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Ezra Karger and Aastha Rajan

May 28, 2020

WP 2020-15

<https://doi.org/10.21033/wp-2020-15>

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Heterogeneity in the Marginal Propensity to Consume: Evidence from Covid-19 Stimulus Payments

Ezra Karger*
Federal Reserve Bank
of Chicago

Aastha Rajan†
Federal Reserve Bank
of Chicago

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We identify 16,016 recipients of Covid-19 Economic Impact Payments in anonymized transaction-level debit card data from Facteus. We use an event study framework to show that in the two weeks following a sudden \$1,200 payment from the IRS, consumers immediately increased spending by an average of \$577, implying a marginal propensity to consume (MPC) of 48%. Consumer spending falls back to normal levels after two weeks. Stimulus recipients who live paycheck-to-paycheck spend 68% of the stimulus payment immediately, while recipients who save much of their monthly income spend 23% of the stimulus payment immediately. Consumer age and location are only marginally correlated with individual MPCs after controlling for each individual's pre-pandemic propensity to save. We use the 2018 American Community Survey to re-weight our data to match the U.S. population. Ignoring equilibrium effects and assuming a constant MPC for each person, we estimate that the CARES Act's \$296 billion of payments to individuals will increase consumer spending by \$138 billion (47% of total outlays). A stimulus bill of the same size targeted at individuals with the highest MPCs would have instead increased consumer spending by \$201 billion (68% of total outlays).

JEL Codes: D04, D12, E21

Keywords: Covid-19, stimulus payments, high-frequency data, marginal propensity to consume

*karger@uchicago.edu; 230 South LaSalle Street, Chicago, IL 60604.

†arajan@frbchi.org; 230 South LaSalle Street, Chicago, IL 60604.

First version posted May 28th, 2020. We thank Facteus for providing us with access to their proprietary data for use in this paper. Any views expressed in this paper do not necessarily reflect those of the Federal Reserve Bank of Chicago or the Federal Reserve System. All errors are our own.

Introduction

This paper measures the effect of Covid-19 Economic Impact Payments on consumer spending. The CARES Act, signed into law on March 27th, 2020, provided for IRS payments of up to \$1,200 per adult and \$500 per child for most Americans in the United States earning less than \$99,000 (or \$198,000 for joint tax filers). Americans with individual income less than \$75,000 (and household income less than \$150,000) received the full payment, and payments phased out at higher income levels.¹ The IRS directly deposited the first payments into bank accounts on April 10th, 2020² and by May 11th, 2020, 130 million stimulus payments (worth \$200 billion) had been received.³ The Joint Committee on Taxation projects that these stimulus payments will cost a total of \$293 billion⁴ when the disbursement process is completed by the end of the summer, or roughly \$881 per U.S. resident.⁵

We use a new anonymized transaction-level dataset from Facteus⁶ describing spending behavior from over one million debit and payroll cards to precisely measure the immediate effect of Covid-19 Economic Impact Payments on consumer spending. We begin by identifying 16,016 active accounts that received a \$1,200 direct deposit from the IRS between April 10th and April 22nd. In an event-study framework, we show that a \$1,200 stimulus payment increased average consumer spending by \$577 in the two weeks after the deposit. We see no evidence of anticipatory increases in spending in the days leading up to the stimulus payments. We show that the increase in spending benefits many firms, with Walmart capturing the largest amount of stimulus-driven spending. Spending at Walmart increases by \$108 per person in the two weeks

¹For more information about the CARES Act, see <https://home.treasury.gov/policy-issues/cares>.

²See additional details here: <https://www.wsj.com/articles/u-s-treasury-starts-sending-individual-stimulus-payments-11586566954>. Conflicting reports from the IRS and news organizations claim that the first stimulus payments were deposited into accounts on April 11th, but that is not consistent with our data: <https://www.cbsnews.com/news/stimulus-checks-irs-deposits-first-wave-of-stimulus-checks-2020-04-12/>

³See <https://www.washingtonpost.com/business/2020/05/11/still-waiting-your-stimulus-check-you-have-until-12-pm-wednesday-give-irs-your-bank-information/>

⁴For a full analysis of the costs, see: <https://www.jct.gov/publications.html?func=startdown&id=5255>. We apply the CARES Act Economic Impact Payment formulas to the 2018 U.S. population using the American Community Survey and independently estimate that the individual payments will total \$296 billion, so that is the estimated cost that we use throughout this paper.

⁵This assumes a population in 2020 of 332.6 million, following the Census Bureau's projection for the 2020 U.S. population: <https://www.census.gov/content/dam/Census/library/publications/2020/demo/p25-1144.pdf>

⁶We describe this dataset in further detail in the Data section. Facteus is a private company that works with debit and payroll-card issuers to aggregate and standardize anonymized transaction-level information. Data are available at a one-day lag for the set of accounts in their data.

following stimulus receipt, or 19% of the overall increase in consumption following the stimulus payment.

While the average MPC in our sample is 0.48, there is significant heterogeneity in the MPC across our sample of stimulus recipients. In the two weeks following a stimulus payment, 18% of the recipients do not increase spending and 14% of recipients spent at least \$1,200 more in the two weeks following the stimulus payment (relative to the two weeks prior to the payment). The remaining 64% of our sample have MPCs that are distributed roughly uniformly between 0 and 1. We investigate five sources of heterogeneity in the MPC: consumer age, pre-pandemic income levels, pre-pandemic spending levels, pre-pandemic propensity to save, and location. We show that these factors explain only 6% of the variation in individual-level MPCs in our sample.

We conclude by using the American Community Survey to re-weight our sample of stimulus recipients to be representative of the U.S. as a whole. This is important, because our sample of stimulus recipients may be unrepresentative of the full set of stimulus recipients in the U.S. We use this re-weighting to estimate the immediate effect of the stimulus payments on consumer spending. Ignoring equilibrium effects and assuming that each stimulus recipient has a constant MPC, we estimate that the \$296 billion of stimulus payments will increase consumer spending by \$138 billion. A stimulus program directed at low-income individuals could increase consumer spending by \$179 billion instead. And a stimulus program that targeted consumers with the highest marginal propensity to consume could increase consumer spending by \$201 billion (or 68% of the program cost).⁷

A large literature explores the marginal propensity to consume. For example, Kan, Peng, and Wang (2017) analyze a \$2.6 billion shopping voucher program in Taiwan and find that each dollar of vouchers leads to \$0.24 of increased spending. Fagereng, Holm, and Natvik (2019) use lottery winners in Norway to measure the MPC for lottery prizes, which range from around 50% for high-liquidity winners of large prizes to 100% for low-liquidity lottery winners who win small prizes. Gross, Notowidigdo, and Wang (2020) use the removal of bankruptcy flags from credit reports to argue that the MPC from sharp increases in credit card limits is 37%. Agarwal, Liu, and Souleles (2007) use an event study framework to measure how consumer spending responds to the 2001 federal tax rebates. And Ganong et al. (2020) use firm-wide

⁷This proposed policy would target consumers with the lowest net savings rate in January–March 2020. Although a similar program targeting the lowest-income consumers could increase consumer spending by close to that amount (\$192 billion). See Figure 8 for a visual representation of the MPC gradient as a function of income and savings rates.

variation in monthly pay to estimate that a \$1 increase in income leads to a \$0.23 increase in consumption, with significantly lower spending responses for high-liquidity households. Much of the prior literature measures MPCs using monthly or quarterly consumer spending data. Our paper adds to this literature by using high-frequency transaction-level data to measure the effect of stimulus payments on daily consumer spending.

Another strand of papers, typified by Sahm, Shapiro, and Slemrod (2010) surveys households to estimate an MPC of 33% in response to the 2008 tax rebates. In a related paper, Parker and Souleles (2017) compare self-reported MPCs to realized MPCs after Federal stimulus payments in 2008. They find that households spend roughly 50% of the \$910 stimulus payment, closely matching our findings. Fuster, Kaplan, and Zafar (2018), survey consumers to identify MPCs in response to hypothetical windfalls. They find that respondents report hypothetical MPCs of only 8%, but among those who expect to spend some of their hypothetical windfall, the average reported MPC is 54%. And in related work, Canbary and Grant (2019) use a survey of households to measure the MPC for households with different socio-economic statuses, arguing that the MPC ranges from 0.53 for high-SES households to 0.94 for low-SES households.

In the paper that is most similar to ours, Baker et al. (2020) identify a set of approximately 1,600 people who received Covid-19 Economic Impact Payments. These recipients all use a financial app called SaverLife, which encourages users to save money. They find that in the first 10 days after a stimulus payment, consumers spent \$0.25-\$0.35 per dollar of stimulus. The two main advantages of our paper are representativeness and precision. SaverLife is an app that encourages saving. Our dataset is also a convenience sample of stimulus recipients, but we have a broad enough sample of stimulus recipients to re-weight our data to match the U.S. population and investigate the representativeness of our sample. We find an average MPC of 0.48 in our panel of individuals who use the debit and payroll cards in our sample as compared to an MPC of 0.47 when we re-weight our data to match the income, location, and age distribution of individuals in the 2018 ACS. Among individuals with a high savings rate in our sample, we estimate an MPC of between 0.20 and 0.30, closely matching the results from the SaverLife users in Baker et al (2020). We can also track more than 10-times as many stimulus recipients. This gives us the ability to more precisely estimate the day-by-day effects of stimulus payments on overall consumption and consumption at individual firms.

Our paper is one of many that uses high-frequency data to measure the economic effects of Covid-

19-associated policies on consumers. For example, a growing set of papers measures the sharp decline in consumer spending, mobility, employment, and business activity in March and April of 2020. These papers use a variety of alternative data sources from companies like Unacast, Second Measure, Womply, Safegraph, ADP, and Burning Glass to track high-frequency measures of consumer behavior. For several relevant examples, see Aaronson et al. (2020); Alexander and Karger (2020); Baker et al. (2020); Carvalho et al. (2020); Chetty et al. (2020); Gupta et al. (2020); and Lewis, Mertens, and Stock (2020).

Our evaluation of the short-run effect of Covid-19 Economic Impact Payments on consumer spending complements Granja et al. (2020) and Ganong, Noel, and Vavra (2020) who present descriptive statistics and policy counterfactuals related to the short-run effects of the Paycheck Protection Program and the unemployment insurance component of the CARES Act (respectively). Together, the Economic Impact Payments, the Paycheck Protection Program, and the expansion of unemployment insurance comprise some of the largest-scale federal policy responses to Covid-19.

Data

We use data from a company called Facteus that standardizes transaction-level data from over one million debit cards, payroll cards, and load cards between 2012 and 2020. Facteus works with hundreds of card-issuers to aggregate, standardize, and anonymize this information, perturbing transaction amounts, demographic information, and transaction timing by randomly chosen values.⁸ We identify 174,469 accounts in the Facteus panel that received a deposit in April 2020 from a government agency, including the IRS, SSA, or state unemployment insurance offices.

In Figure 1, we overlay the distribution of government payment amounts from two groups of accounts: those receiving a government payment from April 1—April 9, and those receiving a government payment from April 10—April 22. In this figure, we can clearly see the stimulus payments. Before April 10, government payments to the accounts in our sample were distributed smoothly (in value) between \$0 and \$2,800

⁸For example, transaction values are perturbed by adding a random number chosen uniformly from a small range surrounding that number. Birth date information is perturbed by up to 1-2 years in either direction, and transaction time is perturbed by several hours to avoid identification of individuals. We ignore these perturbations when estimating our event study results.

with a long right tail. But on and after April 10, the distribution of government payments reflects the lumpiness of the CARES Act's payment amounts. Recall that individuals earning under \$75,000 received a \$1,200 payment and joint filers received a \$2,400 payment. Adults also received a \$500 payment for each child in their household (up to a four child limit). Consistent with this payment algorithm, we see large spikes in payment frequency at \$1,200, \$1,700, \$2,200, \$2,400, and \$2,700. The payment amounts are perturbed in Factiveus's data, so the transaction amounts are not exact. But we will use the large mass of accounts receiving a \$1,200 payment from the IRS between April 10th and April 22nd as our main analysis sample going forward.

We filter our main analysis sample in six steps to ensure that we focus on primary accounts for a set of consumers:

1. We subset to accounts (cards) that recorded at least 10 transactions in January 2020 to ensure that the consumers in our sample are using their accounts actively before the pandemic.
2. We subset to accounts that recorded at least \$1,000 of aggregate spending and \$1,000 of aggregate deposits across January—March 2020.
3. We subset to accounts that received at least one deposit from a government agency in January—April 2020. This could include a federal or state-level tax refund, unemployment insurance, Social Security payments, Disability Insurance benefits, or an Economic Impact Payment.
4. We exclude accounts that received multiple IRS deposits between April 10 and May 8. We do this to remove a handful of accounts that received tax refunds and stimulus payments in close proximity.
5. We subset to accounts for which we can identify the resident state of the account holder. This is done in two ways. First, for each account we look for a known zip code associated with the account at the time that the IRS or a state government made a deposit into the account in 2020. Second, if the state cannot be identified in this way, we assign each account to the most frequently occurring state associated with all other transactions in their account.
6. We subset to four sets of accounts:

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- Accounts that received an IRS payment of (i) \$1,200, (ii) \$1,700, or (iii) \$2,200 between April 10th and April 22nd. We consider the accounts that received an IRS payment of \$1,200 as our main sample of ‘treated’ units. We focus on stimulus payments made between April 10th and April 22nd because early payments were less likely to be anticipated. In mid- and late-April, the IRS heavily publicized a website where consumers could check the expected timing of their upcoming stimulus payment.
 - (iv) Accounts that did not receive any IRS payment worth more than \$500 after April 10th. This is our main sample of ‘control’ units who we will include for visual and regression-based comparisons. Based on the reported deposits into these accounts, we expect that most of these people will receive a stimulus payment over the summer. Once we can see additional recipients from May and June in our transaction-level dataset, we plan to more explicitly compare early and late-recipients of stimulus payments.

These filters leave us with a primary dataset of 24,313 consumers: 16,016 who received a \$1,200 payment between April 10th and April 22nd, and 8,297 who did not receive any stimulus payment from the IRS after April 10th. Borusyak and Jaravel (2017) recommend the inclusion of a never-treated control group of non-recipients in event studies. This never-treated control group helps to pin down the values of unit and time fixed effects while allowing us to separately estimate days-since-event fixed effects. Our full sample consists of 34,971 consumers: with an additional 6,590 consumers who received a \$1,700 payment and 4,068 consumers who received a \$2,200 payment from the IRS between April 10th and April 22nd.

In Table 1, we present summary statistics describing the 16,016 recipients of \$1,200 stimulus payment in our data. The average recipient has aggregate deposits of around \$5,500 from January to March, 2020 and \$4,400 of aggregate spending over that time period. Multiplying by four, this implies an average annual income of roughly \$22,000 and average consumer spending of \$17,600. In the summary table, we separate out different transactions marked as ATM Withdrawals, deposits, government deposits, and loads (onto payroll cards), but in the main analysis we combine all types of deposits into an aggregate deposit measure and all types of spending into an aggregate spending measure. In Table A2, we show the same summary statistics, but for our combined group of \$1,200 stimulus recipients and the control group described above. The aver-

age consumer in our overall sample received payroll and other deposits totalling \$5,300 in January—March, 2020, implying an average annual income of roughly \$21,200.⁹ In Tables A3 and A4, we show the same summary statistics for recipients of \$1,700 and \$2,200 stimulus payment (respectively).

In Figure 2, we plot changes over time in account deposits, spending, and 2020 savings for the accounts in our primary analysis sample. We define ‘savings’ as cumulative deposits minus cumulative spending since January 1st, 2020. We see a linear increase in deposits and spending through the end of March. The time series of spending is smoother than the lumpy time series of deposits because of regular weekly and biweekly direct deposits from employers. On April 15th, when we see the largest number of stimulus payments, we see a sharp increase in aggregate deposits (because of the stimulus payments) and consumer spending.

The data from Factiveus has several advantages for our analyses in this paper: first, we can see daily transactions for a large set of accounts, allowing for precise estimation of daily consumer spending. Second, we can disentangle consumer spending, payroll deposits, government deposits, and ATM withdrawals. And third, we have fine-grained geographic features for each transaction.

The one major concern about the Factiveus data is representativeness. The only demographic information we have for each consumer is their age and geographic location. We do not see information describing each consumer’s gender, household structure, or secondary and tertiary accounts in this data.¹⁰ If a consumer has a credit card, we see when they pay off the credit card, but we do not see the individual credit card transactions. If the consumer has a secondary debit or payroll card, we cannot see deposits or spending from that secondary account if the consumer uses their second account as a main source of deposits and spending. That being said, the consumers in our sample chose the account in Factiveus’s data to receive a direct deposit from the IRS. And aggregate changes in deposits and spending in Figure 2 imply that consumers use these accounts for a large share of deposits and spending. We view this as evidence that many of these consumers are using this account as a primary bank account. If these stimulus recipients have secondary bank accounts or credit cards from which they spend additional money immediately after receiving a stimulus payment, then our estimate of the average MPC (0.48) is likely a lower bound.

⁹Based on their incomes, we expect that these consumers will receive a stimulus payment at a later date.

¹⁰Although, as we show later, the MPC is not measurably different for adults with no dependent children and adults with one or two children. We identify these three groups of consumers using the exact stimulus payment amount.

Empirical Strategy

To quantify the change in deposits and spending in our sample, and to visualize the MPC in calendar time, we focus on two groups of consumers: (1) The 10,966 stimulus recipients who received their payment on April 15th, 2020 and (2) the 8,297 consumers in the control group. In Figure 3, we plot the levels of deposits and spending over time for these two groups. The stimulus payments mechanically increase aggregate deposits by \$1,200 on April 15th. And there is also a sharp increase in consumer spending for stimulus recipients relative to the control group in the two weeks following the receipt of a stimulus payment. The control group spent slightly less money in the days leading up to the stimulus payment. In raw levels, the average stimulus recipient spent \$706 more in the two weeks following the stimulus payment than her peer in the control group of non-recipients. This represents 59% of the \$1,200 stimulus payment. But the stimulus recipients also had higher levels of spending in the two weeks leading up to the stimulus receipt. This could reflect unobservable (or observable) differences between the two groups of consumers.

Our main calculation of the average MPC relies on a basic event study framework to measure the effect of stimulus payments on daily consumer spending, in the style of Agarwal, Lui, and Souleles (2007). We begin with a dataset of all consumers described above in the data section. We collapse the transaction-level data to the individual*day level. We then analyze four event studies, focusing on the simplest models (Models A-B) throughout the paper. Models C and D are presented as robustness checks:

Model A. We focus on consumers who receive a stimulus payment of \$1,200 from April 10th—April 22nd and we require that our panel be balanced by further subsetting our dataset to the two weeks before and after each consumer's stimulus deposit. We analyze this linear regression:

$$Y_{i,t} = \sum_{s=-14}^{13} \beta_s 1(stimulus\ received)_{i,t+s} + \epsilon_{i,t}$$

In our analysis, $Y_{i,t}$ is:

- (1) Individual i 's total spending on day t .
- (2) Individual i 's total deposits on day t .

The coefficients of interest, β_s , represent the days-since-event fixed effects for the two weeks before and

after the stimulus payment. The indicator variable $1(\text{stimulus received})_{i,t+s}$ is 1 if individual i had received a stimulus payment on date $t + s$ and 0 otherwise. Because we do not include additional covariates, this model measures the average level of spending on each day surrounding the stimulus payment.

Model B. In our second model, we analyze the same event study framework as in Model A. However, we estimate it separately for consumers who receive \$1,200, \$1,700 and \$2,220 payments between April 10th - April 22nd. Recall that \$1,700 recipients represent adults with a single dependent child, and \$2,200 recipients represent adults with two dependent children. As illustrated in Figure 5, the three different groups of recipients have virtually identical trends in pre-stimulus spending, but experience different post-stimulus increases in spending.

Model C. In our third model, we add a series of controls to our baseline event study framework (Model A). We regress:

$$Y_{i,t} = \sum_{s=-14}^{13} \beta_s 1(\text{stimulus received})_{i,t+s} + \delta_{i,t} + \epsilon_{i,t}$$

In this model $\delta_{i,t}$ represents state-by-date fixed effects. We include the $\delta_{i,t}$ fixed effects as covariates in this event study to absorb regional time-varying features of our data. One worry is that our baseline estimates may be confounded by systematic variation in stimulus timing for different types of individuals. And indeed, the timing of Covid-19 stimulus payments is correlated with the recipient's state of residence; we see evidence that stimulus recipients in some states received IRS payments 2-5 days earlier on average than stimulus recipients in other states. Second, there is significant evidence that the passage of stay-at-home orders causes sharp changes in consumer spending (see Alexander and Karger, 2020). Because of this, we want to ensure that our estimates of the MPC are not confounded by time-varying state policies (like stay-at-home orders) that affect business closures and consumer spending.

We include in our model the never-treated control group of consumers. This never-treated control group helps to pin down the values of unit and time fixed effects while allowing us to separately estimate event-time fixed effects (as is recommended by Borusyak and Jaravel (2017)). This type of event study can suffer from bias if treatment effects are time-varying. For more information, see Goodman-Bacon (2018), Sun and Abraham (2020), and Borusyak and Jaravel (2017). We are exploring the robustness of our results to time-

varying treatment effects. As we show in Appendix Figure A1, the sharp increase in consumer spending after stimulus receipt is robust to the addition of these controls.

Model D. In our fourth and final model, we address concerns about time-varying treatment effects by estimating an event study model in two steps. First, we regress $Y_{i,t}$ on person-by-day of the week fixed effects during the pre-pandemic period (January 1st, 2020 through March 15th, 2020). We use this regression to calculate a daily residual spending measure for each consumer in our final analysis sample of stimulus recipients. Then, we regress this residual spending measure on days-since-stimulus-receipt fixed effects. This method is similar to one proposed by Goodman-Bacon (2019) who suggests estimating residual outcomes in the pre-period and using those residual outcomes in the main difference-in-difference specification in the post-period. Appendix Figure A2 shows the results from this specification.

Results

Recall that in Figure 3 we plot the average level of deposits and spending for our treatment and control groups. On average, stimulus recipients spent \$706 more in the two weeks following the stimulus payment than the control group of non-recipients. This represents 59% of the \$1,200 stimulus payment. But we can also see that the stimulus recipients have higher levels of spending in the days leading up to stimulus receipt.

In Figure 4, we use our baseline event study framework (Model A) to measure the immediate effect of stimulus payments on consumers. Confidence intervals rely on standard errors that are clustered two-way at the state and date level. In Panel A, we plot the β_s values where the outcome is daily aggregate deposits into each account. In the two weeks immediately preceding and following the \$1,200 stimulus payment, we see no measurable variation in aggregate deposits. But on the exact date when we identify the stimulus payments, we can see an additional \$1,200 deposited into each account. In Panel B, we plot the spending response to this unexpected \$1,200 payment. Spending increases sharply in the two days following the payment, before slowly returning to baseline levels after two weeks. Overall, stimulus recipients increase spending by \$577 in the two weeks following receipt (48% of the stimulus amount).

In Figure 5, we report the event study estimates for different groups of stimulus recipients (Model B). Similar to the results from Model A, there is no significant variation in aggregate deposits for any

of the groups in the period prior to receiving the stimulus payment. The deposit of stimulus payment is very precisely estimated on the day of the receipt of payment. The \$1,700 stimulus recipients and \$2,200 stimulus recipients also show a sharp uptick in aggregate spending on the day of the receipt of the stimulus, which returns to normal over the following two weeks. The 1,700 recipients spend 199 more than the 1,200 recipients in the two weeks following receipt. The 2,200 recipients spend 410 more than the 1,200 recipients in the two weeks following receipt. We can interpret these differences in spending responses as an independent estimate of the MPC, implying an MPC of 40% to 41% when we compare \$1,200, \$1,700, and \$2,200 recipients.

We decompose spending for our main treatment group of \$1,200 stimulus recipients further into spending at specific companies, using merchant codes that Factiveus assigns to each transaction. In Figure 6, we plot the spending response for eight companies that might be especially salient during the Covid-19 pandemic: Walmart, Amazon, Dollar General, 7-Eleven, AT&T, Verizon, Sprint, and Comcast. In Panel A, we see that Walmart captures a full 18% of the increased spending in our sample due to stimulus payments. The other seven firms also see sharp increases in spending, although those increases are of significantly smaller magnitudes.

We now use the same event study framework to calculate each consumer's individual increase in spending in response to a \$1,200 stimulus payment. To do this, we calculate each consumer's abnormal consumption following the stimulus payment as

$$C_i^a = C_{i,r(i)+14}^{14} - C_{i,r(i)}^{14}$$

where $C_{i,t}^{14}$ is consumer i 's total spending in the 14 days preceding date t and $r(i)$ is the date when consumer i received their stimulus payment. The individual-level marginal propensity to consume is then $MPC_i = \frac{C_i^a}{1,200}$. We calculate the MPC using the difference in consumption over a two-week period to account for any constant day-of-the-week effects or biweekly payroll-related spending decisions. We present the distribution of MPCs based on Model A, but these MPCs are numerically equivalent to MPCs that are instead derived from residual spending in Model D. And the MPCs based on Model A correlate highly ($\rho = 0.996$) with the MPCs from Model C that includes state-by-date fixed effects.

In Figure 7 , we plot the distribution of MPCs in our sample of respondents, winsorized at -2 and 2. We see significant variation across stimulus recipients. 64% of our stimulus recipients have an MPC ranging uniformly between 0 to 1, 18% of recipients reduce their spending in the weeks following a stimulus payment, and 14% of recipients increase their spending by more than \$1,200 in the two weeks following the stimulus payment. These negative or large MPCs represent abnormal spending that is not explained by person or day-of-the-week effects. For example, if an April 15th stimulus recipient decided in March to buy a car on April 20th, that would dramatically increase their measurable MPC from the stimulus. But this is not in and of itself due to the stimulus payment.

To explore sources of this individual-level heterogeneity in the MPC, in Figure 8 we plot the average individual-level MPC as a function of total spending, total deposits, and total savings in January—March 2020, as well as consumer age. We define total savings as the difference between deposits and spending in January—March 2020. We do not see account balances in Factiveus's data, so this measure of savings (a 3-month difference in income and spending flows) is the closest we can come to approximating pre-Covid-19 liquidity. We see significant variation in the MPC as a function of the pre-Covid-19 savings rate. Consumers with the highest pre-pandemic savings rate spend only 23% of the stimulus payment on average in the two weeks following receipt. Consumers with low pre-pandemic propensities to save spend 68% of the stimulus payment in the two weeks following receipt. Age and aggregate spending levels are largely uncorrelated with individual marginal propensities to consume. But aggregate deposits in January—March 2020 (a measure of total income) are also highly correlated with MPCs.

In Table 2, we regress individual-level MPCs on quintiles of total deposit amounts and total savings from January—March 2020, along with age quintiles and state of residence fixed effects. Together, these characteristics explain only 6% of the variation in the MPCs, but almost all of that explained variation is driven by total savings in January—March 2020. Consistent with the heterogeneity results presented above, Consumers with high levels of savings have MPCs that are 35% lower than consumers whose spending closely match their income in the first three months of 2020. In future work, we hope to explore additional explanations for the substantial heterogeneity across consumers in the MPC.

Similarly, we also calculate MPCs for \$1,700 and \$2,200 stimulus payment recipients in our sample. The average MPC for \$1,700 and \$2,200 payment recipients is 0.45 and 0.42 (respectively). One might

expect that the marginal propensity to consume for these consumers, who have dependent children, would be higher than the \$1,200 stimulus recipients but the average MPCs for these three groups of stimulus recipients are similar.

Policy Counterfactuals

One concern with the results presented above is that the Factiveus data may not be representative of the U.S. as a whole, which would affect the generalizability of our MPC estimate. We attempt to address this concern by re-weighting our sample of stimulus recipients to match stimulus recipients in the U.S. as a whole. To perform this re-weighting exercise, we rely on the 2018 individual-level ACS data from IPUMS (Ruggles et al., 2020). For each household, we calculate the number of children aged 16 or younger. We assign the household head and his/her spouse an equal fraction of the household's children. In cases where there is no spouse, we assign children to the household head. And in cases where additional adults live in a given household, we treat each of those adults as an independent household.

Then, we assign each adult member of each household (over 16 years of age) a stimulus payment based on their total income and their assigned dependent children using the income eligibility criteria defined by IRS. We assign all individuals with a personal income of up to \$75,000 a stimulus payment of \$1,200. For adults with personal income between \$75,000 and \$99,000, we assign a stimulus payment that is reduced by \$5 for every \$100 earned over \$75,000. We add to each adult's stimulus payment \$500 for each child in their household (including 'partial' children, as assigned above). We do not assign any stimulus payment to those individuals whose personal income might be low enough to receive stimulus payment but who have spouses earning more than \$150,000. After assigning these stimulus payments to each adult, we estimate that the total cost of Covid-19 Economic Impact Payments will be \$296 billion. This is in-line with the Joint Committee on Taxation's estimate of \$293 billion,¹¹ and small discrepancies are to be expected because we rely on data from 2018 to estimate the cost of this 2020 program.

We merge our dataset of individuals from the 2018 ACS onto our dataset of MPCs from the Factiveus panel. We estimate MPCs for each adult in the 2018 ACS by regressing the Factiveus-based MPC on age

¹¹ For a full analysis of the JCT's estimated costs, see: <https://www.jct.gov/publications.html?func=startdown&id=5255>.

fixed effects, state fixed effects, and income ventiles in our Facteus panel. We then use the coefficients from this regression to predict the MPC for each adult in the 2018 ACS. In Table 3, we use this matched dataset to explore the effect of five policies on consumer spending. We first estimate the immediate increase in consumption in response to the \$296 billion Economic Impact Payments. We estimate that the payments will lead to \$138 billion of increased consumer spending. This ignores any equilibrium effect of the stimulus payments on prices, and it also ignores any spillover effects from the initial spending increases.

In rows 2-4 of Table 3, we explore predicted spending responses to more progressive versions of the individual stimulus payments. We keep the overall value of the policy constant, but target lower-income individuals and households. At the most extreme, we evaluate a policy that gives a payment of \$3,700 to any individual earning less than \$10,000 annually. Our back-of-the-envelope calculation based on the Facteus MPCs implies that this would increase consumer spending by \$179 billion. An important (and unrealistic) assumption here is that the MPC is constant for each person and does not change with the size of the individual payment. In the last row of Table 3, we evaluate a policy that would give a \$1,147 payment to each adult in the United States, independent of income. We argue that this policy would increase spending by roughly the same amount (\$134 billion) as the actual CARES Act payments to individuals and households. In other words, while the stimulus bill was means-tested, it will have almost the same effect on consumer spending as a policy that sends a payment to each adult in the United States, irrespective of income.¹²

Conclusion

In this paper, we analyze the short-run effects of Covid-19 Economic Impact Payments on consumer spending. We show that a \$1,200 payment from the IRS leads to an average of \$577 in increased spending for a sample of consumers in data from Facteus. This MPC of 48% masks significant heterogeneity. High-income consumers and consumers who generally save a significant fraction of their income have an MPC closer to 23%; and consumers who live paycheck-to-paycheck, spending all of the income they receive each month, have an average MPC of 68%. We show that consumer age, income, and location are only

¹²Importantly, this last counterfactual policy evaluation relies on the assumption that the highest-income stimulus recipients have MPCs that are representative of non-stimulus recipients—those individuals with individual incomes and household incomes above the CARES Act cutoff.

marginally correlated with individual MPCs after controlling for each individual's pre-pandemic savings behavior. Walmart captures much (18%) of the increase in consumer spending due to Covid-19 Economic Impact Payments.

Ignoring equilibrium effects and assuming a constant MPC for each person, we estimate that the \$296 billion of payments to individuals from the CARES Act will increase consumer spending by \$138 billion (47% of total outlays). A stimulus bill of the same overall size targeted at lower-income individuals earning under \$10,000 would have instead increased consumer spending by \$179 billion. Consumer spending is not the main goal of most stimulus programs. Instead, governments use stimulus programs to keep households afloat during recessions and times of economic uncertainty. Nonetheless, we hope that our findings provide a precise estimate of how government disbursements (with no strings attached) affect consumer spending during a time of economic uncertainty. In future research, we hope to explore additional predictors of the individual-level MPC.

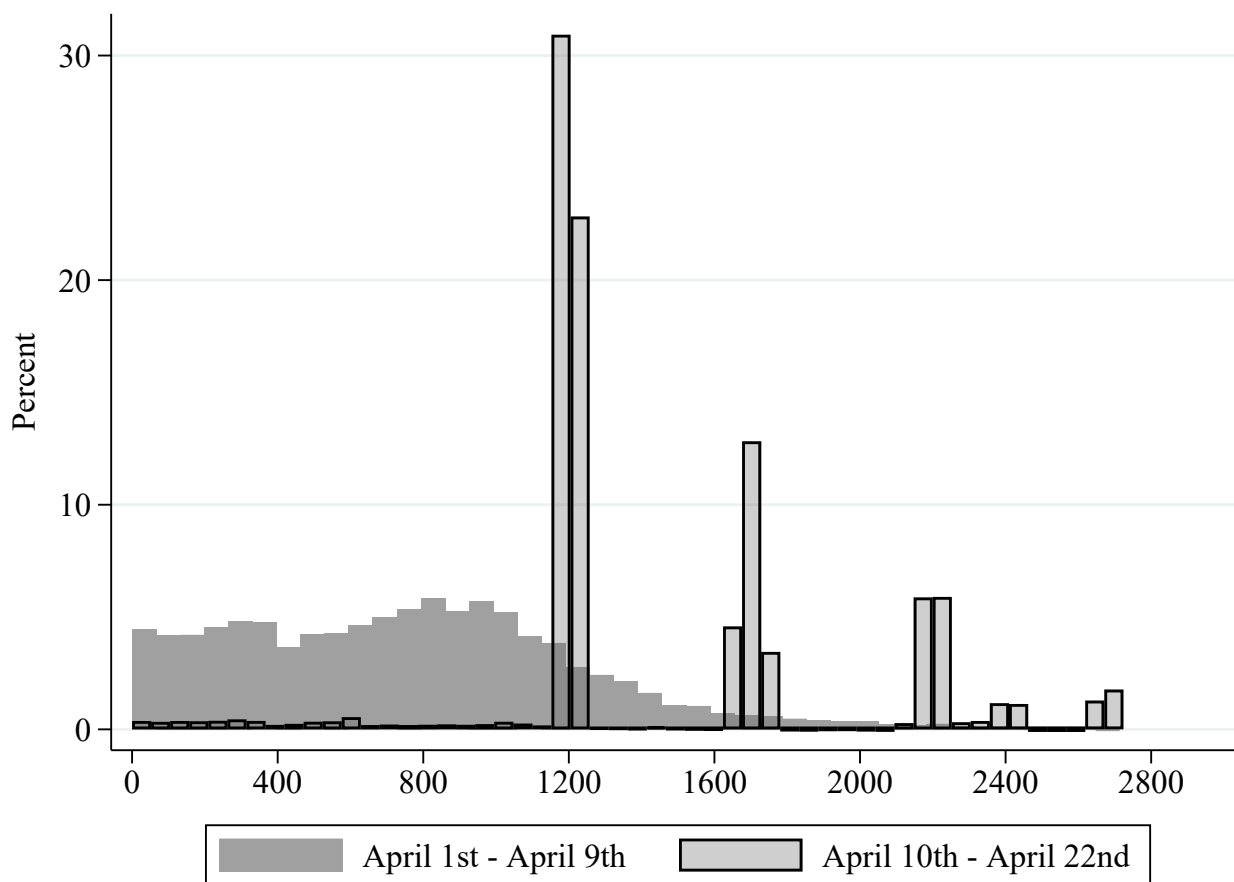
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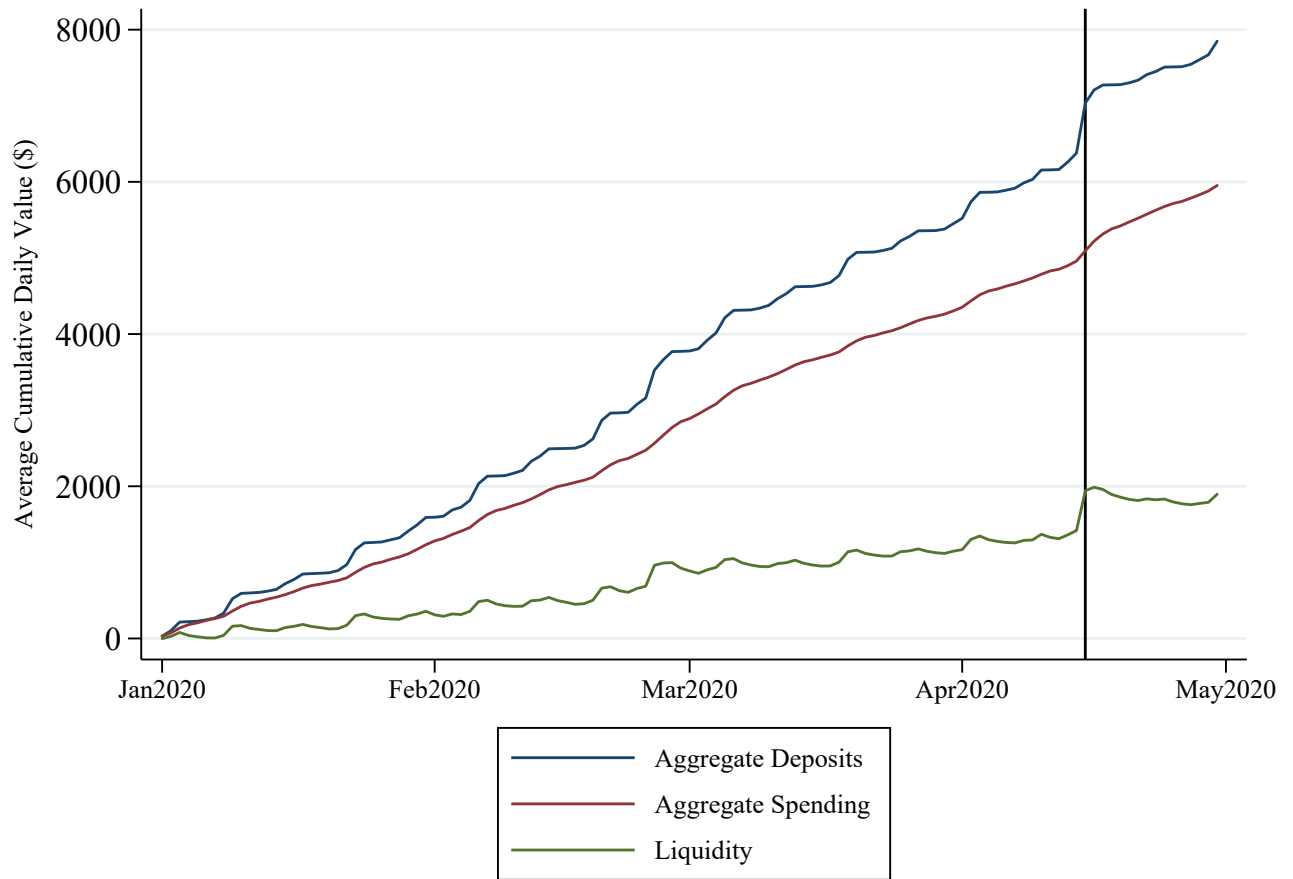
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Figure 1: Distribution of Government Deposits



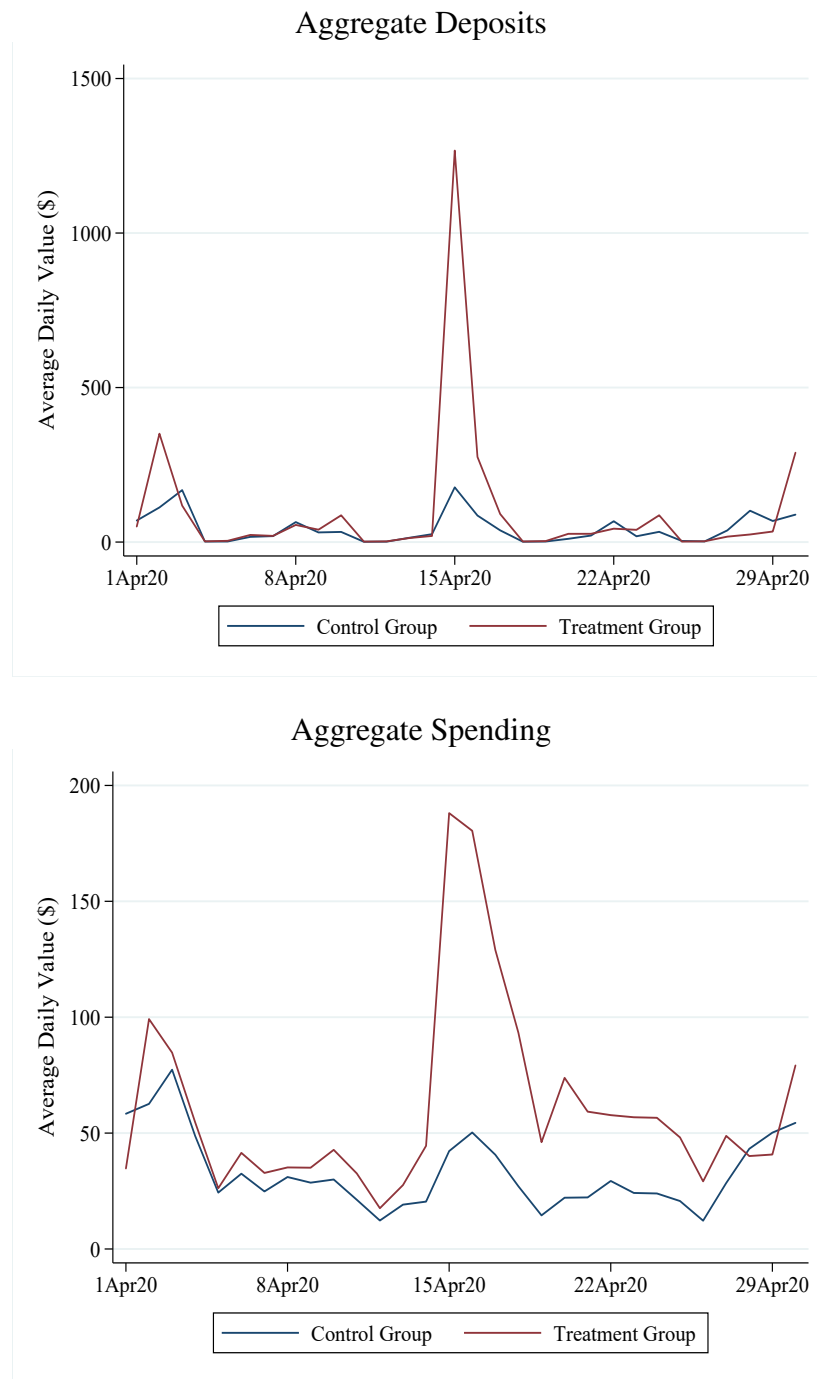
Notes: The graph shows the distribution of government deposits made between April 10th and April 22nd in our sample of accounts from Factiveus overlaid on the distribution of government deposits made between April 1st and April 9th. The values shown are trimmed at the 90th percentile of the distribution.

Figure 2: Time-Trends in Transactions



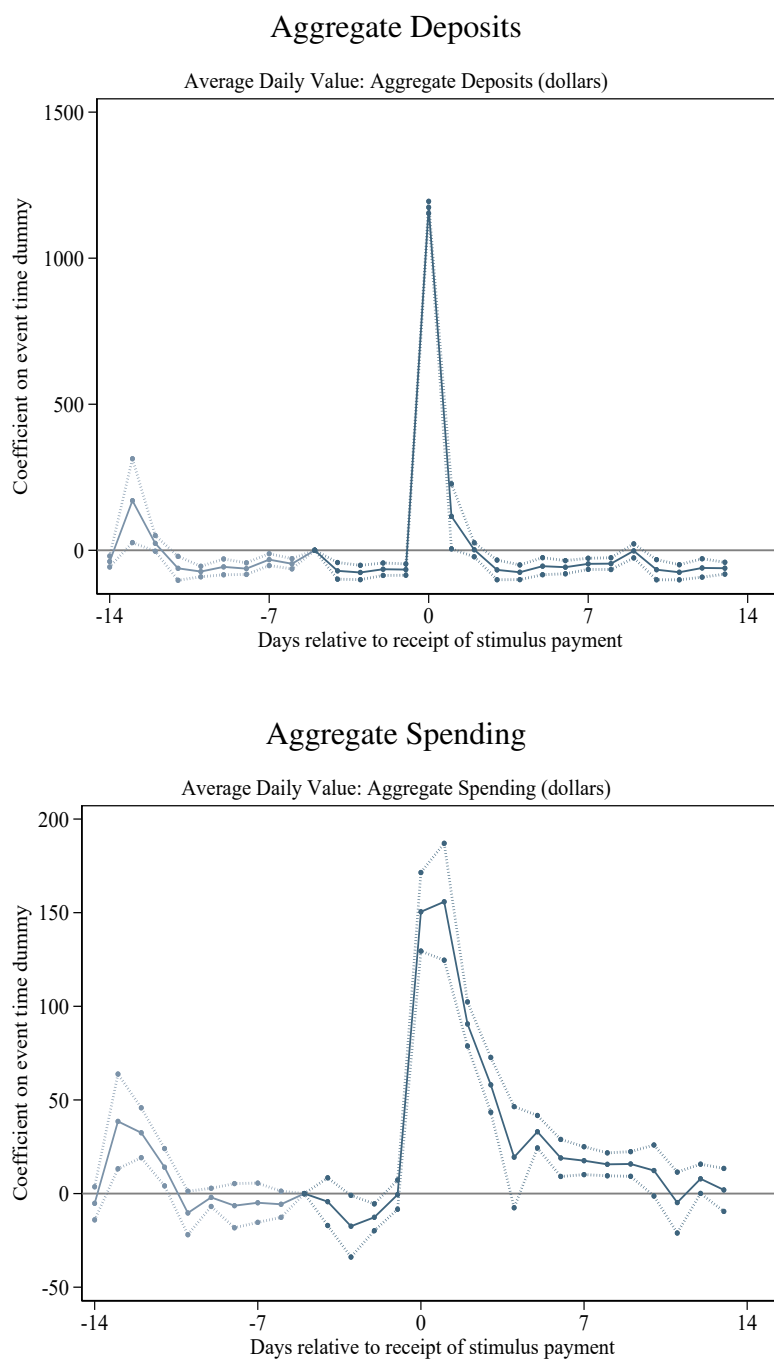
Notes: The vertical line marks April 15th, 2020 when a majority of the accounts in the sample receive stimulus payment deposit. Out of all the accounts that received a \$1,200 stimulus payment between April 10th and April 22nd, 67% receive the stimulus payment deposit on April 15th.

Figure 3: Effect of Stimulus Payments on Spending and Deposits: Calendar Time



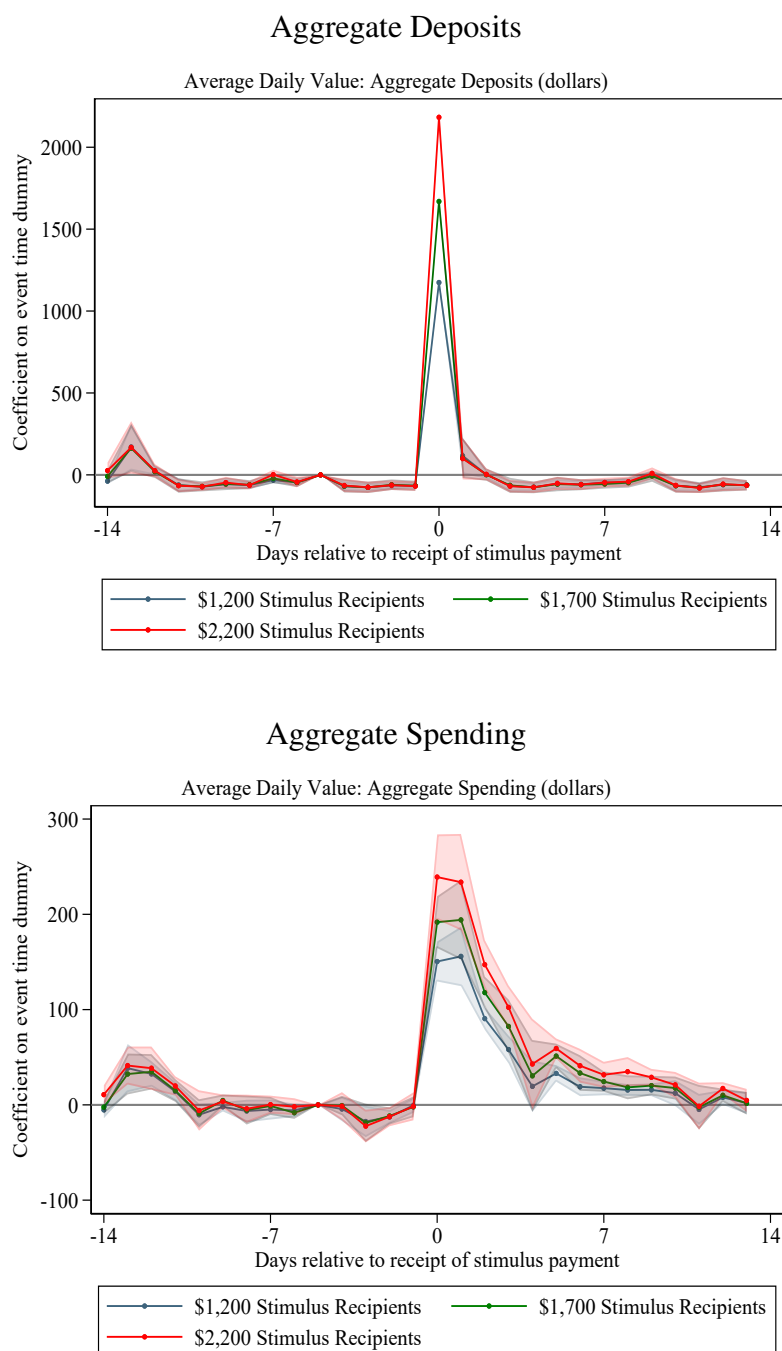
Notes: Plotted are time-series of aggregate per-consumer spending and deposits for April 2020. We separately plot spending and deposits for (1) accounts in the control group and (2) accounts in the main treatment group that received \$1,200 stimulus payment on April 15. Aggregate spending includes transactions labeled as bill pay, fees, spending and ATM withdrawals. Aggregate Deposits include all transactions labeled as deposits, loads, and government deposits (including stimulus payments).

Figure 4: Effect of Stimulus Payments on Spending and Deposits: event time (Model A)



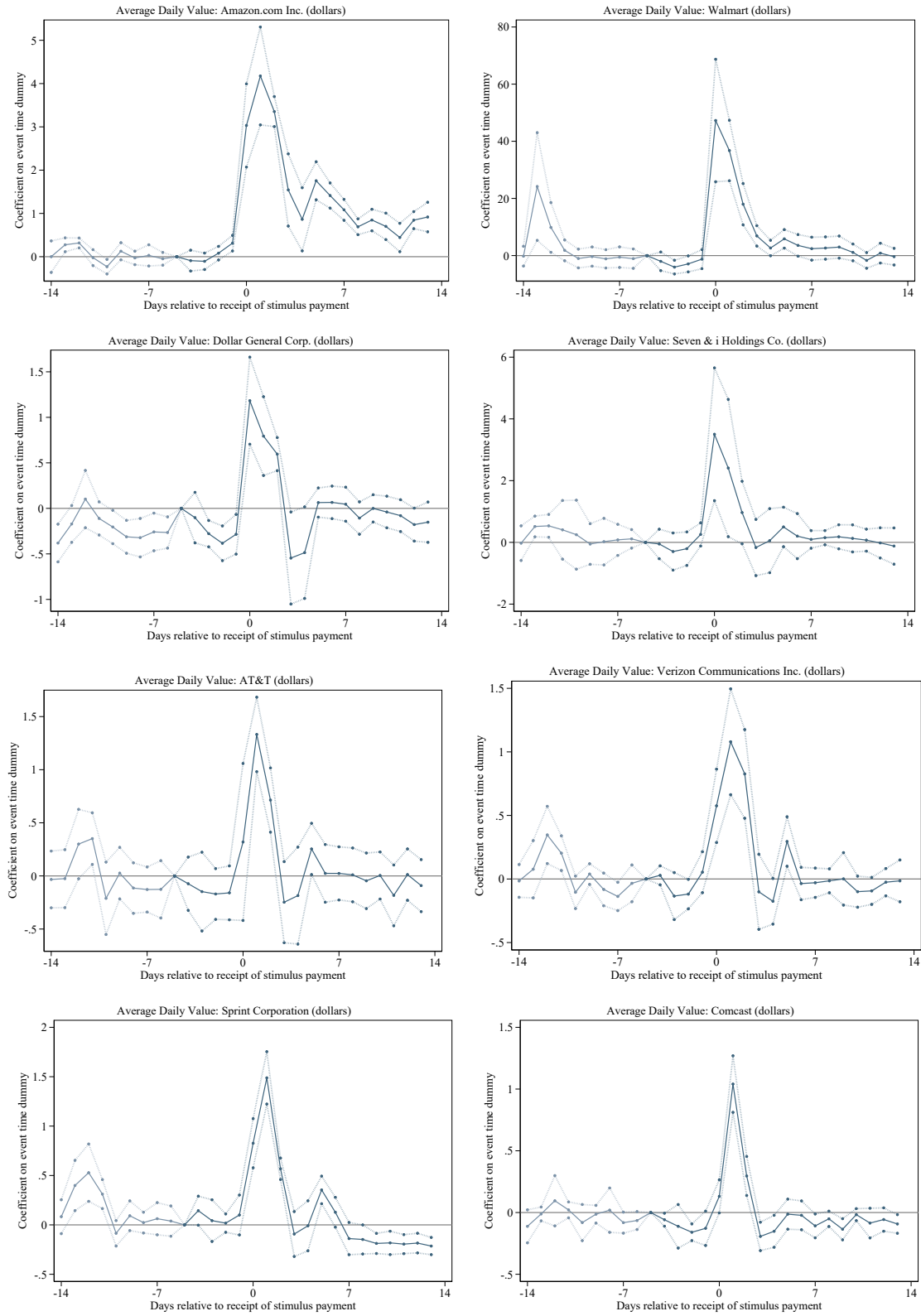
Notes: Data at the account-day level. Plotted are coefficients on event time dummies from regression of aggregate spending or deposits on day-since-event time fixed effects (Model A). Standard errors are clustered two-way by state and calendar date. Time 0 in event time is defined as the date on which the account received a stimulus payment. Aggregate spending includes transactions labeled as bill pay, fees, spending and ATM withdrawals. Aggregate Deposits includes transactions labeled as deposits, loads, government deposits and stimulus payment.

Figure 5: Effect of Stimulus Payments on Spending and Deposits: event time (Model B)



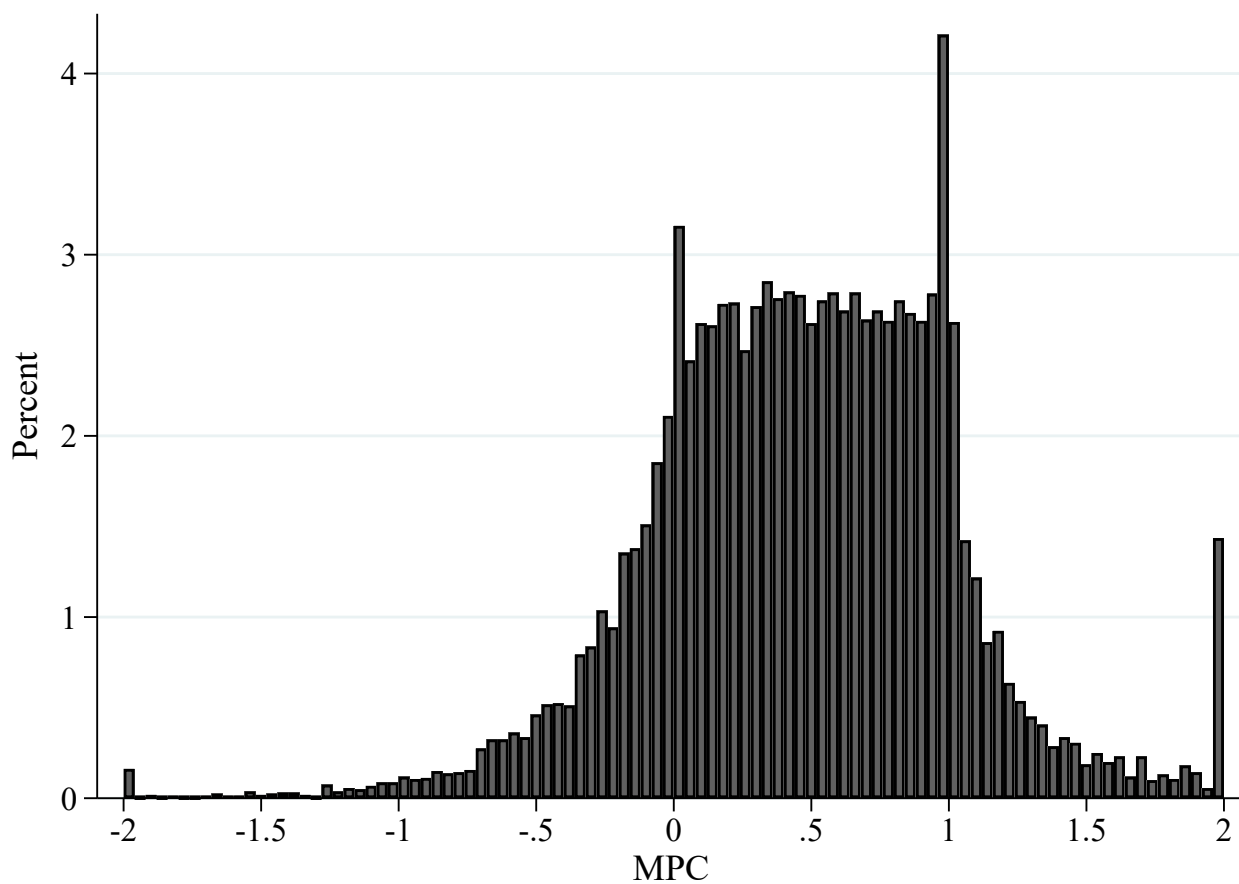
Notes: Data at the account-day level. Plotted are coefficients on event time dummies from regression of aggregate spending or deposits on day-since-event time fixed effects, separately for each group of stimulus recipients (Model B). Standard errors are clustered two-way by state and calendar date. Time 0 in event time is defined as the date on which the account received a stimulus payment. Aggregate spending includes transactions labeled as bill pay, fees, spending and ATM withdrawals. Aggregate Deposits includes transactions labeled as deposits, loads, government deposits and stimulus payment.

Figure 6: Effect of Stimulus Payments on Spending at specific companies: event time



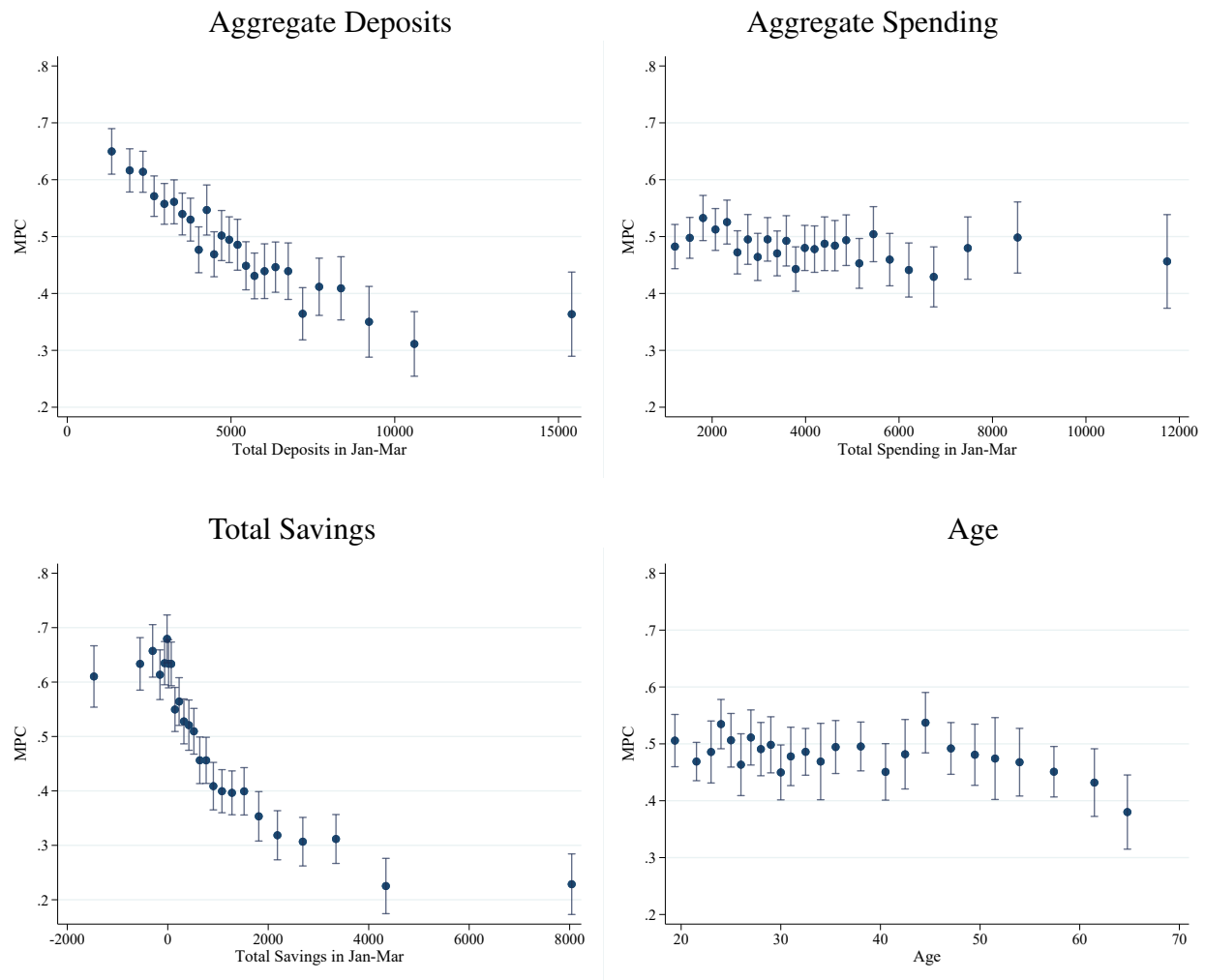
Notes: Data at the account-day level. Plotted are coefficients on event time dummies from regression of aggregate spending or deposits on day-since-event time fixed effects (Model A). Standard errors are clustered two-way by state and calendar date. Time 0 in event time is defined as the date on which the account received a stimulus payment. The aggregate spending at each merchant for each account-date is identified using Factiveus's pre-processed merchant names.

Figure 7: Distribution of MPCs



Notes: Histogram shows distribution of MPCs after winsorizing the values to $[-2, 2]$. MPCs are calculated as the difference between total spending in the two weeks following stimulus receipt and the two weeks preceding stimulus receipt for all accounts in our data that received a \$1,200 stimulus payment between April 10th and April 22nd 2020.

Figure 8: MPC Heterogeneity



Notes: Plotted are binned scatterplots showing the distribution of individual level MPCs by spending levels, deposit levels, savings levels, and consumer age. Aggregate spending includes the sum of all transactions labeled as bill pay, fees, spending and ATM withdrawals in January—March 2020 for each account. Aggregate Deposits includes all transactions labeled as deposits, loads, and government deposits (including stimulus payments) in January—March 2020 for each account. The level of savings is calculated as the difference between aggregate deposits and aggregate spending in January—March 2020.

Table 1: Summary statistics: Stimulus Recipients

Summary Statistics: Total Value (\$) of Transactions, Factiveus
Jan - Mar 2020

Transaction Type	No. of Accounts	Avg.	Med.	10th %	90th %	S.D.	Aggregate Category
Deposit	16,016	962.66	0.00	0.00	4327.44	2325.58	Aggregate Deposits
Government Deposit	16,016	667.19	0.00	0.00	1658.14	1173.87	Aggregate Deposits
Load	16,016	3893.86	3670.29	0.00	7852.65	3329.13	Aggregate Deposits
Atm Withdrawal	16,016	803.33	250.70	0.00	2429.76	1262.54	Aggregate Spending
Bill Pay	16,016	6.44	0.00	0.00	0.00	89.12	Aggregate Spending
Fee	16,016	18.20	9.01	0.00	48.26	25.72	Aggregate Spending
Spend	16,016	3585.25	3170.87	1202.91	6425.19	2313.74	Aggregate Spending
Aggregate Deposits	16,016	5523.72	4942.48	2311.07	9198.57	3166.95	
Aggregate Spending	16,016	4413.22	3980.70	1808.36	7451.15	2436.37	

Notes: Data at account-level. Transaction amounts are totals for January—March 2020.

Table 2: Horse race of account-level characteristics that predict MPCs

	(1)	(2)	(3)	(4)	(5)
2.Deposits	-0.07*** (0.01)			-0.03** (0.01)	-0.03** (0.01)
3.Deposits	-0.12*** (0.01)			-0.04*** (0.01)	-0.03*** (0.01)
4.Deposits	-0.18*** (0.01)			-0.06*** (0.02)	-0.05*** (0.02)
5.Deposits	-0.23*** (0.01)			-0.07*** (0.02)	-0.06*** (0.02)
2.Savings		-0.02 (0.01)		-0.02 (0.02)	-0.02 (0.02)
3.Savings		-0.14*** (0.01)		-0.13*** (0.02)	-0.13*** (0.02)
4.Savings		-0.24*** (0.01)		-0.23*** (0.01)	-0.24*** (0.01)
5.Savings		-0.35*** (0.02)		-0.32*** (0.02)	-0.33*** (0.02)
2.Age			-0.01 (0.02)	-0.00 (0.02)	-0.00 (0.02)
3.Age			-0.01 (0.02)	0.00 (0.01)	0.00 (0.01)
4.Age			-0.01 (0.02)	0.01 (0.02)	0.01 (0.02)
5.Age			-0.06*** (0.01)	-0.03** (0.01)	-0.03** (0.01)
Constant	0.60*** (0.01)	0.63*** (0.01)	0.50*** (0.01)	0.66*** (0.01)	0.66*** (0.01)
State Fixed Effects	No	No	No	No	Yes
Observations	16,016	16,016	13,317	13,317	13,317
R ²	0.018	0.050	0.001	0.054	0.058

Notes: Data at the account-level, which we term consumers. Outcome is each consumer's MPC, equal to the difference in total spending in the two weeks after each account received a stimulus payment minus the account's total spending in the two weeks prior to the stimulus payment. We show regressions of individual MPCs on quintiles of total deposits in January — March, quintiles of savings (levels) in January — March, quintiles of age, and state fixed effects. In the fifth model, we include all controls. Standard errors are clustered at the state-level.

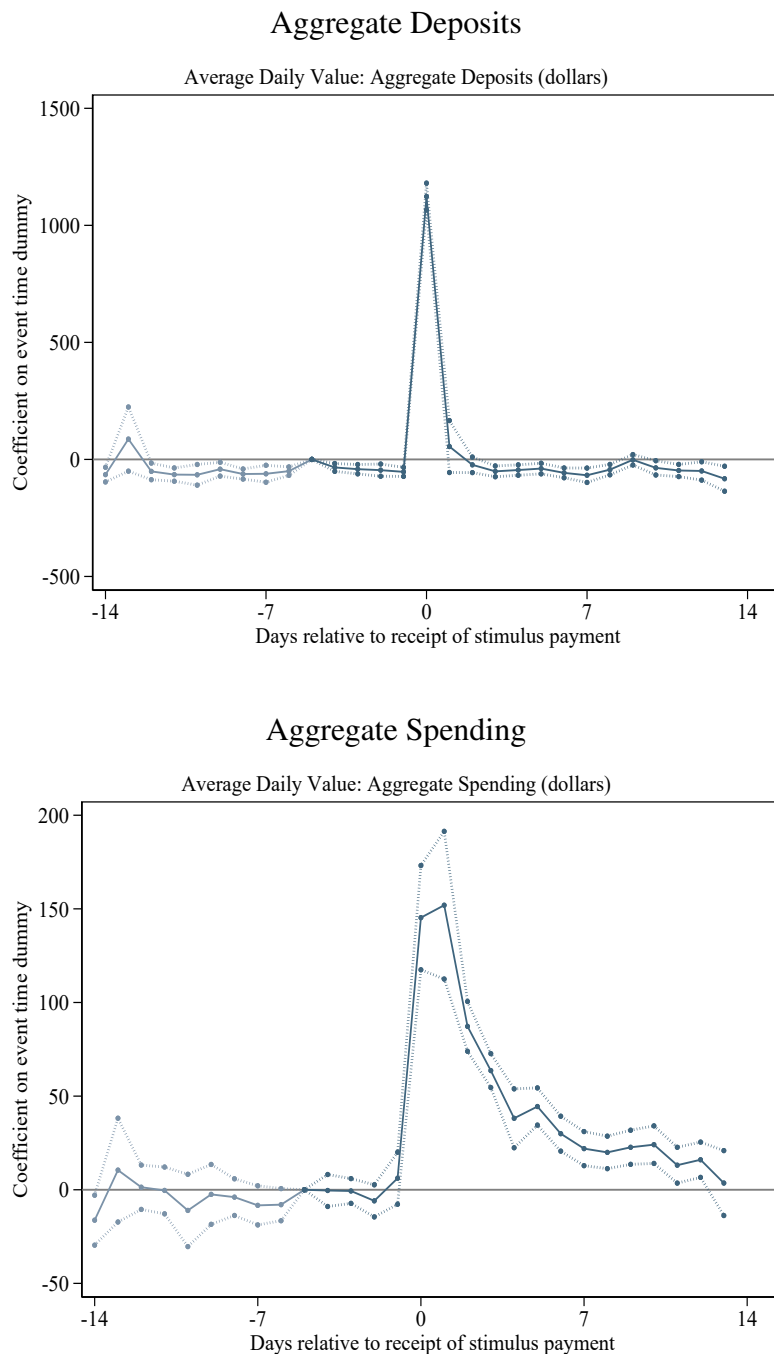
Table 3: Stimulus Payment Counterfactuals

Counterfactual	Stimulus Payment	Cost of Stimulus Bill (USD Billions)	Recipients (Millions)	Fraction of Stimulus Spent	Total Consumer Spending (USD Billions)
Actual stimulus bill	1289.30	296.17	229.71	0.47	137.77
30K individual or 60K household income	1791.14	296.17	165.35	0.51	151.25
20K individual or 40K household income	2310.75	296.17	128.17	0.55	162.52
10K individual or 20K household income	3699.56	296.17	80.05	0.60	179.11
All adults receive same amount	1147.51	296.17	258.09	0.45	133.77

Notes: Stimulus payment refers to the payment received by the average adult who received a stimulus payment in each scenario. The cost of the stimulus bill (in USD billions) is the total amount of the stimulus payments distributed amongst the recipient population. The “Recipients” columns records the total number of adults (in millions) in the U.S. who would receive a stimulus payment under each scenario, as per the population weights in 2018 ACS. The ‘Fraction of stimulus payment’ is the weighted average of the share of stimulus payments that the recipients are expected to spend using the MPC distribution estimated from Factiveus data. Total consumer spending is a weighted sum of the stimulus payment multiplied by the fraction of the payment spent by each recipient.

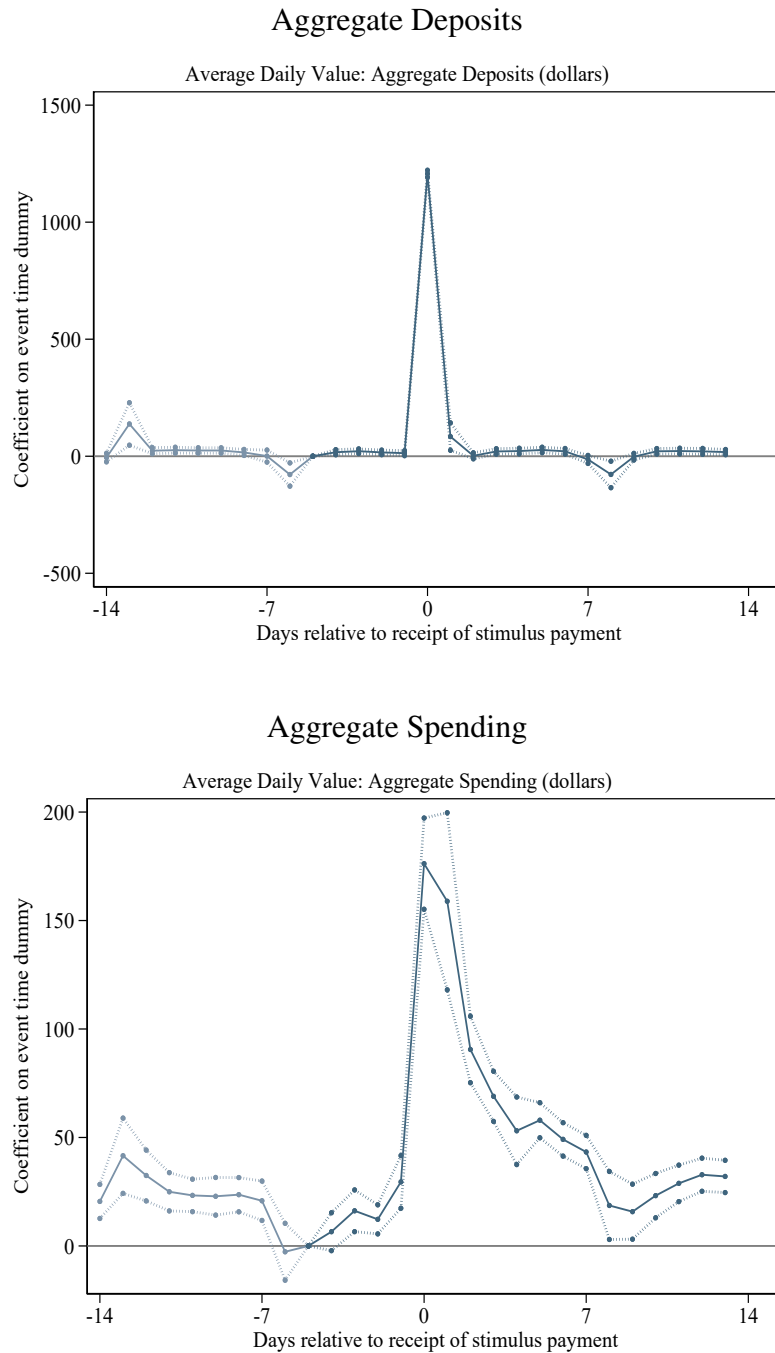
A Appendix

Figure A1: Effect of Stimulus Payments on Spending and Deposits: event time (Model C)



Notes: Data at the account-day level. Plotted are coefficients on event time dummies from a regression which also includes individuals and date-by-state fixed effects (Model D). Standard errors are clustered two-way by state and date. Time 0 in event time is defined as the date on which stimulus payment is received by the account. Aggregate spending includes transactions labeled as bill pay, fees, spending and ATM withdrawals. Aggregate Deposits includes all transactions labeled as deposits, loads, and government deposits (including stimulus payment).

Figure A2: Effect of Stimulus Payments on Spending and Deposits: event time (Model D)



Notes: Data at the account-day level. Plotted are coefficients on event time dummies from a regression of residual spending on days-since-event time (Model C). Residual spending is calculated as the difference between realized consumer spending and predicted consumer spending from a regression of spending on person-by-day-of-the-week fixed effects in January–March, 2020. Standard errors are clustered by state and date. Time 0 in event time is defined as the date on which stimulus payment is received by the account. Aggregate spending includes transactions labeled as bill pay, fees, spending and ATM withdrawals. Aggregate Deposits includes all transactions labeled as deposits, loads, and government deposits (including stimulus payments).

Table A1: Summary statistics: Non-Recipients

Summary Statistics: Total Value (\$) of Transactions, Factiveus
Jan - Mar 2020

Transaction Type	No. of Accounts	Avg.	Med.	10th %	90th %	S.D.	Aggregate Category
Deposit	8,297	354.43	0.00	0.00	0.00	1626.64	Aggregate Deposits
Government Deposit	8,297	2515.44	2085.96	236.08	5349.05	2341.25	Aggregate Deposits
Load	8,297	2442.84	1308.25	0.00	6334.62	3384.75	Aggregate Deposits
Atm Withdrawal	8,297	641.17	83.67	0.00	1904.95	1307.07	Aggregate Spending
Bill Pay	8,297	6.76	0.00	0.00	0.00	101.35	Aggregate Spending
Fee	8,297	23.42	14.83	0.00	58.02	26.87	Aggregate Spending
Spend	8,297	3424.45	2619.84	1079.54	6867.31	2798.26	Aggregate Spending
Aggregate Deposits	8,297	5312.70	3844.14	1794.53	10833.23	4342.65	
Aggregate Spending	8,297	4095.80	3121.87	1515.52	7921.27	3107.39	

Notes: Data at account-level. Transaction amounts are totals for January—March 2020.

Table A2: Summary statistics: Non-Recipients & \$1,200 Stimulus Recipients

Summary Statistics: Total Value (\$) of Transactions, Factiveus

Jan - Mar 2020

Transaction Type	No. of Accounts	Avg.	Med.	10th %	90th %	S.D.	Aggregate Category
Deposit	24,313	755.10	0.00	0.00	3361.74	2132.76	Aggregate Deposits
Government Deposit	24,313	1297.92	694.15	0.00	3640.05	1883.11	Aggregate Deposits
Load	24,313	3398.69	3006.97	0.00	7516.25	3418.10	Aggregate Deposits
Atm Withdrawal	24,313	747.99	199.87	0.00	2289.75	1280.20	Aggregate Spending
Bill Pay	24,313	6.55	0.00	0.00	0.00	93.47	Aggregate Spending
Fee	24,313	19.98	10.85	0.00	52.32	26.23	Aggregate Spending
Spend	24,313	3530.38	2972.66	1153.72	6551.32	2490.82	Aggregate Spending
Aggregate Deposits	24,313	5451.71	4654.49	2054.13	9671.83	3612.74	
Aggregate Spending	24,313	4304.90	3709.94	1680.79	7586.62	2688.43	

Notes: Data at account-level. Transaction amounts are totals for January—March 2020.

Table A3: Summary statistics: \$1,700 Stimulus Recipients

Summary Statistics: Total Value (\$) of Transactions, Factiveus

Jan - Mar 2020

Transaction Type	No. of Accounts	Avg.	Med.	10th %	90th %	S.D.	Aggregate Category
Deposit	6,590	1129.63	0.00	0.00	5195.64	2918.44	Aggregate Deposits
Government Deposit	6,590	1773.50	0.00	0.00	5827.15	2559.21	Aggregate Deposits
Load	6,590	5702.26	5316.76	0.00	11345.01	4831.72	Aggregate Deposits
Atm Withdrawal	6,590	999.46	302.14	0.00	2999.55	1625.86	Aggregate Spending
Bill Pay	6,590	8.67	0.00	0.00	0.00	104.53	Aggregate Spending
Fee	6,590	21.98	13.75	0.00	54.89	26.03	Aggregate Spending
Spend	6,590	5587.14	5307.15	1945.78	9424.25	2999.52	Aggregate Spending
Aggregate Deposits	6,590	8605.39	8585.34	3854.35	12768.52	4240.22	
Aggregate Spending	6,590	6617.24	6401.48	2749.10	10536.15	3116.02	

Notes: Data at account-level. Transaction amounts are totals for January—March 2020.

Table A4: Summary statistics: \$2,200 Stimulus Recipients

Summary Statistics: Total Value (\$) of Transactions, Factiveus

Jan - Mar 2020

Transaction Type	No. of Accounts	Avg.	Med.	10th %	90th %	S.D.	Aggregate Category
Deposit	4,068	1270.68	0.00	0.00	5547.87	3547.31	Aggregate Deposits
Government Deposit	4,068	2278.56	0.00	0.00	8404.67	3521.56	Aggregate Deposits
Load	4,068	7473.98	6977.78	0.00	14503.03	5627.24	Aggregate Deposits
Atm Withdrawal	4,068	1133.21	322.09	0.00	3466.91	1865.26	Aggregate Spending
Bill Pay	4,068	9.67	0.00	0.00	0.00	84.83	Aggregate Spending
Fee	4,068	23.80	14.66	0.00	60.84	29.08	Aggregate Spending
Spend	4,068	7182.94	6852.93	2487.69	12063.50	3782.02	Aggregate Spending
Aggregate Deposits	4,068	11023.22	11295.15	4826.81	15944.81	4697.80	
Aggregate Spending	4,068	8349.62	8214.64	3343.43	13175.27	3887.12	

Notes: Data at account-level. Transaction amounts are totals for January—March 2020.