Five Facts about MPCs: Evidence from a Randomized Experiment*

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October 20, 2023

Abstract

We conduct a randomized controlled trial to study the consumption response of French households to unanticipated one-time money transfers of 300 Euros. Using prepaid debit cards, we consider three implementation designs: (i) a transfer without restrictions; (ii) a transfer where any unspent value expires after three weeks; (iii) a transfer subject to a 10% negative interest rate every week. We observe participants' main bank accounts, such that we can compute the impact of the transfer on their overall spending. We establish five facts about MPCs in this setting. First, we find that participants in the baseline treatment group have an average marginal propensity to consume (MPC) of 22 percent over one month. Second, we find that implementation design matters: the one-month MPC is substantially higher for treatment groups where any remaining balance becomes unusable after three weeks (60%) or where remaining balances are subject to the 10% negative interest rate every week (36%). Third, we document that the cumulative consumption responses are concentrated in the first weeks following the transfer and are flat thereafter. Fourth, we find that there is significant MPC heterogeneity by observed household characteristics, including by liquid wealth, current income, proxies for permanent income, gender, and age; the MPC remains high even for agents with high liquid wealth. Fifth, we estimate the unconditional distribution of MPCs across households and find that a large fraction of households have high MPCs. These facts are difficult to reconcile with the consumption response in standard Heterogeneous Agent New Keynesian models, which is long-lived and driven by households with little liquid wealth. Furthermore, we observe that households in the treatment groups with a short expiry date or a negative interest rate frequently use other means of payment while still having a sufficient balance on the prepaid card to cover their expenses, indicating that participants see money as non-fungible. Our finding that households consume more when presented with an urgent spending need lends support to theories where the salience of treatments affects economic choices. We conclude that implementation design and the targeting of transfers can greatly alter the effectiveness of stimulus policies.

*For helpful comments, we thank Adrien Auclert, Corina Boar, Michael Boutros, Chen Lian, Philippe Martin, Ben Moll, Sarah Mouabbi, Emi Nakamura, Alan Olivi, Jonathan Parker, Valerie Ramey, Xavier Ragot, Ricardo Reis, Jesse Shapiro, Johannes Spinnewijn, Ludwig Straub, Gianluca Violante, Christian Wolf, as well as seminar and conference participants at the Bank of England, the Bank of France, the Bank of Israel, the Center for Economic Studies at the U.S. Census Bureau, the CEPR public economics symposium, the Federal Reserve Board, George Washington University, HEC, the Hebrew University of Jerusalem, the Institute for Fiscal Studies, the London School of Economics, the Paris School of Economics, the SITE conference, UCL and the University of Munich. We are grateful to Emmanuel Giguel, Julien Fournel and the teams at Euro-Information and Crédit Mutuel Alliance Fédérale for their work on the implementation of the experiment. Boehm acknowledges financial support from the Agence Nationale de la Recherche under grant agreement ANR-20-CE26-0006 and from the Banque de France/Sciences Po partnership. We are grateful to Antoine Ding and Tyler Woodbury for excellent research assistance.

1 Introduction

The marginal propensity of households to consume out of a transitory income shock (MPC) is a central object in macroeconomic models and for stimulus policies. It determines the partial equilibrium response to such shocks, and it also has important implications for general equilibrium responses, notably for the ability of monetary and fiscal authorities to increase demand through direct stimulus transfers (e.g., Kaplan et al., 2018, Auclert et al., 2023). Despite a large body of research, estimates of MPC out of transfers remain debated due to limitations arising from data availability and the sources of variation used for causal identification (e.g., Parker et al., 2013, Orchard et al., 2022, Borusyak et al., 2021). In this paper, we overcome these challenges by running a randomized experiment, allocating transfers at random across households. We use high-frequency bank data to measure households' overall consumption response and its heterogeneity across households.[1] Going beyond standard estimation of MPC, we also examine whether transfers with negative interest rates may yield larger MPCs, motivated by the fact that several countries have implemented large-scale household transfers with features akin to negative interest rates, e.g. time-limited consumption vouchers.[2]

Our experiment is designed with scalability and generalizability in mind. We randomly provide stimulus transfers to a sample of about 1,000 French individuals that is representative of the adult French population, and from which we observe detailed financial transactions and consumption expenditure data through bank records. The experiment was launched in May 2022, at a time when interest rates were still at zero in the euro zone. Our baseline treatment evaluates the consumption response to a simple one-off money transfer in the form of a debit card with a balance of 300 Euros. We compare the total consumption spending of treated households, on both the plastic cards and their bank accounts, with those of a large sample of about 90,000 untreated households. In further treatment groups, we investigate two potential ways of increasing the households' overall consumption response by assigning a negative interest rate on the transferred wealth: either by making the card expire after three weeks – at which point any remaining balance is lost to the household – or with a weekly deduction of an amount close to 10 percent of the remaining balance on the card. While households in all treatment groups are free to spend the transfer however they want, we make the interest payments potentially binding by preventing cash withdrawals from the cards. We also assign an additional framing treatment where participants are asked to "spend soon, on French products, and on things [they] would have otherwise not purchased". Using this experimental setup, we establish five facts about MPCs. We then discuss why these facts are informative for macroeconomic models and for the design of stimulus policies.

We start by estimating MPCs depending on the card type, establishing our first two key facts. We find that participants in the baseline treatment group (without an expiry date or negative interest rate) increase their total consumption expenditure after receiving the card, with an average marginal propensity to consume (MPC) of 22 percent over one month (Fact #1). Moreover, we find that implementation design matters: the MPC is substantially higher for treatment groups where any remaining balance becomes

[1] A vast literature has examined MPCs out of various shocks, including typical income shocks (Ganong and Noel, 2019), lottery winnings (Fagereng et al., 2021, Golosov et al., 2021), and recurring lump-sum payments (Kueng, 2018). Instead, we study one-time transfers comparable to those deployed to simulate the economy during an economic downturn.

[2] There are several examples of large-scale stimulus policies using prepaid cards or time-limited consumption vouchers, including Japan in 1999, Taiwan in 2009, California, Milan, and Seoul in 2020, and Hong Kong in 2021.

unusable after three weeks, at 60% (or 70%, when conditioning on take-up), or where remaining balances are subject to the 10% negative interest rate every week, at 36% (Fact #2).

We examine the possibility that the faster spending for cards with an expiry date or negative interest rates could induce detrimental consequences for these households due to behavioral internalities. We find no such evidence: these households do not incur more volatile nondurable consumption in later periods, and they are not more likely to make purchases that could entail adverse health consequences, such as tobacco or gambling.

We next analyze the dynamics of the consumption response – the path of intertemporal MPCs, or iMPCs (Auclert et al., 2023) – yielding our third key fact. We find that, for all treatment cards, the additional spending occurs immediately after the onset of the experiment. Specifically, the consumption responses are concentrated in the first weeks following the transfer and are flat thereafter (Fact #3). We observe that the consumption response is concentrated early on even for non-durables.

To understand the spending behavior of the participants upon receiving the treatment, we administer a survey among participants and we analyze the bank data to assess potential changes in the composition of expenditures. Recipients are well aware that they spend less on their main account (thereby having an MPC below one), and they mention precautionary saving as a key motive. They use the card they receive primarily to cover running expenses, but some also report purchasing a "treat", or making a large expenditure earlier. Treated households have similar expenditure shares on most consumption categories as control households, but purchase relatively more clothing and household equipment. Treated households also spend slightly more on durables and on imported goods.

We then turn to MPC heterogeneity, establishing our fourth and fifth key facts. We find that there is significant MPC heterogeneity by observed household characteristics, including for liquid wealth, current income, proxies for permanent income, gender, and age (Fact #4). The most spectacular source of heterogeneity we document is about gender: the average MPC of men is about twice as high as for women. We also find that households with lower income and households with lower average pre-treatment consumption levels (our proxy for permanent income) have higher MPCs. Liquid wealth plays a limited role in explaining MPC heterogeneity, as MPCs remain high even for households whose liquid wealth exceeds twice their monthly income. Finally, we find that MPCs appear to increase with age, although differences across age groups are relatively noisy. A set of LASSO regressions confirms that the most important predictors of MPC heterogeneity are demographic characteristics (gender, age) and pre-treatment average consumption.

Going beyond heterogeneity that is associated with observed characteristics, we adopt a deconvolution approach to recover the full distribution of MPCs across households. Indeed, thanks to our experimental setting, we know that the distribution of error terms is identical in the treatment and control groups, which allows us to use statistical deconvolution techniques to estimate the full unconditional distribution of treatment effects.[3] Using this methodology, we find large unconditional heterogeneity in consumption responses following the transfer (Fact #5). In the baseline treatment group where households receive a cash-like transfer, a quarter of households increase their consumption expenditure over a 4-week horizon by less than 9 percent of average weekly consumption, and a quarter increase their consumption by more

[3]This approach requires assuming that heterogeneous treatment effect and structural error terms are uncorrelated. We provide empirical support for this assumption through auxiliary tests in Section 4.

than 43 percent. In contrast, in the treatment group where cards expire after three weeks, three quarters of recipients increase their 4-week consumption by more than 41 percent of average weekly consumption. These results again highlight the power of the choice of implementation design to shift MPCs.

Finally, we discuss the implications of these five facts about MPCs for macroeconomic models and for policy. While our MPC estimates do not speak to general equilibrium effects, they are informative about key building blocks of modern macroeconomic models. Our findings contrast with the predictions of the canonical implementation of the benchmark two-asset Heterogeneous-Agents New Keynesian (HANK) model in three ways. First, the magnitude and dynamics of the MPC is difficult to reconcile with HANK models. In all our treatment groups the entire spending response is concentrated in the first weeks (up to three weeks), while the MPC response is much more long-lived according to HANK (Kaplan and Violante, 2014, Kaplan et al., 2018, Auclert et al., 2023). For example, in Kaplan et al. (2018), the MPC out of a \$300 transfer is 17% over a quarter and increases to about 32% over a year. Instead, with our baseline treatment (without an expiry date or negative rates), we obtain a larger MPC in the first month, at 22%, but no further increases in spending in later periods.[4] Laibson et al. (2022) note that durables require special treatment when analyzing the dynamic reponse of spending, since the effective consumption derived from durables occurs over a long period rather than at the time of purchase. However, the concentrated spending response we estimate is not driven by durables. Second, in HANK the MPC is strongly correlated with the level of liquid assets that agents hold; while we do find some heterogeneity of MPCs for groups with different levels of liquid asset holdings, we find that average MPCs are also high for households that have moderate or high levels of liquid asset holdings. Third, our estimates of the unconditional distributions of MPCs reveal that MPCs are high for a large majority of the population, in contrast to standard calibrations of the HANK model, where high MPCs are concentrated among about 40% of people who have little liquid wealth and hit their borrowing constraints. Assessing whether alternative calibrations or extensions of the HANK model can match our five MPC facts is an important direction for future research.

We also show that our results are difficult to reconcile with agents being rational and treating money as fungible. A rational agent that treats money as fungible should first "use up" the treatment card to avoid potentially losing money (through the negative interest rate or expiry) before using their normal debit or credit card. In fact, we observe that households in the treatment groups with an expiry date or a negative interest rate frequently make payments with other means before exhausting the transfer card. Our results thus echo a literature documenting the non-fungibility of money (Hastings and Shapiro, 2013, 2018, Baugh et al., 2021, Geng et al., 2022, Gelman and Roussanov, 2023), and deliver three lessons for behavioral models. First, models of consumption that rely on present bias in preferences (e.g. Laibson, 1997, Maxted, 2020, Laibson et al., 2021) are able to explain why the consumption response to the transfer is concentrated early on, but cannot explain the difference in the magnitude of responses between the treatment groups. Indeed, under such preferences, consumers in all three groups should be present bias but the negative interest rate and the expiry date would remain non-binding constraints, given that it

[4]Our finding is consistent with quasi-experimental evidence on MPCs using the 2008 U.S. tax rebates. Using scanner data to document high-frequency spending responses to tax rebates, Borusyak et al. (2021) show that they are concentrated in the first month after the rebate. Of course, a standard intertemporal budget constraint and a transversality condition imply a long-term MPC of one, but empirical studies – like ours, Borusyak et al. (2021), or any other to our knowledge – lack the statistical power to investigate whether long-term MPCs are indeed one. Instead, we focus on dynamics in the quarters following the transfer.

should be costless for agents to substitute current account spending for prepaid card spending. Second, while implementations of "spender-saver" models (Campbell and Mankiw, 1989) can be made to feature consumption responses that are concentrated very early on, they would also imply strongly bi-modal distributions of MPCs, which we do not find. Third, our finding that households consume more when presented with an urgent spending need (in the form of the negative interest rate or expiry date) is consistent with theories where the salience of treatments affects economic choices by drawing attention away from other considerations (Bordalo et al., 2012, 2013, Ilut and Valchev, 2023).

Our new facts have two implications for policy. First, the large difference in MPCs across treatment groups show that the design of transfers is very important to maximize MPCs. The treatment we find to have the highest MPC takes a particularly simple form: a debit card that features an expiry date, a feature that consumers know from gift vouchers. Second, our estimates of MPC heterogeneity have implications for the targeting of transfers by observable household characteristics.[5] We find that it is possible, based on simple observable characteristics like age and income, to find household populations with significantly higher MPCs than average. However, the change in MPC is smaller than by using a card with an expiry date. We conclude that implementation design choices are a more powerful tool, compared with targeting, to increase the recipients' average MPC.

Related literature. This paper contributes to a vast literature that seeks to estimate marginal propensities to consume. The main MPC estimates used to discipline macro models are based on the staggered disbursement of tax rebates. The seminal papers analyzing staggered tax rebates in the United States (Johnson et al., 2006, Parker et al., 2013, Broda and Parker, 2014) found large MPCs, of about 50% over a quarter. However, these estimates are subject to two limitations. First, due to noise in survey data, it is challenging to reject small MPCs, to estimate the monthly dynamics of MPCs, as well as to estimate MPC heterogeneity across households. Second, the staggered difference-in-differences design raises an identification challenge: a recent literature finds that using difference-in-differences estimators that are robust to treatment effect heterogeneity yields much smaller MPCs of about 25% over a quarter (Borusyak et al., 2021, Orchard et al., 2022). In this paper, we overcome these limitations by directly running an experiment, using high-frequency bank data with rich household covariates to measure the dynamics of the spending response as well as its heterogeneity across households.[6]

Several papers use high-quality administrative data to measure the spending responses to a variety of economic shocks, including typical income shocks (Ganong et al., 2020), lottery wins (Fagereng et al., 2021, Golosov et al., 2021), or recurring payments (Kueng, 2018). Relative to these papers, we focus on transitory transfers whose magnitude is similar to standard stimulus transfers. Indeed, since the marginal propensity to consume depends on the source of the shock, its persistence, and its magnitude, to draw lessons for macroeconomic stabilization policies it is important to directly study the spending response to typical stimulus transfers.

Four other strands of the literature provide MPC estimates. First, a growing literature seeks to estimate the distribution of MPCs (Misra and Surico, 2014, Lewis et al., 2019). A key advantage of our

[5] Aguiar et al. (2023) discuss the targeting of individuals in a model where differences in MPCs originate from preference heterogeneity. Gelman (2021) highlights the importance of discount factor heterogeneity in explaining MPC heterogeneity.

[6] The MPC estimates for our baseline treatment are close to those obtained by Borusyak et al. (2021) and Orchard et al. (2022).

experimental setup is that we can use deconvolution methods to estimate the distribution of treatment effects. Second, another strand of the literature uses theory-informed moment conditions to identify MPCs (Blundell et al., 2008, Commault, 2022a). Third, a number of papers have elicited MPCs from surveys where respondents are asked how they would respond to a hypothetical transfer (Shapiro and Slemrod, 2003, 2009, Bunn et al., 2018, Parker and Souleles, 2019, Fuster et al., 2021, Commault, 2022b). Fourth, a small literature estimates the spending response to consumption vouchers (Hsieh et al., 2010, Kan et al., 2017, Xing et al., 2023, Geng et al., 2022, Ding et al., 2023). A unique feature of our setting is to use an experiment to analyze how the marginal propensity to consume varies with implementation design choices, comparing the effects of standard transfers to transfers featuring an expiry date or a negative interest rate.

More broadly, this paper is the first to use a randomized-experiment to address a macroeconomic question. Our experiment provides causal effects estimates that may have direct relevancy for stimulus policies and that could be used as moments to match in macroeconomic models (Nakamura and Steinsson, 2018).

Outline. The remainder of the paper is organized as follows: Section 2 presents the data and experimental design; Section 3 presents our main MPC estimates, establishing our first three key facts; Section 4 documents MPC heterogeneity, leading to our fourth and fifth key facts; Section 5 uses our five facts to draw lessons for macroeconomic models and stimulus policies.

2 Data and Experimental Design

In this section, we describe our dataset, our main variables, as well as the experimental design.

2.1 Dataset

Our analysis is made possible by running an experiment on a panel of households for which we have access to comprehensive, detailed financial transactions data. This panel of households has been constructed to be representative of the overall French population. For ethical and operational reasons we restricted this sample before randomly drawing treatment assignments. We describe both the larger and the restricted samples in turn, as well as the content of the data.

The bank data and the experimental sample. Our data comes from the French banking group Crédit Mutuel Alliance Fédérale.[7] We work with a panel of 300,000 households that were drawn by the bank in June 2020. These households are representative of the French population in terms of location, age, and socio-economic characteristics. as shown by Bounie et al. (2020) and Bonnet et al. (2023), who compare the bank sample to official statistics (see Appendix A.1).

[7]Crédit Mutuel Alliance Fédérale made de-identified data available to us on a secure server, protecting customer privacy. The bank aims to contribute to the public good and policy debates by facilitating economics research. This is part of Crédit Mutuel Alliance Fédérale's mission as an "*entreprise à mission*", a French legal framework in which businesses pursue a set societal goals. The cost of the experiment, including the transfer and a fee to cover the operational cost, was financed by the researchers through a grant from the French national agency for research (*Agence nationale de la recherche*).

The data provide socioeconomic information about the household, transaction-level information for transaction accounts, transaction-level information for all payment cards linked to the accounts, debt and balances on non-transaction accounts at the monthly frequency, as well as information about real estate assets at a much lower frequency. Card transactions include information on the Merchant Category Code (MCC) of the vendor, which we describe in Appendix A.2, along with additional information on the data.

We use a subset of the full 300,000 household for our experiment. We first define eligibility criteria at the individual level. To be eligible, individuals must be between 25 and 75 years of age, have a known residential address, should not have accounts with another bank (according to the bank's records), and are not deemed by the bank to be financially fragile. In order to obtain a population where we are able to measure spending well, we also exclude those individuals that have been using their debit card infrequently in the months prior to their experiment (suggesting that they may predominantly use cash). After applying all conditions, we obtain a balanced sample of 85,702 unique households who have at least one or at most two eligible persons in the household.[8] Random sampling for participation in the experiment is implemented at the individual – rather than household – level so that we can later on analyze heterogeneity based on individual characteristics, e.g. gender.

Variable definitions. Our main outcome variables is weekly consumption expenditure of the household, defined as the sum of all (credit and debit) card purchases and cash withdrawals of the household between Tuesday and the subsequent Monday at midnight.[9] We winsorize weekly consumption spending using the non-treatment cards at the 99th percentile of the distribution, which is 1940 euros, before adding treatment card expenditures to arrive at total weekly consumption expenditure.[10] Wire transfers and direct debit are not included in our baseline consumption measure, but we analyze an expanded consumption measure including these outflows in robustness checks. Appendix A.3 provides more detail on variable definitions.

Our estimated consumption responses are thus marginal propensities to spend (see Laibson et al., 2022 on the difference between marginal propensities to spend and notional MPCs). For the purpose of studying heterogeneity in consumption responses with respect to observable characteristics, we define time-invariant household characteristics as the average of the corresponding end-of-month characteristic in the 6 months prior to the treatment (November 2021 to April 2022), per capita.

Summary statistics. Table I shows summary statistics of the main variables. The table illustrates the richness of the bank data and the large heterogeneity in observable characteristics. Appendix Tables A1 and A2 provide additional summary statistics.

2.2 Experimental Design

Treatment arms. From the set of eligible individuals, we randomly draw 916 participants over three treatment groups.

[8] We also drop 40 households that were treated in a pilot of the experiment.

[9] We choose this interval to line up with the negative interest payments of Group 3, which take place on Mondays at midnight. One exception to the construction of weekly aggregates is that we assign Monday 2 May (the first day when participants use the card) to the subsequent week. The first post-treatment week is therefore comprised of eight days; this feature does not create any challenge for the estimation of MPCs as we use week fixed effects, as described below.

[10] The results are not sensitive to this winsorization step, as described below.

Table I Summary Statistics

	N	Mean	S.D.
Age of eligible household member	85,702.00	47.03	12.92
Number of eligible household members	85,702.00	1.15	0.36
Avg. monthly incoming transfers, 6m prior	85,687.00	2,654.02	1,439.53
Avg. monthly incoming salaries, social allowance, pensions, benefits, 6m prior	80,036.00	2,109.57	4,968.80
Dummy: has received unemployment benefits within 6m prior	85,687.00	0.14	0.35
Avg. current account balance, 6m prior	85,700.00	4,448.55	19,975.90
Avg. liquid savings, 6m prior	85,700.00	16,896.16	34,537.83
Avg. value of life insurance assets, 6m prior	85,700.00	5,867.47	32,465.81
Avg. illiquid savings , 6m prior	85,700.00	995.71	15,813.25
Avg. total debt, 6m prior	85,700.00	33,298.45	55,006.08
Avg. consumer debt, 6m prior	85,700.00	2,388.21	5,193.96
Avg. mortgage debt, 6m prior	85,700.00	30,869.90	54,286.72
Number of adult members in the household	85,700.00	1.53	0.50
Number of children in the household	85,700.00	0.61	0.96
Avg. monthly consumption expenditures (cash, card payments), 1 year prior	85,700.00	1,205.62	658.22
Avg. monthly outgoing transfers (direct debits, debt payments, Subscriptions), 6m prior	85,700.00	925.40	772.53
Avg. total monthly consumption (broad measure)	85,700.00	2,131.19	1,188.18
Weekly consumption expenditure (cash and cards), total	2,571,060.00	417.66	435.02
Weekly consumption expenditure (broad measure), excl. treatment cards	2,571,060.00	744.75	1,827.28

Notes: This table reports summary statistics for our main analysis sample. The broad measure of consumption includes the total of cash withdrawals, card spending, automatic debits, and wire transfers.

Treatment Group 1 (G1, $N = 380$) participants receive a MasterCard debit card linked to a new transactions account with an initial balance of 300 Euros.[11] The card expires and becomes unusable six months after it has been sent, at which point the participants receive any unspent balance wired to their main transactions account. Prior to this date, the participants are unable to transfer funds from or to the newly created transactions account, except by means of making purchases with the associated debit card. Notably, participants are unable to withdraw cash from those accounts. Otherwise, the participants are free to spend the account balance wherever MasterCard is accepted (i.e. in stores or online).

Treatment Group 2 (G2, $N = 266$) participants receive the same type of account and card as G1 participants, except that the card expires after three weeks; any remaining balance on the account after three weeks is *not* wired to their main checking account, but is deducted from the account and lost to the participants.

Treatment Group 3 (G3, $N = 270$) participants receive the same type of account and card as G1 participants, except that an "interest" payment is deducted at a weekly frequency. We approximate[12] a 10% negative interest rate by decreasing the remaining balance on the account (i) by 30 euros if the remaining euro balance is in the interval $(200, 300]$, (ii) by 20 euros if the remaining euro balance is in

[11]Note that for purchases made in stores, merchants may be willing to split transactions into several payments, thus allowing participant to purchase an item above 300 Euros by combining the balance available on the treatment card with funds from their regular bank account. For online transactions, participants will not be able to purchase items above 300 Euro with the prepaid card.

[12]We approximate the interest rate due to the legal constraints present in the experimental intervention. The deduction rule that we apply has the advantage of being quite similar to a weekly negative rate of 10 percent, while still remaining easy to explain and understand.

the interval $[100, 200]$, and (iii) by 10 euro if the remaining balance is below 100 euros. If the remaining balance is below 10 euros, the entire remaining balance is deducted. The card and account remain active until the balance has reached zero.

Orthogonal to the treatment group status, half of the all treated participants (stratified across treatment groups) were additionally treated with a framing treatment, where they were encouraged to spend the money quickly, on local goods or services, and "on items they would not have purchased otherwise, so that the overall increase of [their] spending and its impact on the French economy is maximized" (transl., for the original see Appendix B.1).

Thanks to these three treatment arms, we can estimate the extent to which transfer design choices might shift the MPC out of one-time transitory transfers. In particular, we can learn about the role of negative interest rates with the cards in treatment group 3 (close to 10% a week) and treatment group 2 (insofar as the expiry date can be viewed as a 100% negative rates after three weeks).[13]

Timeline. Our experiment took place between May and October 2022. On Wednesday April 27th the cards (which from now on we will call "treatment cards" to distinguish them from the households' other means of payment) and accompanying instructions and explanations (see Appendix B.1), as well as pin codes were sent by post to the residential addresses of the selected indidviduals,[14] with expected arrival on or around Monday May 2nd. In the meantime, the bank advisers of the treatment group individuals contact their clients by phone as well as through a banking app, explaining that they have been selected to participate in an academic study, and explaining the terms of the cards according to the treatment arm. Participants are informed that they can opt out from the study (in which case they would be unable to use the money they are set to receive), although nobody expressed a desire to do so. The fact that the bank advisors contacted the clients helps alleviate potential concern about participants' mistrust. Another letter with instructions, serving as a reminder, is sent to all participants on Wednesday, May 11.

On Monday May 9, Treatment Group 3 participants experience the first weekly deduction, for any remaining balance. The second deduction for this group occurs on Monday May 16th, and so on every week from then onward. For Treatment Group 2 participants, the card expires on Tuesday May 24th. An online survey is sent to all participants in the middle of June, which we use to better understand the spending behavior of the participants. Finally, Treatment Group 1 cards expire on October 3rd, and the remaining balances are transferred to the participants' main bank accounts.

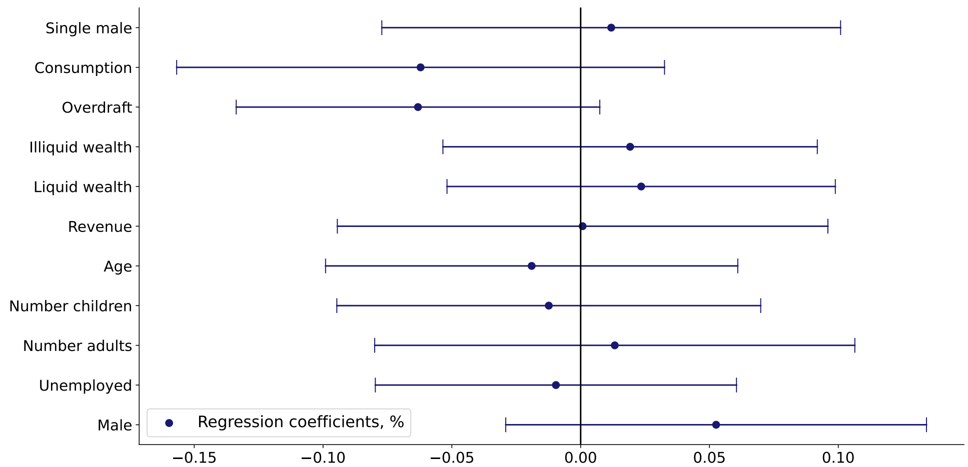
Note that we study a period when the zero lower bound was binding: at the time, interest rates were close to zero and negative at short horizons in France (Appendix Figure A1).

Take-up. Participants started using the card from May 2nd onward. Among the 916 treated households, 831 used the treatment card at least once before 6 October. 85 participants chose not to use the card, possibly for economic reasons (e.g., Group 1 participants can save by not using the card and getting the remaining balance transferred to their account) or for operational reasons (e.g., in Group 2 some participants may have missed the deadline). We do not exclude these households from the sample in

[13]While our experiment directly estimates the impact of transfer design choices on the MPC, it appears difficult to extrapolate from these results to learn about the behavioral response of consumers to a negative interest rate that would be applied on their main bank account.

[14]The pin codes for the treatment cards are set by the bank to the be the same as each participant's main debit card.

Figure 1 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%.

our main results, but investigate in robustness checks how MPC estimates change when conditioning on take-up.[15]

It is also worth noting that the remaining balance on the treatment card (for all treatment groups) appears in the mobile phone bank app of the participants, next to the balance on the main bank account. This implementation features reduces the likelihood that the participants forget that they have available funds on the treatment card.

2.3 Randomization Tests

We now present statistical tests to assess the validity of the randomization protocol.

Since the randomization was done at the level of the individual, but spending is observed at the level of the household, households with multiple eligible members will be over-represented in the treatment. We therefore conduct all our analysis within bins of households that have the same number of eligible members E (which we will refer to as "household size"), always comparing households with one treated member (we do not have households with multiple treated individuals) to households of the same size with no treated individuals. For the sake of brevity, we will refer to households with one treated individual as "treated households", and those without as "control households".

Figure 1 shows the results of randomization tests, where we regress a treatment dummy on a set of standardized household characteristics and a set of dummies for the number of eligible individuals within the household. The coefficients on the household characteristics are all small and not statistically significant, indicating that the means of these characteristics are similar across treated and untreated households (within bins for the number of eligible individuals). These result confirm the validity of the experimental design.

[15]Two participants filed a complaint stating that they did not receive a working card in time (they were issued a replacement several weeks later); we exclude them from the analysis.

3 Main MPC Estimates: Facts #1, #2 & #3

In this section, we report our main MPC estimates. We first consider all treatment cards at once (Subsection 3.1). We then report estimates by card types (Subsection 3.2), establishing our first three key facts about MPCs in this subsection. We also describe the participants' spending behavior by analyzing the composition of expenditure as well as auxiliary survey data (Subsection 3.3). Finally, we report MPC estimates by framing group (Subsection 3.4).

3.1 Pooled MPC Estimates

We first present MPC estimates for all treatment cards, first presenting evidence from the raw data and then turning to a regression framework.

3.1.1 MPC Estimates from Raw Data

Figure 2 presents the MPC estimates from raw data. Panel (a) first documents the timing of purchases that treated households make using the treatment card alone. The figure shows that spending increases rapidly and reaches about 250 euros after two months, i.e. they spend 84% of the transfer within two months. However, this direct spending response may be offset by reduced spending in the households' main bank accounts.

To assess the magnitude of potential substitution effects, we plot the level of spending in each week in the treatment and control groups.[16] Panel (b) of Figure 2 shows clear graphical evidence that treated households spend more upon receipt of the transfer, but the extra spending is short lived, lasting about three to four weeks. A month after the start of the experiment, there is no evidence for any difference in spending patterns between treated and control households. Thus, the response is concentrated in the very short run, with little intertemporal substitution.

Next, we move to a regression framework to provide more precise estimates of MPCs.

3.1.2 MPC Estimates from from Regression Specification

Specification. Our baseline econometric specification to estimate consumption responses is a standard two-way fixed effect linear model:

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

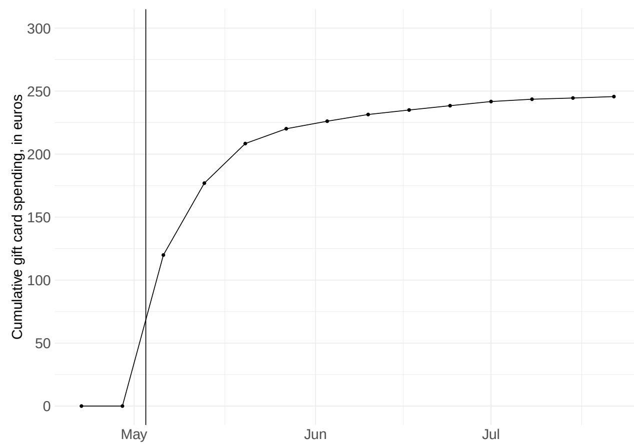
where Y_{it} is the outcome variable, usually consumption spending of household i in week t, the dummy $1(\tau \text{ weeks since } i \text{ treated})_{it}$ is one if and only if i contains a treated individual and week t is τ weeks after the first treatment week (the week of May 2), α_i are household fixed effects, and α_{tE} are fixed effects for "week by number of eligible individuals within the household." Given that treatment is assigned at random across eligible individuals, we only need to control for α_{tE} to achieve identification,[17] but we also

[16] Given that treatment was assigned at the level of eligible individuals, we implement one adjustment to the raw data, reweighting participants by the propensity score, i.e. so that the number of eligible individuals within households is the same across the control and treatment groups.

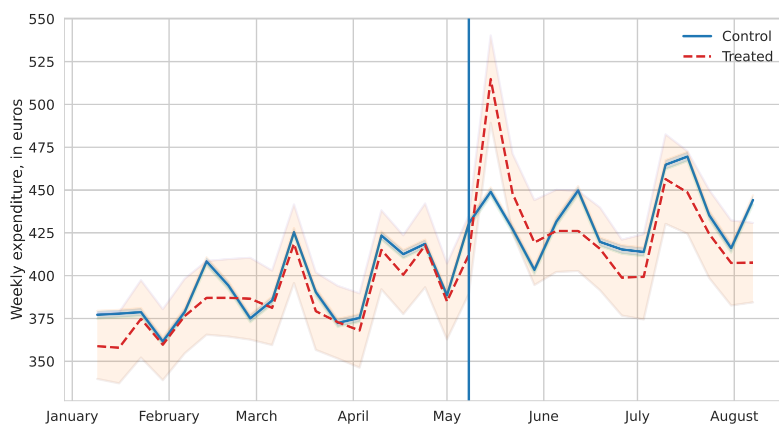
[17] In practice, the estimates remain similar when we don't include this control.

Figure 2 Spending Behavior in the Raw Data

A. Cumulative Spending on Prepaid Card



B. Average Total Spending, Weekly

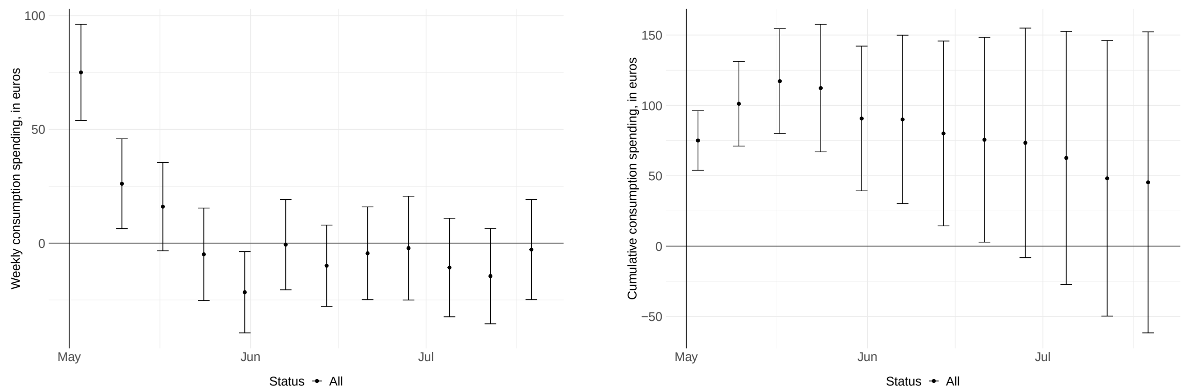


Notes: This figure reports the treatment effects in the raw data, plotting cumulative spending on the prepaid card in panel A for treated households, and avearge weekly spending for control and treated households in panel B. The 95% confidence intervals for mean weekly spending are reported as shaded regions in panel B.

Figure 3 Main MPC Estimates

A. Weekly MPC

B. Cumulative MPC since treatment onset



Notes: This figure reports our main MPC estimates. Panel A reports the weekly estimates, while panel B depicts the cumulative effects. 95% confidence intervals are reported, clustering the data at the household level.

include household fixed effects to reduce noise. Standard errors are clustered at the household level.

Given that a control group of untreated households is available, our two-way specification is not subject to the "negative weights" issue analyzed in recent work on difference-in-differences design (e.g., De Chaisemartin and Haultfoeuille (2020), Borusyak et al. (2021)).

Main results. The results are reported in Figure 3. Panel (a) report the estimates for the β_τ coefficients at a weekly frequency after treatment. The picture shows that, on average, participants' spending increases by 80 euros in the first week, 30 euros in the second week, and 20 euros in the third week. The estimates are not significant in any of the following weeks.

Panel (b) shows the point estimates and standard errors of the cumulative sum since the start of treatment. The point estimate for the cumulative average effect after four weeks is 112 euros, corresponding to a marginal propensity to consume of $112/300 = 37$ percent. The figure suggests that the cumulative MPC is slightly reduced going forward, with a point estimate falling to about 45 euros after three months, or a cumulative MPC of 15 percent. The decrease in point estimates over longer horizon results from a small number of positive outliers in weekly pre-period consumption expenditures, which push up the household fixed effects and make subsequent expenditures appear small in comparison. Appendix Figure A2 shows FGLS estimates that effectively downweigh households with higher consumption volatility, and these estimates are flat over the corresponding horizon.

As in other papers that compare recipients of transfers with non-recipients to estimate MPCs, estimates over longer horizons are becoming increasingly less precise, as the variance of cumulative consumption increases for both treatment and control groups over time due to the presence of idiosyncratic shocks. While theoretical reasoning based on an intertemporal budget constraint and a transversality condition would imply a long-term MPC of one, we lack the statistical power to investigate whether long-term MPCs are indeed one.

Additional results are reported in the appendix. First, Appendix Figure A3 shows that the results are similar when leads are included in specification (1), with no sign of pre-trends. Second, Appendix

Figure A4 depicts our MPC estimates against other estimates in the literature. Third, Appendix Figure A5 documents the characteristics of the households who chose not to use the treatment card. Fourth, Appendix Figure A6 shows that treated households increase their savings in liquid accounts at the bank, with a cumulative increase of about 100 euros after a month.

3.2 MPC Estimates By Card Type

Next, we analyze MPC by card type and establish the key result of the paper: the marginal propensity to consume is larger when treatment cards have negative interest rates.

The estimates are reported in Figure 4 separately for the three treatment groups. Panel (a) shows estimates of the β_τ for households in Group 1, with no restrictions. Card 1 leads household to increase their weekly consumption spending in the two weeks after treatment by about 38 euros; the point estimates thereafter are close to zero and not significant. Panel (b) shows that households in Group 2—who receive a card that expires after three weeks—increase their weekly consumption significantly for the first three weeks after treatment, by about 65 euros in the first week, and by about 50 euros in the second and third weeks. There is no sign of intertemporal substitution, as estimates hover around zero after the third week. Finally, panel (c) shows the response for households in Group 3 – with the negative interest rates –, who increase their spending immediately in the first week of the experiment, by about 130 euros, but not thereafter.

Figure 5 reports the cumulative spending response. The figure shows that the cumulative MPC for group 1 is much lower than for groups 2 and 3. After 4 weeks, the cumulative MPC for group 1 is 68 euros (22%), compared with 178 euros (60%) for group 2 and 108 euros (36%) for group 3. The estimates for MPCs over longer horizons become noisier due to idiosyncratic variation in consumption spending diluting the differences between treatment and control groups, but the point estimates for groups 2 and 3 remain large and above the spending response of group 1.[18]

Panel (b) of Figure 5 shows MPC estimates conditional on using the card (at some point) to make purchases The point estimate for the average 4-week MPC of group 2 participants is about 10 percentage points higher, at 70%. In both figures the consumption response to the stimulus transfer is substantially higher for group 2 compared to group 1, indicating that stimulus design choices can strongly affect the MPC. The consumption response is concentrated early on and the MPC is not increasing with time.

These results establish our first three key facts, about the magnitude of the MPC by card type and its time profile:

Fact 1: The average one-month MPC on a cash-like transfer is 22%.

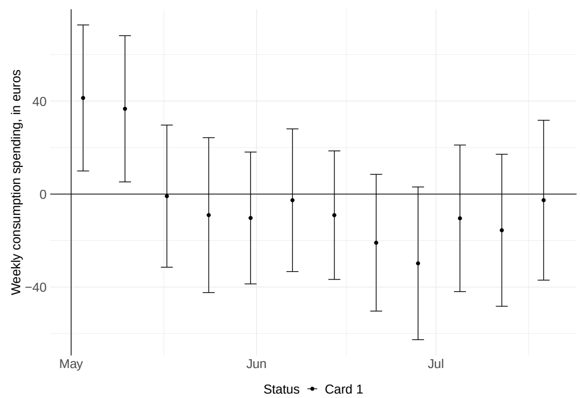
Fact 2: The design of the stimulus transfer can substantially affect the MPC. The average one-month MPC out of a transferred card whose remaining balance expires after three weeks is 60%. The average one-month MPC out of a transferred card whose remaining balance declines every week by about ten percent is 36%.

Fact 3: The consumption response to stimulus transfers is concentrated early on, in the first one to three weeks.

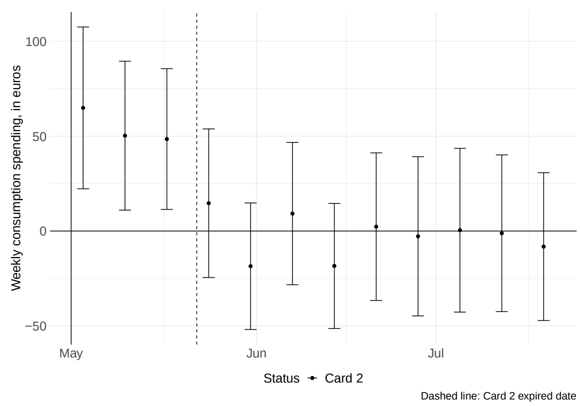
[18] Appendix Figure A2 reports FGLS estimates of cumulative MPCs by card, confirming that the spending response of groups 2 and 3 remain large and above that of group 1 at all horizons.

Figure 4 Consumption Impact by Card Type, Weekly

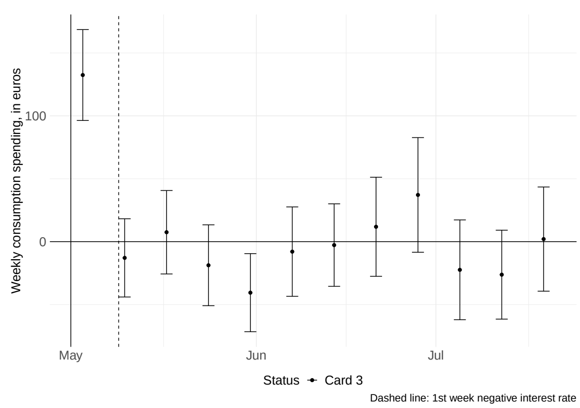
A. Group 1, no restrictions on treatment card



B. Group 2, expiration after three weeks

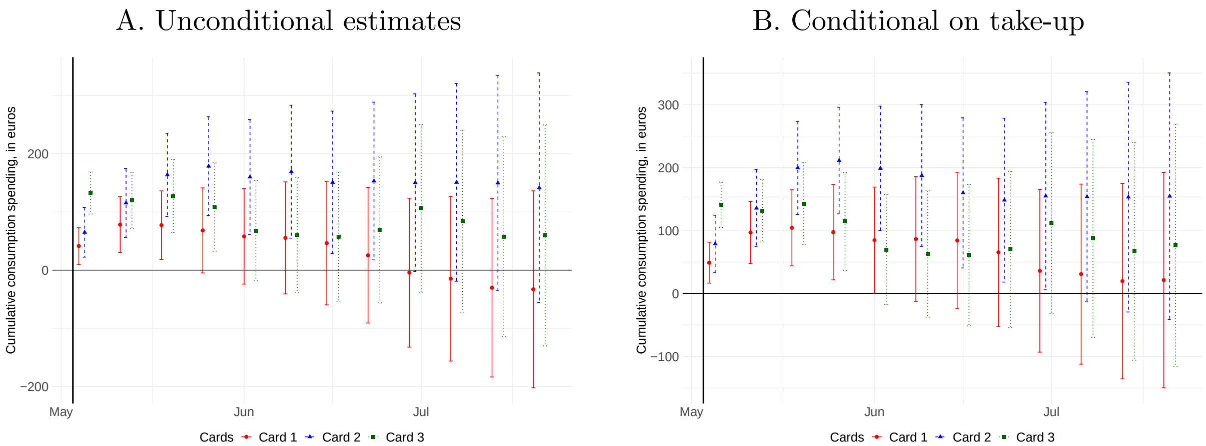


C. Group 3, negative rates every week



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, clustering the standard errors at the household level.

Figure 5 MPC Estimates by Treatment Group



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, clustering the data at the household level.

3.3 Understanding the Spending Response

To better understand participant's spending behavior, we combine two approaches: survey questions to the treatment group,[19] and an analysis of the spending categories for treatment cards and linked bank accounts. We first analyze the patterns for all cards, and then study the three types of cards in turn.

All cards. The results for all cards are presented in Figure 6. Our analysis delivers three takeaways. First, survey responses show that participants are well aware that they spend less on their main account and use the treatment card to substitute for regular spending. They mention precautionary savings as key motive for the money they saved out of the transfer (panel (a) of Figure 6), and they report that they use the treatment card primarily to cover running expenses (panel (b)).

Second, we use the treatment card and the bank data to analyze the composition of expenditures. For each transaction, our data contains the 4-digit merchant category code (MCC) that is associated with the vendor. Panel (c) of Figure 6 shows that treated households spend more on clothing and household equipment (furniture, consumer electronics, etc.). Panel (d) breaks down the purchases on the treatment cards by category, confirming the importance of spending on clothing and electronics.

Next, we examine whether there are significant differences in terms of spending on durables. Extending the product clasisfication from Ganong and Noel (2019), we classify MCC codes into one of four spending categories used by the French National Statistical Institute (INSEE): nondurables (including food and drink, fuel, and items that depreciate quickly), semi-durables (including, notably, apparel, footwear, and other textiles), durables (furniture, electronics, and durable household equipment, as well as leisure items and cars), and services. Appendix Table A3 provides examples of products belonging to each of these categories.We also build a crosswalk to the French input-output table to assess the import content of

[19]The survey was administered via the implementation partner's web platform. The survey response rate is 46% among the participants. We find that the average MPC is the same in the subsample as in the full sample.

households' consumption baskets. We find that the spending share on durables increases to 10 percent upon treatment, relative to about 7 percent in the control group, as reported in panel (e) of Figure 6.

Finally, we analyze the propensity to spend on imports. We measure imports by mapping the MCC codes to the French input-output tables, which provides import penetration rates across categories. We find that treated households make purchases that have on average a higher import content, resulting in an increase in the weighted average import share from 7% in the control group to 9% in the treatment group (panel (f)). While these differences are statistically significant, they are modest from an economic perspective. For example, the 2 percentage point increase in the import share is too small to generate concerns that economic stimulus payment primarily increase aggregate demand for foreign trading partners.

By card type. We now repeat the anlaysis by card type. We first rely on the survey results, reporting the answers in panels (a) and (b) of Figure 7. We find that households in Groups 2 and 3 report that they are less likely to cover running expenses (panel (a)) and more likely to make large purchases earlier (panel (b)), consistent with the higher MPC estimates in the data.

Second, we decompose the consumption expenditure increase by durability. Table II shows the estimated fraction of the expenditure increase on each of the four durability categories by dividing the 4-week cumulative point estimate of a regression of consumption expenditure in the row category on time-since-treatment dummies (and fixed effects as in the baseline specification) by the corresponding 4-week cumulative point estimate in a regression of all consumption expenditures (the baseline specification). Because some expenditures (notably those done with cash) cannot be classified, the coefficients do not add up to exactly 100% across categories.

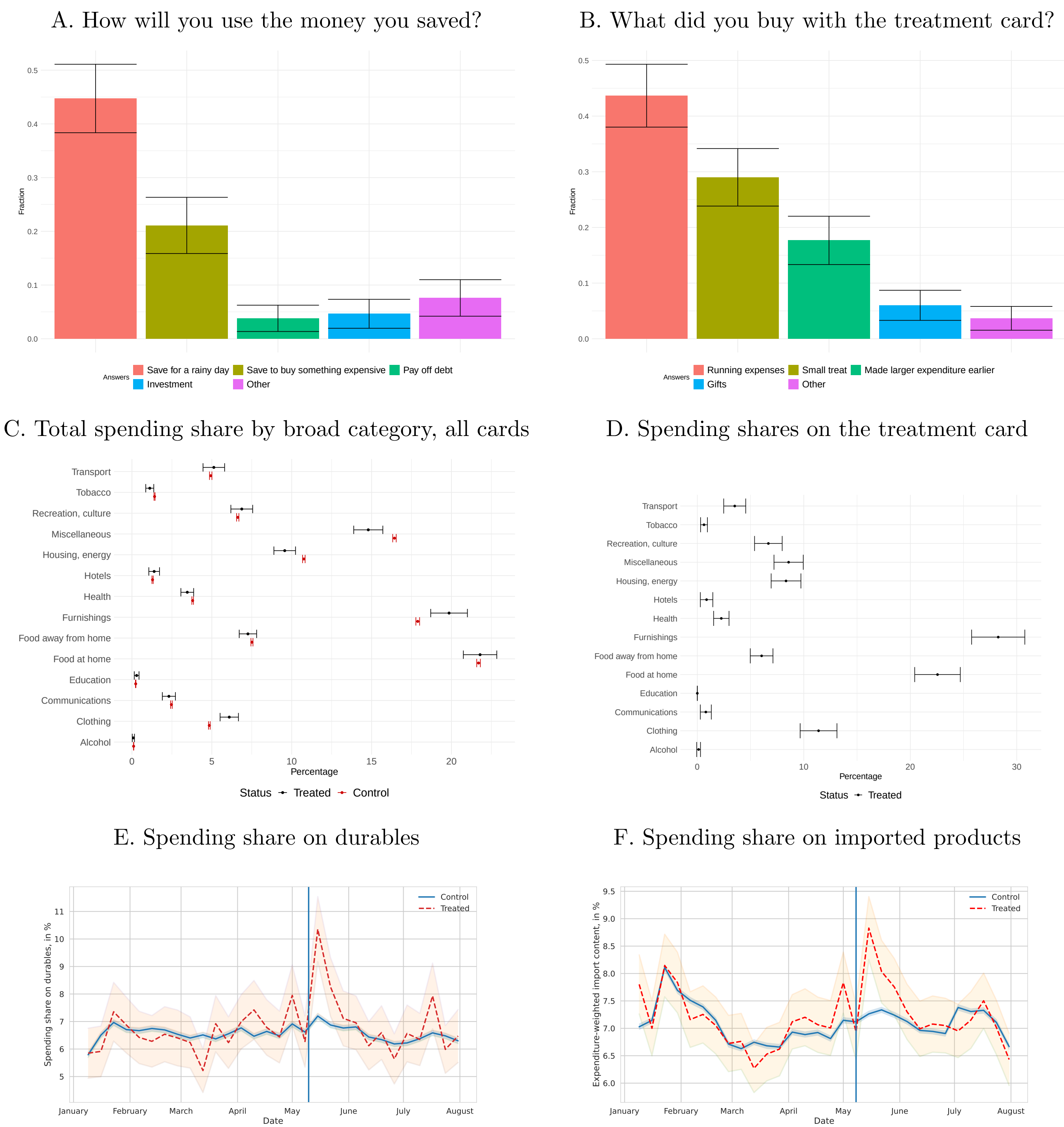
The results show that the consumption expenditure increase goes to a substantial extent into the purchase of semi-durable goods, mirroring the earlier results that clothing purchase shares are higher among treated households. Households that receive treatment card 2 channel a substantial fraction of the additional expenditure into personal services, whereas card 3 households see a disproportionate increase in durables purchases. Considering all three cards together, Table II shows that the short-run spending response isn't driven by spending on durables, as card 3 alone features a substantial increase on this category. Appendix Figure A7 shows the MPCs on these categories across different horizons.

Table II Decomposition of 4-week MPC by type of expenditure

	Card 1	Card 2	Card 3	Average pre-period expenditure share
Nondurables	25%	8%	26%	31%
Semi-durables	49%	35%	33%	9%
Durables	20%	24%	57%	15%
Services	2%	36%	-11%	36%

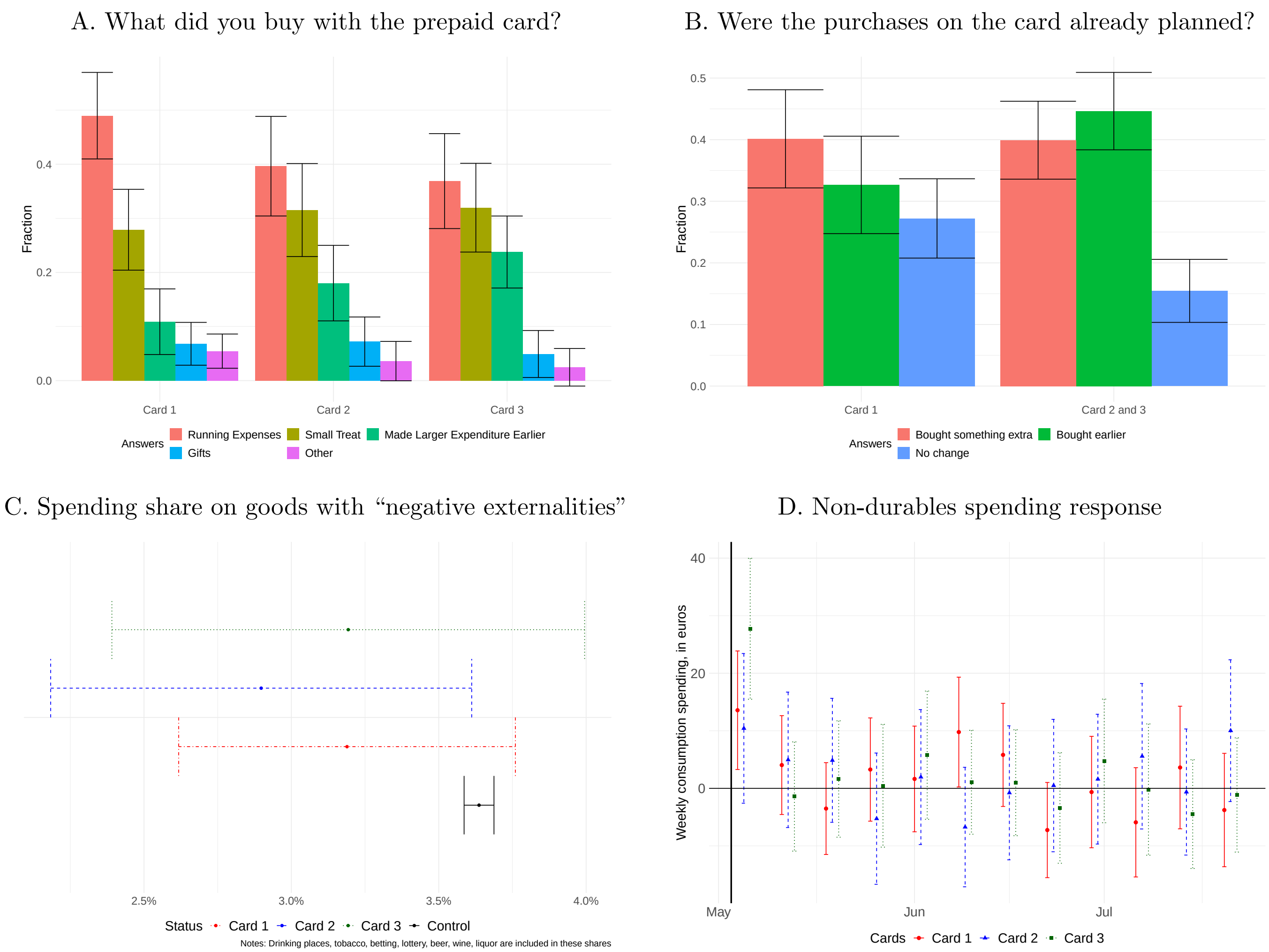
Notes: This table reports the average 4-week MPC on the row category divided by the total 4-week MPC (any consumption expenditure), for treatment groups 1, 2, and 3. The rightmost column shows the average pre-period expenditure shares on the row category. Columns do not add up to 100% because some expenditures cannot be classified into those four categories.

Figure 6 Understanding Participants' Spending Behavior, All Groups



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 across product categories. Panel C shows expenditure shares in the total expenditure basket, panel D shows expenditure shares using the treatment cards only. Panel E shows the weekly average expenditure share on durables (as defined in the PCE classification) for treatment and control groups; panel F shows the import content of households' expenditure baskets. The import content for each household's consumption basket is the expenditure-weighted industry-level import content. The industry-level import content has been constructed using INSEE's input-output tables for France.

Figure 7 Understanding Participants' Spending Behavior by Card Type



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). Panel D documents the spending response for non-durables by card.

A potential concern is that the higher overall spending response wihth Cards 2 and 3 might come at the expense of the "quality" of spending. For example, a recent study by Jaroszewicz et al. (2022) finds that unconditional cash transfer taking place during Covid-19 sometimes had detrimental effects on recipients' self-reported measures of well-being in a sample of about 5,200 US households living in poverty. Other papers have documented that consumption opportunities may lead to a "consumption binge", with the potential to reduce welfare in the long run (Garber et al., 2022). We study survey and spending outcomes to understand whether our transfers could have caused harm to some participants.

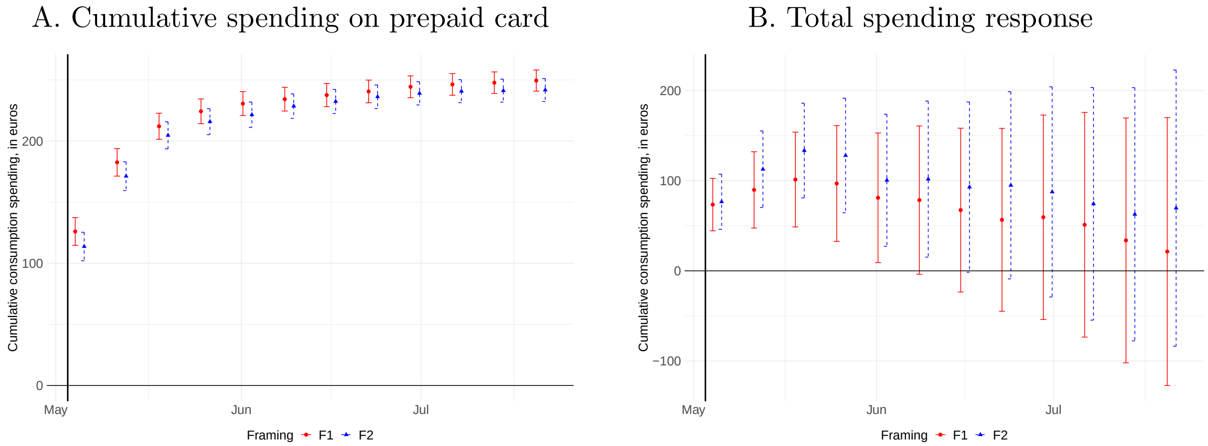
We first examine whether the spending share on goods that can be deemed to have "negative externalities" (drinking, tobacco, better, and lottery products) differs across treatment arm. Panel (c) of Figure 7 shows that there is no significant difference across treatment groups. Second, we analyze whether participants of Groups 2 and 3 experience a fall in nondurable consumption, or higher volatility, which could be caused by an initial "consumption binge". Panel (d) of Figure 7 rejects this hypothesis: participants in Groups 2 and 3 spend more on nondurables in the short run, and experience no fall in the longer-run. Finally, we use the survey to elicit the subjective impact of the transfer. In response to the question: "Has the transfer of the 300 euro card increased your happiness?", only eight out of 391 respondents (or 2%) report that the transfer has not at all increased their happiness. 92% of respondents respond that the transfer has either "very strongly" or "somewhat" increased their happiness. We therefore conclude that it is very unlikely that our implementation design choices have caused harm, while they led to a large increase in MPCs.

3.4 MPC Estimates By Framing Group

Finally, we evaluate whether households in the different framing groups have different average MPCs. Figure 8 reports the results. We find that households that received the additional framing treatment have very similar average consumption expenditure levels overall (difference in MPC $<$ 10pp, and not statistically significant) as households that did not receive the framing treatment. We also examine whether the composition of expenditures varies across groups, finding no difference. For example, spending on imports is similar across the two framing groups (Appendix Figure A8). Households in the framing group are however more likely to respond they used the trasnfer to buy a "treat" for themselves in the post-experiment survey, which is consistent with experimenter demand effects.

Thus, we conclude that implementation design choices are powerful tools to increase the MPC, while written framing treatments have small effects.

Figure 8 MPC Estimates by Framing Group



Notes: This figure reports MPC estimates depending on the framing group. Participants in framing group 2 receive a letter encouraging them to spend quickly, on products made in France that they would not have purchased without the transfer. Participants in framing group 1 receive no such nudge. Panel A reports spending patterns on the prepaid card, while panel B report the overal MPC. In panel B, 95% confidence intervals are reported, clustering the data at the household level.

4 MPC Heterogeneity across Households: Facts #4 & #5

We now turn to the analysis of MPC heterogeneity across households. Estimating MPC heterogeneity is key both for policy – as policymakers may want to target certain households to maximize the aggregate MPC – and for macroeconomics models – as MPC heterogeneity is a useful moment to assess the accuracy of the predictions and potential falsify certain models. We first document MPC heterogeneity by observable household characteristics (Subsection 4.1), establishing our fourth key fact about MPCs. Finally, we present estimates of the unconditional distribution of MPC across households with a deconvolution approach (Subsection 4.2), our fifth key fact about MPCs. We discuss the implications of our findings in Section 5.

4.1 Heterogeneity By Observable Household Characteristics

To examine the important of various observable household characteristics in predicting treatment effect heterogeneity, we first use a simple OLS specification, and then turn to a machine learning (LASSO) analysis.

OLS analysis. We first estimate differences in the marginal propensity to consume for households with different characteristics. Specifically, we estimate specifications of the form:

$$Y_{it} = \sum_{q=1}^{4} \sum_{\tau=0}^{\tilde{T}} \beta_\tau^q 1(\tau \text{ weeks since } i \text{ treated})_{it} 1(X_i \in Q_q^X)_i + \alpha_i + \alpha_{tEQ_q^X} + \varepsilon_{it} \tag{2}$$

where Q_1^X to Q_4^X are the quartiles of the distribution of the time-invariant household characteristic X.

We consider six characteristics: net liquid wealth, net illiquid wealth, average pre-treatment consumption, total revenue, age, and gender. The first four variables are motivated by macroeconomic models, which make predictions about heterogeneity in the MPC by net wealth (e.g., Kaplan and Violante, 2014) and by current or permanent income (e.g., Straub, 2019); we further discuss the relationship between our findings and these models in Section 5.[20] In addition, we consider age and gender, as these characteristics are easily observed and could in principle be used to target transfers toward certain populations.

The variables are built as follows. Net liquid wealth correspond to the sum of household-level current account and liquid saving deposits net of short-term debt (for instance consumption debt) at the bank. Net illiquid wealth captures the sum of illiquid savings, asset level and mortgage debt for the household at the bank level. Average pre-treatment consumption is measured as the average monthly consumption expenditure in the year prior to treatment, at the household level. Lastly, we define revenue at the household level as the sum of all incoming transfers.[21] Except for average pre-period consumption, which is computed as an average over a year, these variables are averages over the monthly levels in the six months prior to the experiment. We obtain similar results when liquid wealth is measured at the beginning of the experiment, rather than as an average over several months. Regarding age and gender, the characteristics pertain to the eligible household member.[22]

Figure 9 reports the results, plotting cumulative MPCs across household groups. We first consider the role of liquid and illiquid wealth, in Panels (a) and (b). Panel (a) shows that MPCs fall with the level of net liquid wealth. Although the standard errors are sizable, there appears to be a systematic negative relationship between the level of liquid wealth and the MPC. Panel (b) turns to illiquid wealth, depicting a negative relationship between MPCs and illiquid wealth quartiles. Despite these negative relationships, Appendix Figure A9 shows that the MPC remains high even for households who have substantial liquid wealth, a fact we will use later on when drawing implications of our findings for consumption models.

Next, we turn to income, in Panels (c) and (d). We first consider our proxy for permanent income, average consumption prior to the experiment. Panel (c) shows that MPCs tend to be lower for households with higher levels of consumption prior to the experiment. The MPC is particularly high for households in the lowest quartile, with a cumulative MPC of about 75% after three months. For the fourth quartile, the cumulative MPC is close to zero starting one month after treatment. Panel (d) reports that MPCs fall with household income. The MPC is again very high for the bottom quartile, around 75% after three months, while it is close to zero for the top quartile.

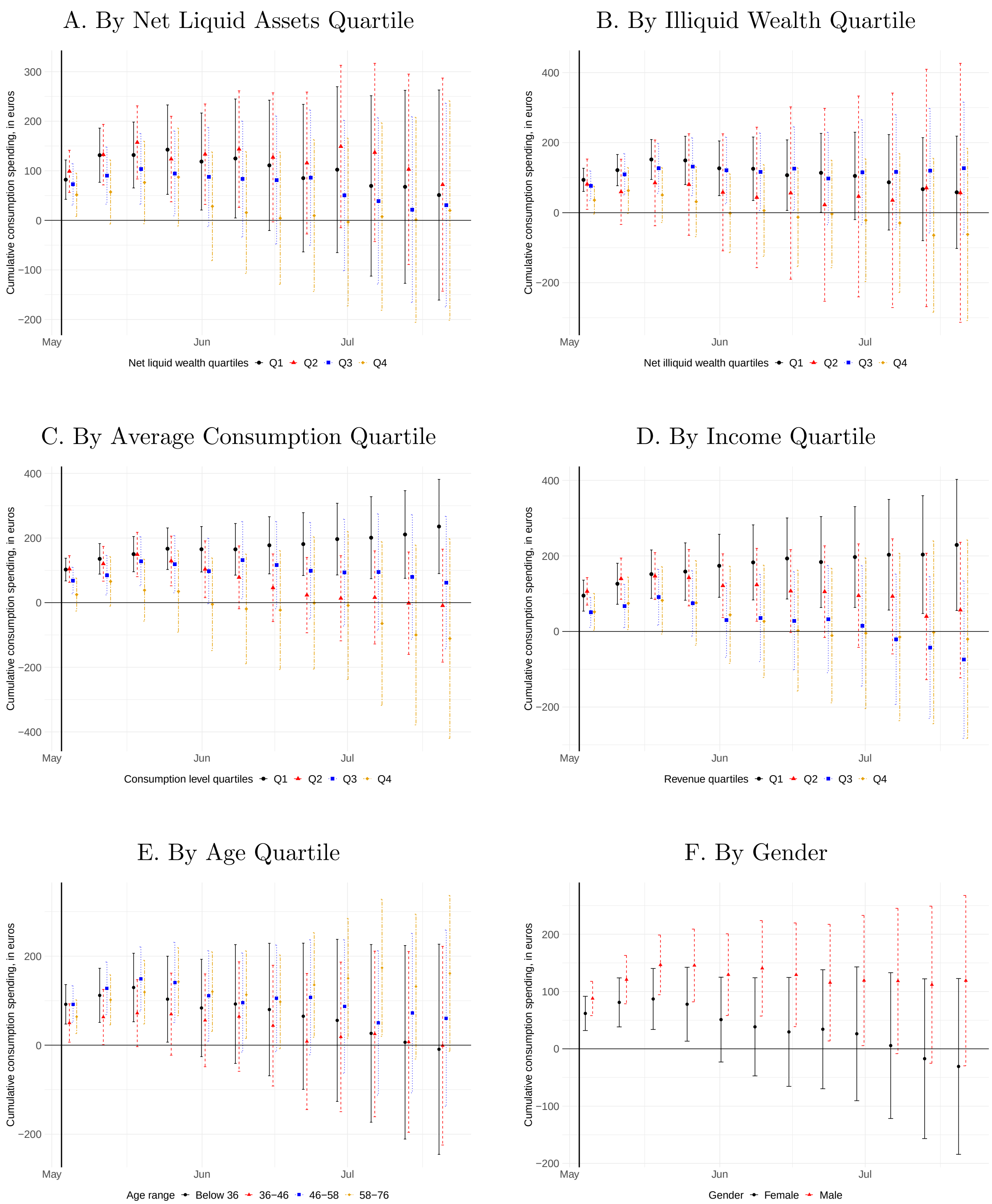
Finally, Panels (e) and (f) consider in turn age and gender. Panel (e) shows that households above the age of 58 have a higher MPC, close to 60% after three month, while at this horizon the MPC is close to zero for households below the age of 46. Turning to gender, Panel (f) show that women have a much lower MPC than men. After three month, the cumulative MPC is close to zero for women while it is around 40% for men. Appendix Figure A10 shows that the higher MPC for women is observed regardless of the number of household members. Overall, income and gender constitute the strongest sources of heterogeneity.

[20] We use average consumption prior to the experiment as a proxy for permanent income.

[21] Inflows above 15 000 euros are trimmed out at the household level.

[22] In the case of multiple eligible household members in the control group, we pick one of the eligible members at random and use their characteristics. For treated households, age and gender are taken from the selected individual.

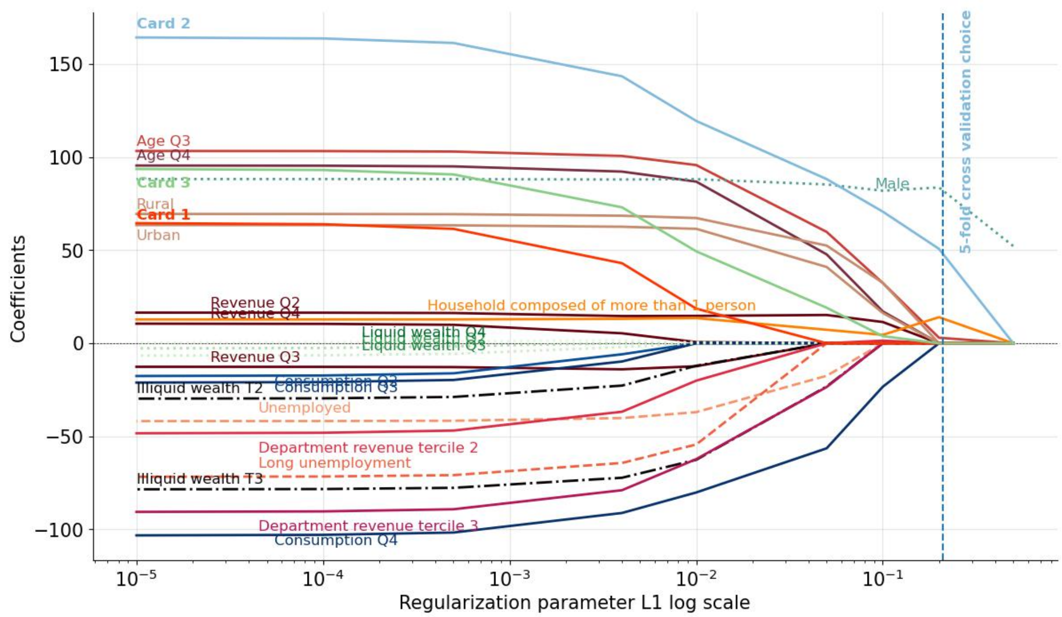
Figure 9 MPC Heterogeneity by Observable Household Characteristics



Notes: This figure reports MPC estimates depending on observable household characteristics. 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.

LASSO analysis. We now turn to a set of regressions that attempts to uncover which household characteristics are most relevant for explaining MPC heterogeneity. We implement specification (2) with all six variables (divided into quartiles when relevant) included jointly. In order to avoid overfitting, we estimate the coefficients using a LASSO estimator, for varying levels of the regularization parameter. Although these results do not isolate causal links, they reveal which variables are the most important predictors when they are used jointly.

Figure 10 LASSO Estimates of Treatment Effect 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). The dashed vertical line shows the regularization parameter chosen by 5-fold cross validation.

Figure 10 shows the results of our estimates on the entire sample of treatment and control group participants.[23] We find that the most important variables to predict treatment effect heterogeneity are demographic characteristics – specifically, gender, high-age dummies, household size, and the location characteristic (urban vs. rural; the omitted category is semi-urban) – as well as the dummy that captures the top quartile of average past consumption (our proxy for permanent income). Conditional on these characteristics, others contribute little to predicting treatment effect heterogeneity. Perhaps surprisingly, revenue and wealth (whether liquid or illiquid) have little predictive power to explaining MPC heterogeneity. The results also clearly show how the variables that capture variation in the treatment design – our treatment group dummies – stand out in explaining treatment effect heterogeneity.

While leading macroeconomic model highlight the role of liquid and illiquid wealth as key predictors of treatment effect heterogeneity, our LASSO analysis show that other predictors are more powerful. We further discuss the implications of these results for household targeting in Section 5.2.

Takeaways. The OLS and LASSO results together establish our fourth key fact:

[23]Results are similar when including only treatment group 1 and control group, see Appendix Figure A11.

Fact 4: MPCs strongly vary across observed characteristics, in particular by gender, age, and proxies for permanent income.

4.2 Unconditional Distributions of MPCs

We now proceed to estimating the unconditional distributions of MPCs across households, regardless of observable household characteritics. Absent additional assumptions, our experimental design does not allow us to recover the distribution of treatment effects, only the average MPC or treatment effects at various quantiles of consumption expenditures. We discuss below the additional assumption necessary to achieve identification of the unconditional distribution of MPCs, and we then present the results.

Setting, identification, and estimation. The fact that we have an experimental setting allows us to recover the full distribution of the marginal propensities to consume under relatively weak assumptions. We consider the model

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

where now, in contrast to the previously studied model, we assume that the β_τ are stochastic, with $\beta_\tau \sim F_\tau$. We further assume that the β_τ are independent from ε_{it}; we discuss and test this key assumption at the end of this section. As before, the treatment dummies are independent from the errors ε_{it}, as well as from the β_τ, due to the experimental design.

We seek to recover the distribution of $\sum_{\tau=0}^{\tilde{T}} \beta_\tau$, which correspond to the $\tilde{T}$-period marginal propensities to consume. Under the assumptions stated above, the distributions F_τ and therefore the distribution of the $\tilde{T}$-period marginal propensity to consume is identified under no parametric assumption.

The model thus takes the same form as a classic measurement error model (see Schennach, 2016 for a survey), and the distribution of the β_τ can be estimated using a deconvolution method: we first estimate the distribution of ε_{it} from the population of untreated households, and we then deconvolve that distribution from the distribution of the dependent variable of the treated at time of treatment. Inutitively, apart from the fixed effects α_i, α_{tE}, the distribution of outcome variables for treated and untreated households differ *only* because of the presence of the treatment effect terms β_τ. Under the assumption that the β_τ are independent from ε_{it}, we can recover the distribution F_τ. Note that the plausibility of the assumption that the treatment and control groups have identical distributions of error terms ε_{it} would be much harder to defend in a non-experimental setting.

We implement this approach in a two-step procedure. In the first step, we estimate α_i and α_{tE} from the set of observations (i, t) where either i is not in the treatment group, or i is in the treatment group but has not been treated yet, in the spirit of Borusyak et al. (2021).[24] In the second step, we construct

[24]Technically, we first estimate household effects α_i from all pre-treatment observations; then, conditional on these estimates, we estimate α_{tE} from control group observations. We choose this sequential procedure to avoid asymmetries across treatment and control groups in the precision of $\hat{\alpha}_i$.

cumulatives of de-meaned log consumption:[25]

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

We estimate the distributions of $\sum_{\tau=0}^{\tilde{T}} \beta_\tau$ through deconvolution, constraining the distribution of the estimand to have only positive support. This constraint is motivated by the fact that we find no evidence for a fall in consumption anywhere in the distribution, as shown in Appendix Figure A12, which reports the quantile treatment effects, i.e. the differences in the quantiles of the distributions of $C_{it}^{\tilde{T}}$ for treated and untreated households, over 4-week, 8-week, and 12-week horizons.[26] The figure shows that the left tail of the distributions of cumulative de-meaned consumption is the same for treated and control, implying that the treatment effect distributions do not have mass on the negative part of the real line.

We use the flexible quadratic-programming-based estimation procedure proposed by Yang et al. (2020), which, compared to standard Fourier-based methods, has the advantage that it also allows the density to be restricted to be non-negative on its support and to integrate to one, restrictions that we also impose. Since deconvolution estimates often suffer from from oscillating densities in the tails, Yang et al. (2020) recommend regularizing the density estimates through a penalty term. We follow this suggestion and penalize oscillations by adding a weighted finite-difference estimate of the second derivative of the density, with a small penalty weight ($\lambda = 10^{-5}$).

Results. Figure 11 shows estimates for the distribution of 4-week and 8-week cumulative treatment effects by treatment group. The median treatment effects are close to the ATE estimates we obtained in Section 3.2 for each card type, at 25%, 53%, and 40% for groups 1, 2, and 3, respectively. These treatment effects are measured as cumulative percentage deviations from the mean weekly consumption (on average 417 euros), and are therefore not directly interpretable as MPCs. Instead, they should be interpreted as deviations from the average consumption.[27]

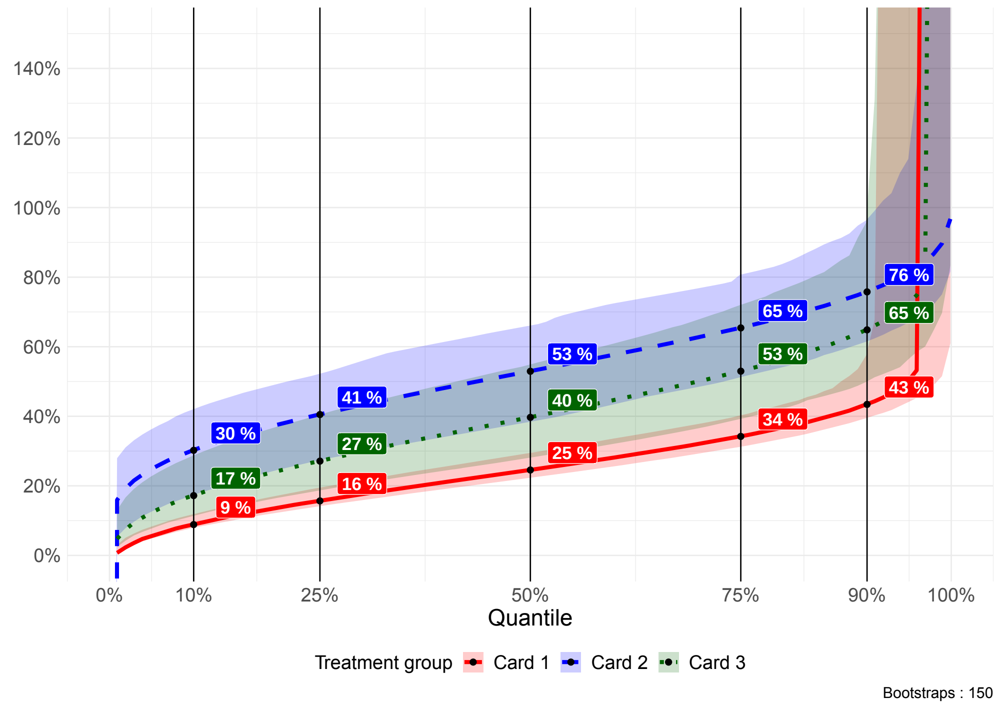
The estimates show a substantial heterogeneity in the propensity to consume out of the transfer, with the bottom quartile increasing their consumption expenditure by less than 16% (card 1), 41% (card 2), and 27% (card 3) of average weekly consumption, while the top decile increases consumption by more than 43% (card 1), 76% (card 2), and 65% (card 3). The distribution of estimated treatment effects for group 2 first-order stochastically dominates the distribution of group 1. Appendix Figure A13 shows results for specifications where we drop nonnegativity constraints and regularization, yielding similar findings.

[25] A model specification where the level (as opposed to the log) of consumption expenditure is linear in the treatment effects would permit direct interpretation of the treatment effect as an MPC. Consumption expenditures, however, are skewed and the deconvolution estimator is sensitive to this skewness, which is why we prefer a model specification in logs.

[26] To avoid confounding treatment effects with the potentially different tails of households of different size, we currently conduct the exercises in this subsection on households with one eligible member only.

[27] Prior work has also attempted to estimate the distribution of MPCs. Misra and Surico (2014) compare spending distributions of US households around the 2001 and 2008 tax rebates using data from the Consumer Expenditure Survey. In contrast to our results, they find that significant shares of households experience negative treatment effects. The fact that the left tails of the spending distributions of treated vs untreated households are very similar (Appendix Figure A12) is difficult to reconcile with negative MPCs in our data. Furthermore, Lewis et al. (2019) use clustering-based Gaussian Mixture linear models to estimate MPC heterogeneity following the 2008 tax rebates. In their model MPCs vary across groups; group memberships and MPCs for each group are identified through parametric assumption on the error terms. In contrast to their approach, our treatment effect distribution is identified and estimated entirely nonparametrically.

Figure 11 Household-level Quantiles of the 4-week Cumulative Percentage Deviation from Mean



Notes: This figure reports the quantiles of the distribution of 4-week treatment effects by treatment group. Note that since the dependent variable is log consumption, the treatment effects are cumulative percentage deviations from the mean consumption level (on average 417 euros), and are therefore not directly comparable to the MPCs reported above. Shaded regions are delineated by the 10th and 90th percent quantile of the bootstrapped simulated distribution of the corresponding moment.

These results establish our fifth key fact:

Fact 5: There is substantial heterogeneity in the unconditional marginal propensity to consume out of a windfall transfer, and a large fraction of households has a high MPC.

Robustness. The key assumption for identification of the treatment effect distribution is that the error term is independent from the treatment effect distribution. This assumption may be violated if, for example, certain subgroups of the population (say, poorer households) that have a higher average treatment effect also happen to have systematically different errors terms ε_{it} shortly after the experiment was conducted (for example, because of calendar events such as bank holidays, where poorer households may increase spending less than others). Our experimental design cannot address this potential threat to identification, which depends on the correlation between the heterogeneous treatment effects and the unobserved error terms.

To investigate the robustness of our estimates we conduct an exercise where, in the first step of the estimation procedure, we project consumption on household fixed effects 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 (instead of projecting it on just household and week fixed effects). The resulting estimates of the treatment effect distribution remain virtually unchanged. Therefore, for our results to be biased, unobservable predictors of MPC heterogeneity should be much more strongly correlated with unobserved shocks ε_{it} than observable predictors. This robustness test, in the spirit of Oster (2019), lends support to our baseline estimates.

Furthermore, Appendix Figure A14 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 the funds available on the treatment card, consistent with the large MPC heterogeneity uncovered by our approach.

Finally, Appendix Figure A15 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 first-order stochastically dominate the MPC distribution from treatment card 1.

5 Implications

We now discuss the implication of our five facts about MPCs, for both macroeconomic models and stimulus policies.

5.1 Implications for Models

Our experiment is not designed to test any particular model of consumption, but to instead robustly estimate moments of consumption responses to transfers that are scalable and therefore relevant for policy. Nonetheless, it is worth discussing which models of consumption can be reconciled with our findings.

5.1.1 Benchmark Rational Models

We first compare our findings with the predictions of canonical "rational" models. In the Heterogeneous-Agent New Keynesian (HANK) model of Kaplan et al. (2018), high average MPCs arise because of precautionary savings in the presence of borrowing constraints. In their baseline calibration, matching moments of the liquid and illiquid wealth distributions and income processes, the simulated consumption response to a one-off lump-sum transfer is long-lived (see Figure 2 in Kaplan et al. (2018)): the estimated MPC is about 17% over a quarter (for a \$300 transfer), about 25% over two quarters, and 32% over one year; furthermore, the high MPCs are entirely driven by households with low levels of liquid wealth. The MPC is long-lived in the benchmark HANK model because agents (rationally) increase spending whenever they hit their borrowing constraints, which happens gradually over time as some agents experience negative idiosyncratic income shocks. Over the first two quarters, the increase in the aggregate cumulative MPC is driven by constrained households, who deplete the rebate in full at this horizon. Afterwards, the aggregate MPC increases more slowly due to the population of unconstrained agents, who consume the annuity value of the transfer. [28]

Our findings stand in contrast with the predictions of the canonical implementation of the benchmark HANK model in three ways. First, even in our treatment group 1 – the group that receives a transfer that is most similar to a cash transfer –, the entire spending response we find is concentrated in the first

[28] See Achdou et al. (2022) for a characterization of how cumulative MPCs vary with the time horizon in the Aiyagari–Bewley–Huggett model.

two weeks after the transfer (panel (a) of Figure 4).[29] In contrast, as previously mentioned the MPC response is much more long-lived in HANK and in canonical buffer-stock saving models.[30] While spending on durables could in principle explain a short-run spending burst in a standard model (Laibson et al. (2022)), we find that the response is also concentrated in the short run for non-durables.

Second, in HANK the simulated MPC is strongly correlated with the level of liquid assets that agents hold. While we do find some heterogeneity of MPCs for groups with different levels of liquid asset holdings, we find that average MPCs are also high for households that have moderate or high levels of liquid asset holdings (Figure 9). In Appendix Figure A9, we show that the MPC remains high even for households that hold wealth above twice their monthly income. These findings echo results from the literature that finds high MPCs even for agents with high liquid wealth, including Kueng (2018) in response to anticipated payouts from the Alaska Permanent Fund, Olafsson and Pagel (2018) in response to regular and irregular income transfers in Iceland, Fagereng et al. (2021) among lottery winners in Norway, and Baugh et al. (2021) in response to expected tax refunds in the United States.[31]

Third, our estimates of the unconditional distributions of MPCs reveal that MPCs are high for a large majority of the population (Figure 11). In contrast, the HANK simulation results that indicate that high MPCs are concentrated among a much smaller fraction of the population, namely agents hitting their borrowing constraint.

Furthermore, our finding that MPCs are higher for households with lower average past consumption (our proxy for permanent income) stands in contrast with standard macroeconomic models featuring homothetic preferences, where the MPC is independent of permanent income. Straub (2019) extends the canonical precautionary savings model to include non-homothetic preferences, allowing for MPCs that vary with permanent income.

Assessing whether suitable calibrations or modifications of the HANK model can match these facts is an important direction for future research.[32] A potential avenue is to augment standard consumption models with certain behavioral frictions. For example, in recent work Boutros (2023) and Lian (2021) develop structural behavioral models in which high-liquidity households have large MPCs because of behavioral biases. Consistent with this line of work, some results of our experiment are difficult to reconcile with agents being rational and treating money as fungible, which we discuss next.

[29]Consistent with our experimental finding, Borusyak et al. (2021) document that the consumption to tax rebates is concentrated in the first two to three weeks after the tax rebate. Likewise, Baugh et al. (2021) find that households spend a significant part of the tax refunds they receive on consumption in the month after receiving the refund. In contrast, analyzing lottery winnings in Norway, Fagereng et al. (2021) estimate a more long-lived MPC response: there is a large consumption response in the first year followed by gradually declining MPCs over several years. This finding could stem from the fact that the lottery winnings are on average larger than tax rebates or tax refunds. The size of the shock matters for the dynamics of the consumption response: for example, Boutros (2023) studies a structural behavioral model in which the planning horizon of the households depends endogenously on the amount of the transitory income shock, such that a larger shock is endogenously smoothed over a longer time horizon.

[30]Auclert et al. (2023) and Angeletos et al. (2023) show how, for certain policy experiments in certain classes of structural macro models, average (intertemporal) MPCs are "sufficient statistics" for the behavior of macroeconomic aggregates.

[31]In contrast to these studies that isolate transitory income shocks, Ganong et al. (2020) study the consumption response to typical month-to-month fluctuations in labor income and find an MPC close to zero for households with high liquid wealth.

[32]See Wolf (2023) for a characterisation of the shape that intertemporal MPCs in HANK models can take, and the extent to which they can be well approximation by simple models with occasionally binding borrowing constraints (as in, e.g., Farhi and Werning, 2019).

5.1.2 Behavioral Models

Our motivation to turn to behavioral models is that the difference in MPCs between households assigned to Group 1 or Groups 2-3 rejects standard rational models where agents treat money as fungible. Indeed, when we consider only transactions below 300 euros (which can be made with the treatment card), we find that 88% of households in Group 2 spent at least 300 euros on the main bank account in the three weeks before the expiry date of Card 2. This indicates that it should be costless for a vast majority of household to substitute current account spending for prepaid card spending. In other words, under the rational benchmark, we expect that the 3-week expiry date for most households in treatment group 2 should not be a binding constraint, i.e., their MPC should be similar to households in treatment group 1, in constrast with our findings.

Figure 12 shows, for each day, the fraction of households in treatment groups 2 and 3 that would have had a high enough balance on the treatment card to cover the day's expenditures (as measured by their spending on non-treatment cards) but for some reason did not use the card. A non-negligible share of households in groups 2 and 3 have a high enough remaining balance on the gift card to cover the day's expenditures but choose to use their regular debit or credit card instead to make purchases. In the first few days of the experiment this ratio may be high because some households had not opened their mail and therefore not started to use the card. But even after more than a week into the experiment, the ratio remains above 50%. Appendix Figure A16 shows that the patterns are the same in a restricted sample of households with a single adult and no children, ruling out the possibility that this phenomenon is driven by multi-person households of whom only one has access to the treatment card.

These facts are hard to reconcile with rational households that treat money as fungible. Indeed, a rational agent that treats money as fungible should first "use up" the treatment card to avoid potentially losing money (through the negative interest rate or expiry) before using their normal debit or credit card. Thus, our results echo a literature in economics (Hastings and Shapiro, 2013, 2018, Gelman and Roussanov (2023)) and in sociology (e.g. Zelizer, 1989) that emphasizes the non-fungibility of money.[33]

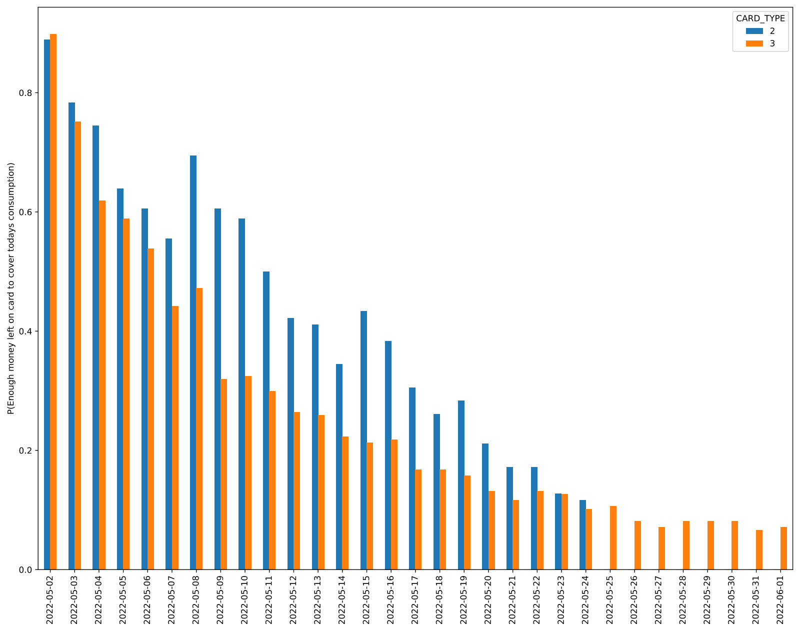
With these patterns in mind, our findings deliver three lessons for behavioral models. First, models of consumption that rely on present bias in preferences (e.g. Laibson, 1997, Maxted, 2020, Laibson et al., 2021, Gelman (2022)) are able to explain why the consumption response to the transfer is concentrated early on, but cannot explain the difference in the magnitude of responses between the treatment groups. Indeed, under such preferences, consumers in all three groups should be present-biased but the negative interest rate and the expiry date would remain non-binding constraints, given that it should be cost-less for agents to substitute current account spending for prepaid card spending. Thus, present bias does not appear to be the key friction explaining our findings.[34]

Second, another class of models that has been used for macro policy analysis is models that feature two sets of agents, "savers" and "spenders", who have low and, respectively, high MPCs (Campbell and Mankiw (1989)). While implementations of such models can be made to feature consumption responses

[33] In contrast to work that has found that the labelling of cash transfers has an impact on spending patterns (Beatty et al., 2014, Benhassine et al., 2015), we detect no significant effect of framing on the magnitude and composition of expenditures.

[34] Loss aversion is another bias that has been widely studies (e.g., Tversky and Kahneman (1992)). It does not appear to be the key friction in our setting because loss aversion does not imply that participants wouldn't treat money as fungible: they could easily avoid any loss – from the expiry date or negative interest rates – by using the prepaid card to cover running expenses.

Figure 12 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 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 gift card (more than 20 euros); (iv) 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 gift card every Monday at 11:59pm.

that are concentrated very early on, they would also imply strongly bi-modal distributions of MPCs, which we do not find (Figure 11). Furthermore, like other models of present bias, this type of model cannot account for the difference in spending patterns by card type.

Third, our results are consistent with models of salience, where small but highly prominent features of the choice set distract the attention of decision makers and distort their choices (Bordalo et al., 2012, 2013). In particular, salience can lead households to engage in "mental accounting" (e.g., Shefrin and Thaler (1988), Thaler (1990), McDowall (2020), Baugh et al. (2021), Boutros (2023)). In Appendix C, we formalize a stylized model of mental accounting that could explain the key empirical patterns we observe for the three treatment groups. In this model, the agent faces a tradeoff when spending the prepaid card on unplanned "treats", i.e., when making purchases akin to surprise gifts. On the one hand, the agent incurs a cognitive dissonance cost if they spend the prepaid card on (planned) regular consumption rather than on an unplanned treat, because of a mental account mechanism: the prepaid card is perceived by the agent to be "special money" meant to be spent on extra consumption, like in the sociology literature (Zelizer, 1989). On the other hand, purchasing treats requires incurring search costs, while using the prepaid card to cover running expenses does not. Resolving this tradeoff in the model, we show that the spending response is concentrated in the short run for all cards and is largest for group 2, followed by group 3 and finally group 1. Intuitively, prepaid cards with an expiry date or a negative interest rate spur the agent to incur the search costs faster, as long as these costs are not too large. This need to take action in the short run is salient and can lead to groups 2 and 3 having higher MPCs than group 1. When the search costs are higher (e.g., when a decision must be made within a week to avoid a negative interest rate, as in group 3), the agent is more likely to cover regular consumption than to purchase unplanned treats, implying a lower MPC than with a longer expiry date (as in group 2).[35]

Another potential mechanism through which the difference in MPCs between groups 2 and 3 could be explained is dual reasoning (Ilut and Valchev, 2023). Agents are confronted with different decision problems and can make decisions either rapidly and intuitively by projecting on past deliberations ("system 1 thinking"), or by carefully considering their choices, which leads to better outcomes but which is also cognitively costly ("system 2 thinking"). Situations where people receive a means of payment that they have a certain time frame to spend, such as in Group 2, are familiar to many from gift vouchers and gift cards, and may lead recipients to behave similarly to how they behaved in such situations (through "system 1 thinking"). In contrast, the situation where the participant receives a means of payment that rapidly loses value is unfamiliar to most, resulting in careful deliberations (activating "system 2 thinking") to avoid the loss of value and, more often than not, the purchase of goods that they would have purchased anyway, implying a lower marginal propensity to consume in Group 3 than in Group 2. Note that we observe that Group 3 participants, triggered by the salience of the one-week ultimatum before they lose money, on average spend more using the treatment card than Group 2 on each day of the first week. Finally, the more careful deliberations of Group 3 participants would lead to fewer "mistakes" in

[35] Analyzing the consumption response to tax refunds and tax payments, Baugh et al. (2021) highlight that the estimates in their study are most consistent with a mental accounting life-cycle model following Shefrin and Thaler (1988). They find that households increase spending when they receive an anticipated tax refund, and that these same households completely smooth consumption when making anticipated tax payments, implying that they have the liquidity to smooth consumption through refunds. Thus, households spend out of tax refunds by choice rather than due to liquidity constraints, consistent with mental acounting. Anticipated tax refunds are part of the "future income" mental account and are not smoothed, while tax payments are part of the "current income" mental account, which leads to consumption smoothing.

the payment choices, explaining why Group 3 participants are seen to have a lower probability of not using the treatment card when they should (Figure 12).

5.2 Implications for Policy

Our results have two immediate implications for policy. First, the large difference in MPCs across treatment groups show that the design of transfers is very important to maximize MPCs. Treatment cards with negative rates — in the form of an expiry date or a weekly negative interest rate – deliver much larger MPCs than a standard cash-like stimulus transfer. Note that because some money ends up being returned in treatment designs 2 and 3, the average consumption stimulus per euro spent by the transferer is actually larger than the MPC estimate reported above. In Appendix Figure A17 we plot the MPC for groups 2 and 3 corrected by the fraction of the money that is being returned in the form of interest payments (group 3) or remaining balance upon card expiry (group 2), which is about 16 percent for both groups. The resulting effective stimulus at the 4-week horizon is about 75 cent per euro of net transfer for group 2, and about 40 cent per euro for group 3.

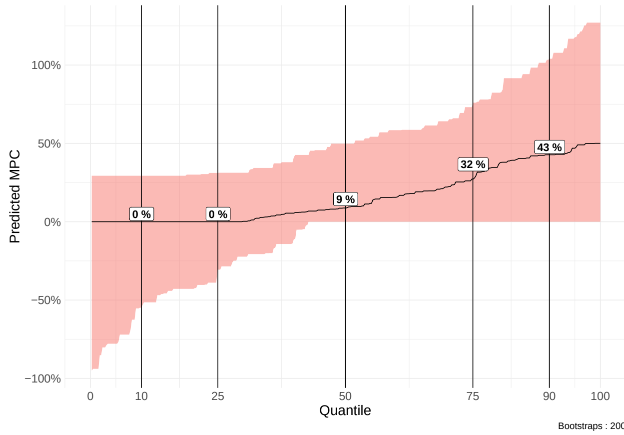
The external validity of our experimental estimates, and its broad applicability to high-income countries, appears plausible given that (i) we used a representative sample of the French population, and (ii) our estimates for group 1 are very similar to those obtained when studying the 2008 tax rebate response in the United States with robust estimators (Borusyak et al. (2021), Orchard et al. (2022)). Our intervention was deliberately designed to be scalable to the macro level, and we note that there are several examples of large-scale stimulus policies using prepaid cards or time-limited consumption vouchers, including Japan in 1999, Taiwan in 2009, California, Milan, and Seoul in 2020, and Hong Kong in 2021. Using prepaid card with negative rates or expiration dates is a promising avenue for stimulus policies going forward, which could potentially be implemented by central banks using central bank digital currencies. It is also worth noting that short-term interest rates were close to zero at the time when our experiment was implemented, indicating the possible potency of particular types of stimulus policies even in a liquidity trap.[36]

Second, our estimates of MPC heterogeneity have implications for the targeting of transfers by observable household characteristics. We documented in Section 4.1 that many household characteristics can be used to predict heterogeneity in MPCs. Thus, transfers could be targeted to the household with the highest MPC. While liquidity is difficult to observe, other predictors are readily accessible to policymakers. To assess the extent to which the average MPC of transfer recipients could be increased by targeting, we conduct a simple exercise: we use the specification from Section 4.1 with two sets of characteristics that policymakers might be able to observe as regressors, and estimate the distribution of MPCs. We estimate the parameters using LASSO to avoid overfitting, in a sample consisting of control group households and households receiving treatment card 1. By plotting the estimated distribution of treatment effects we can thus assess the extent to which household targeting can help increase the MPC for a standard transfer, without negative rates or an expiry date.

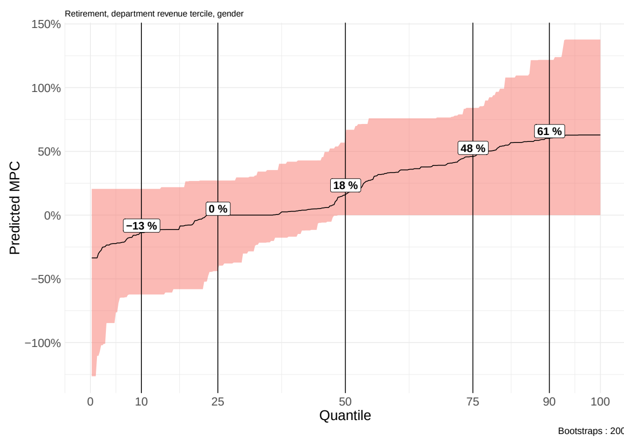
[36]If transfers with expiry dates were used repeatedly, one could worry that households may start viewing these transfers as more fungible with their main bank account, and thus have a lower MPC. However, existing evidence suggest that mental accounting continues to operate even for repeated transitory shocks, as found by Baugh et al. (2021) for tax rebates, by Hastings and Shapiro (2013) for gasoline purchases, and by Hastings and Shapiro (2018) for food stamps.

Figure 13 Predicted MPC Heterogeneity

A. Using age quartiles, income quartiles and unemployment status



B. Using gender, department revenue tercile, and retirement status



Notes: This figure shows the distributions of the predicted MPC heterogeneity, using different sets of characteristics as predictors of the treatment effect in a LASSO specification. Panel A uses age quartiles, income quartiles and unemployment status as features in the LASSO specification, while Panel B uses gender, department revenue tercile, and retirement status as features. The sample is restricted to treatment card 1. The 95% confidence intervals are obtained by bootstrap and shown as shaded regions.

Figure 13 plots the distribution of predicted MPCs. In the first exercise (panel (a)) we run LASSO with age quartiles, income quartiles, and unemployment status. This panel shows that by using these observables it is possible to identify households with substantially above-average MPCs. For example, 10% of households are predicted to have an MPC above 43%. In the second exercise, shown in panel (b), we predict the MPC distribution usind gender, department revenue tercile, and retirement status. The top ten percent of households have an MPC of 61%. Targeting can therefore be a relatively powerful tool to increase the average MPC of recipients, although it is not as potent as changing the design of the treatment card. For example, treatment card 2, with an expiry date, yields an average MPC across *all* participants of 60%. Thus, our estimates highlight that implementation design choices are a more powerful tool, compared to targeting, to increase the recipients' average MPC. In addition, targeting may raise political econonomy or fairness considerations that are avoided by providing a treatment card with an expiry date to all.

6 Conclusion

In this paper we presented five facts about MPCs obtained from a randomized controlled experiment where we provide money transfers to a representative set of French households. These results inform the academic debate on models of consumption, but are also directly relevant for the design of effective stimulus policies. First, we found that the one-month MPC is 22% with a standard treatment card, without negative interest rates. Second, the design of the transfer matters: the one-month MPC is higher when treatment cards feature a negative interest rate: 60% when the remaining balance is reduced to zero after three weeks, and 36% when the remaining balance is reduced by approximately 10 percent every week. Third, the spending responses are concentrated early on, in the first one to three weeks after receiving the transfer. Fourth, heterogeneity in the MPCs that is explained by observed households characteristics is substantial, including by variables distinct from liquid wealth such as current income, proxies for permanent income, and gender. Fifth, the unconditional heterogeneity in MPCs is very large and a large fraction of households have high MPCs.

These five facts are hard to reconcile with standard two-asset models of consumption. They point to the importance of behavioral features (e.g., salience) for macroeconomic model of the consumption response to transfers, such that agents do no treat stimulus transfers as fungible with standard income sources. The "five facts about prices" of Nakamura and Steinsson (2008) called for a reevaluation of menu cost models; much in the same spirit, our five facts about MPCs provide moments that can help discipline consumption and macro models.

From a policy perspective, our findings indicate that implementation design, and to a lesser extent household targeting, are key tools to manipulate MPCs and increase the effectiveness of stimulus. Prepaid cards with negative interest rates or an expiry date deliver much larger MPC than standard fiscal stimulus, and constitute a powerful tool to stimulate demand even when interest rates are low.

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For Online Publication

Appendix to "Five Facts about MPCs"

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October 2023

A 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.

A.1 Sampling and Representativeness

We build on a sample of 300,000 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 revenues 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 regional ("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 slightly over time. We received remote access to anonymized versions of the data that start in January 2019.

The dataset of the 300,000 household is (by design) representative of the population of clients at the bank. However this sample may not be representative of the French population. We can first compare socio-demographic characteristics. Bounie et al. (2020) find that the 300,000 sample is broadly representative of the French population, 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).

Our paper focuses on a subsample of 87,000 households. This sample differs slightly from the full bank sample, with fewer people below 30 and relatively more between 30 and 40. In terms of occupations, our sample under-represent retirees, as well as individuals out of the labor force.

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

A.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. 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.

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

A.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 A.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 gift 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 A.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 A.2).
- Weekly overall expenditure: sum of card purchases and cash withdrawals of the household within the week (according the third table described in Appendix A.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 revenue: 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 identified revenue: average monthly identified transfers to the household's bank account within the six months prior to treatment. Identified transfers correspond to inflows that the bank could classify as salary, social transfers, pensions, or unemployment benefits.

  - Household wealth:

    * Household bank current account: average current account balance over six months prior to treatment. This variable captures the average bank account funds that the household can use at any point in time.

    * Household liquid saving accounts: average liquid saving balance over six months prior to treatment. Ths 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. More information is available here.

    * Household life insurance accounts: average life insurance value over six months prior to treatment.

    * Household illiquid savings: average illiquid saving accounts over six months prior to treatment, including the "share savings plan" (Plan d'épargne en action).

    * Household real estate wealth: real estate wealth reported by the household during a survey conducted in November 2021.

B Experimental Design Appendix

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

B.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 being 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 03/10/2022. 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 15/11/2022 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 15/11/2022 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 15/11/2021). 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 15/11/2021 à 23 heures 59, le solde restant est nul et aucun montant ne sera débité. Si vous dépensez seulement 50 EUR avant le lundi 15/11/2021 à 23 heures 59, le solde disponible sera diminué de 30 EUR et le solde disponible le mardi 05/10/2021 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, 15/11/2021). 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, 15/11/2021, at 11:59 PM, the remaining balance will be zero, and no amount will be debited. If you only spend 50 EUR before Monday, 15/11/2021, at 11:59 PM, the available balance will be reduced by 30 EUR, and the available balance on Tuesday, 05/10/2021, 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:

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: (i) dépenser l'argent aussi rapidement que possible; (ii) 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; (iii) 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: (i) spend the money as quickly as possible; (ii) 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; (iii) 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 27/04/2022 au 03/10/2022 ont été définis par le CAE. Les 1000 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 27/04/2022 to 03/10/2022, have been determined by the CAE. The 1000 participants who are receiving the sum of 300 EUR have been randomly selected under the supervision of a bailiff.*

B.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

Original questionnaire in French:

1. [A tous] Q1. Avez-vous reçu la carte de paiement de 300 euros ?
   - Oui
   - Non
2. [Si Q1=2] Q2. Souhaitez-vous que votre Conseiller CIC vous contacte pour comprendre pourquoi vous n'avez pas reçu la carte de paiement de 300 euros ?
   - Oui
   - Non: [stop interview]
3. [Si Q2 = 1] Q3. Voulez-vous être recontacté(e)... ?
   - Par téléphone
   - Par email
4. [Si Q2 = 1] Q4. Veuillez préciser :
   - [Si Q3= 1 ou 2] Vos nom et prénom
   - [Si Q3 = 1] Votre numéro de téléphone
   - [Si Q3 = 2] Votre email 3 [stop interview]
5. [Si Q1 = 1] Q5. Avez-vous utilisé la carte de paiement de 300 euros ? (que ce soit partiellement ou en totalité)
   - Oui
   - Non
6. [Si Q5 = 1 + si groupes = 2 ou 3 (on exclue ici le groupe 1 car il n'est pas surprenant de ne pas tout dépenser ; les autres groupes perdent de l'argent s'ils ne dépensent pas)] Q6. Vous avez indiqué avoir utilisé la carte de paiement de 300 euros. Vous avez dépensé :
   - L'intégralité des 300 euros ?
   - Seulement une partie des 300 euros ? Pouvez-vous nous expliquer pourquoi vous n'avez dépensé qu'une partie des 300 euros ?

- Je ne sais pas

7. [Si Q5 = 1] Q7. Combien de temps après avoir reçu la carte avez-vous commencé à l'utiliser ?

    - Le jour meme
    - Entre 2 jours et 7 jours après avoir reçu la carte
    - Entre 8 jours et 15 jours après avoir reçu la carte
    - + de 15 jours après avoir reçu la carte
    - Je ne sais pas

8. [Si Q5 = 2] Q8. Vous avez indiqué ne pas avoir utilisé la carte de paiement de 300 euros. Pourquoi ?

    - Parce que j'ai eu des problèmes techniques avec la carte (ex : je n'ai pas compris comment l'utiliser, je ne connaissais pas le code confidentiel pour l'utiliser...)
    - Parce que je n'avais pas confiance, je n'étais pas rassuré(e)
    - Parce que je n'ai pas eu le temps de l'utiliser
    - Parce que je dépenserai l'argent plus tard
    - Parce que j'ai fait le choix de ne pas l'utiliser. Pouvez-vous précisez pourquoi ?
    - Autre. Précisez svp

9. [Si Q5 = 1] Q9. Avez-vous eu un problème dans l'utilisation de la carte pour faire des achats sur internet ?

    - Oui
    - Non
    - Je n'ai pas fait d'achat sur internet avec cette carte

10. [Si Q9 = 1] Q10. Est-ce que ce problème a eu un effet sur le montant total de vos dépenses ?

    - Oui. Pouvez-vous précisez pourquoi ?
    - Non
    - Je ne me prononce pas

11. [Si Q5 = 1] Q11. Globalement, quel est votre niveau de satisfaction à propos de cette carte de paiement d'un montant de 300 euros, qui vous a été offerte ?

    - J'en suis très satisfait(e)
    - J'en suis plutôt satisfait(e)
    - J'en suis plutôt insatisfait(e)
    - J'en suis totalement insatisfait(e). Pourquoi ?

12. [Si Q5 = 1] Q12. Diriez-vous que cette carte de 300 euros :

- a très fortement impacté votre bonheur
- a plutôt impacté votre bonheur
- n'a plutôt pas impacté votre bonheur
- n'a pas du tout impacté votre bonheur

13. [Si Q5 = 1] Q13. Lors de l'utilisation de cette carte de paiement de 300 euros, avez-vous favorisé l'achat de services locaux (ex : coiffeur, fleuriste, maraicher…) ou de produits fabriqués en France ?

    - Oui, tout à fait
    - Oui, plutôt
    - Non, pas vraiment
    - Non, pas du tout

14. [Si Q5 = 1] Q14. Sur l'ensemble des dépenses que vous avez faites sur votre carte de 300 euros, diriez-vous que vous avez utilisé principalement cette somme pour :

    - faire un ou plusieurs achats qui n'étaient pas prévu(s)
    - avancer un ou plusieurs achats qui étaient déja prévu(s)
    - cela n'a rien changé à mes achats

15. [Si Q5 = 1] Q15. Pour quel type de dépenses avez-vous utilisé la somme reçue ?

    - J'ai principalement utilisé la somme pour couvrir des dépenses de consommation courante que j'aurais faites de toutes manières (ex : nourriture, factures habituelles, essence…)
    - J'ai principalement utilisé la somme pour me faire un "petit plaisir" que je ne me serais pas accordé sinon
    - J'ai principalement utilisé la somme pour avancer l'achat de quelque chose de coûteux que je prévoyais déjà d'acheter (ex : achat d'équipement, électro-ménager, matériel informatique, achat d'une voiture, d'un séjour de vacances…).
    - J'ai principalement utilisé la somme pour faire un cadeau à ma famille ou des amis.
    - Autre. Précisez svp.

16. [Si Q5 = 1] Q16. Diriez-vous que cette carte de 300 euros vous a permis de dépenser moins sur votre compte bancaire principal ?

    - Oui
    - Non
    - Je ne me prononce pas

17. [Si Q16 = 1] Q17. A quoi va vous servir l'argent que vous n'avez pas dépensé sur votre compte bancaire principal du fait de cette carte?

- À économiser pour acheter quelque chose de coûteux (ex : achat d'équipement, achat d'une voiture, d'un séjour de vacances. . .)
- À économiser pour faire face aux imprévus
- À investir l'argent non dépensé
- À anticiper le remboursement d'une dette
- Je ne me prononce pas
- Autre. Précisez svp

18. [A tous] S1. Vous êtes :

- Une femme
- Un homme

19. [A tous] S2. Quel est votre age ?

- Entre 18 et 34 ans
- Entre 35 et 49 ans
- Entre 50 et 64 ans
- Entre 65 et 85 ans
- 86 ans et plus

20. [A tous] S3. Quelle est votre profession actuelle ?

- Agriculteur(trice) exploitant(e)
- Artisan(e), commerçant(e), chef d'entreprise
- Profession libérale
- Cadre, profession intellectuelle supérieure
- Profession intermédiaire (agent de maîtrise, technicien . . .)
- Employé(e)
- Ouvrier(ère)
- Retraité(e)
- Autre inactif(ve) (étudiant(e), en recherche d'emploi, invalide, rentier. . .)
- Ne souhaite pas répondre

21. A tous S4. Combien de personnes composent votre foyer ?

- 1 personne
- 2 personnes
- 3 personnes
- 4 personnes

- 5 personnes
- 6 personnes et +

22. [A tous] S5. Le CIC est-il :

- Votre seule banque (tous vos comptes sont au CIC)
- Votre banque principale (la plupart de vos comptes sont au CIC)
- Ou votre banque secondaire (la plupart de vos comptes sont dans une autre banque)
- Ne se prononce pas

Vous êtes arrivé(e) à la fin de l'enquête, merci ! Vos réponses nous sont précieuses et nous permettront d'améliorer nos services.

Translation of survey questionnaire:

1. Q1. Have you received the prepaid card?
    - Yes
    - No
2. Q5. Have you used the 300 euros prepaid card? (either partially or totally)
    - Yes
    - No
3. Q6. You have indicated you have used the prepaid card, you have spent:
    - The whole 300 euros
    - Only part of the sum, please let us know why
    - I don't know
4. Q7. How long have you waited to use the prepaid card?
    - The day I have received the card
    - Between 2 and 7 days after having received the card
    - Between 8 and 15 days after having received the card
    - More than 15 days after card reception
    - I do not know
5. Q11. Globally, how satisfied are you regarding this gifted 300 euros prepaid card?
    - Really satisfied
    - Satisfied

- Not satisfied
- Really not satisfied

6. Q12. Would you say that this 300 euros prepaid card has

   - highly contributed to your happiness
   - rather contributed to your happiness
   - rather not contributed to your happiness
   - not contributed to your happiness

7. Q13. Did you buy local services (i.e : hairdresser, florist, market gardener...) /products made in France?

   - Yes, completely
   - Rather yes
   - Not really
   - Not at all

8. Q14. Were the purchases on the prepaid card planned?

   - I bought earlier something planned
   - I bought an unplanned extra
   - I did not change my purchases

9. Q15. What did you buy with the prepaid card?

   - I spent on running expenses
   - I made myself a small treat
   - I made a larger expenditure on something already planned
   - I made a gift to my relatives, friends
   - Other

10. Q16. Would you say that you have spent less on your main bank account?

    - Yes
    - No

11. Q17. How will you use the money you saved?

    - Save to buy something expensive
    - Save for a rainy day
    - Invest it
    - Pay off debt
    - Other

C 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 "treats" 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 treats, except for some agents who remember "treat 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 "treat opportunities", it is optimal to purchase treats 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 treats 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 treats 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.[2]

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

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

[2]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 treat consumption, while λ_t is a marginal utility shifter for treats. s_t captures the idea that agents must incur calculation costs to find treats that suit their tastes (in the spirit of Evans and Ramey (1992) and Orchard et al. (2022)); the convexity of costs is akin to Ellison and Wolitzky (2012).

The parameter λ_t captures the idea that utility for specific goods like treats 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 a treat rather than on regular consumption.[3] To capture the idea that the marginal utility of spending on treats is larger when spending from the prepaid card, we use a simple functional form:

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

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.[4] G_t denotes the amount available on the prepaid card at time t, equal to 300 euros in our experiment. 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. Thus, through mental accounting, treat utility exists only when the agents purchase treats using the prepaid card.

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

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

where e_{it} denotes an individual-specific "endowment" of ideas about which treats to consume. The functional form for $v(g_t, s_t)$ captures the idea that to enjoy treat consumption the agent needs to purchase g_t units of treats 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 treats to purchase – as if they remembered past opportunities to consume certain treats. These agents can purchase up to $e_0 < G$ units of treat 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

[3]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 disproportionatley spend them on treats (rather than regular consumption, e.g. laundry supplies). Intuitively, households incur a cognitive dissonance cost if they spend a windfall on regular consumption rather than on a treat.

[4]Note that in the functional form for λ_0, the budget constraint is intertwined with the utility function. This approach is standard to model 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 puchase, which is the very idea of a "mental account."

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

this group given the limited time avaialble.

Thus, spending the prepaid card on treats 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 consumption on treats, 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 treats 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 treats – net of search costs and scaled by the price of treats – 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

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

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 treats 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 treat 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 treats. Considering an interior solution for search effort and

[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 treats or regular consumption.

treat 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 treats 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:

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

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 "treat 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 treats is larger, through λ, in this period alone. The agent thus buys $e_{i0} + s_0^*$ treats at price p_g and spends the remainder on regular consumption, with perfect consumption smoothing over time (i.e., consuming $\frac{r}{1+r} \cdot [G - p_g(e_{i0} + s_0^*)]$ 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 treats equates the marginal utlity of spending on regular consumption in the initial period:

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

This characterizes the optimal choice of search effort s_0, and thus of treat purchases g_0; optimal choices

[7] Note that in this tractable version of the model, with parameter restrictions such that the card is entirely spent on treats, 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.

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 treats (net of search costs) to the marginal utility of regular consumption, while in the case of Group 1 the marginal utility of spending on treats 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 treats 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 treats 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 treats 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 subsample 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 subsample of Group 1 participants: their MPC is close to that of Group 2 participants. 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.

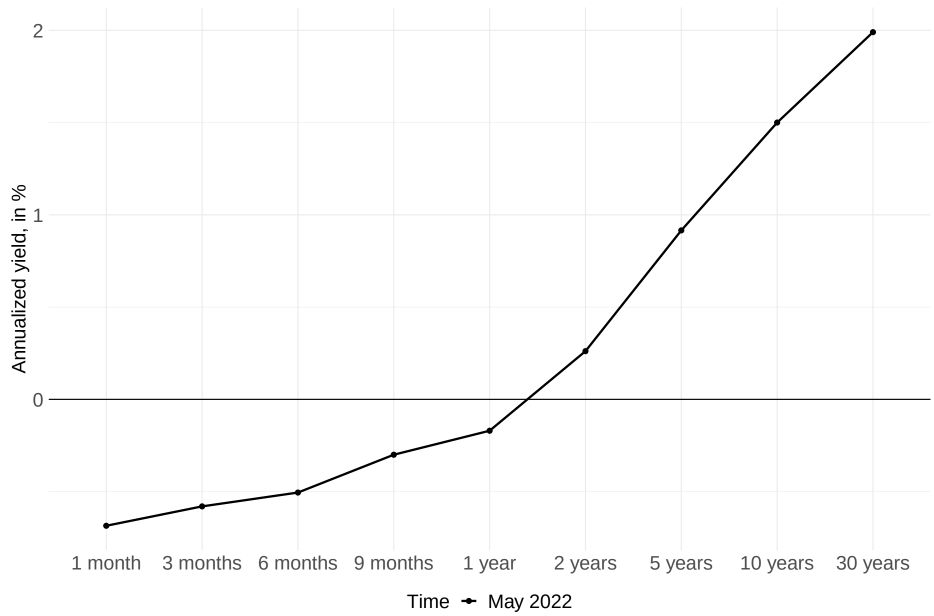
Extension: time-varying salience. Note that the salience effects above are only tied to the prepaid card. An alternative modelling approach could assume that λ_t falls over time, i.e. the reference point for salience is not just the card but also the time of receipt. This assumption would also yield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

[8]The parameters are as follows:

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

D Additional Figures and Tables

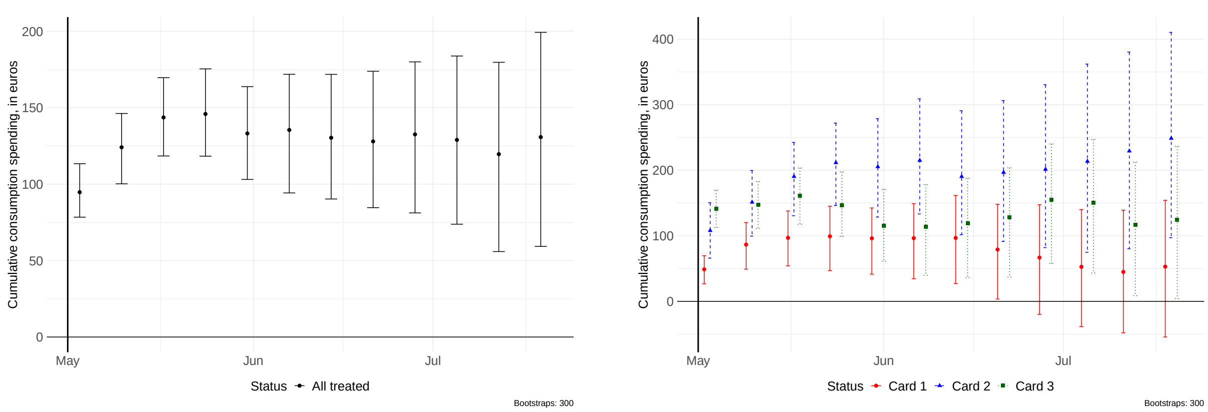
Figure A1 Yield Curve for French bonds, May 2022



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).

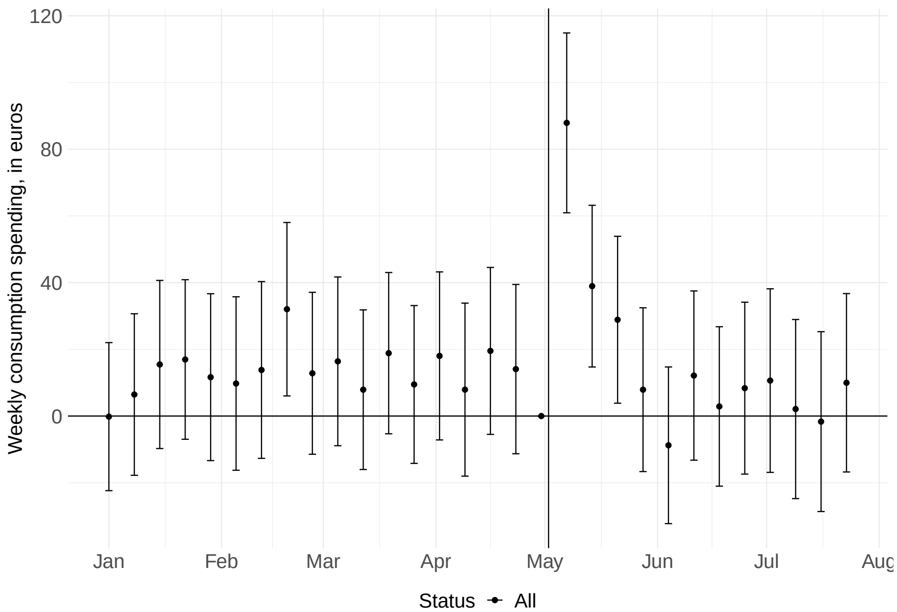
Figure A2 FGLS estimates of the MPC, by treatment group

A. For all cards B. By treatment group



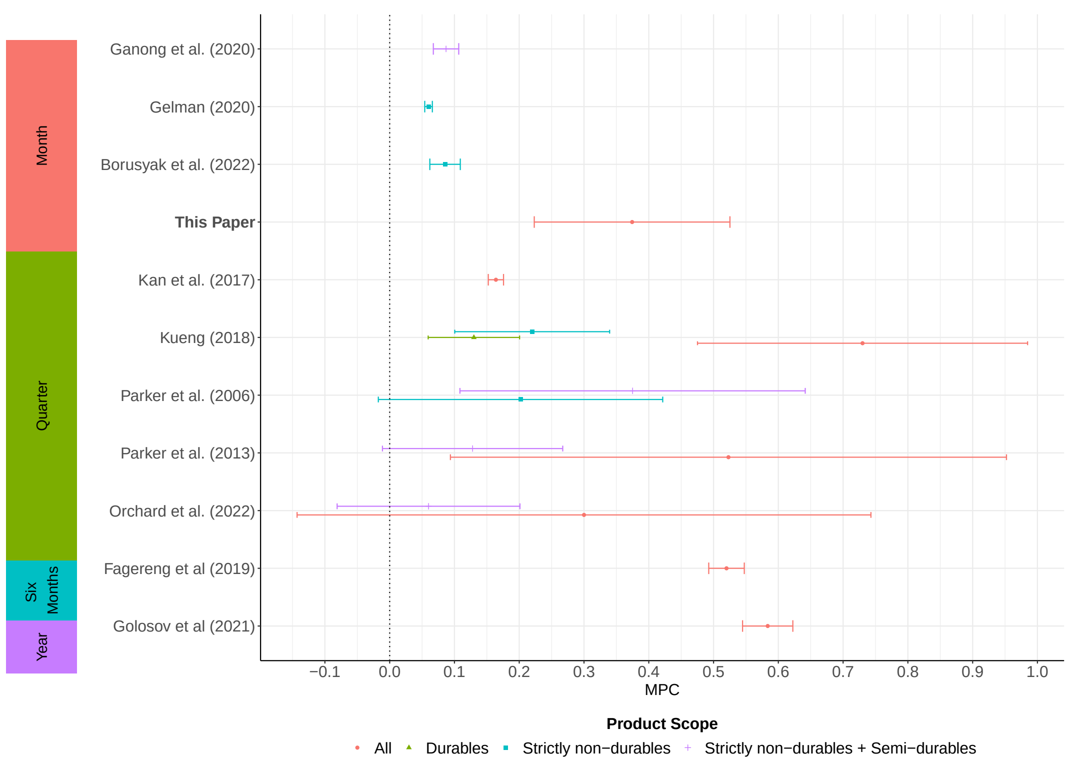
Notes: This figure shows the estimated MPC using a feasible generalized least square (FGLS) procedure, where standard errors of each household's error term are parameterized to be able to vary with each bin of time-invariant characteristics calculated from pre-period data (10 age bins, 10 income bins, gender dummy, 10 liquid wealth bins, 10 average consumption expenditure bins, 95 *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. While Panel A considers all cards, Panel B presents the estimates by treatment group. The 95% confidence intervals are obtained by bootstrap.

Figure A3 Total Spending Response, Weekly, with Treatment Leads



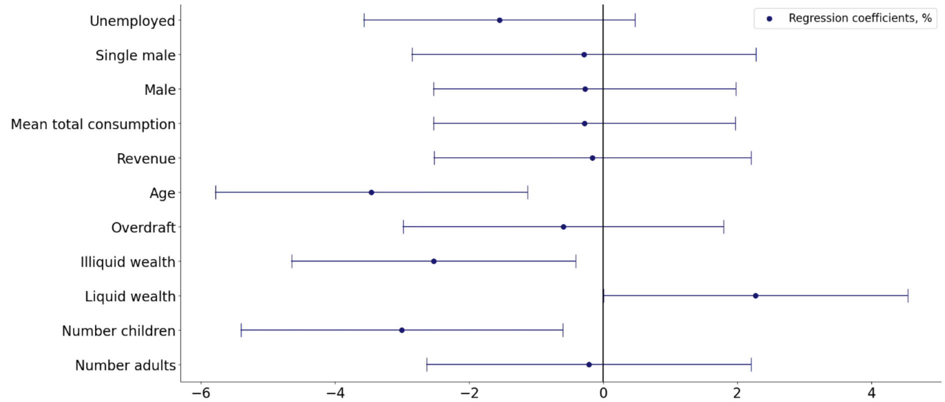
Notes: This figure shows the results of a regression estimating a specification analogous to equation 1, but including pre-treatment leads.

Figure A4 Summary of MPCs estimates



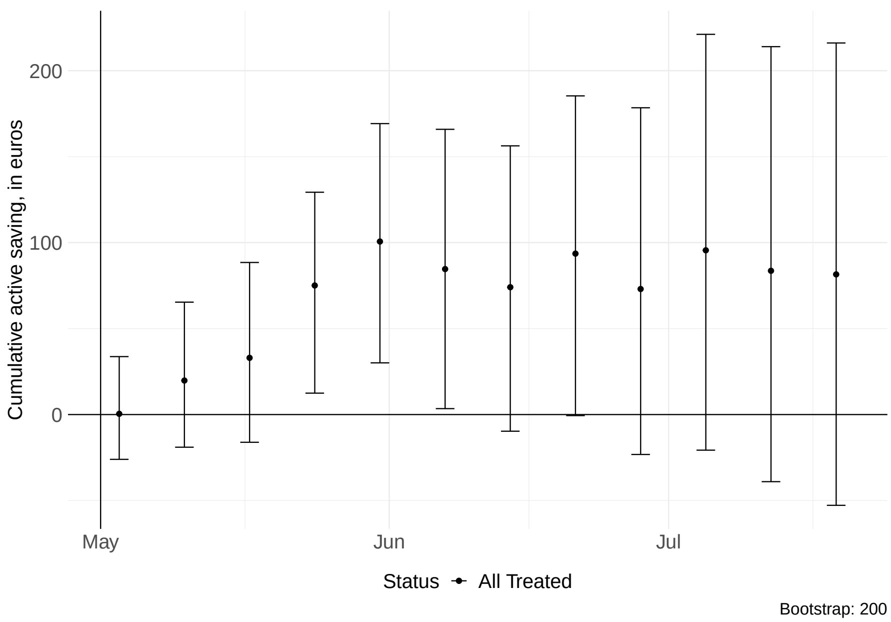
Notes: This figure reports the estimates of MPCs in the literature (typically from their baseline specifications), coded by time horizon and expenditure categories; 95% confidence intervals are also reported.

Figure A5 Observable Predictors of Non-Take-Up



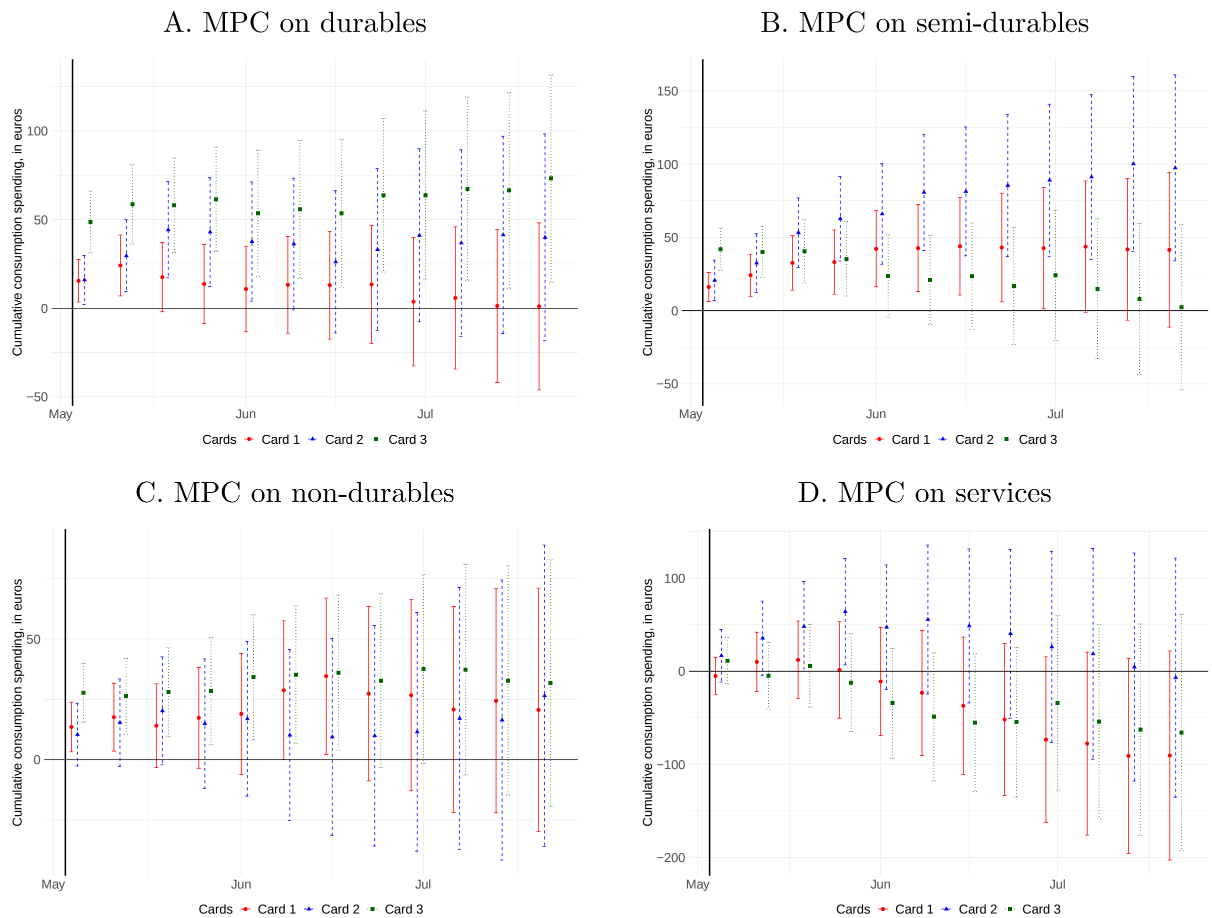
Notes: This figure reports the predictors of non-take-up of the treatment card, using the full sample of treated households. We find that households who do not use the treatment card tend to be younger, with fewer children, higher liquid wealth, and lower illiquid wealth.

Figure A6 Savings into liquid savings accounts



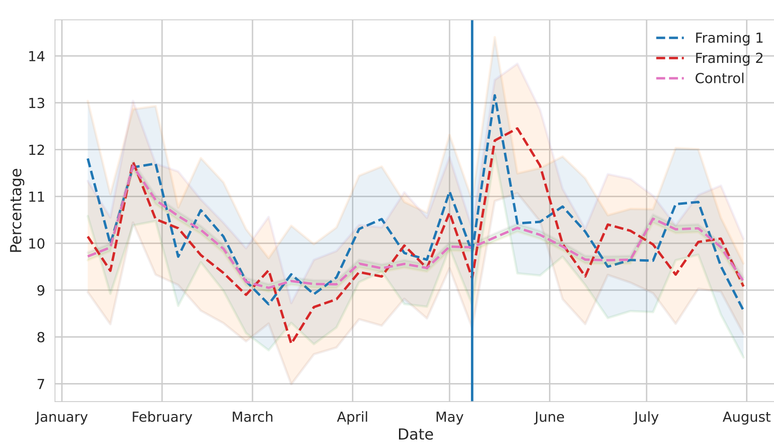
Notes: This figure analyzes the resposne of savings into liquid savngs accounts at the bank (e..g, "Livret A") for the treated participants. The figure reports the cumulative netw flows of savings after the start of the experiment.

Figure A7 MPC by Spending Category



Notes: This figure reports MPCs by spending category.

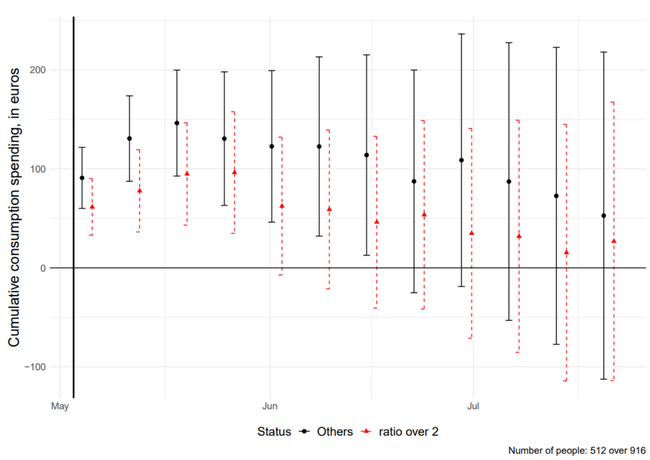
Figure A8 Spending on Imports, by Framing Group



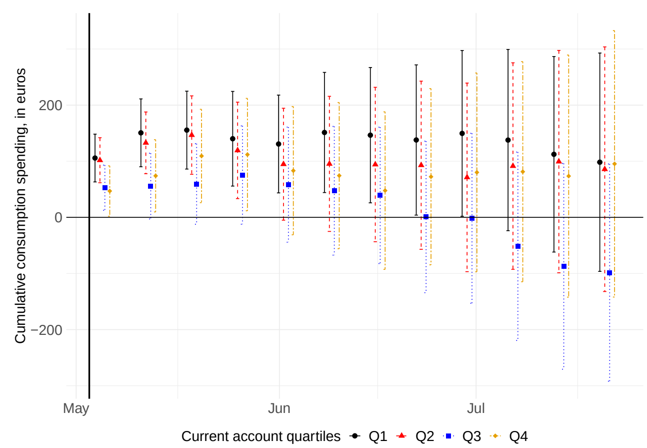
Notes: This figure shows the average expenditure share on imports for households in the two framing groups and the control group. Imports are calculated as the fraction of each product category that is directly imported from abroad, using the Input-Output table provided by the Frenc statistical institute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

Figure A9 Total spending response, weekly, for households with high liquid wealth

A. Liquid wealth > 2 × monthly income

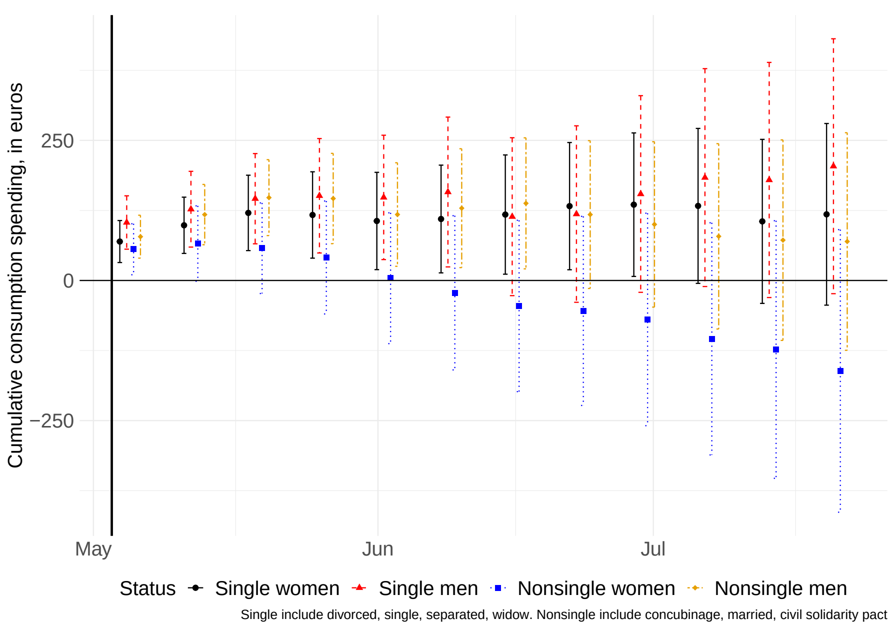


B. By quartile of current account wealth



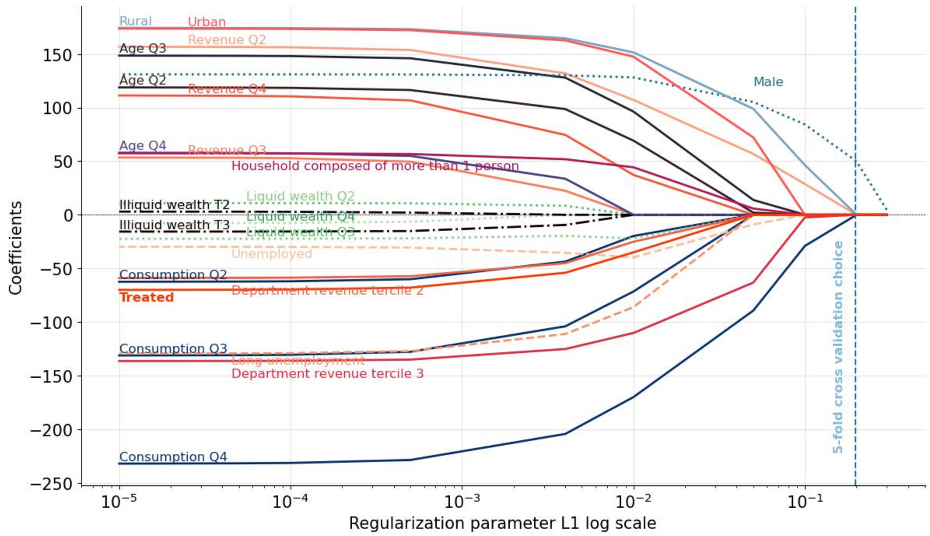
Notes: The panels of this figure shows the results of estimating equation 1 in a subsample of households whose liquid wealth is larger than twice their monthly income, and by quartiles of current account wealth. The figure plots the estimates for the cumulative MPC at different time horizons.

Figure A10 Heterogeneity by Gender and Marital Status



Notes: This figure shows the cumulative MPC by gender and marital status.

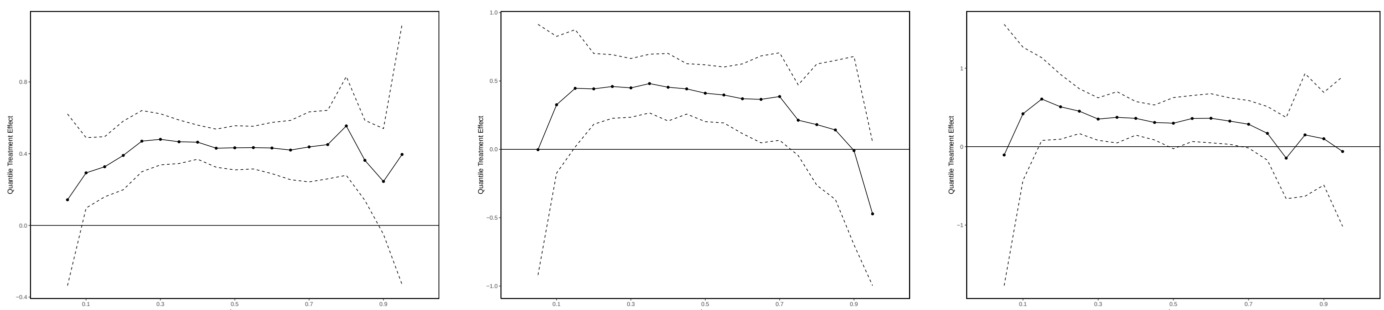
Figure A11 LASSO estimates of treatment effect heterogeneity coefficients, group 1 and control group



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.

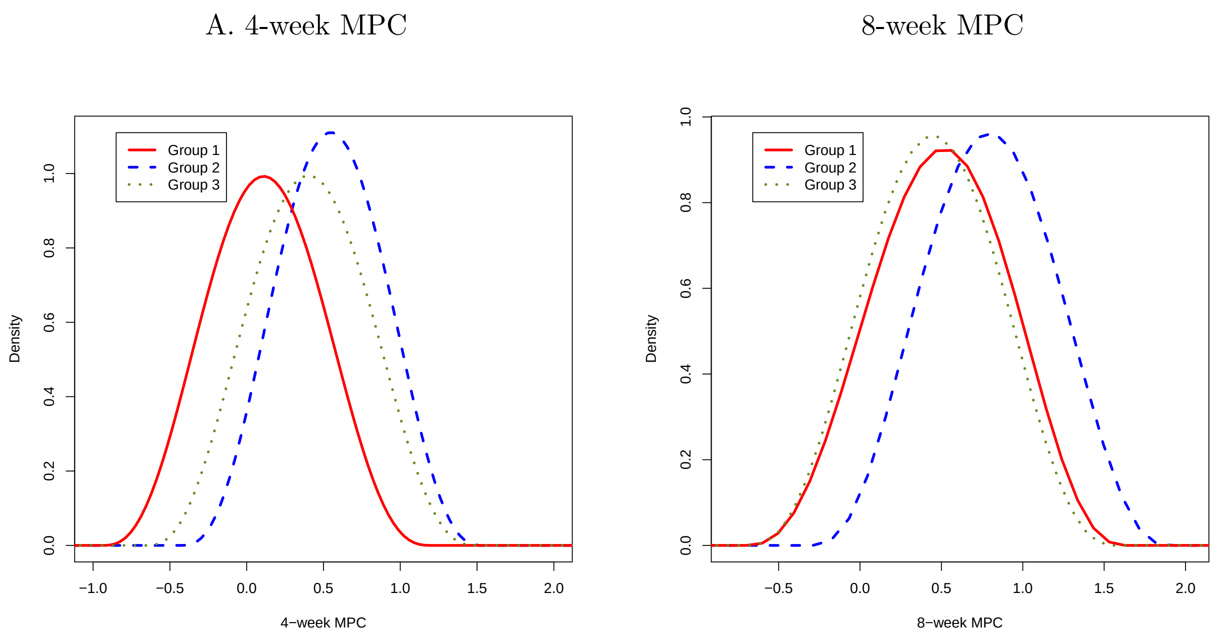
Figure A12 Quantile treatment effects: de-meaned cumulative consumption, treated vs. control

A. 4-week horizon B. 8-week horizon C. 12-week horizon



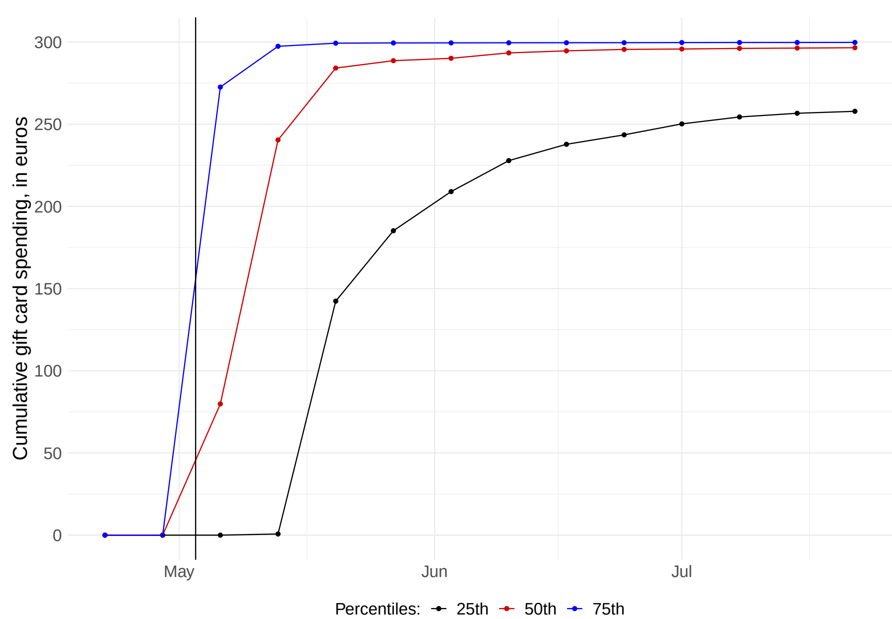
Notes: This figure shows quantile treatment effects—the difference between the quantiles of the distribution of treated and control groups—for cumulative de-meaned consumption expenditures. Standard errors are estimated using the bootstrap.

Figure A13 Estimated distribution of MPCs without constraining it to have no mass on negative values



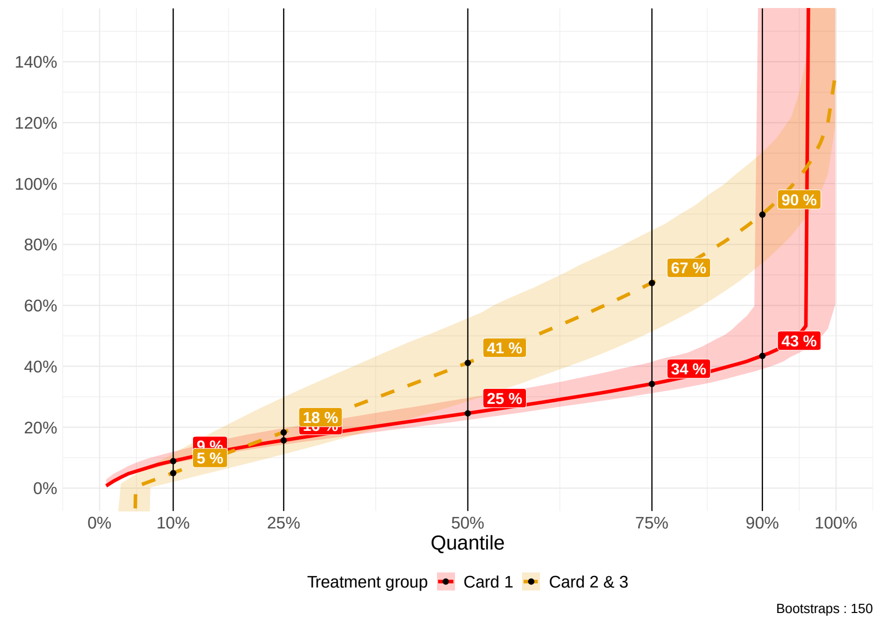
Notes: The figure shows the estimated distribution of MPCs using the flexible deconvolution procedure of Yang et al. (2020) when the support of the density of the distribution is not constrained to lie on the positive part of the real line.

Figure A14 Distribution of cumulative spending on treatment card, across households



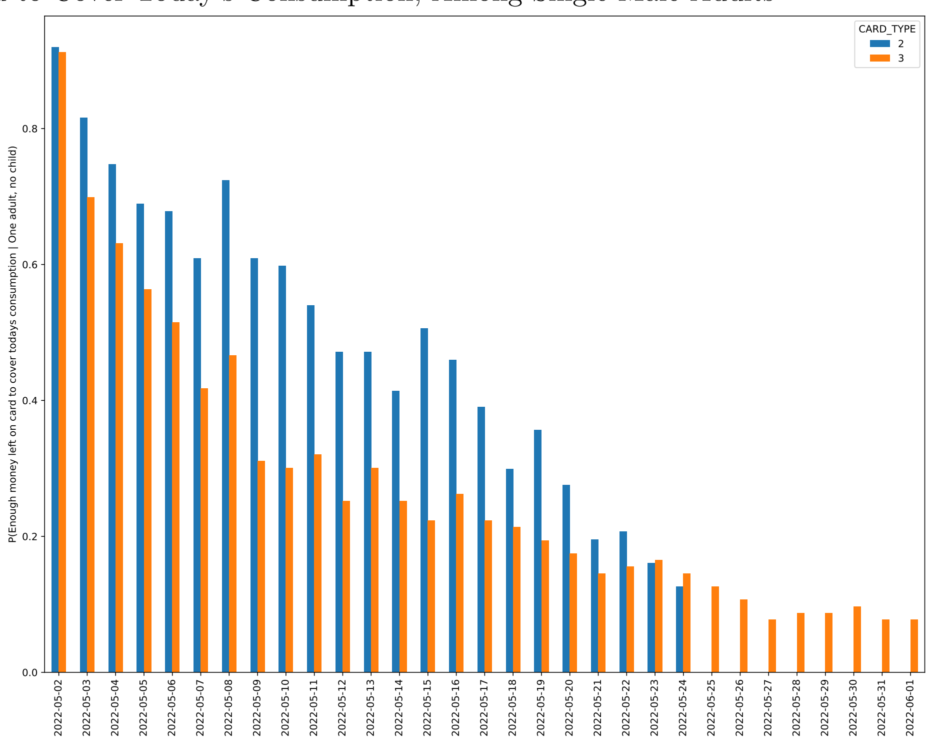
Notes: The figure shows moments of the distribution of cumulative expenditures on the treatment card, for each week.

Figure A15 MPC Distribution, Group 1 vs Groups 2 and 3 combined



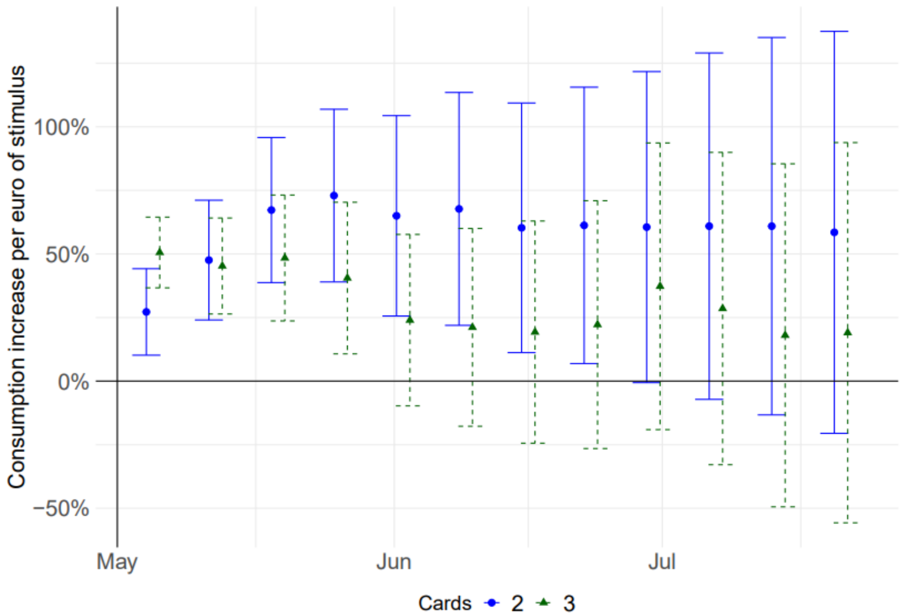
Notes: The figure shows the quantiles of the estimated distribution of MPCs, when the estimation is performed separately for treatment group 1 and for treatment groups 2 and 3 (jointly). Standard errors are estimated using a bootstrap with 150 draws.

Figure A16 A Simple Test of the Fungibility of Money: Fraction of Households that Do Not Use the Treatment Card to Cover Today's Consumption, Among Single Male Adults



Notes: This figure shows the same result as Figure 12 – 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. 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.

Figure A17 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 5) 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.

Table A1 Summary statistics, weekly consumption spending

	count	mean	std	10%	25%	50%	75%	90%
Weekly cons. expend. (cash and cards), total	2,571,060	417.66	435.02	67.30	163.25	315.95	542.63	848.64
Direct debits, debt payments, Subscriptions	2,571,060	327.18	1,753.87	0.00	18.00	108.97	351.08	892.83
Weekly cons. expend. (broad measure), excl. treatment cards	2,571,060	744.75	1,827.28	136.21	274.99	519.88	928.78	1,542.97
Weekly cons. expend. (cash and cards), excl. treatment cards	2,571,060	417.57	434.99	67.25	163.19	315.88	542.53	848.50
Weekly cash withdrawals	2,571,060	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.

Table A2 Summary statistics, household characteristics

	count	mean	std	min	10%	25%	50%	75%	90%	max
Age of eligible household member	85,702.00	47.02	12.92	26.00	30.00	36.00	46.00	58.00	65.00	76.00
Number of eligible household members	85,702.00	1.15	0.36	1.00	1.00	1.00	1.00	1.00	2.00	2.00
Avg. monthly incoming transfers, 6m prior	85,687.00	2,654.02	1,439.53	0.00	1,317.66	1,796.14	2,381.15	3,159.75	4,217.26	38,824.37
Avg. monthly salaries, social allowance, pensions, benefits, 6m prior	80,036.00	2,109.57	4,968.80	4.17	493.01	1,049.97	1,667.97	2,348.71	3,259.74	371,639.03
Avg. monthly incoming salaries, 6m prior	80,036.00	1,630.62	5,003.72	0.00	0.00	95.69	1,171.66	2,077.50	3,053.81	371,639.03
Avg. monthly incoming pension payments, 6m prior	80,036.00	300.71	691.81	0.00	0.00	0.00	0.00	0.00	1,464.31	10,844.21
Avg. monthly incoming social allowances, 6m prior	80,036.00	98.06	199.80	0.00	0.00	0.00	0.00	110.93	298.31	4,284.88
Avg. monthly incoming unemployment benefits, 6m prior	80,036.00	80.18	284.12	0.00	0.00	0.00	0.00	0.00	242.26	8,911.42
Dummy: has received unemployment benefits within 6m prior	85,687.00	0.14	0.35	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Avg. current account balance, 6m prior	85,700.00	4,448.55	19,975.90	-25,827.17	63.50	424.17	1,006.33	2,487.57	7,563.75	1,555,218.17
Avg. liquid savings, 6m prior	85,700.00	16,896.16	34,537.83	0.00	17.30	617.67	5,461.82	19,253.29	44,882.88	1,500,313.07
Avg. value of life insurance assets, 6m prior	85,700.00	5,867.47	32,465.81	0.00	0.00	0.00	0.00	373.10	8,924.30	2,768,882.29
Avg. illiquid savings , 6m prior	85,700.00	995.71	15,813.25	0.00	0.00	0.00	0.00	0.00	0.00	1,995,602.84
Avg. total debt, 6m prior	85,700.00	-33,298.45	55,006.08	-1,646,719.34	-99,125.30	-52,929.67	-5,640.50	0.00	0.00	382.57
Avg. consumer debt, 6m prior	85,700.00	-2,388.21	5,193.96	-233,574.70	-7,590.37	-2,979.42	0.00	0.00	0.00	382.57
Avg. mortgage debt, 6m prior	85,700.00	-30,869.90	54,286.72	-1,646,719.34	-96,399.22	-50,404.17	0.00	0.00	0.00	0.00
Number of adult members in the household	85,700.00	1.53	0.50	1.00	1.00	1.00	2.00	2.00	2.00	4.00
Number of children in the household	85,700.00	0.61	0.96	0.00	0.00	0.00	0.00	1.00	2.00	8.00
Avg. monthly consumption expenditures (cash, card payments), 6m prior	85,692.00	1,205.62	658.22	-306.50	545.96	794.63	1,102.84	1,480.69	1,940.18	25,030.82
Avg. monthly outgoing transfers, 6m prior	85,687.00	925.40	772.53	0.17	265.95	485.56	799.52	1,148.75	1,621.97	24,024.51
Avg. total monthly consumption (broad measure)	85,691.00	2,131.19	1,188.18	10.24	1,035.80	1,439.85	1,941.27	2,546.65	3,328.61	30,449.02

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, automative debits, and wire transfers.

Table A3 Examples 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.