Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments*

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April 2020

Abstract

In response to the ongoing COVID-19 pandemic, the US government brought about a collection of fiscal stimulus measures: the 2020 CARES Act. We study direct payments to households starting in April 2020 using high-frequency transaction data. We explore the response of household spending to these stimulus payments in the short run as well as heterogeneity by income levels, recent income declines, and liquidity. We find that households respond rapidly to receipt of stimulus payments, with spending increasing by \$0.25-\$0.35 per dollar of stimulus during the first 10 days. Households with lower incomes, greater income drops, and lower levels of liquidity see higher responses. Liquidity plays the most important role, with no observed spending response for households with high levels of available cash on hand. Relative to the effects of previous economic stimulus programs in 2001 and 2008, we see much smaller increases in durables spending and larger increases in spending on food, likely reflecting the impact of shelter-in-place orders and supply disruptions. In turn, we discuss the fiscal stimulus and multiplier effects that may result from these payments.

JEL Classification: D14, E21, G51
Keywords: Consumption, COVID-19, Stimulus, MPC, Household Finance, Transaction Data

*The authors wish to thank our colleagues for helpful discussions and comments. Constantine Yannelis is grateful to the Fama Miller Center for generous financial support. R.A. Farrokhnia is grateful to Advanced Projects and Applied Research in Fintech at Columbia Business School for support. We are grateful to Suwen Ge, Spyros Kypraios, Rebecca Liu and Sharada Sridhar for excellent research assistance. We are grateful to SaverLife for providing data access. This draft is preliminary and comments are welcome.

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1 Introduction

Governments often respond to recessions with cash payments to households. These payments are meant to alleviate the effects of a recession and stimulate the economy through a multiplier effect, i.e., by first increasing households' consumption which then translates to more production and employment. The effectiveness of these payments relies on households' marginal propensities to consume, or MPCs, out of these stimulus payments. In this paper, we estimate households' MPCs in response to the 2020 CARES Act stimulus payments. We also look at how these MPCs vary with household characteristics, such as income, income declines, and cash on hand. Understanding these MPCs is key to targeting policies to households where effects will be largest, as well as testing between different models of household consumption behavior.

Currently, the global economy is in the midst of a recession induced by the ongoing pandemic of the novel Coronavirus disease (COVID-19). The Covid-19 outbreak was first noted in Wuhan, Hubei province, China, in December 2019. The World Health Organization (WHO) declared the outbreak to be a Public Health Emergency of International Concern on January 30, 2020 and recognized it as a pandemic on March 11, 2020.

By mid-March schools and non-essential businesses across the US were shutting down to combat the spread of the virus which caused an unprecedented increase in unemployment and decline in economic activity. In response to this new recession, the US government brought forward an unprecedented collection of fiscal stimulus measures: the 2020 CARES Act. Among other measures, the act directed payments to households starting in April 2020. We use high-frequency transaction data from SaverLife, a non-profit Fintech, to study household responses to these stimulus payments.

Our detailed data allow us to observe not only income and spending in close to real-time, but also income declines and cash on hand, or liquidity. We find large and immediate responses to stimulus payments in the first ten days after receiving payments. The average household in our sample spends 29 cents of every dollar received within ten days. Most of the payments are spent on food, non-durables, and rent and bill payments. Lower-income households spend slightly more of the stimulus payments, as do households that saw large income drops between January and March, however liquidity is a much stronger predictor of MPCs than income or income declines.

MPCs are particularly important to both policy and economic theory as they determine multipliers in a wide class of models. In particular, heterogeneity in MPCs can impact which households are most responsive to stimulus payments, which in turn can have large impacts on the effectiveness of stimulus payments on consumption and the aggregate economy. This paper shows that liquidity is a key determinant of MPC heterogeneity, with highly liquid households showing no response to stimulus payments.

We explore responses to stimulus payments and individual heterogeneity in MPCs by using high frequency transaction data from SaverLife, a non-profit Fintech which encourages individuals to save.[1] Customers link their accounts to the app, and we have access to de-identified bank account transactions and balances data from August 2016 to April 2020 for 44,660 users. The fact that we observe inflows and outflows from individual accounts in this dataset allows us to explore heterogeneity in overall income levels, drops in income, and liquidity.

We use this high-frequency detailed data and exploit the stimulus payments distributed by mid April 2020. Stimulus payments began on April 9 via direct deposit from the IRS, and we can observe spending at a high frequency before and after stimulus payments are made. The fact that we observe payment amounts and the exact timing of payments allows us to identify MPCs. We see sharp and immediate responses to the stimulus payments, and continued elevated spending even ten days after payments were received. Within ten days, users spend 29 cents of every dollar received in stimulus payments. The largest increases in spending are on food, non-durables, and rent and bill payments. In contrast to the 2008 stimulus payments, there is relatively little spending on durables (Parker, Souleles, Johnson and McClelland, 2013).

We exploit the fact that we observe paychecks and balances to explore heterogeneity. Greater income, larger income drops, and less liquidity are all associated with larger MPCs – with liquidity being the strongest predictor of MPCs. Individuals with less than $500 in their accounts spend almost half of their stimulus payments within ten days – 44.5 cents out of every dollar – while we observe no response for individuals with more than $3,000 in their accounts. These results are important in terms of targeting stimulus policies towards groups most impacted by the policies. The

[1] In Baker, Farrokhnia, Meyer, Pagel and Yannelis (2020b), we study the spending response at the onset of the pandemic in early March 2020 and in response to the economic lockdown and shelter-in-place policies that were enacted in mid-March 2020. Carvalho, Garcia, Hansen, Ortiz, Rodrigo, Mora and Ruiz (2020) and Andersen, Hansen, Johannesen and Sheridan (2020) perform similar analyses for Spain and Denmark.

theory behind stimulus payments rests of multipliers, which in turns are, in most models, determined by MPCs. The results of this study suggest that targeting stimulus payments to households with low levels of liquidity will have the largest effects on MPCs, and hence multipliers.

Stimulus payments have been used repeatedly as a response to fight large economic downturns. For example in 2001 and 2008 following the financial crisis. There is a large literature on how households respond to these rebates and stimulus payments. The existing studies exploit the differences in timing of the arrival of the payment to infer causal effects.

Using spending data from the Consumer Expenditure Survey Johnson, Parker and Souleles (2006) and Parker, Souleles, Johnson and McClelland (2013) look at the tax rebates granted in 2001 and the economic stimulus payments in 2008. For the 2001 rebates Johnson, Parker and Souleles (2006) find that 20-40% were spent on non-durable goods during the quarter in which they received the rebate. The effect also carried over to the next quarter. Parker, Souleles, Johnson and McClelland (2013) focusing on the stimulus payment in 2008 also find large and positive effects on spending. They document positive effects on spending in both nondurable and durable goods. The same result has been obtained by Broda and Parker (2014) using high-frequency scanner data as well as a large number of follow-up studies. In Section 5.1, we discuss some of the differences between our estimates and the previous literature.

Besides looking at aggregate effects, studies have also found heterogeneous effects across agents. Agarwal, Liu and Souleles (2007) work with credit card accounts and found that customers initially saved the tax rebates in 2001 but later then increased spending. In their setting, customers with liquidity constraints were most responsive. Misra and Surico (2014) use a quantile framework to look at the 2001 tax rebates and the 2008 economic stimulus payments on the distribution of changes in consumption.

Kaplan and Violante (2014) focus on the 2001 tax rebates and use a structural model to document that responsiveness to rebates is driven by liquid wealth. Households with sizable quantities of illiquid assets are an important driver of the magnitude of the response. To our knowledge, our study is the first to study stimulus payments using high-frequency transaction data, as these data did not exist in 2008. The use of transaction data allows us to explore very-short term responses across categories, minimize measurement error and explore individual daily heterogeneity in income declines and available cash on hand.

We also focus on a very different crisis stemming from an infectious disease outbreak. In comparison, to the crises in 2001 and 2008 the economic downturn due to COVID-19 happened at a faster pace and destroyed jobs much more quickly. In addition, the pandemic comes more as a surprise and has a large effect initially on income and liquidity rather than on future income and wealth. While previous studies have pointed out, that stimulus payments have positive but heterogeneous effects on spending, the differences in circumstances may help us learn more on how a stimulus affects spending and households in different economic circumstances. In particular, this crisis was so fast moving that households little ability to anticipate income declines and increase savings.

Our results are also important for the ongoing discussion of Representative Agent Neo-Keynesian (RANK) and Heterogeneous Agent Neo-Keynesian (HANK) models. RANK and HANK models offer starkly different predictions, and the observed MPC heterogeneity highlights the importance of the HANK framework. In a recent attempt to study the current pandemic in a HANK framework, Kaplan, Moll and Violante (2020) show that for income declines up to 70%, consumption declines by 10%, and GDP per capita by 6% in a lockdown scenario coupled with economic policy. In another recent working paper, Bayer, Born, Luetticke and Müller (2020) calibrate a HANK model to study the impact of the quarantine shock on the US economy in the case of a successful suppression of the pandemic. In their model, the stimulus payment stabilizes consumption but it still decreases by roughly 50% in 2020 which is in line with our estimates and will result in an output decline less than 3.5%. Hagedorn, Manovskii and Mitman (2019) study multipliers in a HANK framework, whose size can depend on market completeness and targeting of the stimulus.

This paper also joins a fast growing literature on the effects of 2020 COVID-19 pandemic on the economy. Several papers develop macroeconomic frameworks of epidemics, e.g. Jones, Philippon and Venkateswaran (2020), Barro, Ursua and Weng (2020), Eichenbaum, Rebelo and Trabandt (2020) and Kaplan, Moll and Violante (2020). Gormsen and Koijen (2020) use stock prices and dividend futures to back out growth expectations. Coibion, Gorodnichenko and Weber (2020) study short-term employment effects and Baker, Bloom, Davis and Terry (2020a) analyze risk expectations. Granja, Makridis, Yannelis and Zwick (2020) study the targeting and impact of the PPP on employment. Barrios and Hochberg (2020) and Allcott, Boxell, Conway, Gentzkow, Thaler and Yang (2020) show that political affiliations impact the social distancing response to the pandemic, and Coven and Gupta (2020) study disparities in COVID-19 infections and responses. Our related paper, Baker, Bloom, Davis and Terry (2020a), studies household consumption during this period using the same data source. We join this emerging and rapidly growing literature by providing early evidence on how households responded to the crisis and the impact of federal stimulus policy. The results suggesting that MPCs are much higher for low liquidity households are important in designing future rounds of stimulus, if the effects of the epidemic persist over the next months.

The remainder of this paper is organized as follows. Section 2 provides background information regarding the 2020 stimulus and Section 2.2 presents our empirical strategy. Section 3 describes the main transaction data used in the paper. Section 4 presents the main results and Section 5 discusses heterogeneity by income, income drops, and liquidity. Section 6 concludes and presents directions for future research.

2 Institutional Background and Empirical Strategy

2.1 2020 Household Stimulus

COVID-19, the novel coronavirus first identified in Wuhan, China spread worldwide in February 2020. The new virus had a mortality rate which, by some estimates, is ten times higher than the seasonal flu and has at least twice its infection rates. The first case in the United States was identified in late January in Washington State and slowly spread throughout February. By mid-March, the virus spread rapidly, with significant clusters in the greater New York, San Francisco, and Seattle areas. Federal and many state governments responded to the COVID-19 pandemic in a number of ways, for example by issuing travel restrictions, shelter-in-place orders, and closures of all non-essential businesses.

The federal government passed legislation aimed to ameliorating economic damage stemming from the spreading virus and shelter-in-place policies. The CARES Act was passed on March 25, 2020 as a response to the economic damage of the new virus. The act cost approximately \$2 trillion and included a number of provisions for households and businesses, including direct crash transfers to the vast majority of American households which are the focus of this study. These one-time payments consist of \$1,200 per adult and an additional \$500 per child under the age of

17. For an overview see 1. These amounts are substantially larger than the 2008 stimulus program (Parker, Souleles, Johnson and McClelland, 2013; Parker and Souleles, 2019). In 2020, a married couple with two children would thus earn \$3,400, a significant amount particularly for liquidity constrained households.

The vast majority of American households qualified for payments. All independent adults who have a social security number, filed their tax returns, and earn below certain income thresholds qualify for the direct payments. Payments begin phasing out at \$75,000 per individual, \$112,500 for heads of households (single parents with children), and \$150,000 for married couples. The phase-out was completed and payments were not made to individuals earning more than \$99,000 or married couples earning more than \$198,000.[2]

Payments are made by direct deposit whenever available, or by check when direct deposit information was unavailable. Funds are disbursed by the IRS, and the first payments by direct deposit were made on April 9th. The IRS expected that direct deposits would largely be completed by April 15th. In practice, this varied across financial institutions, with some making payments available earlier than others, and direct deposits being spread out across more than one week. Amounts and accounts for direct deposits were determined using 2019 tax returns, or 2018 tax returns if the former were unavailable.

For individuals without direct deposit information, paper checks were scheduled to be mailed starting on April 24th. Approximately eight in ten taxpayers use direct deposit to receive their refund. In the case of paper checks, assignment is nonrandom. The IRS directed to send individuals with the lowest adjusted gross income checks first in April, and additional paper checks will be sent throughout May.

2.2 Empirical Strategy

Our empirical strategy exploits our high-frequency data and the timing of payments to capture spending responses. We first show estimates of β_i from the following specification:

$$c_{it} = \alpha_i + \alpha_t + \sum_{i=-4}^{9} \beta_i \mathbb{1}[t = i]_{it} + \varepsilon_{it} \tag{1}$$

[2]In identifying stimulus payments, we ignore these higher-income households who receive only partial payments, as these are a very small fraction of total households.

c_{it} denotes spending by individual i aggregated to the daily level t. α_i are individual fixed effects, while α_t are day fixed effects. Individual fixed effects α_i absorb time invariant user-specific factors, such as some individuals having greater wealth, and the time period fixed effects α_t absorb time-varying shocks that affects all users, such as the overall state of the economy and economic sentiment. In some specifications we interact individual fixed effects with day of the week or date of the month, to capture consistent time varying spending patterns. For example, some individuals may spend more on the weekends, or on their paydays. $\mathbb{1}[t = i]$ is an indicator of a time period t days after receipt of the stimulus payments.

Standard errors are clustered at the individual level. The coefficient β_i captures the excess sensitivity of spending on a given day before and after stimulus payments are made. In our graphs, the solid lines show point estimates of β_i, while the dashed lines show 95% confidence intervals.

We identify daily MPCs using the following specification:

$$c_{it} = \alpha_i + \alpha_t + \sum_{i=-4}^{9} \gamma_i P_{it} \times \mathbb{1}[t = i]_{it} + \varepsilon_{it} \tag{2}$$

where P_{it} are stimulus payments for individual i at time t. To identify cumulative MPCs since the first payment, we scale indicators of a time period being after a stimulus payment by the amount of the payment over the number of days since the payment. That is, our estimate of an MPC ζ comes from the following specification:

$$c_{it} = \alpha_i + \alpha_t + \zeta \left(\frac{Post_{it} \times P_i}{D_{it}} \right) + \varepsilon_{it} \tag{3}$$

where P_i is the stimulus payment an individual i is paid, and D_{it} is the total number of days over which we estimate the MPC and $Post_{it}$ is an indicator of the time period t being after individual i receives a stimulus payment.

3 Data

3.1 Transaction Data

We use de-identified transaction-level data from a non-profit Fintech company called SaverLife. SaverLife offers customers to link their (main) banking relationship to their service. Customers can link their checking, savings, as well as their credit card accounts. Customers opt for the service for two main reasons. First, the Fintech offers an information aggregation service, provides tools to aid personal financial decision making, and offers financial advice. Second, SaverLife also offers rewards and lotteries when customers with linked accounts achieve pre-specified savings goals. Figure 1 shows two screenshots of the non-profit Fintech online interface. The first is a screenshot of the linked main account while the second is a screenshot of the savings and financial advice resources that the website provides. This data is described in more detail in Baker, Farrokhnia, Meyer, Pagel and Yannelis (2020b).

Overall, we have been granted access to de-identified bank account transactions and balances data from August 2016 to April 2020. We observe 44,660 users in total who live across the United States. In addition, for a large number of users, we are able to link financial transactions to demographic and spatial information. For instance, for most users, we are able to map them to a particular 5-digit zip code. Many users also self-report demographic information such as age, education, family size, and the number of children they have.

Looking only at the sample of users who have updated their accounts reliably in March of 2020, we have complete data for 5,746 users. These users are required to have several transactions per month in 2020 and have transacted at $1,000 in total during these three months of the year. Requiring regular prior account usage is frequently used as a completeness-of-record check when using bank-account data (Kuchler and Pagel, 2019; Ganong and Noel, 2019).

In Table 2 we report descriptive statistics for users' spending in a number of selected categories as well as their incomes at the monthly level. We note that income is relatively low for many SaverLife users, with an average level of income being approximately $25,000 per year. In addition, we show the distribution of balances across users' accounts during the week before most stimulus checks arrived. Consistent with the low levels of income, we see that most users maintain a fairly low balance in their financial account, with the median balance being only $141.02. Finally, we report the distribution of some demographic characteristics for users. The average user is 38 years old and lives in a household of 3.3 people.

We also observe a category that classifies each transaction. Spending transactions are categorized into a large number of categories and subcategories. As an illustration, the parent category 'Shops' is broken down into 53 unique sub-categories including 'Convenience Stores', 'Bookstores', 'Beauty Products', 'Pets', and 'Pharmacies'. For most of our analysis, we examine spending across a majority of categories, excluding spending on things like bills, mortgages, and rent. We also separately focus on a number of individual categories including 'Grocery Stores and Supermarkets' as well as 'Restaurants'.

We identify stimulus payments using payment amounts stipulated by law, identifying all payments at the specific amounts paid after April 9 in the categories 'Refund', 'Deposit' and 'Credit.' Figure 2 shows the identified number of payments, relaxing the time restrictions in 2019 and 2020. While there are a small number of payments in these categories at the exact stimulus amounts prior to the beginning of payments, there is a clear massive spike after April 9th. This suggests that there are relatively few false positives, and that the observed payments are due to the stimulus program and not other payments.

As of April 21st, approximately 28% of users have received a stimulus payment into their linked account. The remainder of the sample may be still waiting for a stimulus check or may be ineligible for one. Some banks and credit unions had issues processing stimulus deposits and these deposits were still pending for a number of Americans. In addition, users may not have had direct deposit information on file with the IRS and would then need to wait for a check to be mailed. Finally, users may be ineligible for stimulus checks due to their status as a dependent, because they did not file their taxes in previous years, or because they made more than the income thresholds for receipt. We run regressions at a daily level to examine more precisely the high frequency changes in behavior brought about by the receipts of the stimulus payments.

While most American households were due to receive a stimulus check, the amount varied according to the number of tax filers and numbers of children. Each qualifying adult could receive up to $1,200 and an additional $500 for each dependent child. Table 1 gives an accounting of amounts due to a range of household types. While we cannot observe the exact household composition for each user, we are able to observe a self-reported measure of household size.

In Figure 3, we plot the average size of the identified stimulus by users who report living in a household of a given size. In general, we see a clear upward trend in stimulus check size received as households get larger, again reinforcing the likelihood that we are truly picking up stimulus check receipt by users. Because of our identification strategy for picking out stimulus checks, being within the 'phase-out' region of income would mean that we would falsely classify an individual as having not received a stimulus check, since his or her check would be for a non-even number. This would likely attenuate our empirical estimates slightly.

4 Effects of Stimulus Payments

Figure 4 shows mean daily spending before and after the receipt of a stimulus payment (conditional on receiving the stimulus payment) without any controls. Prior to receiving a check, the typical individual in the sample is spending under \$100 a day. There is a sharp and immediate increase in spending following the receipt of a stimulus deposit. Mean daily spending rises on the day of receipt to approximately \$150 and continues to increase, to over \$200, for the two days after the receipt of the stimulus payment.

Observed spending declines substantially in the third and fourth days, though most of this is driven by the fact that a majority of 'treated' users in our sample received the stimulus check on Wednesday, April 15th and spending tends to decline on weekends. After the weekend period, observed spending rises to \$250 before beginning to decline somewhat.[3]

Figure 5 shows estimates of β_i from the equation: $c_{it} = \alpha_i + \alpha_t + \sum_{i=-4}^{9} \beta_i \mathbb{1}[t = i]_{it} + \varepsilon_{it}$. 'Time to Payment' is equal to zero for a user on the day of receiving the stimulus check. Here, we see that users who receive stimulus checks tend to not behave differently than those that do not in the days before they receive the checks. Upon receiving the stimulus check, users dramatically increase spending relative to users who do not receive the checks.

Similar to what we saw in Figure 4, users show large increases in spending in the first days following the stimulus check receipt and keep spending significantly more than those who have not received checks for the entirety of the post-check period that we observe. The relative difference

[3] Observed spending declines dramatically on weekends throughout our sample. This is likely driven by two factors. The first is that actual transactions and spending declines during these days. The second is that transactions that occurred during the weekend may process only on the Monday that follows. We are unable to distinguish between these cases using our data.

in spending declines during weekends, mostly driven by the fact that observed spending tends to be depressed during these days for reasons described above.

In Figure 6, we break down users' spending responses by categories of spending. We map our categories to roughly correspond to those reported in Parker and Souleles (2019): Food, household goods, and personal care, durables like auto-related spending, furniture, and electronics, non-durables and services, and payments including check spending, loans, mortgages, and rent. Across all categories, we find statistically significant increases in spending following the receipt of a stimulus check. These responses are widely distributed across categories, with spending on food, household, non-durables, and payments each increasing by approximately \$50-\$75 in the three days following receipt of a check. Durables spending sees a significant increase, but it is much smaller in economic terms with only a \$20 relative increase in spending during the first three days.

Table 3 presents similar information. Columns 1-3 test how total user spending responds with three different sets of fixed effects. Column 1 presents results using individual and calendar date fixed effects. Column 2 also includes individual-by-day-of-month fixed effects, and Column 3 includes individual, calendar date, and individual-by-day-of-week fixed effects. We find similar effects across all specifications, with spending among those who received a stimulus check tending to increase substantially in the first 9 days after stimulus receipt. Spending on days during this period are economically and statistically significantly higher for those receiving stimulus checks and there are no days with significant reversals – days with stimulus check recipients having lower spending than those who did not. Overall, for each dollar of stimulus received, households spent approximately \$0.25-\$0.35 more in the day of and the 9 days following the stimulus.

The remainder of the columns in Table 3 decompose the effect that we see in overall spending according to the category of spending. We split spending into 5 categories: Food, non-durables, household goods and services, durables, and other payments. We find significant increases in spending in all of these categories, with the largest increases coming from spending on food, non-durables, and household goods and services. We find highly muted effects of the stimulus payments on durables spending. In previous recessions, noted by Parker and Souleles (2019), spending on durables (mainly auto-related spending), was a large component of the household response to stimulus checks. At least in the short-term, we find significantly different results, with durables spending (including cars, home furnishings, electronics, etc.) contributed only negligibly to the overall household response. This may be driven by the fact that car usage has dropped precipitously with the shelter-in-place orders enacted around the country.

5 Income, Income Declines and Liquidity

The stimulus payments employed to mitigate the 2020 COVID outbreak in the United States were sent to taxpayers with little regard for current income, wealth, and employment status. While there was an income threshold above which no stimulus would be received, this threshold was fairly high relative to average individual income and most Americans were therefore eligible for stimulus payments. During debates about the size and scope of the stimulus, a common question was whether Americans with higher incomes, unaffected jobs, and higher levels of wealth needed additional financial support. With data on both the income and bank balances of SaverLife users, we are able to test whether the consumption and spending responses differed markedly between users who belonged to these different groups.

In Figures 7-9, we show the cumulative estimated MPCs from regressions of spending on an indicator of a time period being after a stimulus payment is received. Each figure contains the results of multiple regressions, with users broken down into subsamples according to a number of financial characteristics that we can observe. That is, the graphs represent the sum of daily coefficients seen in a regression as in Table 3, by group. In these figures, we divide the samples of users by their level of income, the drop in income we observed over the course of 2020, and their levels of liquidity prior to the receipt of stimulus payments.

Figure 7 splits users by their average income in the six months prior to March 2020. We see clear evidence that users with lower levels of income tended to respond much more strongly to the receipt of a stimulus payment than those with higher levels of income. Users who had typically earned under $1,000 per month saw an MPC approximately twice as large as users who typically earned $5,000 a month or more.

We also examine whether a similar pattern can be seen among users who have had declines in income following the COVID outbreak. In Figure 8, for each user, we measure the change in monthly income between January and February 2020 as compared to March 2020. We split users into those who had a decline in income of 50% or more, those who had declines in income of less than 50%, and those who saw no decline in income (or an increase). In general, we see that users who saw larger declines in income tended to have larger spending responses to the receipt of stimulus checks, though the differences are not as substantial as those in Figure 7.

Finally, we split our sample of users according to their accounts' balances at the beginning of April. We separate users into four groups: those with balances under \$500, those with balances between \$500 and \$1,500, those with balances between \$1,500 and \$3,000, and those with balances over \$3,000. Figure 9 displays results from these four regressions. We see dramatic differences across groups of users. Users with the highest balances in their bank accounts tend not to respond to the receipt of stimulus payments, while those who had under \$500 respond the most. The low balance group has an MPC out of the stimulus payment of almost 0.4 in the first 9 days of receipt.

Table 4, Table 5, and Table 6 display some of these results in regression form. In general, we find that users with lower incomes, larger drops in income, and lower pre-stimulus balances tend to respond significantly more strongly than other users. Again, across all subsamples of our users based on financial characteristics, we see that low liquidity tends to be the strongest predictor of a high MPC and high liquidity tends to be the strongest predictor of low MPCs.

5.1 Comparison to Previous Economic Stimulus Programs

Johnson, Parker and Souleles (2006) and Parker, Souleles, Johnson and McClelland (2013) examine the response of households to economic stimulus programs during the previous two recessions (2001 and 2008). These programs proceeded similarly to the current stimulus program in 2020 but were smaller in magnitude. In 2001, individuals generally received \$300 rebates, with married couples generally eligible for \$600. In 2008, couples could receive \$1,200 and \$300 for each dependent child. In the 2020 stimulus program, individuals could each receive \$1,200, couples could receive \$2,400, and each dependent child would be eligible for \$500.

In these previous stimulus programs, households also tended to respond strongly to the receipt of their checks. For instance, in 2008, Parker, Souleles, Johnson and McClelland (2013) estimated that households spent approximately 12-30% of their stimulus payments on non-durables and services and a total of 50-90% of their checks on total additional spending (including durables) in the six months following receipt. In 2001, approximately 20-40% of stimulus checks were spent on nondurables and services in the six months following receipt.

While they were unable to examine the timing of spending in more detail due to data limitations in previous recessions, we demonstrate that households respond extremely quickly to receiving stimulus checks. Rather than taking weeks or months to spend appreciable portions of their stimulus checks, we show that households react extremely rapidly, with household spending increasing by approximately one third of the stimulus check within the first 10 days. Given that previous stimulus programs saw sustained increases in spending lasting six months or more, we would expect that the long-run impact of the current stimulus program would be much larger than the short-run effect that we have seen so far.

One notable difference from previous recessions and stimulus programs is the spending response across categories of spending. In previous recessions, stimulus checks seemed to induce large responses in spending on durables, especially on automobiles (about 90% of the estimated impact on durables spending in the 2008 stimulus program was driving by auto spending). In contrast, despite a sizable response in nondurables and service spending, we see little immediate impact on durables. Even if we attribute the entirety of our observed response in the 'Payments' category to spending on durables, the magnitude is much smaller than the combined response in Food and Nondurables categories. This difference becomes even starker if we consider the fact that some prior literature has shown that larger payments often result in spending increases that skew more towards durables. Given the size of the 2020 stimulus checks, we might expect large impacts on categories like automobile spending, electronics, and home furnishings.

In part, this discrepancy with past recessions may be driven by the fact that automobile use and spending is highly depressed, with many cities and states being under shelter-in-place orders and car use highly restricted. Similarly, as these orders hinder home purchases and moves, spending on home furnishings and other related durables may be lower, as well (the stimulative effects of home purchases are demonstrated in Benmelech, Guren and Melzer (2019)).

While increases in durables spending were limited in the current setting, we do find substantial increases in spending on food. This again stands in contrast to some of the effects seen in earlier stimulus programs. Again, it may reflect the unique economic setting in which the 2020 economic stimulus took place. While many outlets for consumer spending were closed by government order, restaurants remained open; we find that household spending on food delivery was one category in particular that increased following the receipt of a stimulus check.

Finally, across both 2001 and 2008, Parker, Souleles, Johnson and McClelland (2013) note that lower income households tended to respond more, and that households with either larger declines in net worth or households with lower levels of assets also tended to respond more strongly to stimulus checks. These results are largely consistent with the patterns we observe in 2020. We find that households with low levels of income and lower levels of wealth tend to respond much more strongly. In addition, our measure of available liquidity is arguably suffers from much less measurement error than the measures used in previous research on stimulus checks, giving additional confidence in our estimates.

6 Conclusion

This paper studies the impact of the 2020 CARES Act stimulus payments on household spending using detailed high-frequency transaction data from a non-profit Fintech. We utilize this dataset to explore heterogeneity of MPCs in response to the stimulus payments, an important parameter both in determining multipliers and in testing between representative and heterogeneous agent models.

We find large consumption responses to fiscal stimulus payments and significant heterogeneity across individuals. Income levels, income declines, and liquidity all play important roles in determining MPCs. In this context, liquidity is the strongest predictor of MPC heterogeneity. We find substantial responses for households with low levels of liquidity and no response to stimulus payments for households with high levels of cash on hand. The results will potentially be important to policy in terms of designing future rounds of stimulus if the current crisis persists. Our results suggest that the effects of stimulus are much larger is targeted to households with low levels of liquidity.

While this paper shows that liquidity is an important determinant of MPC heterogeneity in response to stimulus payments and that targeted payments can be more effective at increasing consumption which imply larger multipliers, there remains important future work to be done. In particular, more work should be done to study how targeting can be designed to have large impacts on consumption, without significant behavioral effects. Just as unemployment benefits may increase unemployment durations (Meyer, 1990; Chetty, 2008), policies targeting stimulus payments towards households with low levels of liquidity could discourage liquid savings.

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Figure 1: Example of Platform

Notes: The figures show screenshots of the app provided by SaverLife the app. The first screenshot shows the landing page when entering the app and the second screenshot below illustrates its financial advice page. Source: SaverLife.

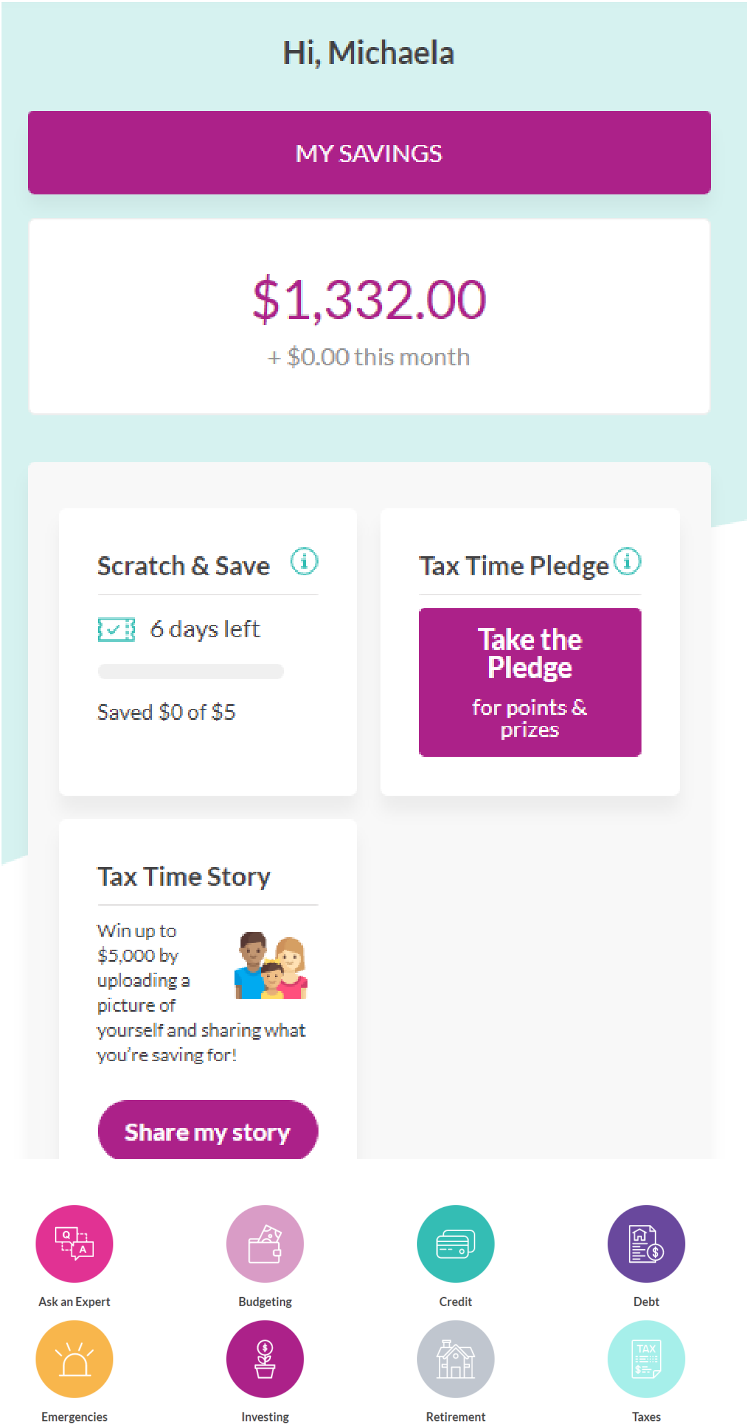

Figure 2: Daily Number of Government Payments at Stimulus Amounts

Notes: This figure shows the number of payments users receive that match the amounts of the 2020 government stimulus payment by day in 2019 and 2020. Potential payments are classified by the specified amounts of the stimulus checks and need to appear as being tax refunds, credit or direct deposits. Source: SaverLife.

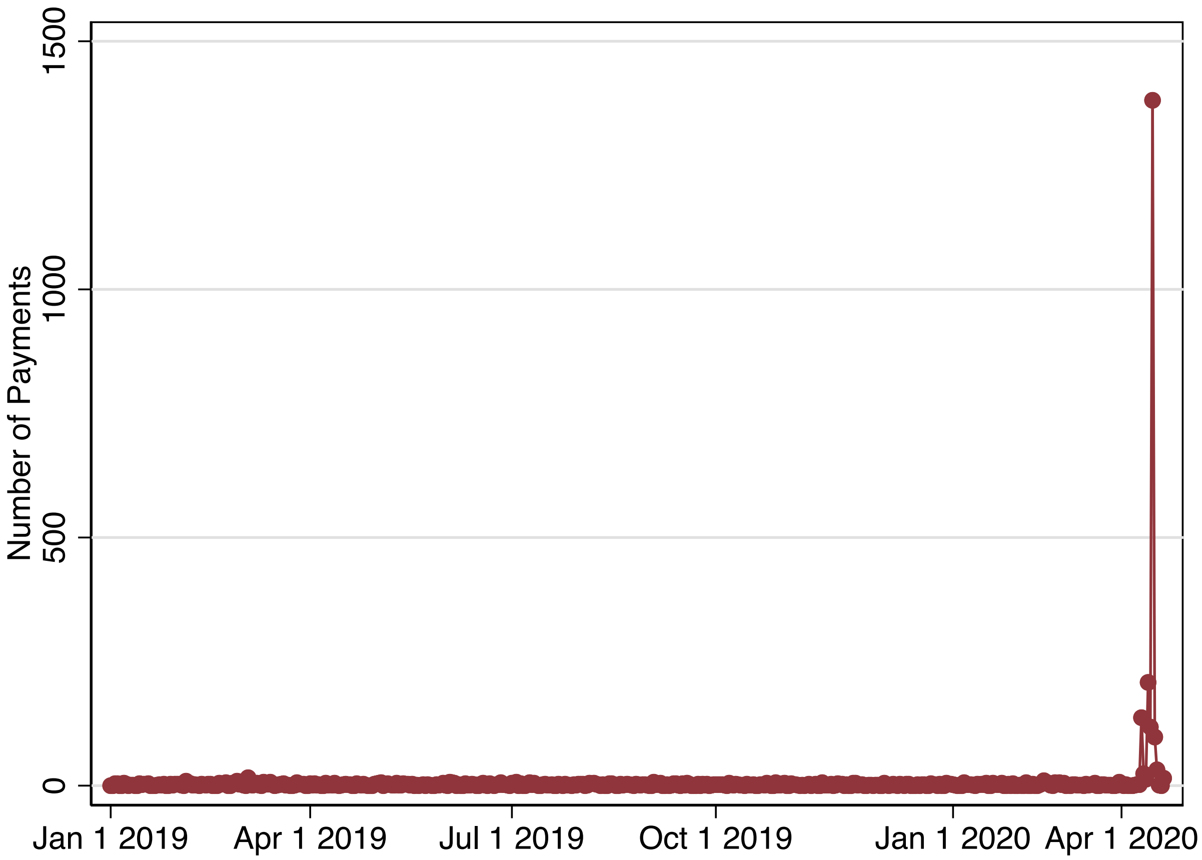

Figure 3: Daily Number of Government Payments at Stimulus Amounts

Notes: This figure shows the average stimulus amount for users receiving stimulus checks, by self-reported household size. Source: SaverLife.

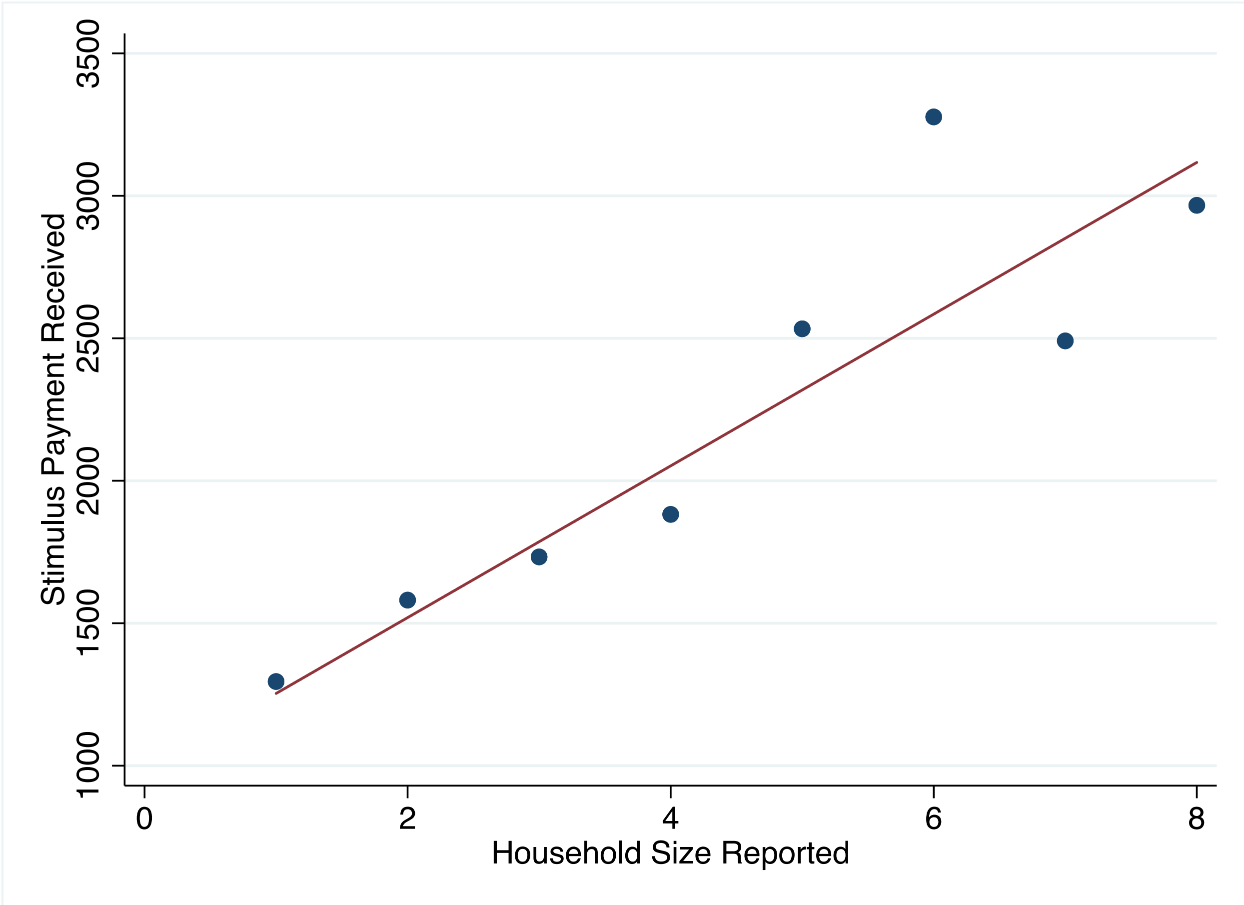

Figure 4: Mean Spending Around Receiving the Stimulus Payments - Raw Spending

Notes: This figure shows mean spending around the receipt of stimulus payments. The vertical axis measures spending in dollars, and the horizontal axis shows time in days from receiving the stimulus check which is defined as zero (0). Shaded days represent weekends for the majority of stimulus-recipients who receive their payment on Wednesday April 15th. The graph is based on data from SaverLife.

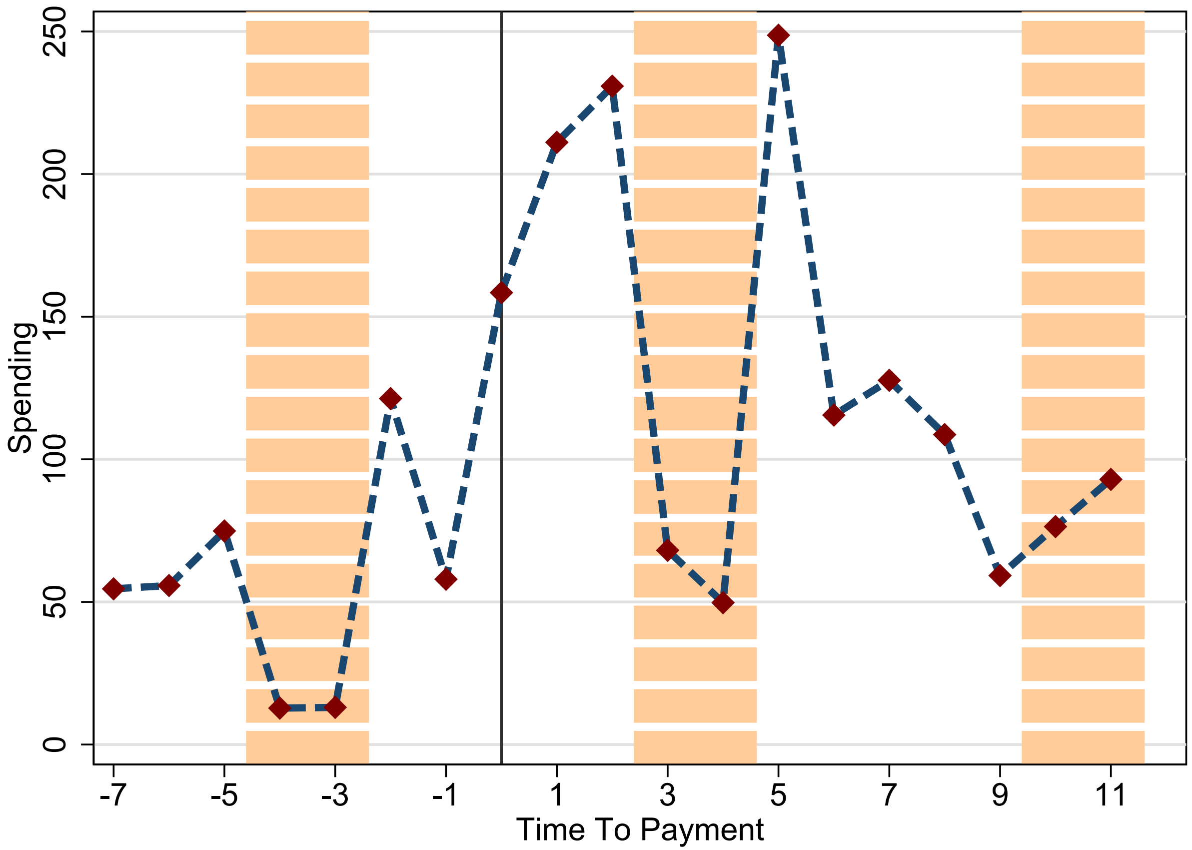

Figure 5: Spending Around Stimulus Payments - Regression Estimates

Notes: This figure shows estimates of β_i from $c_{it} = \alpha_i + \alpha_t + \sum_{i=-4}^{4} \beta_i \mathbb{1}[t = i]_{it} + \varepsilon_{it}$. The solid line shows point estimates of β_i, while the dashed lines show 95% confidence interval. Time to Payment is equal to zero on the day of receiving the stimulus check. Source: SaverLife.

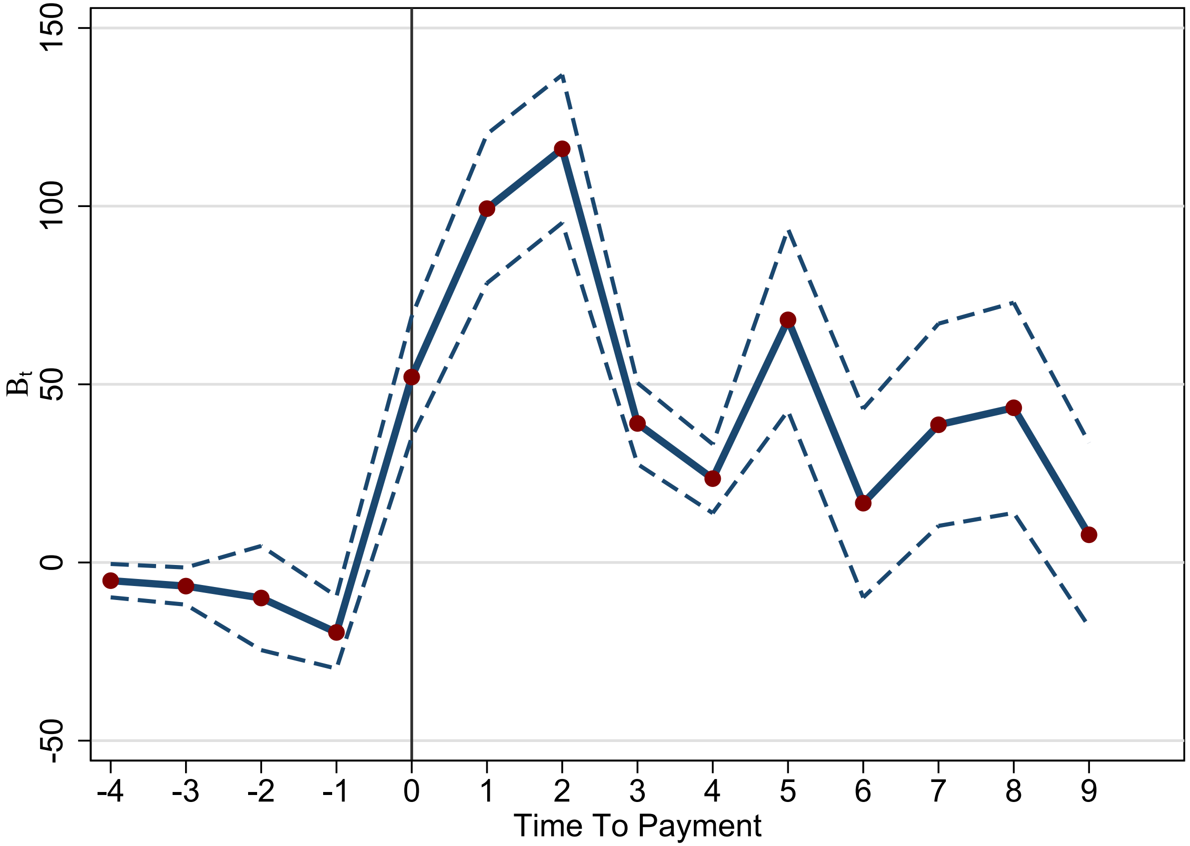

Figure 6: Spending Around Stimulus Payments by Categories

Notes: This figure shows estimates of β_i from $c_{it} = \alpha_i + \alpha_t + \sum_{i=-4}^{9} \beta_i \mathbb{1}[t = i]_{it} + \varepsilon_{it}$, broken down by spending categories. The solid line shows point estimates of β_i, while the dashed lines show the 95% confidence interval. Time to Payment is equal to zero on the day of receiving the stimulus check. Source: SaverLife.

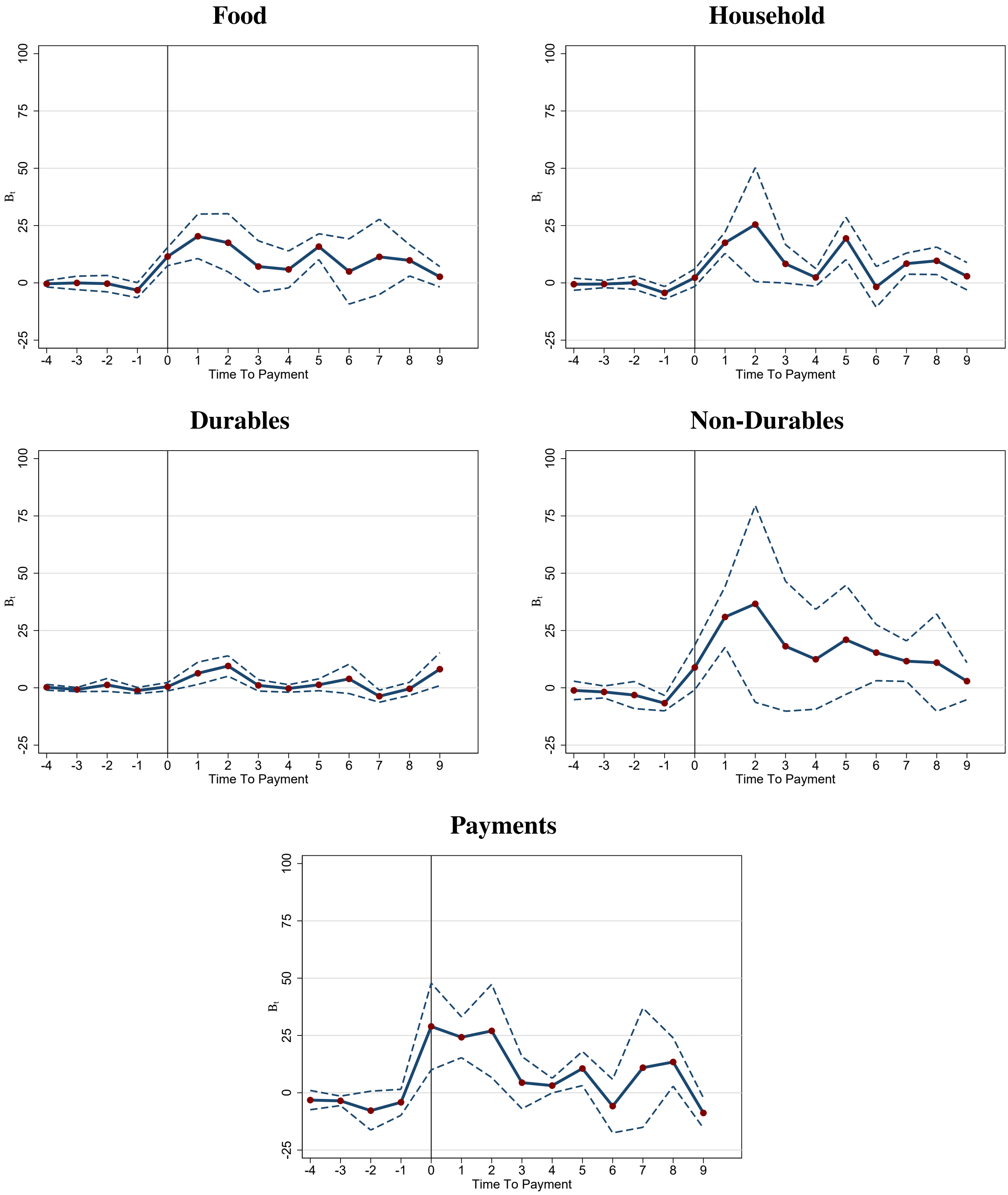

Figure 7: MPC by Income Groups

Notes: This figure shows cumulative MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. That is, of ζ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times Stimulus_i}{Days_{it}} + \varepsilon_{it}$, broken down by monthly income groups. Year and week by individual fixed effects are included. Standard errors are clustered at the user level. The bar shows point estimates, while the thin lines show the 95% confidence interval. Source: SaverLife.

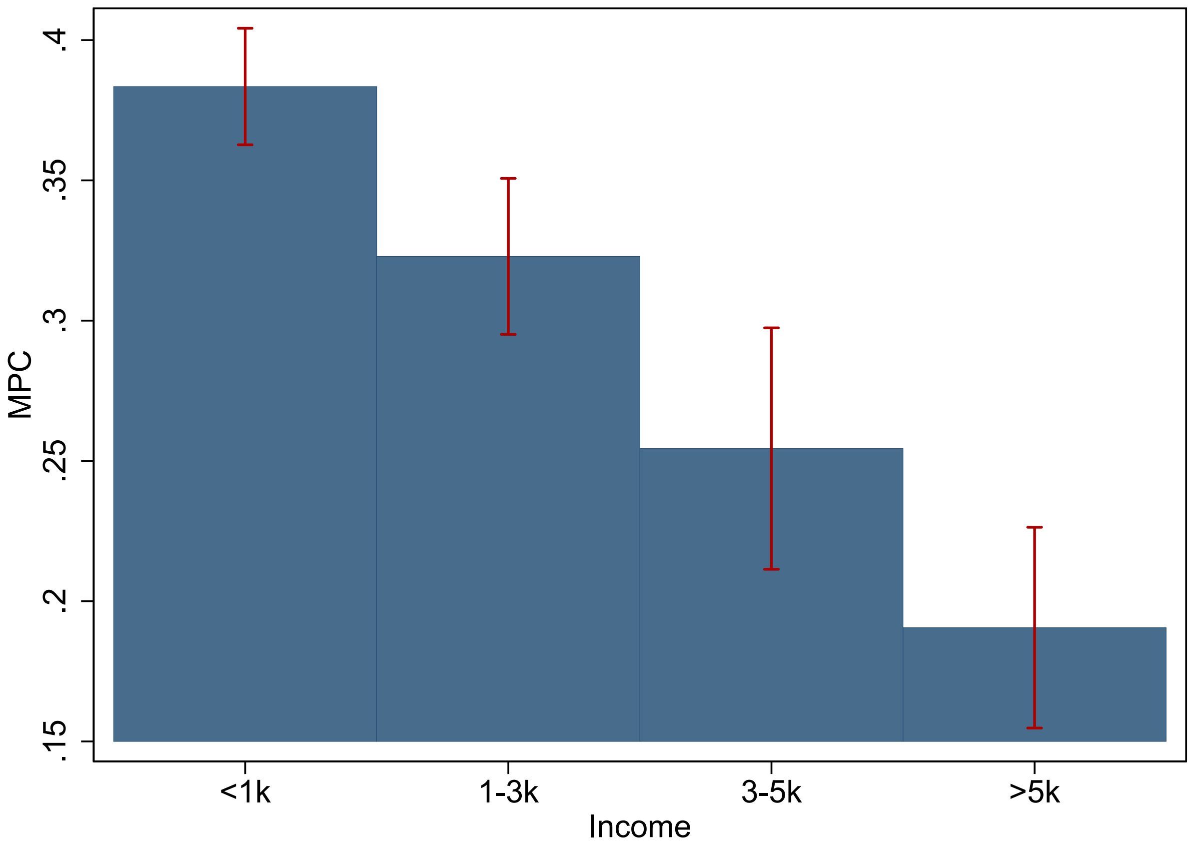

Figure 8: MPC by Drop in Income

Notes: This figure shows cumulative MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. That is, of ζ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times Stimulus_i}{Days_{it}} + \varepsilon_{it}$, broken down by the drop in income between January/February and March. Year and week by individual fixed effects are included. Standard errors are clustered at the user level. The bar shows point estimates, while the thin lines show 95% confidence interval. Source: SaverLife.

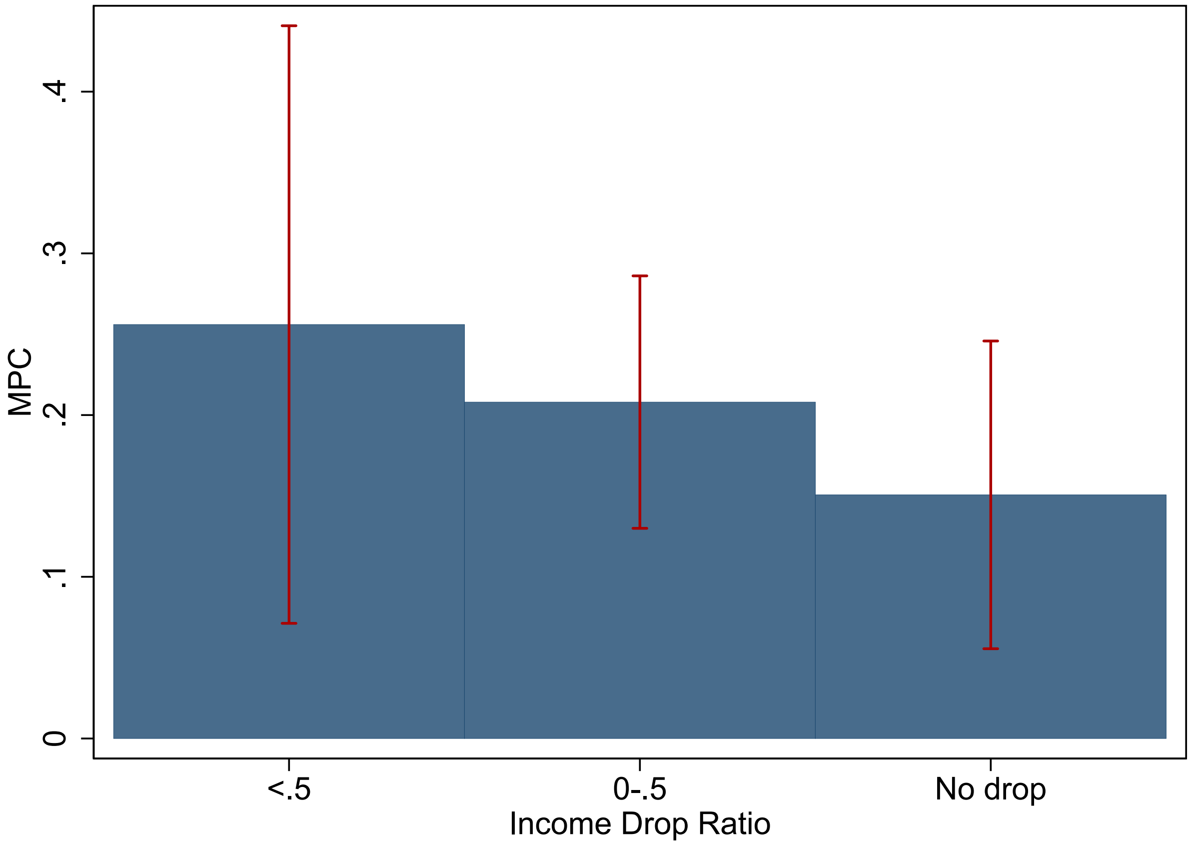

Figure 9: MPC by Liquidity

Notes: This figure shows cumulative MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. That is, of ζ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times Stimulus_i}{Days_{it}} + \varepsilon_{it}$, broken down by account balances. Year and week by individual fixed effects are included. Standard errors are clustered at the user level. The bar shows point estimates, while the thin lines show 95% confidence interval. Source: SaverLife.

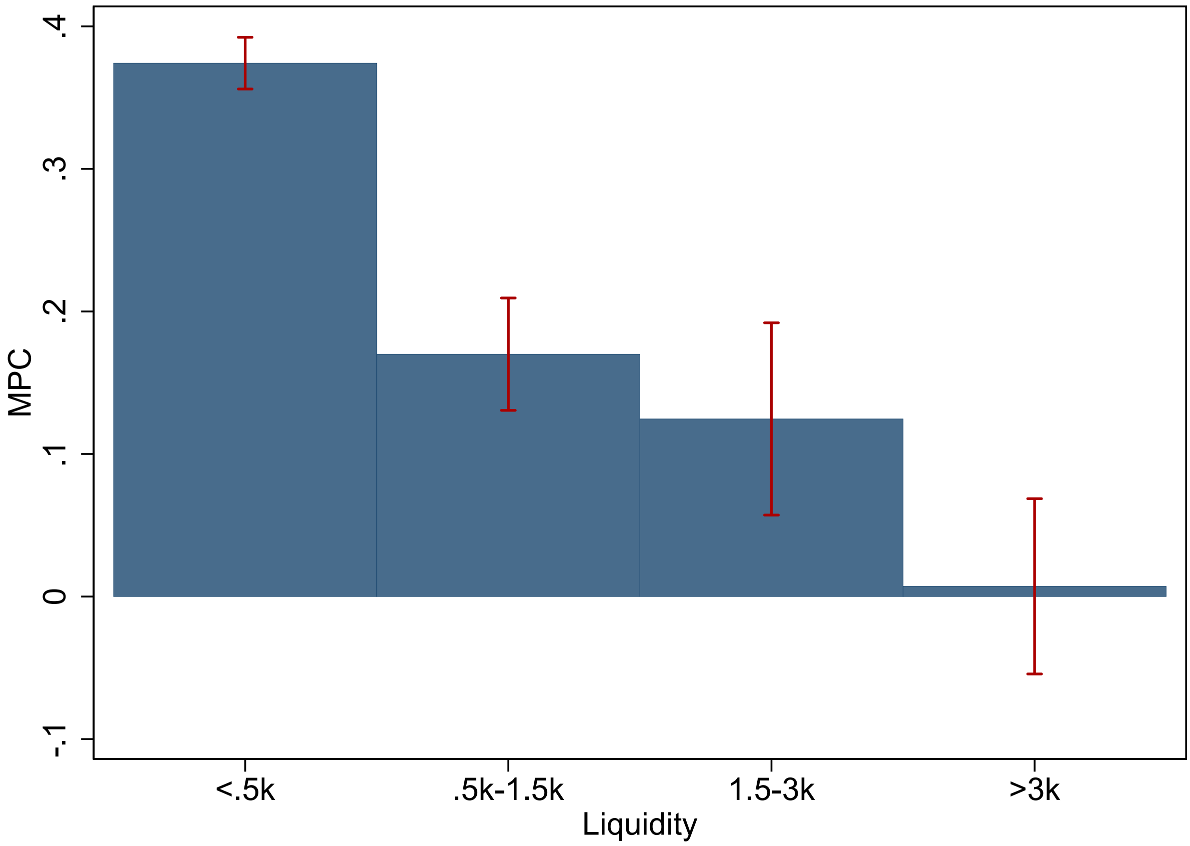

Table 1: Household Composition and Stimulus Payment Under CARES

Notes: This table shows statutory payment amounts for household stimulus payments under the CARES act (for households not subject to an income-based means test).

Household type	# Expected stimulus payment
Single	$1,200
Single with one kid	$1,700
Single with two kids	$2,300
Single with three kids	$2,800
Single with four kids	$3,200
Adult Couple	$2,400
Couple with one kid	$2,900
Couple with two kids	$3,400
Couple with three kids	$3,900
Couple with four kids	$4,400

Table 2: Summary Statistics

Notes: Summary statistics for spending and income represent user-month observations. Statistics regarding user characteristics are given at a user level.

Variable	# Obs.	Mean	10th	25th	Median	75th	90th
				User-Month			
Income	22,665	2,005.06	110.00	615.00	1,560.70	2,920.62	4,458.78
Balance	22,665	747.86	0.00	3.51	141.02	811.70	2,405.00
Durables	22,665	44.70	0.00	0.00	0.00	26.58	143.91
Food	22,665	243.48	0.00	21.04	146.78	358.57	628.40
Household	22,665	231.29	0.00	28.87	149.72	343.49	578.47
NonDurables	22,665	332.49	1.59	51.23	209.49	468.34	835.90
Payments	22,665	440.08	0.00	0.00	140.00	650.64	1,266.99
				User			
Stimulus Income	5,746	432.77	0	0	0	1,200	1,700
Age	5,746	38.4	25	30	36	48	54
Household Size	5,746	3.3	1	2	3	4	5
Children	5,746	0.12					

Table 3: Stimulus Payments and Spending

The table shows regressions of overall spending and categories of spending on the one-day lag of the stimulus payment. We run separate regressions for overall spending, spending in restaurants, spending on food delivery, healthcare, services, art & entertainment, and retail products. For total spending, we run three specifications with varying fixed effects. We use individual and calendar date fixed-effects, individual and calendar date and individual times day of month fixed-effects, or individual and calendar date and individual times day of week fixed-effects. Standard errors are clustered at the user level. *$p < .1$, ** $p < .05$, *** $p < .01$. Source: SaverLife.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Total	Total	Total	Food	NonDurables	Household	Durables	Payments
Stimulus Payment_$\{t+1\}$	0.0563***	0.0517***	0.0550***	0.0103***	0.0195***	0.00920***	0.00423***	0.0131***
	(0.00670)	(0.00621)	(0.00808)	(0.00247)	(0.00339)	(0.00159)	(0.000764)	(0.00142)
Stimulus Payment_$\{t+2\}$	0.0634***	0.0604***	0.0649***	0.00760**	0.0224**	0.0120**	0.00717***	0.0142**
	(0.0230)	(0.0211)	(0.0218)	(0.00342)	(0.00951)	(0.00533)	(0.000821)	(0.00555)
Stimulus Payment_$\{t+3\}$	0.00306	0.0180	0.00305	0.00151	0.00570	0.00137	-0.000567	-0.00496*
	(0.0174)	(0.0141)	(0.0214)	(0.00472)	(0.00842)	(0.00277)	(0.000443)	(0.00250)
Stimulus Payment_$\{t+4\}$	-0.00394	0.0102	-0.00155	-0.000555	0.00271	-0.000766	-0.000493	-0.00484***
	(0.0107)	(0.00817)	(0.00998)	(0.00231)	(0.00519)	(0.00159)	(0.000627)	(0.00152)
Stimulus Payment_$\{t+5\}$	0.0531***	0.0386***	0.0577***	0.0136***	0.0155**	0.0134***	0.00302**	0.00757***
	(0.00779)	(0.00632)	(0.00733)	(0.00327)	(0.00674)	(0.00335)	(0.00139)	(0.00232)
Stimulus Payment_$\{t+6\}$	0.0217	0.0121	0.0250***	0.00577*	0.0133**	0.00260	0.00327	-0.00319
	(0.0147)	(0.00944)	(0.00868)	(0.00315)	(0.00511)	(0.00351)	(0.00199)	(0.00398)
Stimulus Payment_$\{t+7\}$	0.00270	0.0195	0.00880	0.000453	0.000953	0.00353*	-0.00160**	-0.000639
	(0.0247)	(0.0134)	(0.0255)	(0.00567)	(0.00609)	(0.00182)	(0.000778)	(0.0108)
Stimulus Payment_$\{t+8\}$	0.0386***	0.0171*	0.0623***	0.00752***	0.0122	0.00667**	0.000422	0.0118***
	(0.00966)	(0.00916)	(0.0112)	(0.00176)	(0.00916)	(0.00268)	(0.00149)	(0.00425)
Stimulus Payment_$\{t+9\}$	0.0138**	-0.00321	0.0179**	0.00300	0.00388**	0.00376**	0.00327**	-0.000143
	(0.00637)	(0.00494)	(0.00697)	(0.00202)	(0.00169)	(0.00163)	(0.00149)	(0.00114)
Date FE	YES	YES	YES	YES	YES	YES	YES	YES
User FE	YES	YES	YES	YES	YES	YES	YES	YES
User*Day of Week FE	NO	YES	NO	NO	NO	NO	NO	NO
User*Day of Month FE	NO	NO	YES	NO	NO	NO	NO	NO
Observations	542742	542569	532058	542742	542742	542742	542742	542742
R^2	0.111	0.211	0.410	0.080	0.057	0.077	0.024	0.053

Table 4: Stimulus Payments, Spending and Income

This figure shows cumulative MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. That is, of ζ and ξ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times Stimulus_i}{Days_{it}} + \xi \frac{Post_{it} \times Stimulus_i}{Days_{it}} \times I_i + \varepsilon_{it}$. Average monthly income is approximately $1,700, yielding a logged income value of 7.4. Columns (4) and (5) drop the interaction, and split the sample by January and February monthly income above and below $2,000. The inclusion of fixed effects is denoted beneath each specification. Standard errors are clustered at the user level. *$p < .1$, ** $p < .05$, *** $p < .01$. Source: SaverLife.

	(1)	(2)	(3)	(4)	(5)
	Total	Total	Total	Total - Low Inc	Total - High Inc
Post-Stimulus*Stimulus	0.864***	0.886***	0.643**	0.434***	0.271***
	(0.307)	(0.227)	(0.288)	(0.0995)	(0.0703)
Post-Stimulus*Stimulus*ln(Inc)	-0.0681	-0.0699***	-0.0367		
	(0.0415)	(0.0249)	(0.0399)		
Date FE	YES	YES	YES	YES	YES
User FE	YES	YES	YES	YES	YES
User*Day of Week FE	NO	YES	NO	NO	NO
User*Day of Month FE	NO	NO	YES	NO	NO
Observations	592396	592396	586111	329548	262848
R^2	0.109	0.203	0.390	0.091	0.111

Table 5: Stimulus Payments, Spending and Income Declines

This figure shows cumulative MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. That is, of ζ and ξ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times Stimulus_i}{Days_{it}} + \xi \frac{Post_{it} \times Stimulus_i}{Days_{it}} \times D_i + \varepsilon_{it}$. Columns (4) and (5) drop the interaction, and split the sample by income drops between January and February versus March, separately examining the top and bottom quartiles of income declines in this period. The inclusion of fixed effects is denoted beneath each specification. Standard errors are clustered at the user level. *$p < .1$, ** $p < .05$, *** $p < .01$. Source: SaverLife.

	(1)	(2)	(3)	(4)	(5)
	Total	Total	Total	Total - High Drop	Total - Low Drop
Post-Stimulus*Stimulus	0.348***	0.350***	0.389***	0.290***	0.233***
	(0.0635)	(0.0568)	(0.0626)	(0.0580)	(0.0629)
Post-Stimulus*Stimulus*Inc Drop	-0.142***	-0.129***	-0.169***		
	(0.0470)	(0.0446)	(0.0532)		
Date FE	YES	YES	YES	YES	YES
User FE	YES	YES	YES	YES	YES
User*Day of Week FE	NO	YES	NO	NO	NO
User*Day of Month FE	NO	NO	YES	NO	NO
Observations	416,975	416,975	415,919	105,198	101,215
R^2	0.178	0.296	0.440	0.176	0.185

Table 6: Stimulus Payments, Spending and Liquidity

This figure shows cumulative MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. That is, of ζ and ξ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times Stimulus_i}{Days_{it}} + \xi \frac{Post_{it} \times Stimulus_i}{Days_{it}} \times L_i + \varepsilon_{it}$. The second row interacts with the individual's bank account balance prior to the arrival of the stimulus payment, in thousands of dollars. Columns (4) and (5) drop the interaction, and split the sample by having more or less than \$500 in a bank account. The inclusion of fixed effects is denoted beneath each specification. Standard errors are clustered at the user level. $*p < .1$, $**\ p < .05$, $***\ p < .01$. Source: SaverLife.

	(1) Total	(2) Total	(3) Total	(4) Total - Low Bal	(5) Total - High Bal
Post-Stimulus*Stimulus	0.374***	0.382***	0.400***	0.445***	0.114**
	(0.0958)	(0.0800)	(0.0997)	(0.110)	(0.0544)
Post-Stimulus*Stimulus*Balance	-0.0546***	-0.0538***	-0.0510***		
	(0.0108)	(0.0129)	(0.00838)		
Date FE	YES	YES	YES	YES	YES
User FE	YES	YES	YES	YES	YES
User*Day of Week FE	NO	YES	NO	NO	NO
User*Day of Month FE	NO	NO	YES	NO	NO
Observations	532081	532017	523608	353890	178191
R^2	0.110	0.204	0.392	0.081	0.063