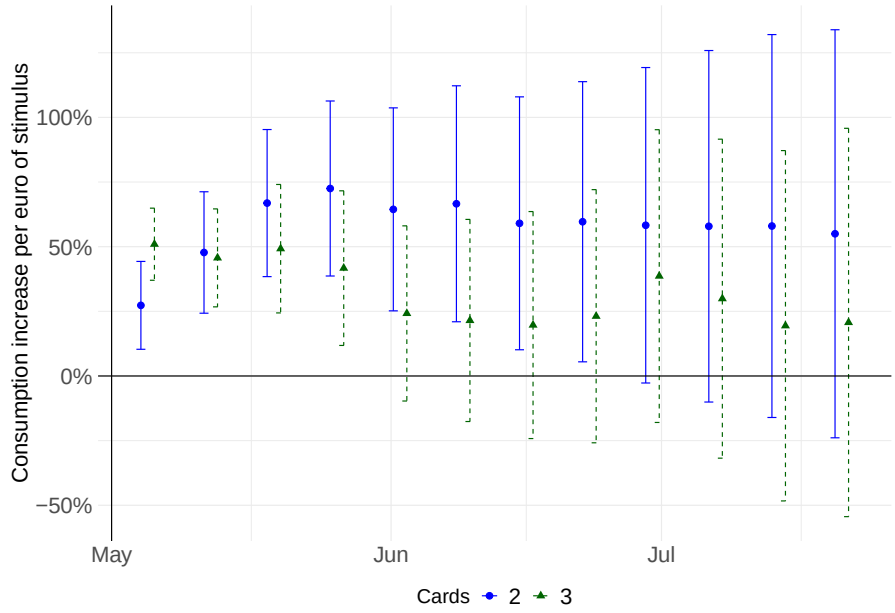
Notes: This figure shows the fraction of households that should have used the treatment card but did not, by day and card type. Specifically, the figure shows the fraction of households that satisfy the following conditions (i) at the start of the day, they have a higher remaining balance on the treatment card than the realized consumption expenditure on other cards during the day; (ii) they do not use the treatment card during that day; (iii) they have a nontrivial amount of money left on the treatment card (more than 20 euros); (iv) they have positive consumption expenditures on that day (that are not auto-pay transactions); (v) they use the treatment card at some point during the experiment. The results are reported separately for Card 2, which expires after three weeks, and Card 3, which implements a negative interest rate of approximately 10% on the remaining balance on the treatment card every Monday at 11:59pm.

Figure D15 Fraction of households that should have used the treatment card but did not: narrow sample



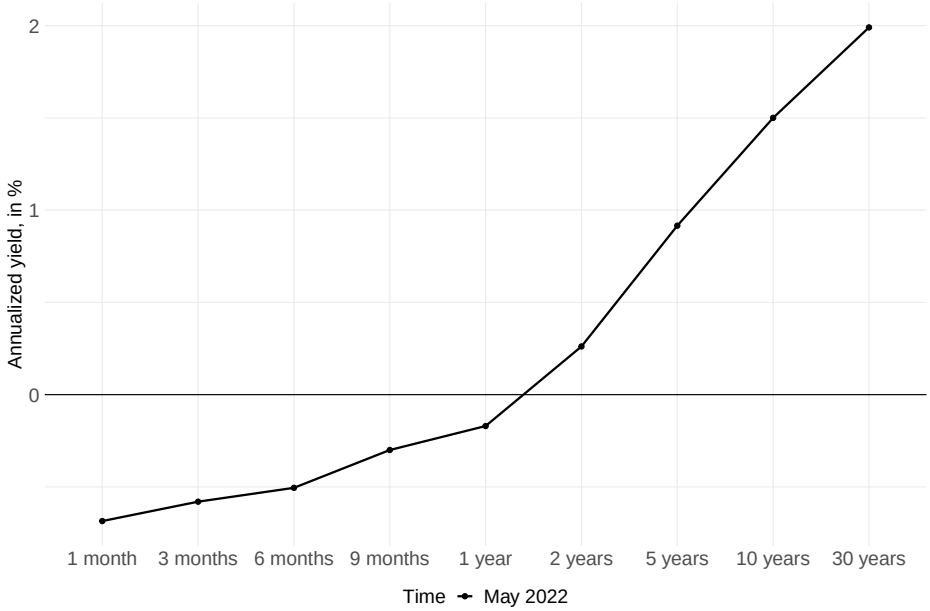
Notes: This figure shows the same result as Figure D14 – the fraction of households that should have used the treatment card but did not – but only among the population of households that consist of a single adult and no children, and conditioning on making consumption expenditures on that day in physical stores only (i.e. not online or via phone). This is to rule out the possibility that this phenomenon is driven by multi-person households of whom only one has access to the treatment card, or by households that are not aware that they could use the card online.

Figure D16 Effective stimulus, for cards where not all money is spent



Notes: This figure shows the MPC estimates for cards 2 and 3 (panel A of Figure 4) divided by the fraction of the 300 euro treatment card value that is spent by the average treated household in that group (i.e. that is not returned through the weekly interest payments in group 3, or that is returned upon expiry in group 2). The resulting number shows the average consumption stimulus per euro spent by the transferer.

Figure D17 Yield Curve for French bonds, May 2022



Notes: This figure shows the yield curve for French Treasury bonds at the start of our experiment, i.e. in May 2022 (source: Bank of France).

Table D1 Summary statistics, weekly consumption spending

	N	Mean	SD	p10	p25	p50	p75	p90
Weekly cons. expend. (cash and cards), total	2,571,000	417.66	435.02	67.30	163.25	315.95	542.63	848.64
Direct debits, debt payments, Subscriptions	2,571,000	198.55	1718.03	0.00	11.00	81.89	224.30	452.71
Outgoing transfers	2,571,000	111.50	845.94	0.00	0.00	0.00	0.00	100
Weekly cons. expend. (broad measure), excl. treatment cards	2,571,000	727.63	1992.72	133.55	269.78	498.72	848.24	1,337.29
Weekly cons. expend. (cash and cards), excl. treatment cards	2,571,000	417.57	434.99	67.25	163.19	315.88	542.53	848.50
Weekly cash withdrawals	2,571,000	23.74	83.71	0.00	0.00	0.00	0.00	70.00

Notes: The table shows summary statistics on different consumption categories by week. The sample consists of all household-weeks since January 2022. The broad measure of consumption includes the total of cash withdrawals, card spending, automatic debits, and wire transfers.

Table D2 Summary statistics, household characteristics

	N	Mean	SD	p10	p25	p50	p75	p90
Age of eligible household member	85,700.00	47.03	12.92	30.00	36.00	46.00	58.00	65.00
Number of eligible household members	85,700.00	1.15	0.36	1.00	1.00	1.00	1.00	2.00
Avg. monthly incoming transfers, 6m prior	85,685.00	2,654.04	1,439.56	1,317.69	1,796.14	2,381.15	3,159.71	4,217.33
Avg. monthly salaries, social allowance, pensions, benefits, 6m prior	80,034.00	2,109.55	4,968.86	493.06	1,049.91	1,667.95	2,348.71	3,259.71
Avg. monthly incoming salaries, 6m prior	80,034.00	1,630.59	5,003.78	0.00	95.65	1,171.51	2,077.47	3,053.53
Avg. monthly incoming pension payments, 6m prior	80,034.00	300.72	691.85	0.00	0.00	0.00	0.00	1,464.42
Avg. monthly incoming social allowances, 6m prior	80,034.00	98.06	199.81	0.00	0.00	0.00	110.932	298.32
Avg. monthly incoming unemployment benefits, 6m prior	80,034.00	80.18	284.12	0.00	0.00	0.00	0.00	242.28
Dummy: has received unemployment benefits within 6m prior	85,685.00	0.14	0.35	0.00	0.00	0.00	0.00	1.00
Avg. net liquid wealth, 1m prior	85,700.00	19,265.55	46,067.40	121.38	1,506.66	7,599.54	23,854.85	55,256.41
Avg. current account balance, 6m prior	85,698.00	4,448.41	19,976.04	63.50	424.17	1,006.25	2,487.53	7,563.32
Avg. liquid savings, 6m prior	85,698.00	16,896.51	34,466.19	17.30	617.74	5,462.02	19,253.96	44,896.89
Avg. value of life insurance assets, 6m prior	85,698.00	5,867.43	32,466.19	0.00	0.00	0.00	372.91	8,924.360
Avg. net illiquid wealth , 6m prior	85,700.00	64,746.97	185,159.99	-43,194.32	0	1,285.04	93,451.46	211,111.53
Avg. total debt, 6m prior	85,698.00	-33,300.8	55,007.44	-99,130.28	-52,931.94	-5,641.02	0.00	0.00
Avg. consumer debt, 6m prior	85,698.00	-2,388.27	5,194.01	-7,590.37	-2,979.42	0.00	0.00	0.00
Avg. mortgage debt, 6m prior	85,698.00	-30,872.90	54,288.18	-96,402.39	-50,413.24	0.00	0.00	0.00
Number of adult members in the household	85,698.00	1.53	0.50	1.00	1.00	2.00	2.00	2.00
Number of children in the household	85,698.00	0.61	0.96	0.00	0.00	0.00	1.00	2.00
Avg. monthly consumption expenditures (cash, card payments), 1 year prior	85,698.00	1,205.52	658.29	545.84	794.55	1,102.82	1,480.65	1,940.18
Avg. monthly direct debits, debt payments, subscriptions, 1year prior	85,698.00	631.29	1,154.20	181.44	290.02	451.20	708.47	1,080.92
Avg. monthly outgoing transfers, 1 year prior	85,698.00	316.24	639.88	0.00	4.44	83.33	368.72	868.07
Avg. total monthly consumption (broad measure)	85,698.00	2,153.05	1,736.50	1,001.33	1,359.67	1,823.69	2,484.41	3,446.92

Notes: This table report the distributions of the household charactersitics used in our analysis. The variable "Avg. monthly outgoing transfers" includes direct debits, debt payments, and subscriptions. The variable "Avg. total monthly consumption (broad measure)" includes the sum of cash withdrawals, card spending, automatic debits, and wire transfers.

Table D4 Examples of MCCs Classified across Product Categories

Description of MCC Product Category	Product Type
Veterinary Services	S
Agricultural Co-operatives	S
Horticultural Services, Landscaping Services	S
General Contractors-Residential and Commercial	S
Air Conditioning Contractors , Sales and Installation, etc.	S
Electrical Contractors	S
Insulation , Contractors, Masonry, Stonework Contractors, etc.	S
Carpentry Contractors	S
Roofing , Contractors, Sheet Metal Work, etc.	S
Motor vehicle supplies and new parts	D
Office and Commercial Furniture	D
Construction Materials, Not Elsewhere Classified	D
Office, Photographic, Photocopy, and Microfilm Equipment	D
Computers, Computer Peripheral Equipment, Software	D
Men's Women's and Children's Uniforms and Commercial Clothing	SD
Commercial Footwear	SD
Home Supply Warehouse Stores	SD
Variety Stores	SD
Misc. General Merchandise	SD
Grocery Stores, Supermarkets	ND
Meat Provisioners , Freezer and Locker	ND
Candy, Nut, and Confectionery Stores	ND
Dairy Products Stores	ND
Bakeries	ND
Misc. Food Stores , Convenience Stores and Specialty Markets	ND

Notes: This table illustrates the classification of product categories, defined by their Merchant Category Code (MCC), into four groups: services (S), durables (D), semi-durables (SD), and nondurables (ND). This table only focuses on a subset of products, out of the total of 933 MCC categories in our data.

Table D3 Cumulative MPC Differences by Card Type at Longer Horizons

Comparison	Horizon	OLS		FGLS	
		Difference (euros) (1)	p-value (2)	Difference (euros) (3)	p-value (4)
Card 2 - Card 1	4 weeks	114.92	0.045	109.30	0.026
	8 weeks	113.50	0.145	114.18	0.142
	12 weeks	188.22	0.158	185.73	0.114
Card 2 - Card 3	4 weeks	81.99	0.159	60.01	0.230
	8 weeks	98.73	0.294	56.13	0.501
	12 weeks	99.81	0.477	97.90	0.423
Card 3 - Card 1	4 weeks	32.92	0.538	49.30	0.279
	8 weeks	34.76	0.687	58.05	0.436
	12 weeks	88.42	0.494	87.83	0.405

Notes: This table report the differences in cumulative MPCs by card type after one, two and three months. We report the point estimate and p-values using eithr OLS, in columns (1) and (2), or FGLS, in columns (3) and (4).

E Other Robustness Checks

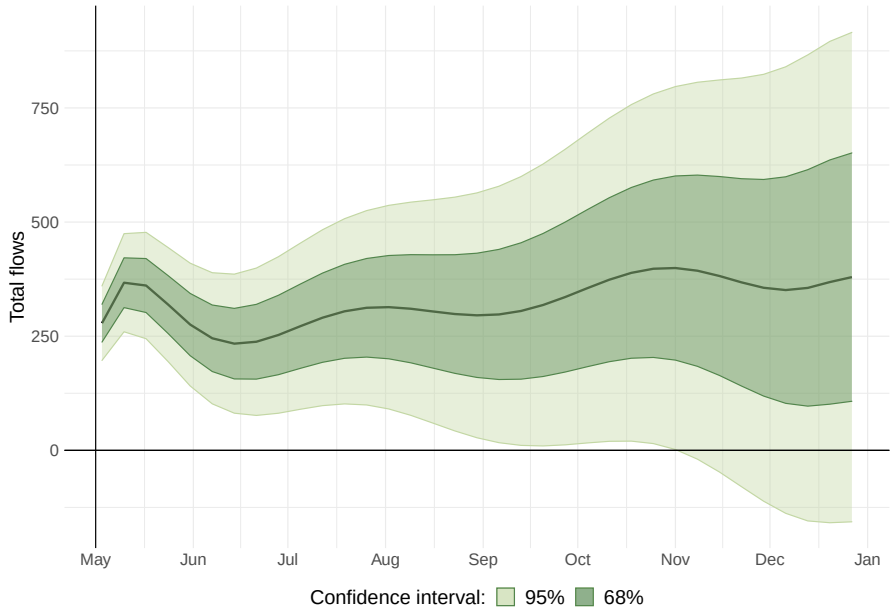
In this section, we discuss additional empirical results, assessing the robustness of our main results.

E.1 Robustness Checks for Pooled MPC Estimates

We conduct several robustness checks for the pooled MPC estimates.

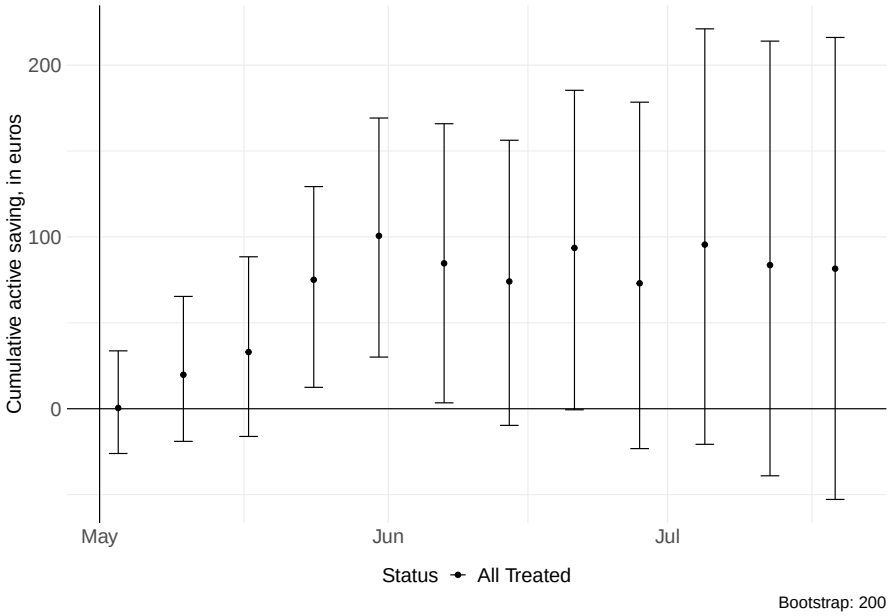
First, we estimate specification (1) with a different outcome, adding to our consumption measures the observed savings at the bank in checking accounts and liquid or illiquid savings accounts. Appendix Figure E1 shows that the cumulative sum of consumption and savings increases by 300 euros immediately at the start of the experiment and hovers around this value for the following quarters, confirming that we correctly measure all flows. Appendix Figure E2 documents the increase in savings in liquid accounts for treated households, with a cumulative increase of about 100 euros after a month.

Figure E1 The Response of Consumption and Savings



Notes: In this figure, we run a specification analogous to (1), except that the outcome is the sum of consumption flows and savings into the checking account and liquid or illiquid savings accounts at the bank. Furthermore, to reduce noise we use a seventh-order polynomial to model the weekly outcome response after treatment: $Y_{it} = \sum_{k=1}^{8} \beta_{\tau}^{k-1} \cdot \tau_{it}^{k-1} + \alpha_i + \alpha_{tE} + \varepsilon_{it}$, which we estimate with the same FGLS procedure as in Figure D2. The figure reports the cumulative change in the outcome and both the 95% and 68% confidence intervals, clustered at the household level.

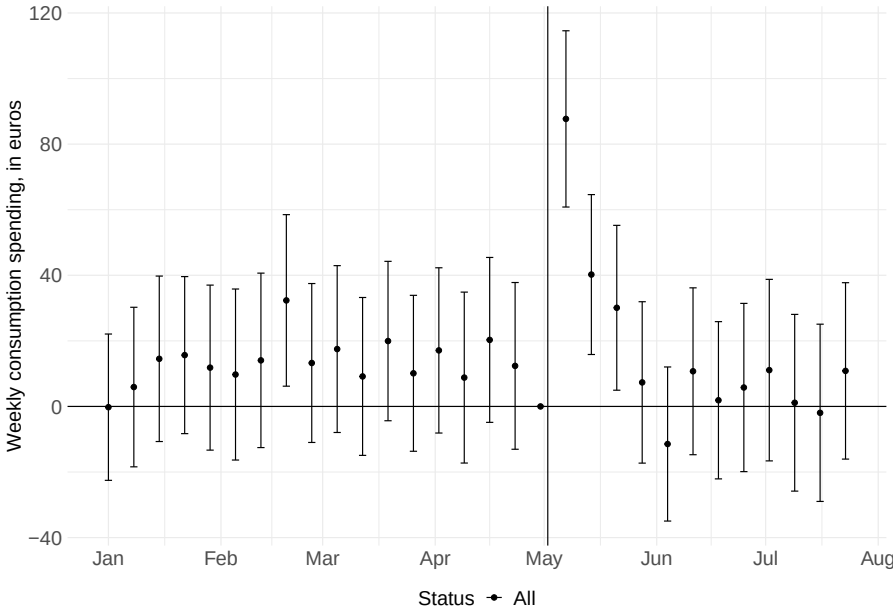
Figure E2 Savings into liquid savings accounts



Notes: This figure analyzes the resposne of savings into liquid savings accounts at the bank (e..g, "Livret A") for the treated participants. The figure reports the cumulative net flows of savings after the start of the experiment.

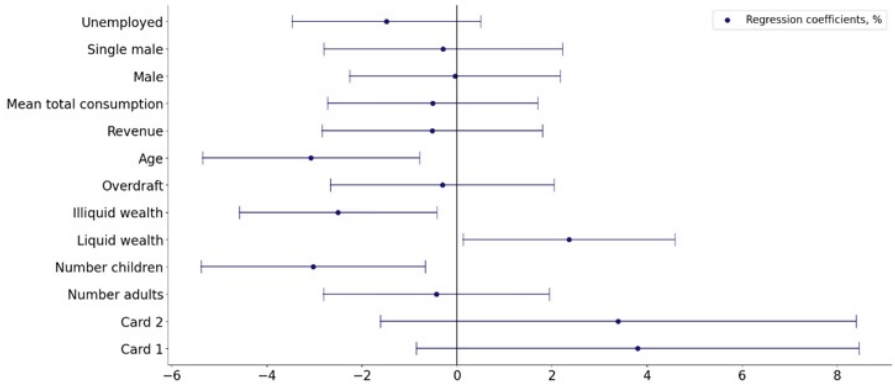
Second, Appendix Figure E3 shows that the results are similar when leads are included in specification (1), with no sign of pre-trends. Third, Appendix Figure E4 documents the characteristics of the households who chose not to use the treatment card. Fourth, we obtain similar results with alternative consumption measures including direct debit transactions and wire transfers (Appendix Figure E5).

Figure E3 Total Spending Response, Weekly, with Treatment Leads



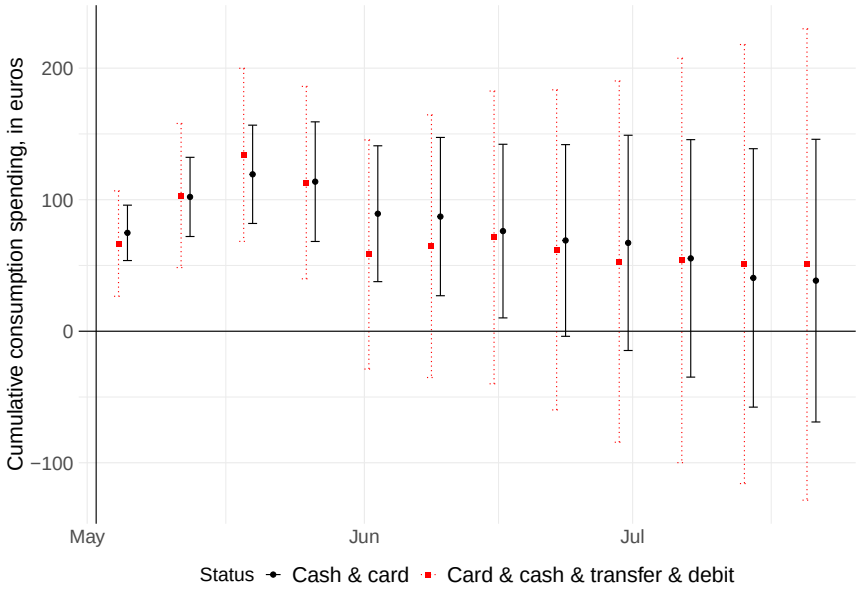
Notes: This figure shows the results of a regression estimating a specification analogous to equation 1, but including pre-treatment leads.

Figure E4 Observable Predictors of Non-Take-Up



Notes: This figure reports the predictors of non-take-up of the treatment card, using the full sample of treated households. We use a range of characteristics to predict whether the household never used the prepaid card during the six months following the experiment. We find that households who do not use the treatment card tend to be younger, with fewer children, higher liquid wealth, and lower illiquid wealth. Card type does not affect take-up.

Figure E5 Cumulative MPC Estimates with Broader Consumption Measure



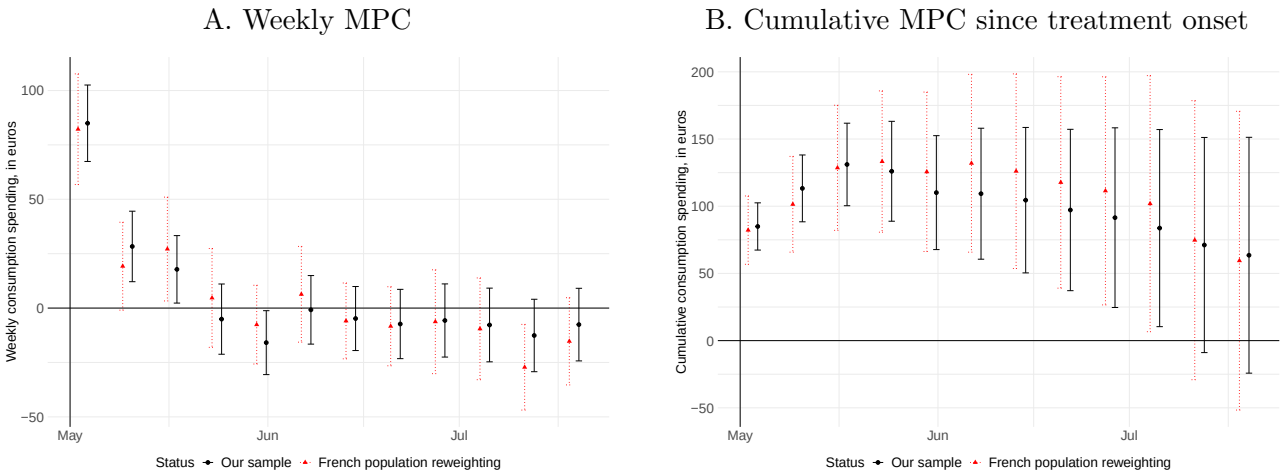
Notes: This figure reports the results from specification (1), with a broader measure of consumption including all direct debit transactions as well as wire transfers.

Fifth, Appendix Figure E6 shows that the estimates remain very similar with a reweighing scheme to ensure that the sample is representative of the French population by local area, income, gender, age, and family structure. Note that this analysis also helps address attrition in our sample. Attrition occurs in our sample because some households do not survive, all household members leave the bank, or because they no longer use their checking account at the bank. Starting from the households included in the panel in June 2020, attrition amounts to 5.7% of households by March 2023. Predicting attrition using observable characteristics, we find that the most significant predictors are age, household size, and income. Our

reweighting analysis in Figure E6 accounts for these compositional changes, leaving the estimated MPC unchanged in practice.

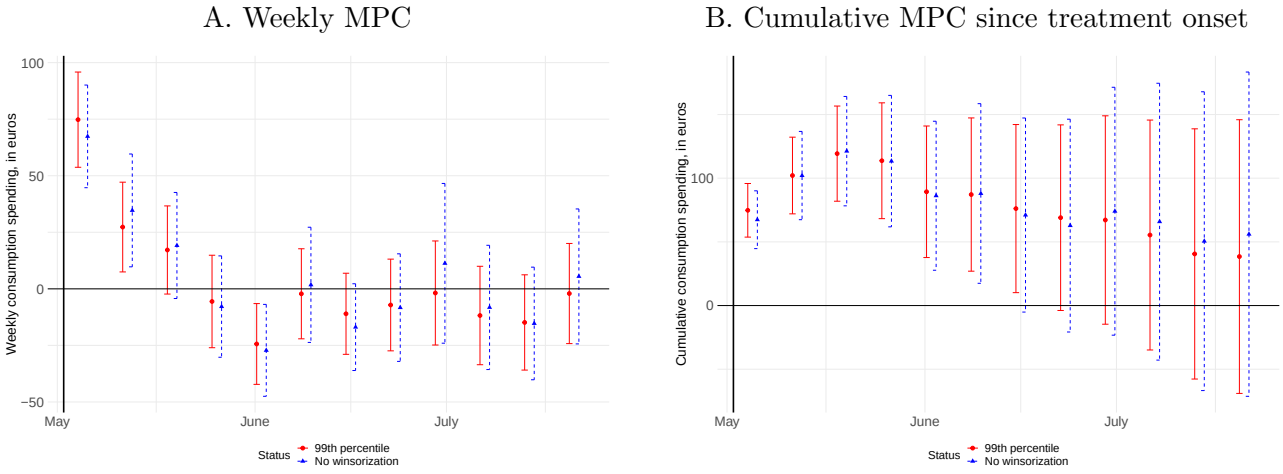
Sixth, Appendix Figure E7 reports the results without winsorizing consumption expenditures, which again yields very similar estimates. Finally, Appendix Figure E8 shows that the confidence intervals are virtually identical when obtained via bootstrapping.

Figure E6 MPC Estimates for Reweighted Sample



Notes: This figure reports the results from specification (1) in a weighted OLS regression such that our sample is representative of the French population by local area (""), income decile, age, gender and family structure. The population weights are obtained from the French statistical institute INSEE.

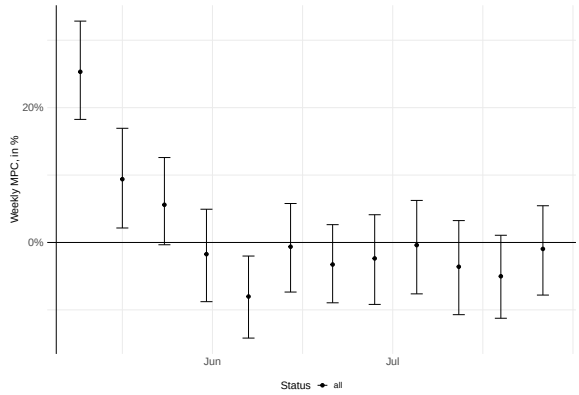
Figure E7 MPC Estimates without Winsorization



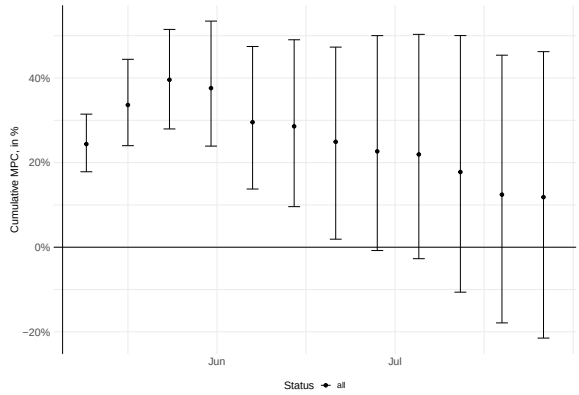
Notes: This figure reports the results from specification (1), comparing the results in our main sample (winsorizing consumption expenditures at the 99th percentile) and without winsorization.

Figure E8 Bootstrapped confidence intervals for pooled MPC estimates

A. Weekly MPC



B. Cumulative MPC since treatment onset



Notes: This figure reports our main MPC estimates, with confidence intervals estimated by a bootstrap with 300 draws. Panel A reports the weekly estimates, while panel B depicts the cumulative effects.

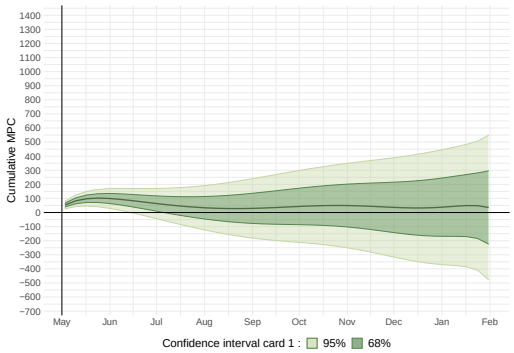
E.2 Robustness Checks for MPC Estimates by Card Type

We now conduct robustness check for MPC estimates by card type.

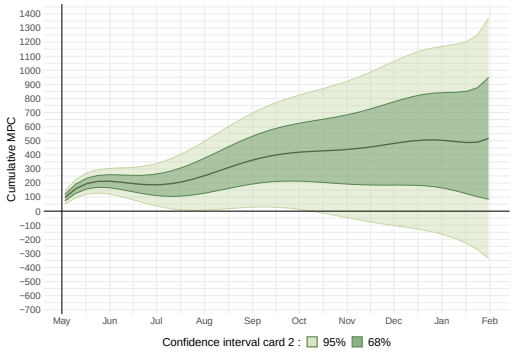
Appendix Figure E9 reports long-term MPC dynamics by card type over three quarters. We find that the cumulative MPC remains higher at longer horizons for Cards 2 and 3, compared to Card 1. Next, Appendix Figure E10 reports cumulative spending on prepaid cards. In the short run, participants in Groups 2 and 3 spend down the prepaid card much faster than those in Group 1. But after three months, the total cumulative spending is approximately the same across the three card types. Thus, Group 1 participants do not have a lower overall MPC simply because they do not spend down the prepaid card. Rather, the substitution patterns differ depending on the card: Group 1 participants spend down about 85% of the prepaid card after three months but primarily cover expenses that they would have incurred otherwise as well.

Figure E9 Long-term MPC Estimates by Card Type

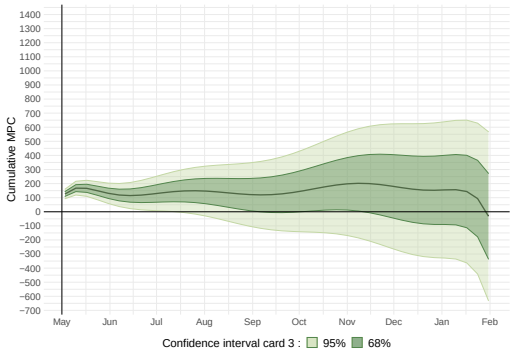
A. Group 1, no restrictions on treatment card



B. Group 2, expiration after three weeks

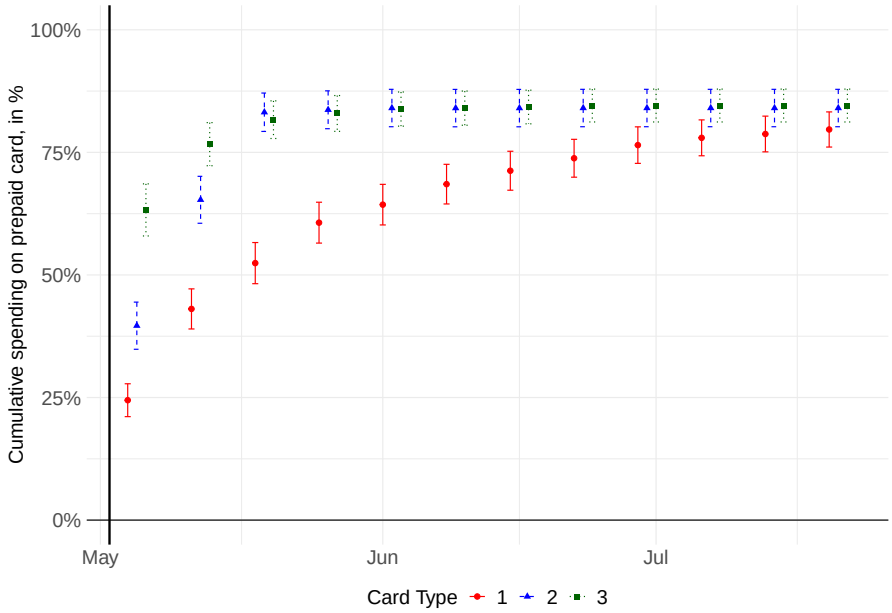


C. Group 3, negative rates every week



Notes: This figure plots the cumulative MPC by card type over a long horizon. To reduce noise we use a seventh-order polynomial to model the weekly outcome response after treatment: $Y_{it} = \sum_{k=1}^{8} \beta_{\tau}^{k-1} \cdot \tau_{it}^{k-1} + \alpha_i + \alpha_{tE} + \varepsilon_{it}$, which we estimate with the same FGLS procedure as in Figure D2. The figure reports the cumulative change in the outcome and both the 95% and 68% confidence intervals, clustered at the household level.

Figure E10 Cumulative Spending on the Prepaid Card by Card Type

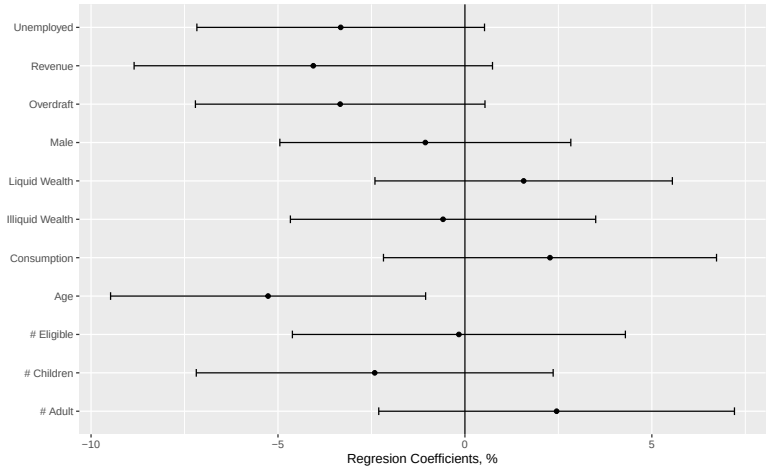


Notes: This figure reports average cumulative spending on the preaid card for the three types of card. The figure shows that households in Groups 2 and 3 lost 49.25 euros on average by not spending down the available funds by the deadlines. 8.75% of households in these groups did not take up the card, accounting for a loss of 26.25 euros. Conditional on using the card at least once, the median participant in Groups 2 and 3 lost only 3 euros. However, a small number of households used the card very little before the deadlines: 5% of households lost at least 126 euros. On average, conditional on using the cards participants lost 23 euros (7.67% of the total amount). Thus, the losses on Cards 2 and 3 were not driven by widespread card usage frictions (which could have made it difficult for most households to spend down the cards before the deadlines), but rather by a limited set of households who decided not to use the cards at all or to use them very little.

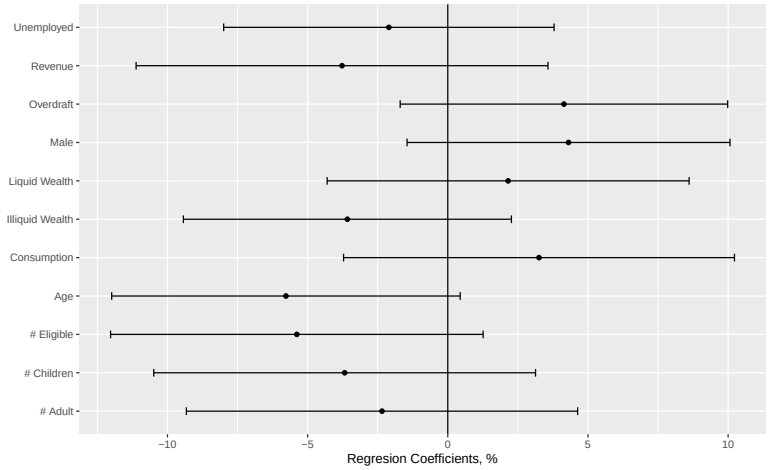
Appendix Figure E11 documents that socio-demographic characteristics are not significant predictors to identify the subset of households from Group 1 who did not use the card by July 1st, nor the subset of households from Groups 2 and 3 who lost significant funds. Finally, Appendix Figures E12 and E13 show that the confidence intervals are very similar when obtained via bootstrapping.

Figure E11 Characteristics of Households with Low Take-Up by Card Type

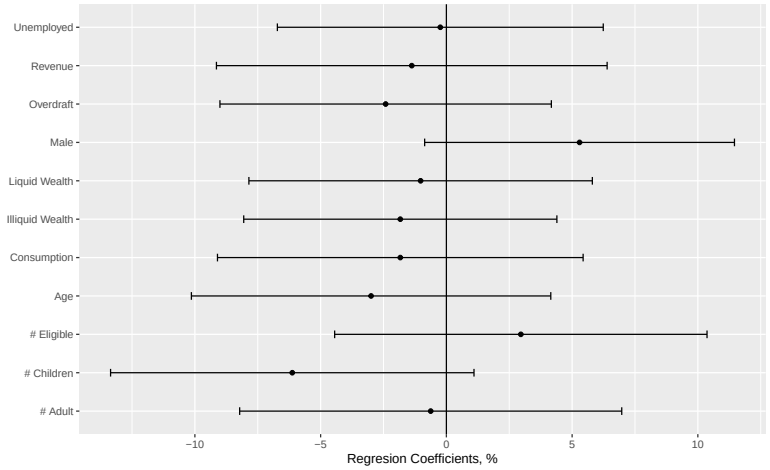
A. Group 1, no restrictions on treatment card



B. Group 2, expiration after three weeks



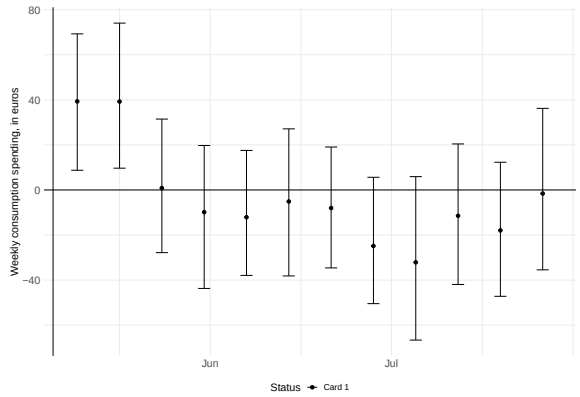
C. Group 3, negative rates every week



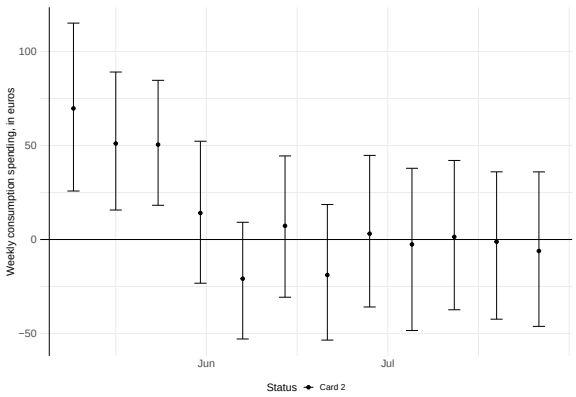
Notes: This figures analyzes the socio-demographic characteristics of Group 1 participants who did not use the card by July 1st (panel A), and those of Group 2 and 3 participants who lost at least 50 Euros (panels B and C).

Figure E12 Bootstrapped confidence intervals for MPC by Card Type, Weekly

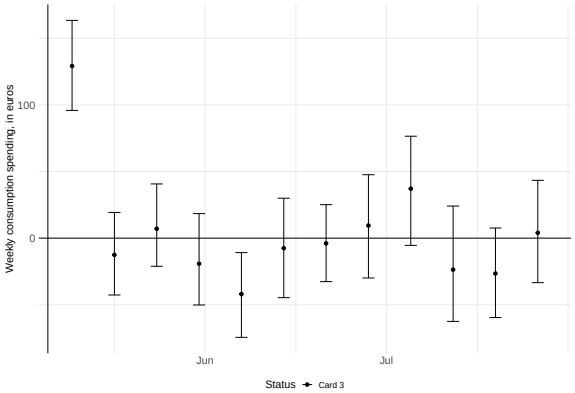
A. Group 1, no restrictions on treatment card



B. Group 2, expiration after three weeks



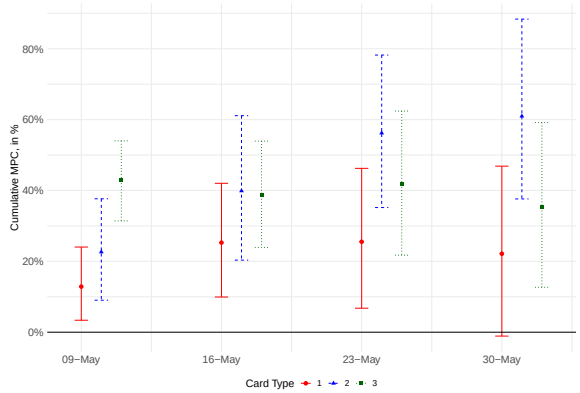
C. Group 3, negative rates every week



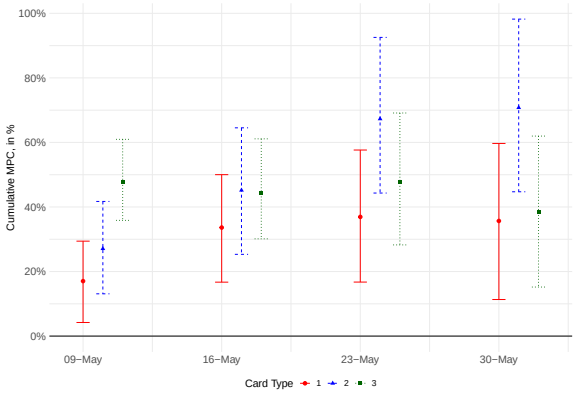
Notes: This figure reports MPC estimates depending on the card type. Panel A reports the weekly estimates for Group 1, panel B for Group 2, and panel C for Group 3. Card 1 has no restrictions, while Card 2 expires three weeks after the onset of the experiment, and Card 3 applies a negative interest rate on the remaining balance every Monday at 11:59pm. 95% confidence intervals are reported, obtained from a bootstrap with 300 draws.

Figure E13 Bootstrapped confidence intervals for Cumulative MPC Estimates by Treatment Group

A. Unconditional estimates



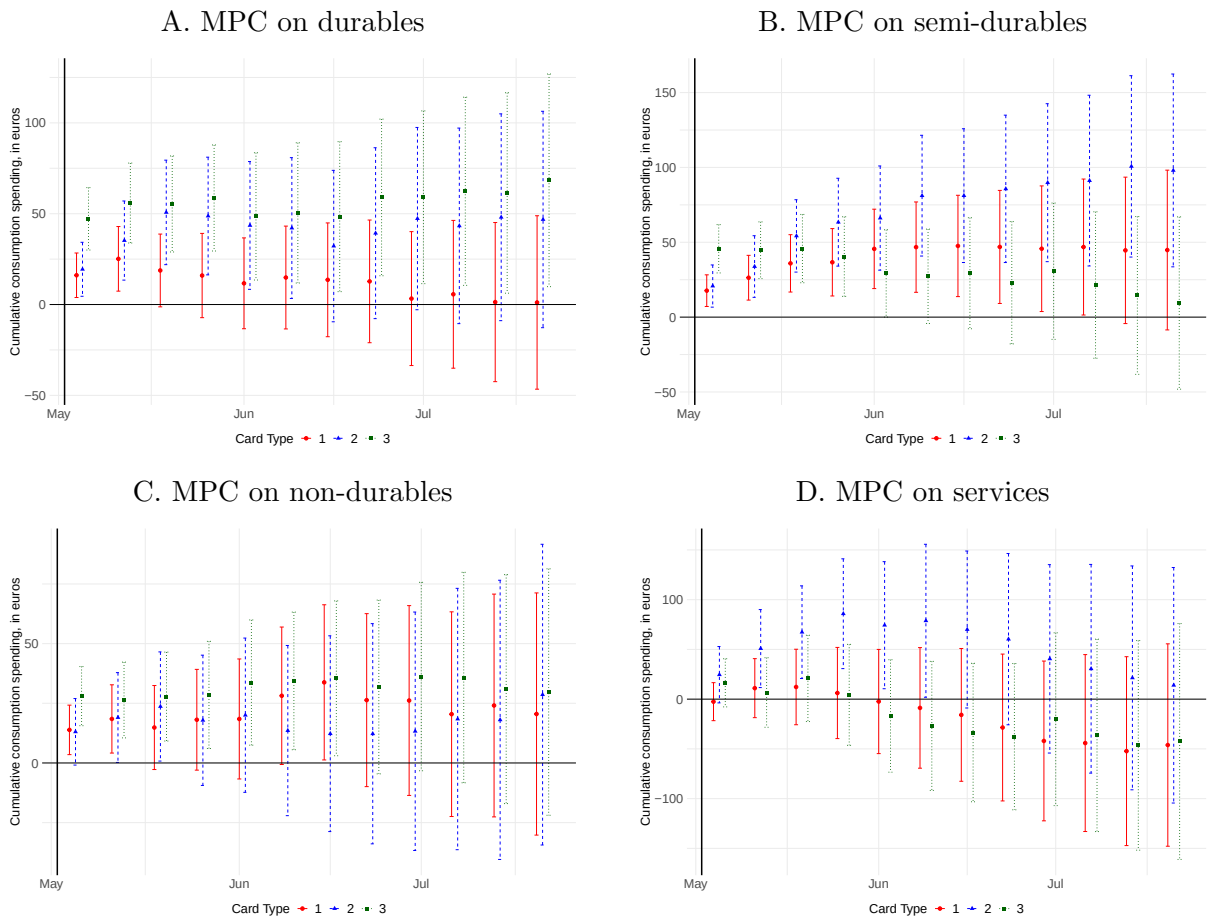
B. Conditional on take-up



Notes: This figure reports cumulative MPC estimates depending on the card type. Card 1 has no restrictions, while Card 2 expires three weeks after the onset of the experiment, and Card 3 applies a negative interest rate on the remaining balance every Monday at 11:59pm. Panel A includes treated households that do not use the card in the treatment groups; panel B does not. 95% confidence intervals are reported, obtained from a bootstrap with 300 draws.

We also present additional results regarding the composition of spending by card type. Appendix Figure E14 shows the MPCs on these categories in the months following treatment. Appendix Figure E15 shows the response of durables over a longer time horizon for each card type, highlighting that the higher spending on durables for Card 3 is sustained in the following quarters.

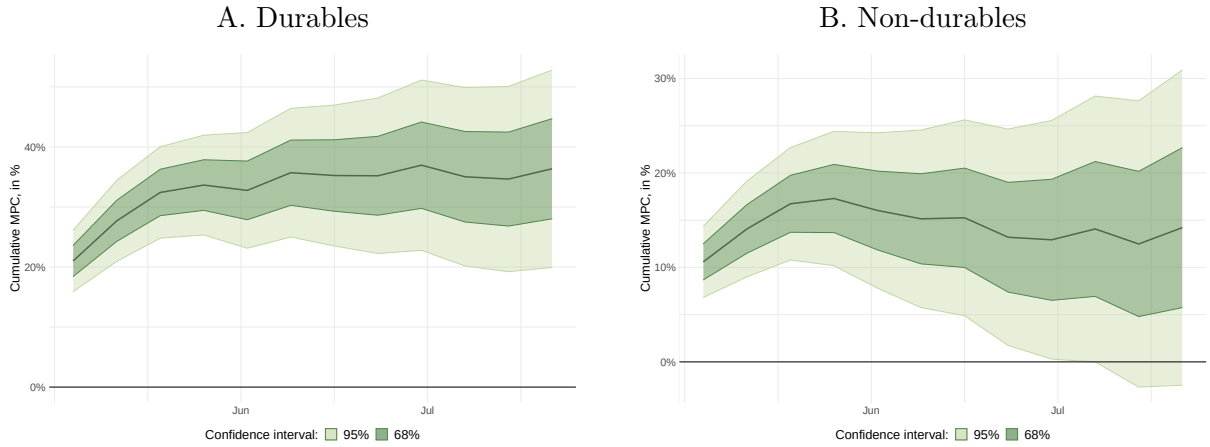
Figure E14 MPC by Spending Category



Notes: This figure reports MPCs by spending category and card type.

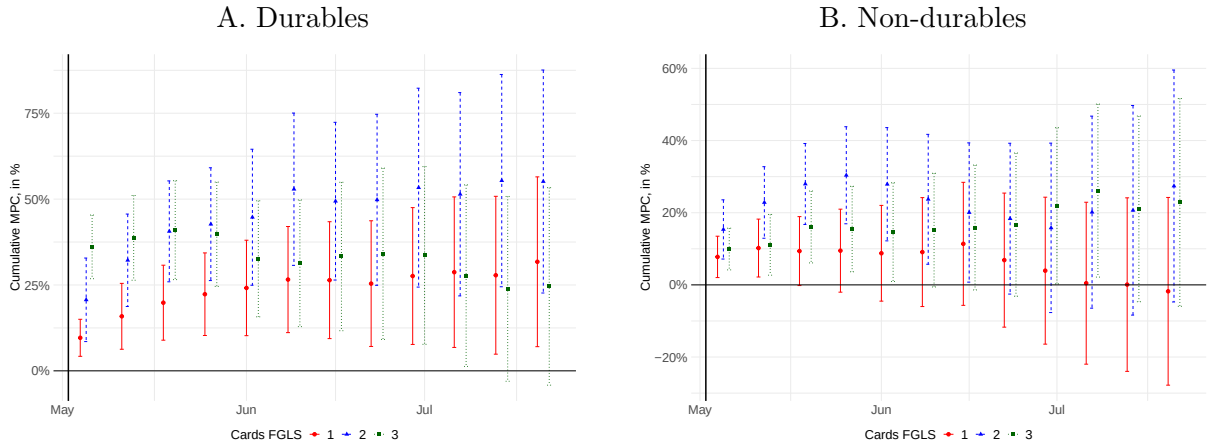
As complementary evidence on the role played by various types of expenditure, we build an alternative classification of products allocating the semi-durables and services categories either into durables or nondurables. The results are reported in Appendix Figure E15 for all products and Appendix Figure E16 by card type. We find a sustained increase in spending for both types of products, for the three treatment cards. Thus, the differences in the estimated marginal spending increase across groups do not arise merely from differences in durables purchasing behavior.

Figure E15 MPC Estimates for Durables and Non-durables, Alternative Classification



Notes: This figure reports the cumulative MPC estimates for spending on durables (panel A) and non-durables (panel B), considering all cards together. In this figure, we classify all types of spending into either durable or nondurable purchases, instead of retaining the distinction between services, durable goods, nondurable goods, and semi-durable goods as in Table II. To reduce noise we use a seventh-order polynomial to model the weekly outcome response after treatment: $Y_{it} = \sum_{k=1}^{8} \beta_{\tau}^{k-1} \cdot \tau_{it}^{k-1} + \alpha_i + \alpha_{tE} + \varepsilon_{it}$, which we estimate with the same FGLS procedure as in Figure D2. The figure reports the cumulative change in the outcome and the 95% confidence intervals, clustered at the household level.

Figure E16 MPC Estimates for Durables and Non-durables, Alternative Classification



Notes: This figure reports the cumulative MPC estimates for spending on durables (panel A) and non-durables (panel B), by card type. In this figure, we classify all types of spending into either durable or nondurable purchases, instead of retaining the distinction between services, durable goods, nondurable goods, and semi-durable goods as in Table II. To reduce noise, we estimate the specification separately for each card type with the same FGLS procedure as in Figure D2. The figure reports the cumulative change in the outcome and the 95% confidence intervals, clustered at the household level.

E.3 Robustness Checks for the Estimates of Heterogeneity in MPCs by Observables

We now report complementary analyses of the heterogeneity in MPCs by observable characteristics.

First, we consider an alternative definition of liquidity. In Appendix Figure E17, we take as our measure of a household's liquid wealth the minimum level of liquidity attained on any day in April 2022 (for a vast majority of households, this occurs within the last five days of the month, i.e. likely right

before payday). With this measure, a household is considered to live "hand to mouth" if they ran down their account to low levels of liquidity at any point in April 2022. Repeating the heterogeneity analysis with this alternative measure, we obtain results similar to our baseline estimates for quartiles 2, 3, and 4. However, the 4-week cumulative MPC is now lowest for the bottom liquidity quartile, rather than highest as in our baseline specification. This result confirms that high average MPCs do no appear to be driven by a group of low-liquidity households.

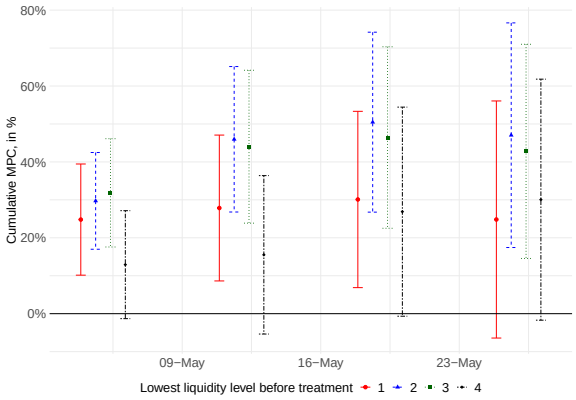
Second, we provide complementary results for MPC differences by gender. Appendix Figure E18 shows that the higher MPC for women is also observed in the subsample of households with a single member, rejecting the hypothesis that the allocation of shopping duties in the households could be the main driver of the MPC differences by gender. Appendix Figure E19 reports differences in spending composition by gender, suggesting than women spend more on food at home and clothing after receiving the prepaid card – however, these differences are not statistically significant and are too small to drive the difference in overall MPCs by gender. Developing and testing a theory of MPC differences by gender would be a fruitful direction for future research.

Third, Appendix Figure E20 shows that the results for each of the six dimensions of heterogeneity we study remain similar when using a FGLS estimator to reduce noise, reporting the results over longer horizons.

Fourth, we analyze the statistical significance of the difference in 4-week cumulative MPCs by observables. For each of observable predictors, using quartiles as in the main text, we test the null of equality of the 4-week cumulative MPCs. The p-values of the F-tests are reported in Column (1) Table 4.1. The table shows that these differences are noisy, with p-values ranging from 0.124 for gender to 0.453 for liquid assets. To reduce noise, we regress consumption on a linear function of the quartiles. The regression coefficients are reported in Column (2) of Table 4.1, with the p-values in Colunm (3). Illiquid assets and past consumption (our proxy for permanent income) are significant at the 10% level.

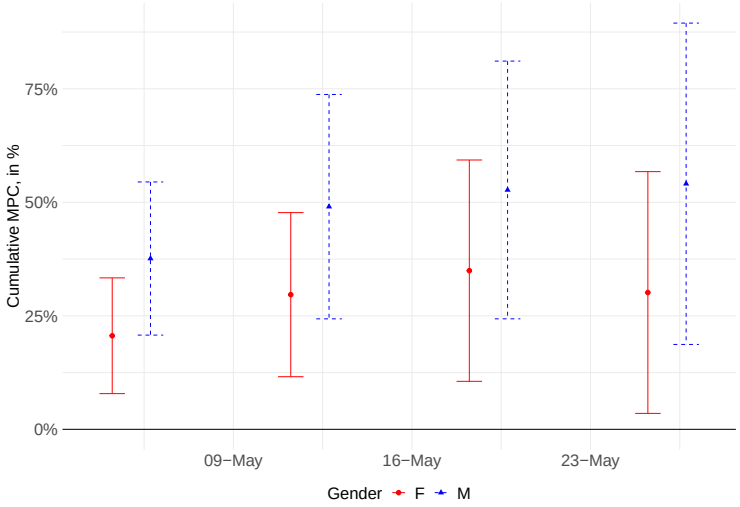
Finally, we conduct complementary analyses for the LASSO estimates. In Appendix Figure E21, we document that results are similar when including only treatment group 1 and the control group. In Appendix Figure E22, we repeat the analysis at a 12-week horizon to assess policymakers' ability to target households with high long-term MPCs based on observable characteristics. With the optimal regularization parameter set by cross-validation, only gender is selected as a significant predictor of long-term MPC heterogeneity. Applying the same LASSO methodology by interacting household characteristics with the type of prepaid card, we examined whether the differences in consumption response between Card 1 and Card 2 were driven by a specific subset of households; we did not find significant differences by household characteristics.

Figure E17 Heterogeneity Analysis with Alternative Definition of Liquid Wealth



Notes: This figure reports MPC estimates depending on households' liquid wealth. Quartiles of household's liquid wealth are defined using the minimum level of liquidity attained on any day in April 2022. The figure plots the estimates for the cumulative MPC at different time horizons.

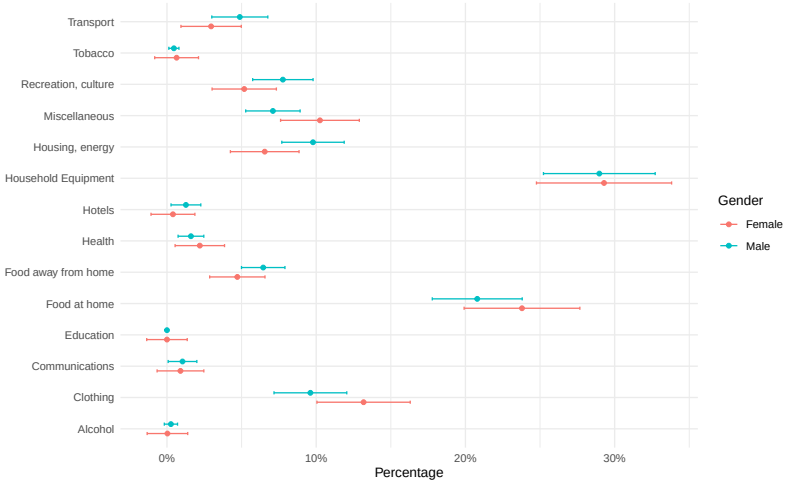
Figure E18 Heterogeneity by Gender for Single-Member Households



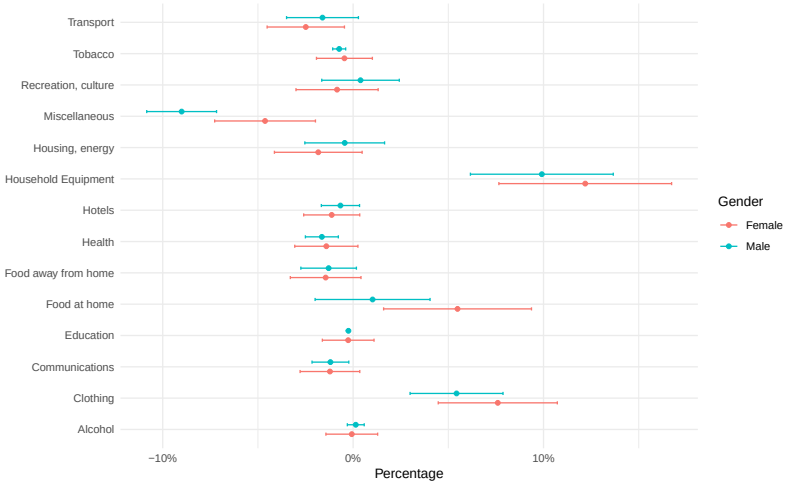
Notes: This figure shows the cumulative MPC by gender, using regressions where treatment and control households are restricted to the subset of households with one adult member and no children.

Figure E19 Spending Composition by Gender

Panel A: Prepaid card alone, spending shares



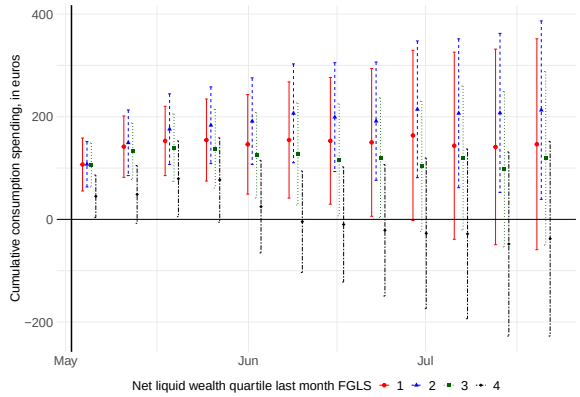
Panel B: Bank account spending and prepaid card, differences relative to the control group



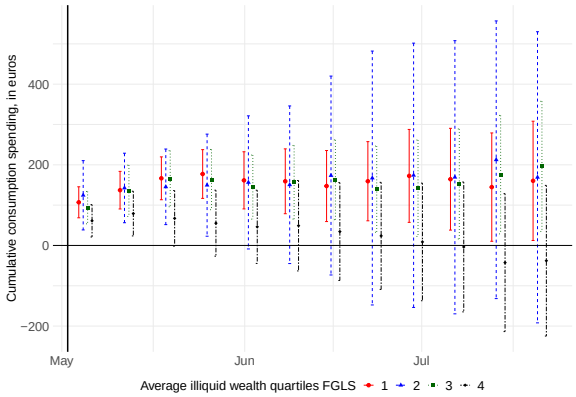
Notes: Panel A shows the spending shares by gender for the prepaid card alone. Panel B shows differences in spending shares by gender for the treated households compared to control households when considering both the prepaid card and the household's bank account

Figure E20 MPC Heterogeneity by Observable Household Characteristics

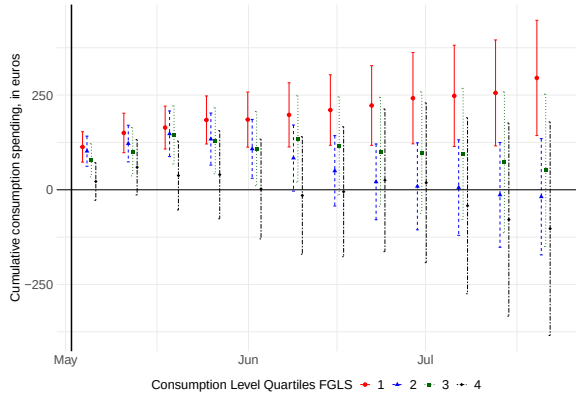
A. By Net Liquid Assets Quartile



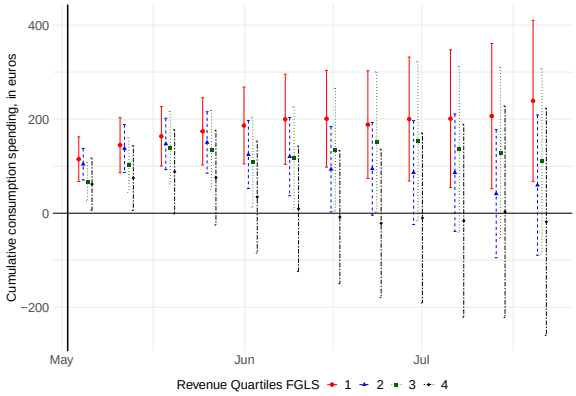
B. By Illiquid Wealth Quartile



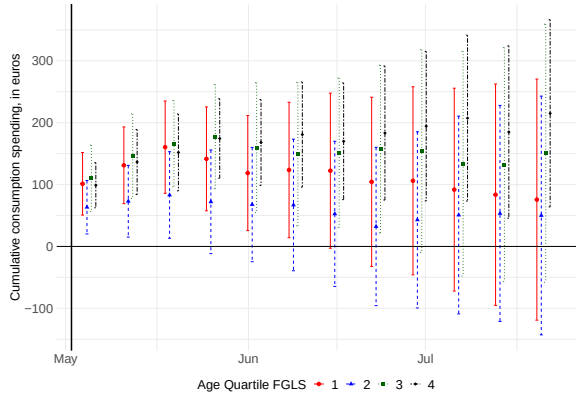
C. By Average Consumption Quartile



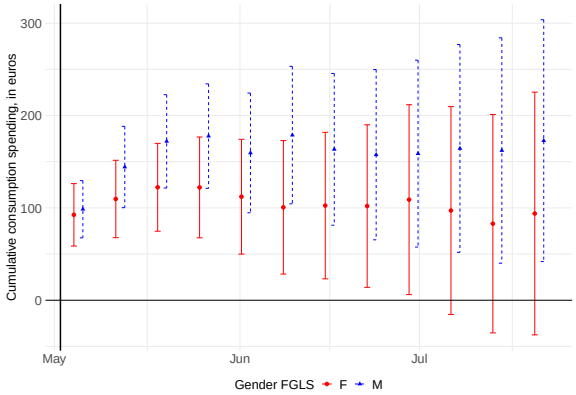
D. By Income Quartile



E. By Age Quartile

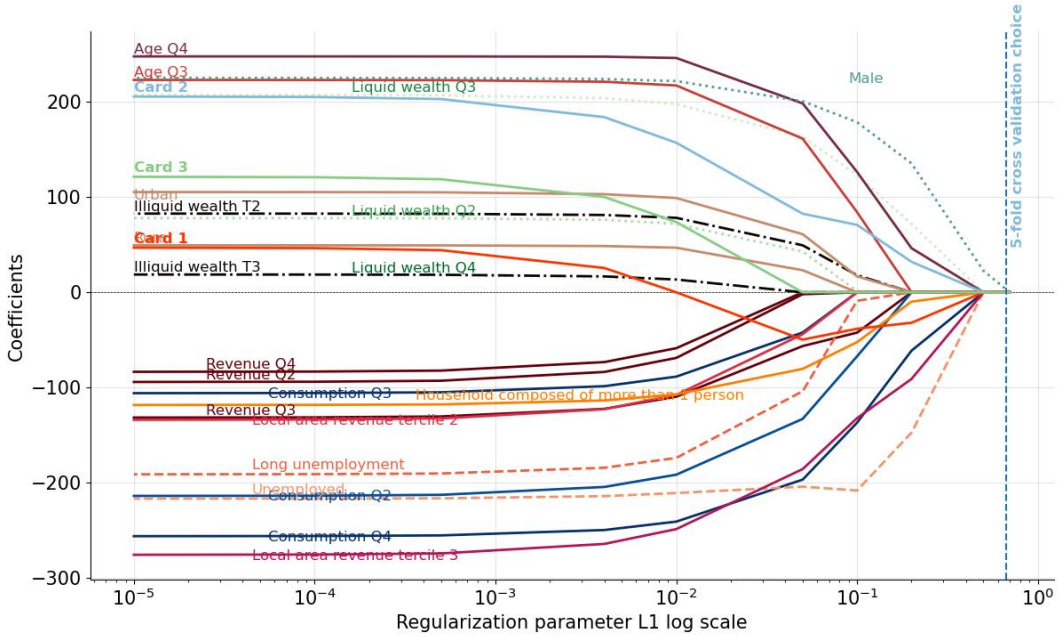


F. By Gender



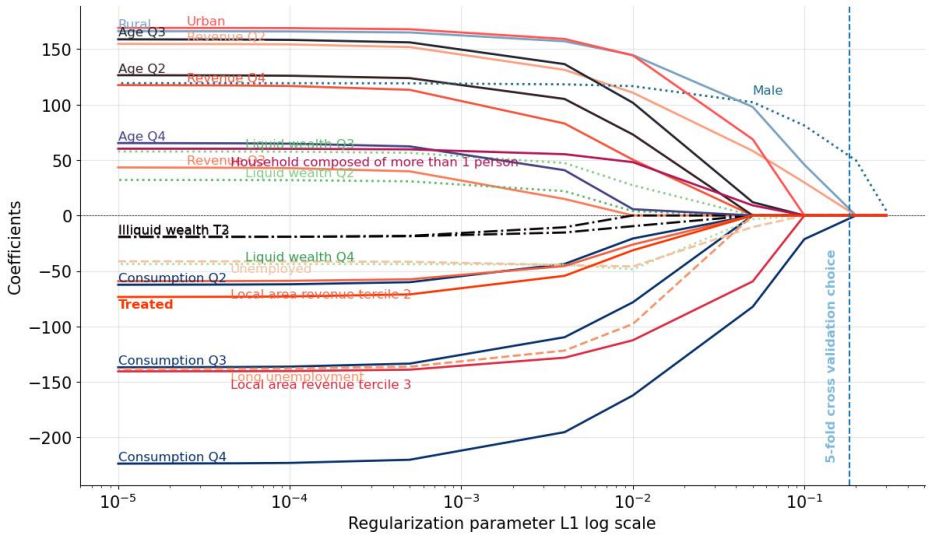
Notes: This figure reports MPC estimates depending on observable household characteristics using a feasible generalized least square (FGLS) procedure, where standard errors of each household's error term are parameterized to be able to vary with each bin of time-invariant characteristics calculated from pre-period data (10 age bins, 10 income bins, gender dummy, 10 liquid wealth bins, 10 average consumption expenditure bins, 95 *departement* dummies), i.e. in each iteration we calculate weights from $1/\hat{\sigma}_i^2$, where $\hat{\sigma}_i$ is the predicted standard error from a regression of the household-level standard error in the previous iteration on characteristic bin dummies. We document heterogeneity in turn by net liquid wealth, illiquid wealth, average consumption prior to the experiment (as a proxy for permanent income), income, age, and gender and marital status. 95% confidence intervals, with standard errors clustered at the household level, are reported in all panels.

Figure E22 LASSO Estimates of 12-week MPC Heterogeneity



Notes: The figure shows LASSO estimates of coefficients of interactions of the respective characteristic with a treatment dummy in specification (2), for varying regularization parameters (horizontal axis). We predict the cumulative MPC after twelve weeks. The dashed vertical line shows the regularization parameter chosen by 5-fold cross validation.

Figure E21 LASSO estimates of treatment effect heterogeneity coefficients, group 1 and control group



Notes: This figure shows estimates of specification (2) on the set of observations pertaining to treatment group 1 and control observations, for varying levels of the regularization parameter.

Table E1 Statistical Significance Tests of Differences in 4-Week Cumulative MPCs by Observables

	p-value of F-test for	Linear Specification in Quartiles	
	4-week Cumulative MPC	OLS coeff.	p-value
	(1)	(2)	(3)
Liquid Assets	0.453	-26.99	0.209
Illiquid Asset	0.244	-32.43	0.09
Consumption	0.322	-38.89	0.082
Income	0.39	-31.66	0.148
Age	0.62	19.02	0.349
Gender	0.124	N/A	

Notes: This table report tests to assess whether there is a statistically significant difference in 4-week cumulative MPCs. We the null of equality of the 4-week cumulative MPCs in Column (1), reporting the p-values of the F-tests. We also run a regression using a linear function of the quartiles as predictor, reporting the OLS coefficient in Column (2) and the p-value in Column (3).

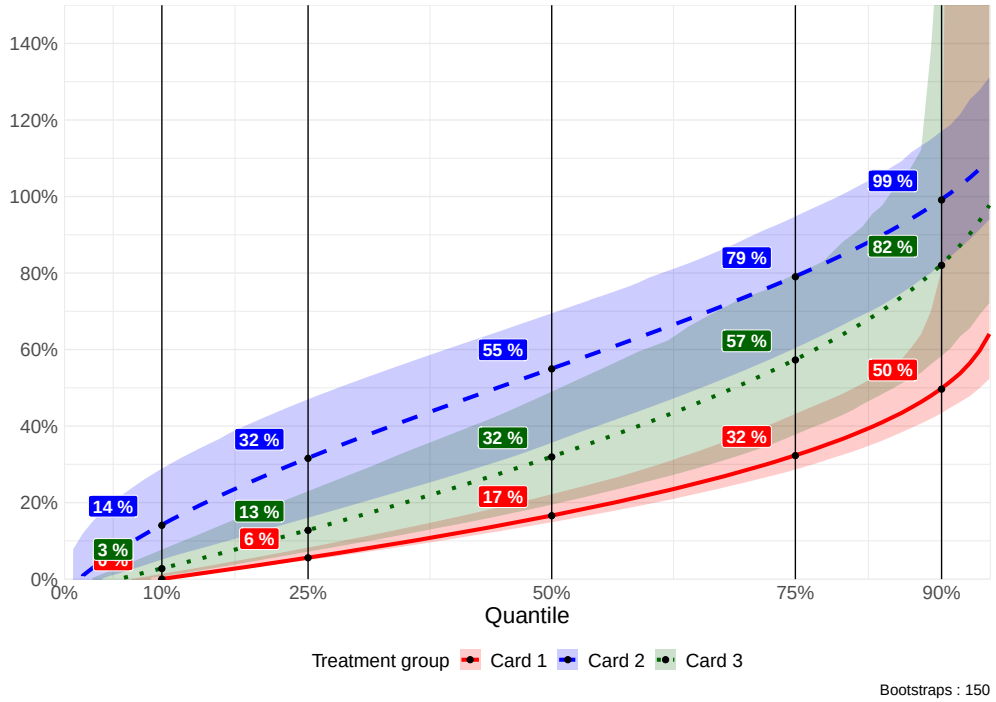
E.4 Robustness Checks for the Estimates of the Unconditional Heterogeneity in MPCs

We carry our several robustness checks to assess the sensitivity of our estimates of the unconditional heterogeneity in MPCs.

First, we estimate a model that is linear in log consumption. A disadvantage of such a model is that the treatment effect distribution estimates cannot be directly interpreted as MPCs, but instead as cumulative percentage deviations from the household's average level of consumption. The results are reported in Appendix Figure E23 and lead to a shape of treatment effect distributions similar to our baseline analysis.

Second, Appendix Figure E24 shows results for specifications where we drop non-negativity constraints and regularization, yielding similar findings. Third, Appendix Figure E25 reports the results of the deconvolution by pooling together treatment cards 2 and 3, obtaining more precise estimates that confirm that the cards with negative rates yield MPCs that are higher than those associated with treatment card 1. Finally, consistent with the large MPC heterogeneity uncovered by our deconvolution approach, Appendix Figure E26 plots the quantiles of spending on the treatment card and shows that there is a lot of heterogeneity in the speed at which households spend these funds.

Figure E23 Quantiles of the 4-week cumulative percentage deviation from mean household consumption expenditure



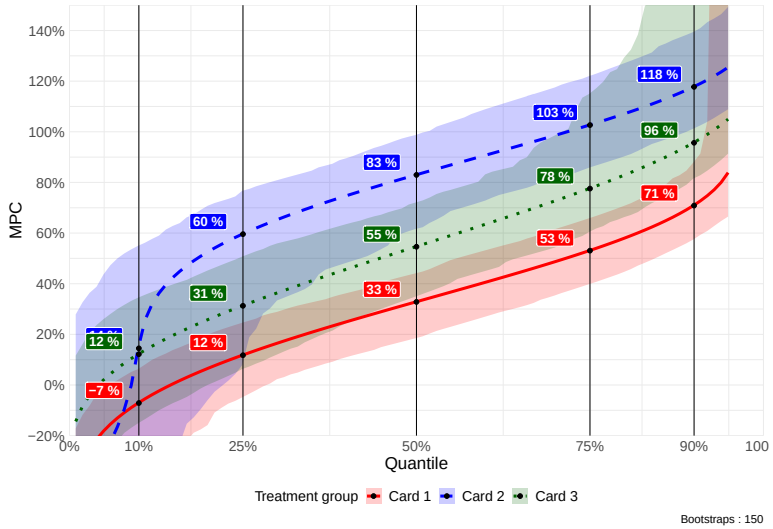
Notes: This figure reports the quantiles of the distribution of 4-week treatment effects by treatment group. In contrast to the model from the baseline specification, the log of weekly consumption expenditure is here linear in treatment effects and fixed effects. Specifically, we estimate a specification in log weekly average consumption:

$$\log Y_{it} = \sum_{\tau=0}^{\tilde{T}} \beta_\tau 1(\tau \text{ weeks since } i \text{ treated})_{it} + \alpha_i + \alpha_{tE} + \varepsilon_{it}$$

$$C_{it}^{\tilde{T}} = \sum_{\tau=0}^{\tilde{T}} (\log Y_{it} - \hat{\alpha}_i - \hat{\alpha}_{tE}).$$

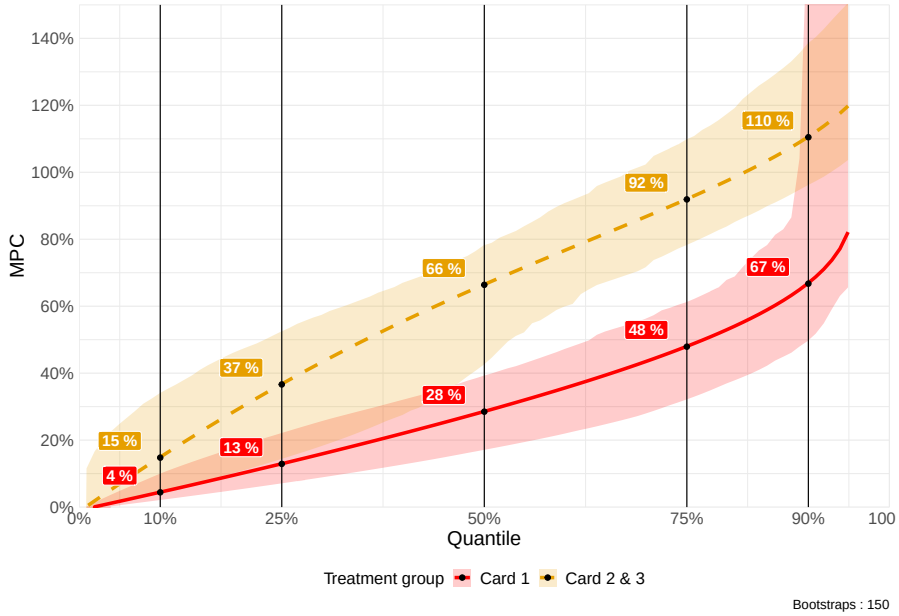
We estimate the distribution of treatment effects in this model using the same deconvolution approach as in the main text. Since the dependent variable, log consumption expenditure, is much less skewed than in the baseline model from Section 4.2, we winsorize it only at the 99th percentile. Note that here the treatment effect is not a marginal propensity to consume, but a cumulative percentage deviation from the household's mean consumption expenditure level (on average 417 euros). The estimates from this model show similar economic effects to the benchmark specification. Shaded regions are delineated by the 10th and 90th percent quantile of the bootstrapped simulated distribution of the corresponding moment.

Figure E24 Estimated distribution of MPCs without constraint to have no mass on negative values



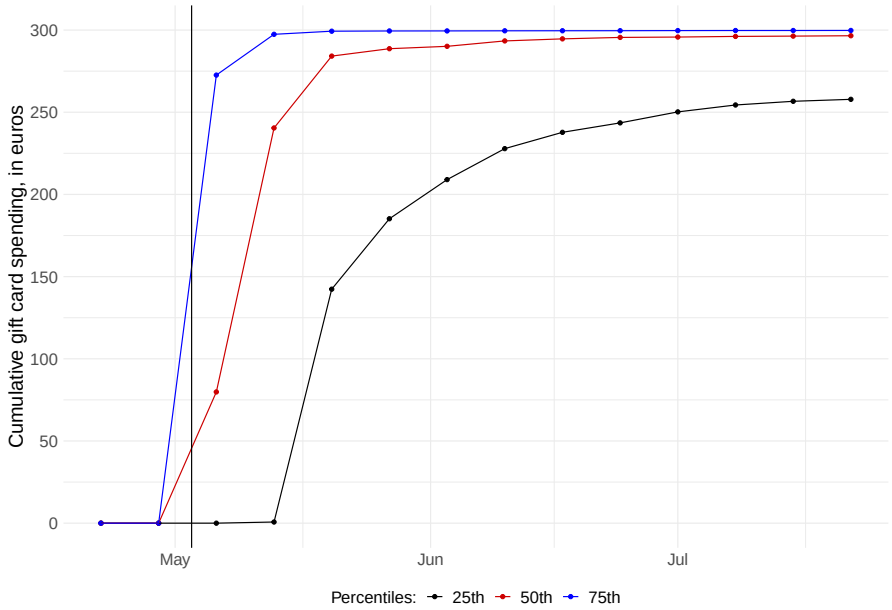
Notes: The figure shows the estimated distributions of 4-week MPCs using the flexible deconvolution procedure of Yang et al. (2020) when the support of the density of the distribution is not constrained to lie on the positive part of the real line.

Figure E25 MPC Distribution, Group 1 vs Groups 2 and 3 combined



Notes: The figure shows the quantiles of the estimated distribution of MPCs, when the estimation is performed separately for treatment group 1 and for treatment groups 2 and 3 (jointly). Standard errors are estimated using a bootstrap with 150 draws.

Figure E26 Distribution of cumulative spending on treatment card, across households



Notes: The figure shows moments of the distribution of cumulative expenditures on the treatment card, for each week.

F A Stylized Model

In this appendix, we present a simple model to make predictions that qualitatively match our main empirical results.

Overview. The model relies on three key ingredients: (i) mental accounts; (ii) search costs; (iii) memory (i.e., certain agents can make purchases without incurring search costs). In our model, spending the prepaid card on "windfall consumption" involves a key tradeoff: (1) it delivers a utility boost λ because of mental accounts; but (2) it requires incurring search costs to find suitable windfall purchases, except for some agents who remember "windfall purchase opportunities".

We summarize below the three key results we obtain in the model, thanks to the three key ingredients:

- For Group 1 participants, the spending response is concentrated in the short run.
  - Key channel: for Group 1 participants who remember suitable "windfall purchase opportunities", it is optimal to purchase immediately.
- For Group 2 participants, the spending response is larger than for Group 1.
  - Key channel: while Group 1 participants smooth search costs across a large number of periods, Group 2 participants search for and buy more windfall consumption goods and services in period 0 using the prepaid card, in order spend it down before it expires in period 1.
- For Group 3 participants, the spending response lies in between Group 1 and Group 2.
  - Key channel: the search costs are higher for Group 3 participants, leading them to prefer to spend relatively more on regular consumption (compared to Group 2) rather than incurring very high search costs for windfall consumption goods and services in period 0.

Note that the model below produces these results with a common "mental account" parameter for all three groups – rather than assuming different types of mental accounts for each card, which would be mechanical. Although the simple model below makes predictions that qualitatively match the main patterns in our data, it is not meant to provide a quantitative match of the estimated marginal propensities to consume.

Setting. Agents in the model receive a prepaid card and optimize consumption at an infinite horizon. There are three treatment groups, motivated by our experiment. Group 1 participants have access to the remaining balance on the prepaid card for $T+1$ periods. In contrast, Groups 2 and 3 both lose access to the remaining balance on the card after the initial period.[3]

Preferences. The agent optimizes consumption over an infinite horizon with two goods, general consumption c_t and "windfall consumption" g_t. The utility function is:

$$U = \sum_{t=0}^{\infty} \beta^t \left[\lambda_t \cdot v(g_t, s_t) + u(c_t) - \psi(s_t)\right],$$

[3] In our experiment, Group 3 has a high negative interest rate, which we could model as well. However, for simplicity we can model Group 3 by varying the search cost parameter, as discussed below.

where s_t denotes search costs that help increase the marginal utility of windfall consumption, while λ_t is a marginal utility shifter for windfall consumption. s_t captures the idea that agents must incur calculation costs to find windfall consumption goods and services that suit their tastes (in the spirit of Evans and Ramey (1992) and Orchard et al. (2023b)); the convexity of costs is akin to Ellison and Wolitzky (2012).

The parameter λ_t captures the idea that utility for specific windfall goods and services may shift because of mental accounting (in the spirit of Shefrin and Thaler (1988), Thaler (1990), and Baugh et al. (2021)). Specifically, we assume that the households who receive a prepaid card in our experiment perceive it as a windfall, akin to a gift, and that they incur a utility boost if they spend this windfall on unplanned "windfall consumption" (e.g., going to a fancy restaurant, going out more frequently than usual, purchasing a durable good earlier than they otherwise would have, purchasing a treat, etc.) rather than on regular consumption.[4] To capture the idea that the marginal utility of spending on windfall consumption goods and services is larger when spending from the prepaid card, we use a simple functional form:

$$\lambda_0 = \lambda \cdot 1_{\{p_g g_0 = G_0 - G_1 > 0\}},$$

with $\lambda > 0$, i.e. marginal utility is positive when the agent buys a positive amount of treats using the prepaid card, while it is null otherwise. G_t denotes the amount available on the prepaid card at time t, equal to 300 euros in our experiment. Note that in the functional form for λ_0, the budget constraint is intertwined with the utility function. This approach is standard in models of mental accounts, going back to Shefrin and Thaler (1988). In this way, the utility derived from a purchase differs depending on the income source used to make the purchase, which is the very idea of a "mental account." Our chosen functional form simply means that the marginal utility of purchasing windfall consumption goods and services is positive only when spending down the prepaid card to purchase these products.

For subsequent periods, the functional form is the same for Group 1, i.e. $\lambda_t = \lambda 1_{\{p_g g_t = G_t - G_{t+1} > 0\}}$. We set $\lambda_t = 0$ for $t \geq 1$ for Groups 2 and 3, because these participants lose the remaining balance on the prepaid card after the initial period.

We make additional simple parametric assumptions to obtain closed-form solutions:

$$\begin{aligned} \psi(s_t) &= \frac{\kappa}{\eta} s^{\eta}, \eta > 1, \\ u(c) &= \log(c), \\ v(g_t, s_t) &= \min(g_t, s_t + e_{it}), \end{aligned}$$

where e_{it} denotes an individual-specific "endowment" of ideas about which windfall consumption goods and services to purchase. The functional form for $v(g_t, s_t)$ captures the idea that to enjoy windfall consumption the agent needs to purchase g_t units of windfall consumption but also to incur search costs s_t, or leverage their search endowment e_{it}. We set $e_{i0} = e_0 > 0$ for a fraction of agents, i.e. these agents know which windfall consumption goods and services to purchase – as if they remembered past

[4] This assumption is a line with the economics and sociology literature on the non-fungibility of money. To illustrate our assumption, consider a different context: our assumption means that a households receiving money for Christmas or a birthday will disproportionately spend them on windfall consumption goods and services (rather than regular consumption, e.g. laundry supplies).

opportunities to consume such goods and services. These agents can purchase up to $e_0 < G$ units of windfall consumption without the need to incur search costs. The endowment is set to zero for other agents.[5]

Furthermore, we assume that search costs are larger for Group 3, which we will study below with comparative statics on κ. This is motivated by the fact that, in our experiment, Group 3 participants faced a large negative interest rate after a week only: search costs can be seen as particularly costly for this group given the limited time available.

Thus, spending the prepaid card on windfall consumption involves a key tradeoff in the model: (i) it delivers a utility boost λ; but (ii) it requires incurring search costs. To obtain simple closed-form solutions, we study the case of quadratic search costs, i.e. $\eta = 2$.

Budget constraint. The household faces a stream of per-period income z growing at rate g. The amount available on the prepaid card is denoted G. The budget constraint is:

$$\sum_{t=0}^{\infty} \left(\frac{1+g}{1+r}\right)^t z + G = \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} c_t + \sum_{t=0}^{\infty} p_g \cdot g_t,$$

using the price of general consumption as the numeraire and denoting the interest rate by r.[6] Note that the interest rate does not apply to future period windfall consumption, because in equilibrium the agent purchases treats with the prepaid card, where interests do not accrue.

We make the standard assumptions $\beta = \frac{1}{1+r}$ and $g < r$ so that the equilibrium is well-behaved.

Equilibrium. To solve the consumption problem, we first consider the standard problem without a prepaid card, setting $G = 0$. In this case, utility maximization yields the standard result that it is optimal to equate consumption in each period:

$$c_t^* = r \cdot \frac{z}{r-g} \, \forall t,$$

i.e. the agent consumes the annuity value of their total income stream in each period.

Group 1 participants. We now consider participants with a prepaid card expiring after $T+1$ periods. We first discuss some parameter restrictions so that we can focus on an equilibrium in which the agent finds it optimal to spend the entire balance available on the prepaid card, G, on windfall consumption across the $T+1$ periods, and nothing on regular consumption. This equilibrium is sustained if, in each period until T, the marginal utility of spending on windfall consumption – net of search costs and scaled by the price of windfall consumption – is above the marginal utility of regular consumption in that period, equal to $u'(c_t^*) = 1/c_t^*$. Algebra yields that this is satisfied if

$$\frac{\lambda - \kappa s_0^*}{p_G} > \frac{r-g}{r \cdot z}, \tag{A1}$$

[5] In equilibrium, the endowment is depleted in the initial period as we discuss below, i.e. $e_{it} = 0$ for all i and $t \geq 1$.

[6] Note that, in principle, agents in Groups 2 and 3 could lose some of the prepaid card balance G due to the expiration date. However, in our model, by utility maximization agents never lose money and always spend it either on windfall consumption or regular consumption.

where s_0^* is defined below in terms of exogenous parameters. We assume that this condition holds, which is guaranteed when λ is large enough.

Next, we consider an interior solution for search costs, i.e. the agent will decide to spend the entire prepaid card balance on windfall consumption but will not do it at once in order to smooth the search costs across all $T+1$ periods. For Group 1 participants endowed with $e_0 > 0$, it is optimal to buy at least g_0 units of windfall consumption at no search cost: it would be suboptimal to wait until later periods to spend the endowment, since later periods are discounted at rate β and the prepaid card yields no interest rate. In addition, the agent exerts some search effort to buy additional windfall consumption. Considering an interior solution for search effort and windfall consumption spending in all periods up to T, the first-order conditions yield:

$$\beta(\lambda - \kappa s_{t+1}) = \lambda - \kappa s_t \, \forall t < T-1.$$

Since the agents purchase windfall consumption with the prepaid card only, we have the budget constraint:

$$\frac{G}{p_G} - e_0 = \sum_{t=0}^{T} s_t$$

From this we obtain:

$$s_0^* = \left(\frac{G}{p_G} - e_0\right) \frac{1 - 1/\beta}{1 - 1/\beta^{T+1}} + \nu$$
$$s_{t+1}^* = \frac{1}{\beta} s_t^* - \frac{\lambda}{\kappa} \frac{(1-\beta)}{\beta} \;\; \forall t \in [1, T]$$

with $\nu = \frac{\lambda}{\kappa} \frac{(1-\beta)}{\beta} T \frac{1-1/\beta^T}{1-1/\beta^{T+1}} + \beta \frac{(1-1/\beta)(T/\beta^{T+1}) - 1/\beta^2(1-1/\beta^T)}{(1-1/\beta^{T+1})(1-1/\beta)}$.

This yields the optimal allocations:

$$g_0^* = e_{i0} + s_0^*,$$
$$g_t^* = s_t^* \;\; \forall t \in [1, T],$$

Note that $g_0^* > g_t^* \;\; \forall t \in [1, T]$, especially for households endowed with $e_0 > 0$. This establishes our first key result: for Group 1 participant, the extra spending is concentrated in the short run. Intuitively, households who remember "windfall purchase opportunities" buy them immediately, at no search cost. They then smooth the search costs over time.[7]

Group 2 participants. For Group 2 participants, the problem is the same as above except that $\lambda_t = 0 \; \forall t > 0$. The agent now exerts optimal search effort s_0^* in period 0 to take advantage of the fact that the marginal utility of spending on windfall goods and services is larger, through λ, in this period alone. The agent thus buys $e_{i0} + s_0^*$ windfall consumption goods and services at price p_g and spends the remainder on regular consumption, with perfect consumption smoothing over time (i.e., consuming

[7]Note that in this tractable version of the model, with parameter restrictions such that the card is entirely spent on windfall consumption, the marginal propensity to consume out of the prepaid card is 100 % over T periods. To be in line with our empirical findings of a modest MPC concentrated in the short run for Group 1 participants, we can set $T \to \infty$ to obtain a small cumulative MPC over time, with a burst of spending in the initial period.

$\frac{r}{1+r} \cdot [G - p_g (e_{i0} + s_0^*)]$ every period). We assume that the optimum satisfies an interior solution, i.e. the agents exerts search effort up to the point where the marginal utility of getting more windfall consumption equates the marginal utility of spending on regular consumption in the initial period:

$$\begin{aligned} \frac{\lambda - \kappa s_0^*}{p_g} &= u'(c_0^*) \\ &= \frac{1}{r \cdot \frac{z}{r-g} + \frac{r}{1+r} \cdot [G - p_g (e_{i0} + s_0^*)]} \end{aligned} \tag{A2}$$

This characterizes the optimal choice of search effort s_0, and thus of windfall purchases g_0; optimal choices can be found by solving the quadratic formula: $A + Bs_0^* + Cs_0^{*2} = 0$.[8]

To compare the consumption response of Group 2 to Group 1, note that when G is small relative to lifetime income $\frac{z}{r-g}$, as in the data, the right-hand side of equation (A2) remains essentially unchanged regardless of the choice of s_0^*. Group 2 now equates the marginal utility of spending on windfall consumption (net of search costs) to the marginal utility of regular consumption, while in the case of Group 1 the marginal utility of spending on windfall goods and services remains larger, per equation (A1). Indeed, Group 1 agents are able to smooth the search costs over many periods. Instead, Group 2 agents search more and buy more windfall consumption in the initial period. We thus obtain our second key result: Group 2 participants have a larger increase in spending than Group 1 participants in the short run.

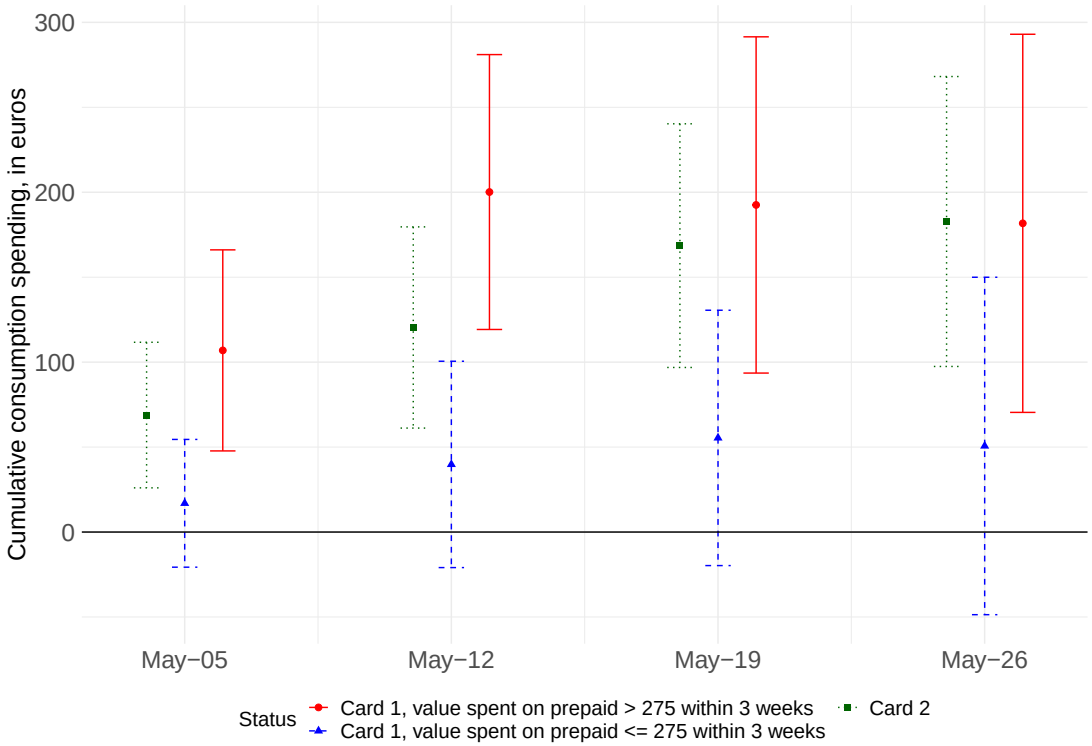
Group 3 participants. For Group 3 participants, the optimal allocation is also given by the equation (A2), but with the higher value of κ that characterizes Group 3. We can directly infer from equation (A2) that the equilibrium levels of search and spending on windfall goods and services fall with higher search costs κ (again noting that G is small relative to lifetime income $\frac{z}{r-g}$ on the right-hand side). Per the comparison of equation (A2) to equation (A1), the spending of Group 3 remains larger than the spending of Group 1 in the initial period. This establishes our third key result: the extra spending of Group 3 falls between that of Group 1 and Group 2.

Additional prediction. The model above highlights that Group 1 participants who spend early on after receiving the prepaid card should have a large MPC. In the model, these agents are endowed with $e_0 > 0$ and are able to buy windfall consumption immediately at no search cost, while other agents smooth search costs over time and experience no spending burst upon receiving the card. Taking this prediction to the data, we analyze the sub-sample of Group 1 participants who spent the prepaid card within the first three weeks. Consistent with the prediction, we estimate a large MPC in this sub-sample of Group 1 participants: their MPC is close to that of Group 2 participants, as reported in Appendix Figure F1. This finding provides additional evidence about the channel whereby the expiry date can act as a spur to make purchases for Group 2 participants, which in our model requires incurring higher search costs that Group 1 participants prefer to avoid.

[8] The parameters are as follows:

$$\begin{aligned} A &= \frac{\lambda}{p_g}\left[r \cdot \frac{z}{r-g} + \frac{r}{1+r}(G - p_g e_{i,0})\right] - 1, \\ B &= -\lambda \frac{r}{1+r} - \frac{\kappa}{p_g}\left[r \cdot \frac{z}{r-g} + \frac{r}{1+r}(G - p_g e_0)\right], \\ C &= \frac{r}{1+r}\kappa. \end{aligned}$$

Figure F1 Testing an Auxiliary Prediction of the Simple Model



Notes: Motivated by the auxiliary prediction of the simple model in Appendix F, this figure reports the cumulative MPC for three groups of participants: all participants in Group 2, participants in Group 1 who used the prepaid card to make purchases of a total value of more than 275 euros in the first three weeks of the experiment, and other Group 1 participants who did not spend down the prepaid card as quickly.

Extension: time-varying salience. Note that the salience effects above are only tied to the prepaid card. An alternative modeling approach could assume that λ_t falls over time, i.e. the reference point for salience is not just the card but also the time of receipt. This assumption would also yield a spending response concentrated in the short run, without the need for the assumption that agents have a "search endowment".

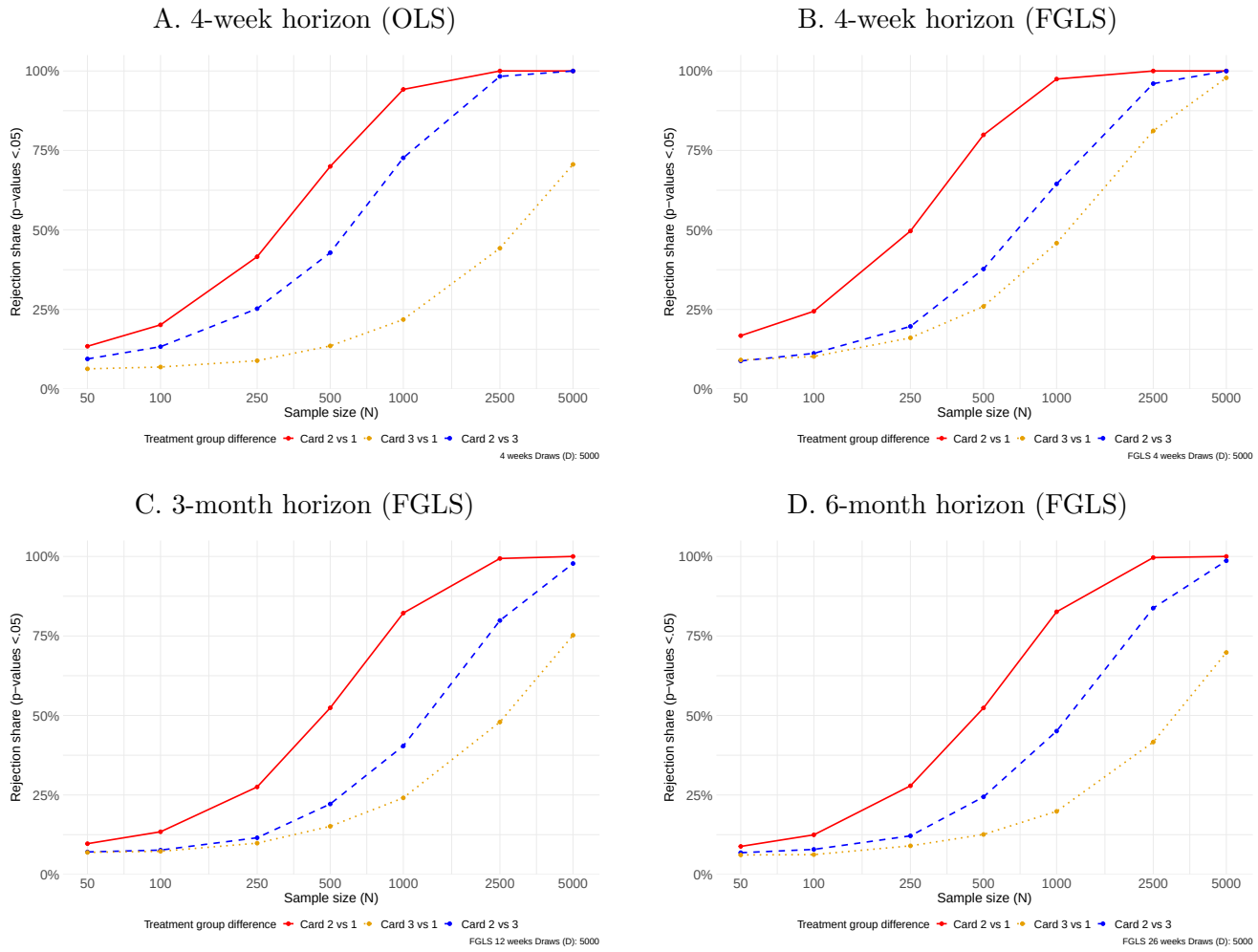
G Power Calculations based on Estimated Effect Sizes

To guide the design of future experiments, we conduct power calculations that we calibrate with effect sizes obtained from the point estimates in our experiment. The first set of simulations estimates the number of observations required to find, with a certain probability, statistically significant differences between treatment groups average MPCs. A second set of simulations shows the distribution of standard errors that one can expect on average MPCs.

G.1 Power for Detecting Differences in Average MPCs across Treatment Groups

We first investigate the statistical power to detect differences in average MPCs across treatment groups. We draw $D = 5,000$ times repeated samples of N households from the empirical distribution of households

Figure G1 Power Curves for Detecting Differences in Average MPCs across Treatment Groups



Notes: This figure reports power curves for rejecting $H_0 : MPC_{g_i} = MPC_{g_j}$ versus $H_1 : MPC_{g_i} \neq MPC_{g_j}$ using a two-sided t-test with 95% size. N is the size of each treatment group; the size of the control group is constant at 10,000 households. Estimates are obtained using a bootstrap with 5,000 draws.

in each treatment group, as well as $10,000$ households from the control group.[9] We then estimate the baseline specification (i.e. the same as for Figure 4) to estimate average MPCs for each group. In each draw, we conduct a t-test to test whether the null hypothesis of same T-week average MPCs is rejected or not at 95% test size, for T equal to 4, 12, or 26 weeks.

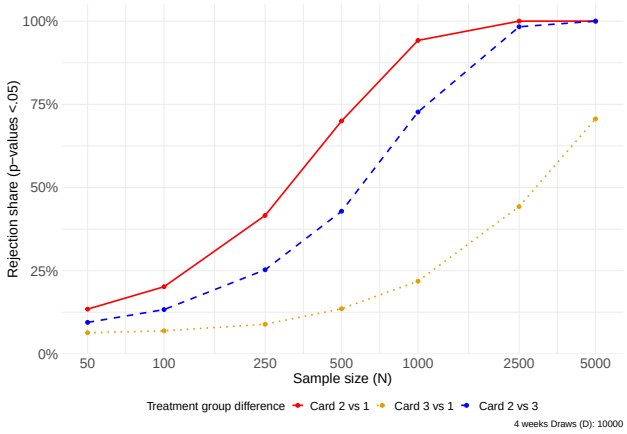
Figure G1 shows an estimate of the power curve, i.e. the fraction of the $5,000$ draws where the null is rejected as a function of treated sample size N. We report calculations for OLS estimates in the short run (4 week horizon, panel A) and for FGLS estimates at longer horizons (up to 6 months, see panels B, C, and D).[10]

The estimates show that, with the sample size of 300 households per treatment group, at a 4-week horizon the rejection share when comparing Cards 1 and 2 is around 50%, compared to about 30% or

[9] We restrict the control group to 10,000 households for computational reasons but discuss at the end of this section that the estimates are not sensitive to the size of the control group

[10] As explained in the main text, for longer horizons FGLS estimates are more reliable.

Figure G2 4-week Power curve, Robustness



Notes: This figure reports power curves for rejecting $H_0 : MPC_{g_i} = MPC_{g_j}$ versus $H_1 : MPC_{g_i} \neq MPC_{g_j}$ using a two-sided t-test with 95% size. N is the size of each treatment group. Estimates are done using a bootstrap with 10,000 draws and using control groups of 85,000 households drawn from the population of untreated households.

Cards 2 and 3, and only 12% for Cards 1 and 3. For Cards 1 and 2, a sample size of 1,000 participants per treatment group gives power above 80% at any horizon. For Cards 2 and 3, a sample size of 2,500 participants is required to achieve 80% power. Because our point estimate for the difference between Cards 1 and 3 is much lower, the statistical power for detecting differences between groups 1 and 3 remains low even for larger treatment group sizes.

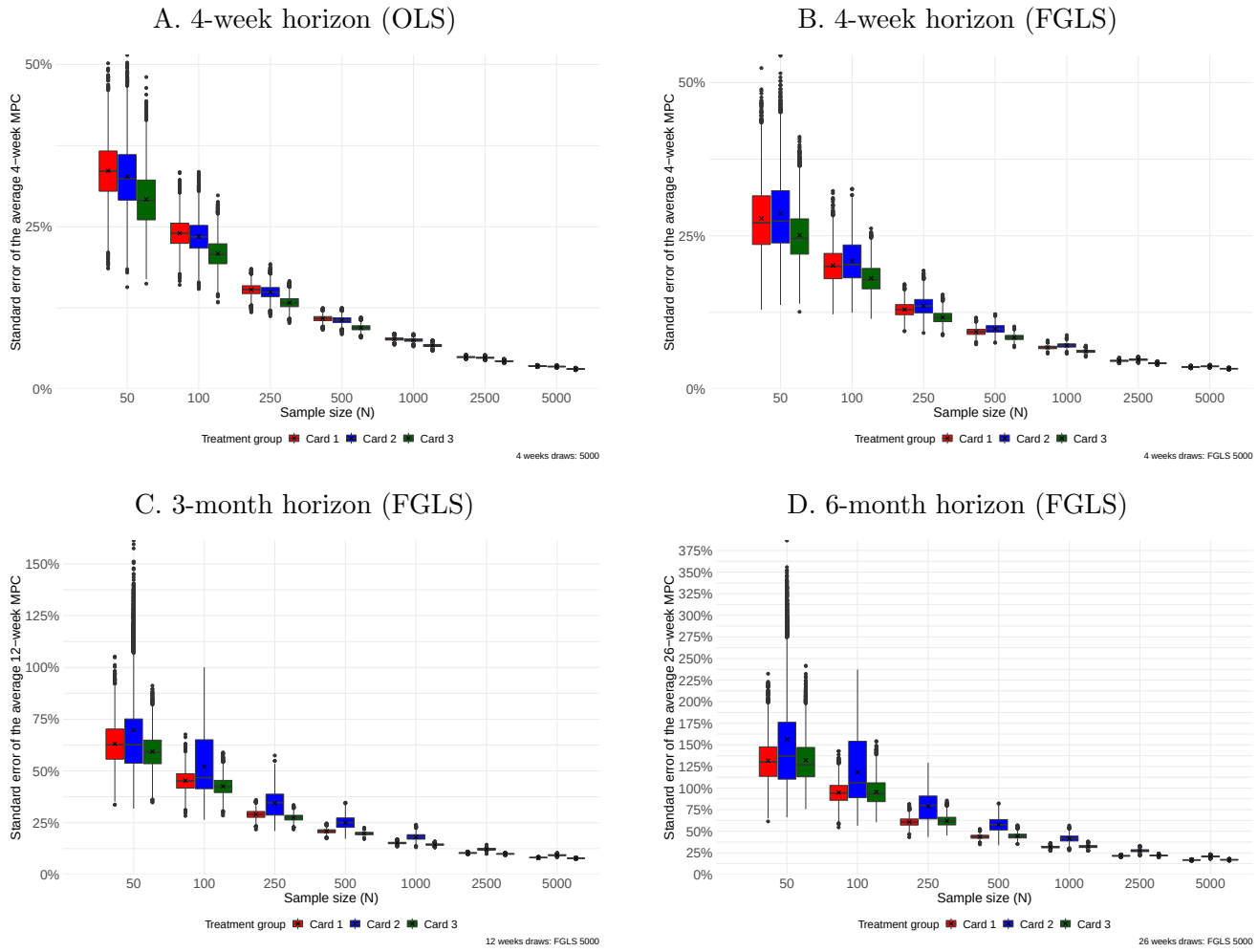
We find that the estimates remain very similar when using a larger control group, and when doing more bootstrap draws: see Figure G2, which reports 4-week estimates for a control group of 85,000 households, and twice as many bootstrap draws. We focus on the estimates with fewer bootstrap draws for the control groups for tractability, as the FGLS specification take a significantly longer time to run.

Overall, these simulation results suggest that a sample size of about 1,000 to 2,500 participants per treatment group would allow future experiments to achieve good power. With transfers of 300 euros per participant, the implied cost of about 900,000 to 2,250,000 euros, instead of about 300,000 euros in our experiment. While substantial, these costs are not larger than the costs of the typical RCT in fields such as development economics. We hope that future RCTs can use the simulations above to mobilize sufficient resources to obtain precise and appropriately powered estimates. Doing so is an important task for future work.

G.2 Statistical Precision for Average MPCs Out of Standard Money Transfers

We now conduct simulations to understand the precision of the estimates of average MPCs of standard money transfers like in our treatment group 1. Figure G3 shows the distribution of standard errors on the 4-week, 3-month, and 6-month MPCs for treatment groups 1, 2, and 3, depending on the treatment group sizes. These distributions are estimated using the bootstrap with 5,000 draws, by each time drawing a sample of the given size for each treatment group, and a control group of 10,000 households, from the respective empirical distributions. We report the distribution of standard errors of the average MPC, using the same specification as the baseline event study regressions, with household and time fixed effects.

Figure G3 Distribution of Standard Errors for Average MPC out of Card 1



Notes: This figure reports box plots of the simulated distribution of standard errors for the estimate of the T-week average MPC in our baseline specification, when the control group consists of 10,000 households and each treatment group consists of N households receiving Card 1. Estimates are obtained using a bootstrap with 5,000 repetitions.

Panels A and B shows that, at a 4-week horizon, obtain a standard error of 5% requires a sample size of about 2,500 households. This sample size would yield a standard error of about 12.5% at a 3-month horizon (Panel C), and of about 20% at a 6-month horizon (Panel D). With 5,000 households, the standard error at a 6-month horizon is around 10%. Thus, obtaining precise estimates of MPCs at long horizons would require a large sample size of about 5,000 households.