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

Scott R. Baker[1], Robert A. Farrokhnia[2], Steffen Meyer[3], Michaela Pagel[4], and Constantine Yannelis[5]

[1]Northwestern University, Kellogg, NBER, USA, [2]Columbia Business School, Columbia Engineering School, USA, [3]Aarhus University and Danish Finance Institute (DFI), Denmark, [4]Columbia Business School, NBER, and CEPR, USA, and [5]University of Chicago Booth School of Business, NBER, USA

Abstract

The 2020 CARES Act directed large cash payments to households. We analyze households' spending responses using data from a Fintech nonprofit, exploring heterogeneity by income, recent income declines, and liquidity as well as linked survey responses about economic expectations. Households respond rapidly to payments, with spending increasing by about \$0.14 per dollar during the first week and plateauing around \$0.25–\$0.30 over 3 months. In contrast to previous stimulus programs, we see little response of durables spending. Households with lower incomes, greater income declines, and less liquidity display stronger responses whereas households that expect employment losses and benefit cuts display weaker responses.

Keywords: Household finance, CARES, Consumption, COVID-19, Stimulus, MPC, Survey data

JEL classification: D14, E21, G51

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1. Introduction

In three recent instances, the US government made direct cash payments to households in response to economic downturns. These payments are generally meant to alleviate the effects of a recession and stimulate the economy through a multiplier effect, that is, by increasing households' consumption which then translates into more income, production, and employment. The onset of the COVID-19 pandemic brought about a massive world-wide economic shock, prompting many national governments to turn to direct stimulus payments to both bolster the economy as well as provide immediate liquidity to households affected by the crisis. While the unprecedented and multifaceted nature of the COVID-19 shock makes extrapolation to all household stimulus programs more difficult, this article provides estimates that are, at the very least, important for understanding responses to this singular shock.

The impact of household stimulus payments on the broader economy relies on households' marginal propensities to consume, or MPCs which, in turn, may depend on households' expectations (Barro, 1989). Because some households are more responsive to stimulus payments, targeting can have large effects on the effectiveness of stimulus payments on aggregate consumption throughout the economy. Additionally, heterogeneity in MPCs helps distinguish between different models of household consumption behavior at play in this unique period.

In this article, we estimate households' MPCs in response to the 2020 CARES Act stimulus payments distributed in April and May 2020 using high-frequency transaction data from SaverLife, a nonprofit financial technology firm. As opposed to many other Fintech firms, individuals in our sample consist primarily of lower- and middle-income households. For these users, we have access to de-identified bank account transactions and balances data from August 2016 to August 2020. The fact that we observe inflows and outflows from individual accounts as well as balances in this dataset allows us to explore heterogeneity in levels of income, changes in income, and liquidity. We also describe how household MPCs vary across categories of consumption and how these categorical responses differ from those seen in previous recessions. Finally, we are able to link the bank account transactions data to survey data about economic expectations.

The first CARES Act stimulus payments were made in mid-April via direct deposit from the Internal Revenue Service (IRS). We observe user-specific stimulus amounts as well as spending daily before and after stimulus payments are received. We see immediate responses to the stimulus payments; within the first week, users spend about 14 cents of every dollar received in stimulus payments. In the 3 months following stimulus receipt, excess spending of over 25 cents per dollar is observed, with almost all of this spending occurring in the first month. The largest increases in spending are on food, nondurables, and payments like rent, mortgages, and student loans.

Looking at heterogeneity across financial characteristics, we find that lower-income and less liquidity are associated with larger MPCs while recent drops in income seem to have only small effects. Individuals with less than \$100 in their accounts spend over 50% of their stimulus payments over 3 months, while we observe individuals with more than \$1,000 in their accounts spend only about 15% of their payments.

We further explore how beliefs about personal and aggregate outcomes impact the response to stimulus payments, utilizing a survey of our users which we can then link to the transaction data. Theoretical work has long noted that expectations can play an important role in the efficacy of stimulus (Barro, 1974, 1989; Seater, 1993; Galí, 2019). In particular, households may respond to debt-financed spending increases by cutting spending today if they anticipate future tax hikes or other changes in income (Cochrane, 2009).

In our survey, users are asked about their expectations regarding unemployment, salary cuts, tax increases, benefit cuts, stock market performance, and the duration of the pandemic. We received 1,011 unique responses and find that our users are relatively pessimistic about the length of the pandemic and their own future income and employment opportunities.[1] While we do not find evidence that anticipated tax increases impact MPCs, we do find that households who anticipate unemployment or benefit cuts save a significantly larger fraction of their stimulus checks.

The theory behind stimulus payments links MPCs directly to the ultimate fiscal multiplier effect, that is, the effectiveness of the payments in stimulating aggregate consumption. The results of this study suggest that targeting stimulus payments to households with low levels of liquidity in a type of recession where large sectors of the economy are shut down will have the largest effects on MPCs, and hence on fiscal multipliers.

Our study is the first to empirically explore the comprehensive spending impacts of the 2020 stimulus at an individual level. Moreover, by linking transaction and survey data, we are the first to examine more generally how expectations affect MPCs out of stimulus payments. Additionally, to our knowledge, our study is the first to look at stimulus payments using high-frequency transaction data, as such data did not exist in 2008.[2] 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.

There is an extensive literature on households' responses to tax rebates and previous stimulus payments. Using spending data from the Consumer Expenditure Survey, Johnson, Parker, and Souleles (2006) and Parker *et al.* (2013) look at the tax rebates granted in 2001 and the economic stimulus payments in 2008. The authors document positive effects on spending in both nondurable and durable goods. Broda and Parker (2014) use high-frequency scanner data and find large positive effects on spending. Besides looking at aggregate effects, studies have also found heterogeneous effects across agents. Agarwal, Liu, and Souleles (2007) work with credit card accounts and find that customers initially saved the tax rebates in 2001, but then increased spending later on. In their setting, customers with low liquidity 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.

1 SaverLife conducted our survey from mid-May to the end of July. This survey also elicited self-reported information on the receipt and use of the stimulus checks. In terms of the fiscal stimulus use, our survey results line up closely with the empirics. Of the individuals, 60% report that they will not use any portion of the check for durables consumption and 50% of the users are using at least part of the check amount for food spending. A large majority of users also reported using at least a portion of the stimulus check for payment of current or past due bills. Finally, 15% of users are reporting to save most of the check amount and 45% report to save none of the check amount.

2 A number of papers use transaction-level data to look at spending responses to other income fluctuations, such as Baker (2018), Kuchler and Pagel (2020), Olafsson and Pagel (2018), Baker and Yannelis (2017), Baugh *et al.* (2018), and Kueng (2018). Broda and Parker (2014) explore some higher frequency weekly responses using Nielsen Homescan data.

In this article, we focus on a very different type of contraction relative to those faced during previous stimulus programs: one stemming from an infectious disease outbreak that caused widespread business and government shutdowns. In comparison to the 2001 and 2008 economic downturns, the downturn due to COVID-19 was inflicted on households at a much faster pace, causing large job losses much more quickly. In addition, the stimulus program we examine was comparatively larger than those in 2001 and 2008, with individual stimulus amounts of two to four times the size.

While previous studies have pointed out that stimulus payments have positive but heterogeneous effects on spending, analyzing the 2020 stimulus program will help us learn more about effects on spending in a quite different economic circumstance. In particular, this crisis was so fast moving that households had little ability to increase precautionary savings. Additionally, many sectors of the economy were shut down due to state and local orders, which can impact the effectiveness of fiscal stimulus, as discussed above. Some policymakers argued that shutdowns make conventional fiscal stimulus obsolete.[3]

In Section 4.3, we discuss the differences between our estimates and the previous literature that analyze past stimulus programs. While the economic setting was quite different than the previous two American recessions, our results for magnitudes of spending responses to the 2020 stimulus are generally comparable. The three main differences are: (i) during the 2020 stimulus, households spend much of their stimulus checks in a shorter period of time, (ii) they spend more on food and nondurables than on durable consumption like furniture, electronics, or cars, and (iii) they repay credit cards, rent, mortgages, and other overdue bills.

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 often offer starkly different predictions, and the observed MPC heterogeneity highlights the importance of the HANK framework. In a recent attempt to study pandemics in a HANK framework, Kaplan, Moll, and Violante (2020a) 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 responses. In another recent working paper, Bayer *et al.* (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 help stabilize consumption and results in an output decline of less than 3.5%. Additionally, Hagedorn, Manovskii, and Mitman (2019) study multipliers in a HANK framework, whose size can depend on market completeness and the targeting of the stimulus. More broadly, our article also links to literature on how consumption responds to income changes. For example, see Pistaferri (2001), Blundell *et al.* (2006), Agarwal, Liu, and Souleles (2007), Jappelli and Pistaferri (2010), Aaronson, Agarwal, and French (2012), Baker (2018) and Di Maggio, Kermani, and Majlesi (2020).

This article also joins a fast-growing literature on the effects of the COVID-19 pandemic on the economy, and policy responses. Several papers develop macroeconomic frameworks of epidemics, for example, Jones, Philippon, and Venkateswaran (2020), Barro, Ursua, and Weng (2020), Eichenbaum, Rebelo, and Trabandt (2020), and Kaplan, Moll, and Violante (2020b). Gormsen and Koijen (2020) use stock prices and dividend futures to back out

3 For example, Joshua Rauh, the former chair of the President's Council of Economic advisers, noted that: "A contraction cannot be addressed via conventional fiscal stimulus since no increase in consumer demand will cause restaurants closed on government orders to re-open."

growth expectations. Coibion, Gorodnichenko, and Weber (2020b) study short-term employment effects and Baker *et al.* (2020a) analyze risk expectations. Granja *et al.* (2022) study the targeting and impact of the Paycheck Protection Program (PPP) on employment. Barrios and Hochberg (2021) and Allcott *et al.* (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.[4] Chetty *et al.* (2020) use aggregate data to study the effects of the stimulus, and Coibion, Gorodnichenko, and Weber (2020a) provide survey evidence on how households spent their stimulus payments. We join this emerging and rapidly growing literature by providing individual-level data on comprehensive spending responses to the 2020 stimulus payments and how these responses varied across individuals' financial characteristics. The results suggesting that MPCs are much higher for low-income and low-liquidity households are important in designing future rounds of stimulus.

We also contribute to literature on how expectations affect households' economic behavior. A newer and growing body of recent work also shows that expectations about individual and aggregate outcomes impact behavior, studying households (Manski, 2004; Armona, Fuster, and Zafar, 2019; Giglio *et al.*, 2019; Kuchler and Zafar, 2019; D'Acunto, Hoang, and Weber, 2020) and firms (Gennaioli, Ma, and Shleifer, 2016; Landier, Ma, and Thesmar, 2017; Bouchaud *et al.*, 2019; Landier and Thesmar, 2020). During the debate about the efficacy of the 2008 stimulus, the role that expectations would play in the program's efficacy and stimulating consumption was discussed at length. However, there is little empirical work exploring how expectations affect the MPCs out of stimulus payments.

The remainder of this article is organized as follows. Section 2 provides background information regarding the 2020 stimulus and our empirical strategy. Section 3 describes the main transaction data used in the article as well as the linked survey data. Section 4 presents the main results and Section 5 discusses heterogeneity by income, income drops, and liquidity. Section 6 explores how expectations interact with stimulus payments to affect consumption responses. Section 7 concludes and suggests directions for future research.

2. Institutional Background and Empirical Strategy

2.1 2020 Household Stimulus

COVID-19, a novel coronavirus, was first identified in Wuhan, China and subsequently spread worldwide in early 2020. By some estimates, the new virus had a mortality rate that is ten times higher than the seasonal flu and has at least twice the rate of infection. The first case in the USA was identified in late January in Washington state and spread within the country in February. By mid-March, the virus was spreading rapidly, with significant clusters in New York, San Francisco, and Seattle. Federal, state, and local governments responded to the COVID-19 pandemic in a number of ways: by issuing travel restrictions, shelter-in-place orders, and closures of many nonessential businesses.

4 Our related paper, Baker *et al.* (2020b), studies household consumption during the onset of the pandemic in the USA using a smaller sample drawn from the same data source. Carvalho *et al.* (2020), Andersen *et al.* (2020), Bounie, Camara, and Galbraith (2020), and Chen, Qian, and Wen (2020) perform similar analyses as performed in this article using transaction-level data from Spain, Denmark, France, and China. Dunn, Hood, and Driessen (2020) use transaction-level data from the US provided by merchants rather than individual-level data and find similar results to Baker *et al.* (2020b).

The federal government soon passed legislation aimed at 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 deployed nearly $2 trillion across a range of programs for households and businesses. This study focuses on the portion of the Act that directed cash transfers to the vast majority of American households. These one-time payments consist of $1,200 per adult and an additional $500 per child under the age of seventeen. For an overview of amounts by household, see Supplementary Appendix Figure A.1. These amounts are substantially larger than the 2001 and 2008 stimulus programs. In 2020, a married couple with two children would be sent $3,400, a significant amount, particularly for liquidity-constrained households.

Most American households qualified for these payments. All independent adults who have a social security number, filed their tax returns, and earn below certain income thresholds qualified 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. No payments were made to individuals earning more than $99,000 or married couples earning more than $198,000.[5]

Payments are made by direct deposit whenever available, or by paper check when direct deposit information was unavailable. Funds are disbursed by the IRS, and the first payments by direct deposit were made on April 9. The IRS expected that direct deposits would largely be completed by April 15. In practice, the timing varied across banks and financial institutions, with some making payments available earlier than others, and direct deposits being spread out across more than 1 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 24. Approximately 70–80% of taxpayers use direct deposit to receive their tax refunds. However, given changes in banking information or addresses, many individuals were unable to receive their payments through direct deposit even when they had received prior tax refunds via direct deposit. In the case of paper checks, the order of payments across households is not random. The IRS directed to send individuals with the lowest adjusted gross income checks first in late April, and additional paper checks were sent throughout May. Supplementary Appendix A provides further details regarding the timing of payments and the stimulus.

2.2 Empirical Strategy

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

$$c_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{23} \beta_k \mathbb{1}[t = k]_{it} + \varepsilon_{it} \tag{1}$$

c_{it} denotes spending by individual i aggregated to the daily level t. α_i are individual fixed

5 Due to data limitations, in identifying stimulus payments, we are unable to identify these partial payments from these higher-income households. However, these individuals are a very small fraction of total households, both overall and particularly among our sample which is skewed toward lower-income households.

effects, while α_t are date fixed effects. Individual fixed effects α_i absorb time-invariant user-specific factors, such as some individuals having greater average income or wealth. The date fixed effects α_t absorb time-varying shocks that affect all users, such as the overall state of the economy and economic sentiment. $\mathbb{1}[t=k]_{it}$ is an indicator of the time period k days after receipt of the stimulus payment for individual i at time t.

In some specifications, we interact individual fixed effects with day-of-the-week or day-of-the-month fixed effects to capture individual-level time-varying spending patterns over the week and month. For example, some individuals may spend more on weekends, or on their paydays. We run regressions at an individual-day level to examine more precisely the high-frequency changes in behavior brought about by the receipts of the stimulus payments. Standard errors are clustered at the individual level. The coefficient β_k captures the excess spending on a given day before and after stimulus payments are made. In our graphs, the solid lines show point estimates of β_k, while the dashed lines show 95% confidence intervals.

We identify daily MPCs using the following specification:

$$c_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{23} \gamma_k P_i \times \mathbb{1}[t=k]_{it} + \varepsilon_{it} \tag{2}$$

where P_i are stimulus payments for individual i. To identify cumulative MPCs since the 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 a cumulative 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, 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. The coefficient ζ thus captures the aggregate effect of the stimulus in the time period in question, by scaling the average effect per day by the number of days since receipt. The resulting coefficients can be interpreted as the fraction of stimulus money spent during that period: a coefficient of 0.05 corresponds to the user spending 5% of their stimulus check during their observed post-stimulus period. Our primary estimates are calculated using a 3-month post-stimulus period, though MPCs from a range of horizons are also calculated.[6]

3. Data

3.1 Transaction Data

In this article, we utilize de-identified transaction-level data from SaverLife, a nonprofit fintech helping working families meet financial goals. As with a number of other personal

6 As an example to illustrate this, imagine that a \$1 transfer leads to \$1 dollar of additional spending in the day immediately after receipt. Thus, if we estimated the effect over one day, we would scale by 1 and $\zeta = 1$. If we estimate the effect over 10 days, the average effect each day is 0.1, which would be the coefficient on a regression of $Post_{it} \times P_i$ and we scale by 10, so again $\zeta = 1$. If we estimate the effect over 100 days, the average effect per day is 0.01. Again we would scale by 100 and so on.

financial apps, SaverLife allows users to link their main bank accounts to their service. Users can link their checking, savings, as well as their credit card accounts. The sample is skewed toward lower-income individuals, given that the nonprofit fin-tech targets assisting households that have difficulty saving and meeting budgetary commitments. SaverLife offers users the ability to aggregate financial data and observe trends and statistics about their own spending.

Figure 1 shows two screenshots of the online interface in the app. 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. These data are described in more detail in Baker *et al.* (2020b).

Overall, we have been granted access to de-identified bank account transactions and balances data from August 2016 to August 2020. We observe 90,844 users in total who live across the USA. In addition, for a large number of users, we are able to link financial transactions to self-reported demographic and spatial information such as age, education, ZIP code, family size, and the number of children they have.

We also observe a category that classifies each transaction into a large number of categories and subcategories. For this article, we mostly analyze and report spending responses into the following aggregated categories: food, household goods, and personal care, durables like auto-related spending, furniture, and electronics, nondurables and services. Across all specifications, we exclude transactions that represent transfers between accounts like transfers to savings or investment accounts.

Looking only at the sample of users who have updated their accounts reliably up until August 2020, we have complete data for 38,379 users to analyze in this article. We require these users to have at least two transactions in December 2019 and more than twenty transactions adding up to at least $1,000 in 2020. Additionally, we drop all user–month pairs with less than five transactions per month. We require five transactions in account usage as a completeness-of-record check for bank-account data following Ganong and Noel (2019). We aggregate all transactions to the daily level. If a user does not have a transaction for a particular category on a given day, we fill in a zero if that user had other transactions earlier or later than that day.

While our sample is not representative of the nation as a whole, we are able to reweight based on observable demographic, financial, and geographic characteristics using Current Population Survey (CPS) weights. After doing so, we match well with other aggregate pictures of consumer behavior during this period. Supplementary Appendix Table A.3 and Supplementary Appendix Figure A.2 both display comparisons with aggregated data from more representative data sources. We find close correlations between our aggregated data and these alternate sources, suggesting that our re-weighting procedure can correct for much of the sample selection inherent to our data.

In Table I, 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 observed income being approximately $36,000 per year. Note that this observed income is what arrives in a user's bank account and is therefore post-tax and post-withholding. In addition, we show the distribution of balances across users' accounts during the week before most stimulus checks arrived (the first week of April). Consistent with the low levels of income, we see that most users maintain a fairly low balance in their linked financial account, with the median balance being only $98.

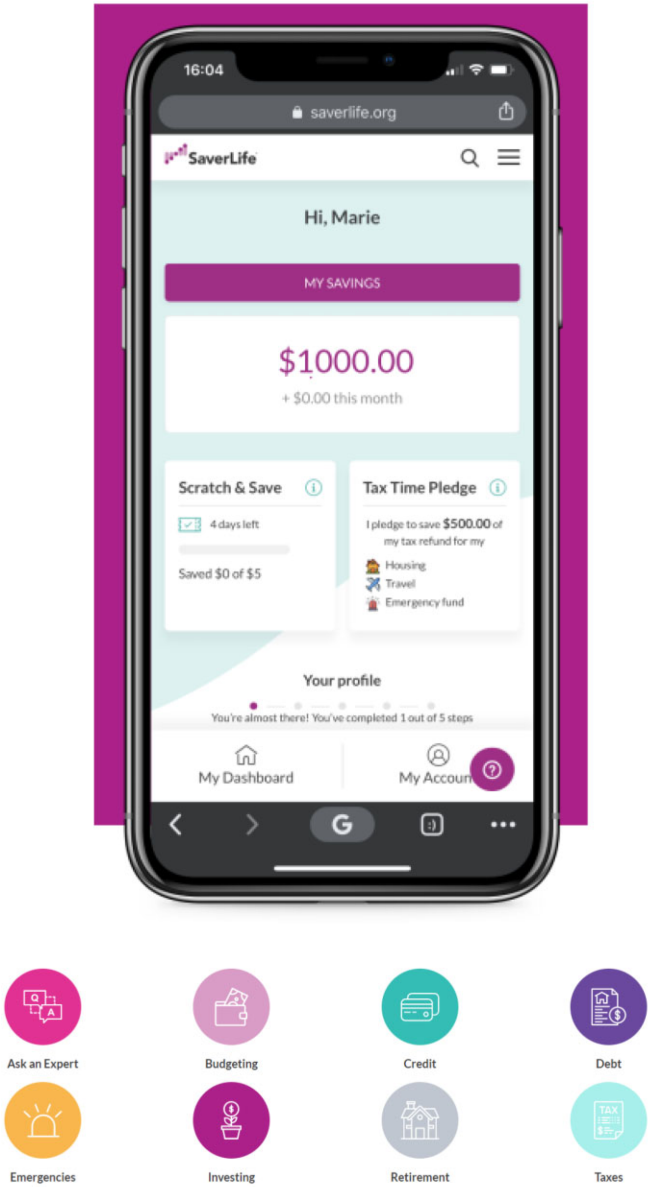

Figure 1. Example of platform.
Notes: This figure shows screenshots of the SaverLife website. The top panel shows the app's landing page and the bottom panel illustrates the offered financial advice pages.
Source: SaverLife.

We identify stimulus payments using payment amounts stipulated by the CARES Act, identifying all payments at the specific amounts (e.g., $1,200, $1,700, and $2,400) paid after April 9 in the categories 'Refund', 'Deposit', 'Government Income', and 'Credit.' Figure 2 shows the identified number of payments of this type, relaxing the time restrictions

Table I. Summary statistics

Summary statistics for spending and income are computed using the user–month level. The number of observations refers to the user–month count from January 1 to August 23, 2020 for the user–month pairs that passed the completeness-of-records checks described in Section 3. We have 38,379 distinct users. Stimulus Income (Cond) refers to the distribution of stimulus income conditional on receiving a stimulus payment (22,765 users). Income (self-reported) refers to annual income self-reported upon account opening (available for a subset of 8,734 users). The balance in the beginning of April 2020 is the mean amount in users' checking accounts in the first week of April 2020 (available for a subset of 23,682 users). Annual income is self-reported in a survey and available for a subset of 8,734 users.

Variable	# Obs.	Mean	10th	25th	Median	75th	90th
Monthly income	254,206	2,988	140	740	2,152	4,301	6,772
Stimulus income (cond)	22,765	2,086	1,200	1,200	1,700	2,400	3,600
Annual income (self-reported)	57,378	32,009	450	9,000	25,000	45,000	80,000
Spending	254,206	2,157	25	260	1,192	3,026	5,545
Durables	254,206	46	0	0	0	11	131
Food	254,206	210	0	0	74	285	601
Household	254,206	180	0	0	58	258	522
Nondurables	254,206	283	0	2	91	385	807
Payments	254,206	354	0	0	24	430	1,091
Transfers	254,206	871	0	10	251	1,137	2,511
Balance beg of April 2020	171,866	293	−29	15	98	354	994

in 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 increase in frequency after April 9. This suggests that there are relatively few false positives, and that the observed payments are due to the stimulus program and not due to other payments of the same amount. Stimulus checks for individuals in 'phase-out' would not be even numbers, meaning that we would falsely classify an individual as having not received a stimulus check. This would likely attenuate our empirical estimates somewhat, biasing our estimates of the stimulus receipt downwards.

As of August, approximately 60% of users have received a stimulus payment into their linked account. The remainder of the sample may have not linked the account that they received the stimulus check in, be still waiting for a stimulus check, or maybe ineligible for one.[7] 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

7 According to the IRS, about 75% of adults were eligible for a stimulus check. Our sample may have some ineligible populations overrepresented such as residents without Social Security Numbers or dependents (e.g., college students who file as dependents). We are also unable to identify partial payment checks (due to income thresholds) or physical checks that were deposited alongside other cash or checks (which has the effect of making the deposit size not match the exact stimulus amounts). We note that the completeness-of-record checks we employ following Ganong and Noel (2019) are not too stringent. However, keeping a fraction of inactive users in the sample does not affect our results as we can restrict our analysis to users for which we observe the stimulus payments obtaining the same results.

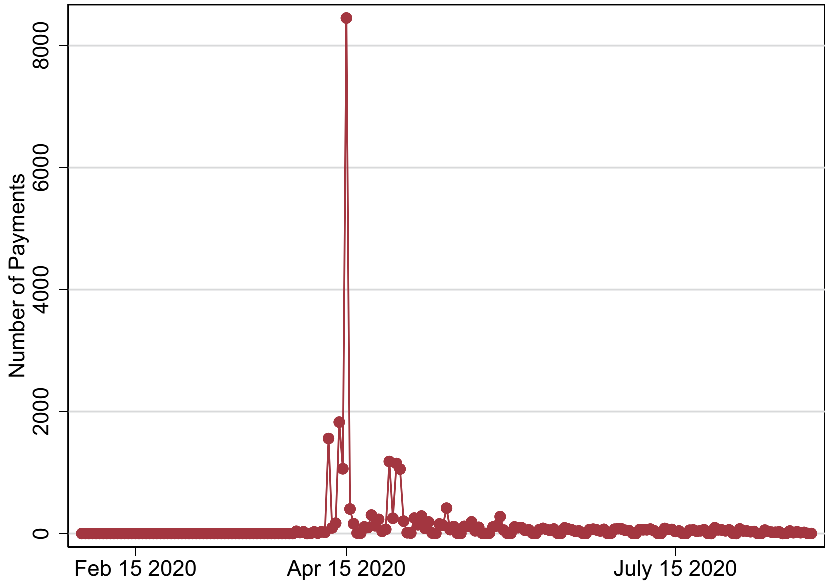

Figure 2. Daily number of government payments at stimulus amounts.
Notes: This figure shows the number of payments users receive that match the amounts of the 2020 government stimulus payment by day from February 2020 onwards. Potential payments are classified by the specified amounts of the stimulus checks and need to appear as being tax refunds, credit, or direct deposits.
Source: SaverLife.

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 eligible income thresholds for receipt. Of those who receive payments, two-thirds received them by April 15, with 40% of all payments occurring on April 15. In our sample, 92% of those who received payments did so in April.

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. Supplementary Appendix Figure A.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. This measure is highly correlated with the observed stimulus payments.

Supplementary Appendix A provides further details regarding payments in our sample. We conduct a placebo exercise in the Supplementary Appendix, and look at spending around April for households that do not receive a check (see Supplementary Appendix Figure A.3). We do not see any sharp breaks in spending beyond day-of-the week effects, suggesting that the impact of miscategorization is small and that these users did not link either their main tax or spending accounts.

3.2 Survey Data

SaverLife conducted a survey between mid-May to the end of July to elicit self-reported information on the receipt and use of the stimulus checks, expectations about personal financial situations, and the duration of the pandemic. Participants were sent emails and text messages by SaverLife, and offered $3–$10 for participation. If individuals did not respond initially, they were sent email and text reminders. Users could take the survey on a computer or mobile device, and they were allowed to skip questions. The survey was sent to 6,060 individuals, who were longer-term active users of the platform and identified as being potentially responsive to surveys in the past. We received 1,011 unique responses, indicating a response rate of around 16.7%. The survey questions are loosely based on the Federal Reserve Bank of New York Survey of Consumer Expectations. The survey focused on the following areas:

- Expectations regarding income, the economy, and benefits.
- Expectations regarding the length of the pandemic.
- Self-reported difficulties in paying bills and anxiety.
- Credit.
- Stimulus check spending.
- Political affiliation.

In the Supplementary Appendix, we report raw survey responses and questions. Supplementary Appendix Figure B.1 shows the survey instrument on a smartphone, and lists all questions in the survey and Supplementary Appendix Figures B.2–B.4 show the raw averages of the survey responses. In Supplementary Appendix Figure B.2, we can see that at the time 70% of the users replied that they received a stimulus check while 15% of the users were still waiting. This lines up closely with the 66% of users we identify as receiving checks in the data. Additionally, our user population was subject to a number of financial hardships and subject to difficulties in payment bills, rents, and mortgages. Whereas 70% received new credit primarily through a new credit card, 30% of users reported they had difficulty obtaining credit. Our users are relatively pessimistic about the lasting effects of the pandemic.

In Supplementary Appendix Figure B.3, we can see that our empirical results in terms of the fiscal stimulus use line up with the survey data. Whereas 50% of the users are using part of the check amount for food spending, 60% of individuals report to not use the check amount for durables consumption. Additionally, only 15% of users said they would not use the check to pay past bills or would use it for future bills. Finally, 15% of users report saving most of the check amount and 45% report to save none of the check amount.

In Supplementary Appendix Figure B.4, we can see our survey results for expectations other than the duration of the crisis. Individuals have mixed expectations about the prospects of future stimulus payments and taxes as well as the stock market. A substantial fraction of users believes they will have lower salaries in the future or become unemployed.[8]

8 Supplementary Appendix Figure B.5 further shows correlations between survey responses as a validation exercise. Households more pessimistic about stock market performance are more likely to believe that they will become unemployed or see salary cuts. Households that anticipate tax increases also anticipate benefit cuts, consistent with beliefs about greater fiscal pressures. Beliefs about unemployment and salary cuts are also highly correlated.

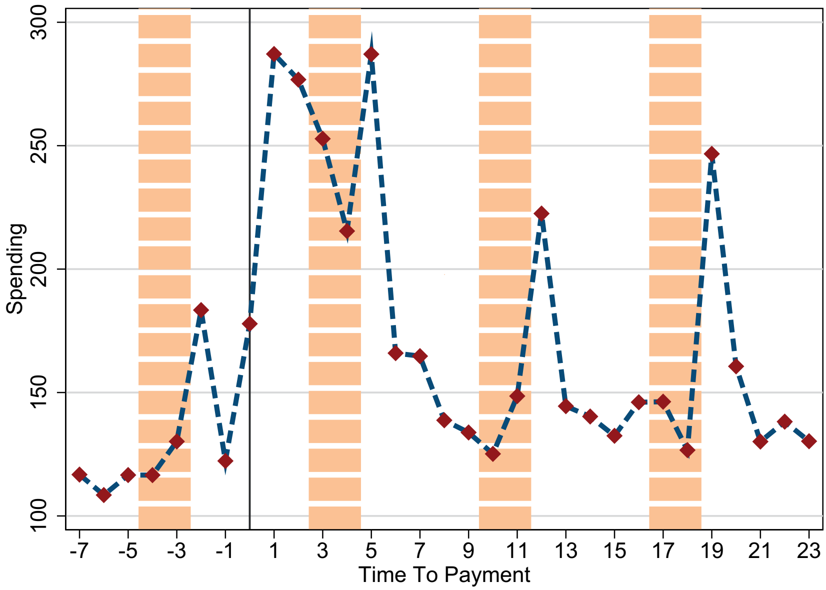

Figure 3. Mean spending around receiving the stimulus payments—raw spending.
Notes: This figure shows mean spending around the receipt of stimulus payments. The sample includes only users who receive a stimulus payment during our sample period. The vertical axis measures spending in dollars, and the horizontal axis shows time in days from receiving the stimulus check which is defined as zero. Shaded days represent weekends for the majority of stimulus-recipients who receive their payment on Wednesday, April 15.
Source: SaverLife.

4. Effects of Stimulus Payments

Looking at the raw levels of spending for users receiving stimulus payments, Figure 3 shows mean daily spending before and after the receipt of a stimulus payment without any other controls or comparison group. In this figure, we only show spending data for users who receive a stimulus check in our sample period. Prior to receiving a check, the typical individual in the sample who receives a stimulus check is spending around \$90 per day.[9] Mean daily spending rises to about \$250 for the days after the receipt of the stimulus payment.

To identify the direct impacts of the stimulus check payments, we effectively compare users receiving stimulus payments to themselves before and after the event as well as to those that did not receive one on that day. Figure 4 shows estimates of β_k from the equation: $c_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{23} \beta_k \mathbb{1}[t = k]_{it} + \varepsilon_{it}$. '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

9 There are substantial intraweek patterns in spending, with Mondays typically seeing the highest levels of posted transactions and spending, as transactions that occurred during the weekend sometimes process only on the Monday that follows.

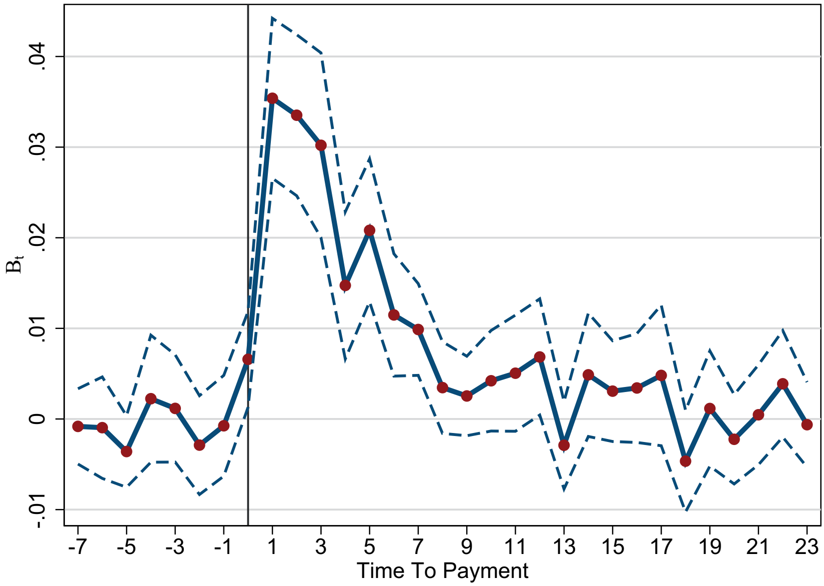

Figure 4. Spending around stimulus payments—regression estimates.
Notes: This figure shows estimates of β_k from $c_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{23} \beta_k \mathbb{1}[\mathrm{t} = \mathrm{k}]_{\mathrm{it}} + \varepsilon_{\mathrm{it}}$. The sample includes all users in our sample period (both those who do and do not receive stimulus payments). The solid line shows point estimates of β_k, while the dashed lines show 95% confidence interval. Date and individual times day-of-week fixed effects are included. Standard errors are clustered at the user level. Time to payment is equal to zero on the day of receiving the stimulus check.
Source: SaverLife.

to users who do not receive the checks. Because our sample is not representative of the nation as a whole, our main specifications reweight our sample on several dimensions using CPS weights: age, sex, state, and income bins.[10]

Table II presents similar information, presenting coefficients from the regression $c_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{23} \beta_k \mathbb{1}[t = k]_{it} \times P_i + \varepsilon_{it}$. That is, we examine the excess spending among users who received stimulus payments on each day following the receipt of their stimulus checks, scaled by the size of their payment. A value of 0.03 can be interpreted as the user spending, on day *t*, 3% of their stimulus check (e.g., \$36 out of a \$1,200 stimulus check) more than a user who did not receive a check. In our sample, the average stimulus check size was \$2,166 (median of \$1,700).

Columns (1)–(3) test how total user spending responds with three different sets of fixed effects. Column (1) presents results using individual and day-of-the-month fixed effects.

10 Supplementary Appendix Figure A.4 includes additional days in advance of the stimulus check's arrival. We see that there is only a single, relatively small, coefficient that is significantly different than zero in the 23 days prior to a stimulus check arriving (this length of time extends backward from the date when a plurality of stimulus checks were received to just prior to the passage of the CARES Act into law). This helps to demonstrate that there were not any substantial pretrends or anticipatory spending among households who would later receive a stimulus check.

Table II. Stimulus payments and spending

The table shows regressions of overall spending and categories of spending on lags of an indicator for receiving a stimulus payment. For total spending, we run three specifications with varying fixed effects. We use individual by day-of-the-month fixed effects, individual and calendar date and individual times day-of-month fixed effects, or individual and day of the month and individual times day-of-week fixed effects. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: SaverLife.

	(1) Total	(2) Total	(3) Total	(4) Food	(5) Nondurables	(6) Household	(7) Durables
Stimulus payment	0.000882	0.00479**	0.00189	0.00585**	−0.000736	−0.00296	0.00103
	(0.00231)	(0.00230)	(0.00267)	(0.00295)	(0.00257)	(0.00221)	(0.000765)
Stimulus payment$_{t+1}$	0.0287***	0.0310***	0.0264***	0.00586**	0.0239**	0.0132**	0.00605***
	(0.00394)	(0.00407)	(0.00472)	(0.00261)	(0.0112)	(0.00561)	(0.00210)
Stimulus payment$_{t+2}$	0.0249***	0.0272***	0.0275***	0.00563***	0.0108***	0.00992**	0.00835**
	(0.00369)	(0.00363)	(0.00417)	(0.00167)	(0.00305)	(0.00485)	(0.00353)
Stimulus payment$_{t+3}$	0.0263***	0.0288***	0.0175***	0.00591**	0.0221*	0.0133*	0.00714**
	(0.00539)	(0.00520)	(0.00513)	(0.00263)	(0.0132)	(0.00740)	(0.00363)
Stimulus payment$_{t+4}$	0.0155***	0.0156***	0.0190***	0.00490**	0.00651*	0.00332	0.00123
	(0.00429)	(0.00404)	(0.00425)	(0.00193)	(0.00374)	(0.00246)	(0.00156)

(continued)

Table II. Continued

	(1) Total	(2) Total	(3) Total	(4) Food	(5) Nondurables	(6) Household	(7) Durables
Stimulus payment$_{t+5}$	0.0244***	0.0180***	0.0256***	0.0141*	0.0117***	0.00888***	0.00340**
	(0.00505)	(0.00417)	(0.00545)	(0.00730)	(0.00414)	(0.00280)	(0.00156)
Stimulus payment$_{t+6}$	0.00980**	0.00865**	0.0118***	0.00416	0.00640	0.0169	0.000188
	(0.00412)	(0.00426)	(0.00403)	(0.00307)	(0.00415)	(0.0143)	(0.00102)
Stimulus payment$_{t+7}$	0.00947**	0.0129***	0.00858**	−0.000715	0.00776	0.0183	0.000367
	(0.00384)	(0.00378)	(0.00426)	(0.00140)	(0.00545)	(0.0156)	(0.000836)
Stimulus payment$_{t+8}$	0.00751**	0.00880**	0.00522	0.00349	−0.0000900	0.00312	0.00321
	(0.00349)	(0.00348)	(0.00365)	(0.00301)	(0.00239)	(0.00312)	(0.00314)
Stimulus payment$_{t+9}$	0.00204	0.00414*	0.00240	−0.00240**	0.00257	0.000108	−0.000683
	(0.00211)	(0.00240)	(0.00234)	(0.00106)	(0.00198)	(0.00160)	(0.000506)
Date FE	X	X	X	X	X	X	X
User FE	X	X	X	X	X	X	X
User × Day-of-month FE		X					
User × Day-of-week FE			X				
Observations	499,945	499,945	499,945	499,945	499,945	499,945	499,945
R^2	0.202	0.306	0.515	0.100	0.062	0.094	0.039

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 week after stimulus receipt. Spending on days during this period is 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.

4.1 Spending across Categories

The remainder of the columns in Table II decompose the effect that we see in overall spending according to the category of spending. We find significant increases in spending in all of these categories, with the largest increases coming from nondurables and payments. We find the most muted effects of the stimulus payments on durables spending. In previous recessions, 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 contributing negligibly to the overall household response. We discuss some of these differences relative to past stimulus programs in Section 4.3. To compare our estimated coefficients to other studies using a broader sample, we also run the equivalent of the stimulus regression as done in the paper by Chetty *et al.* (2020) and obtain statistically indistinguishable results.[11]

There is a sharp and immediate increase in spending following the receipt of a stimulus deposit; 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. In Figure 5, we break down users' spending responses by categories of spending. We map our categories to roughly correspond to those reported in the Consumer Expenditure Survey: food, household goods, and personal care, durables like auto-related spending, furniture, and electronics, nondurables, and services.

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 cumulative spending on food, household, nondurables, and durables all seeing increases in spending in the first week following. These effects are concentrated in the near term, with excess spending declining substantially following the first week.

In Figure 6, we also note the impact of the stimulus check on financial payments and transfers. In particular, we examine the impact on total transfers out of an individual's checking account, financial payments and credit card payments, and rent and mortgage payments. Most of the transfers, in the top left panel, are likely transfers to things like

11 In particular, we replicate the regression in their main stimulus Table IV. Exactly following their analysis, we first aggregate our data to the daily level, then express spending as the percentage change relative to the mean spending between January 4 and 31, 2020, then residualize the variable with respect to day-of-week and first-day-of-the-month fixed effects, and then regress this variable on a dummy for the day being on or after April 15, 2020, restricting the regression window to April 1–30, 2020. We obtain a coefficient of 27.31 which is well within one standard deviation of their estimated coefficient of 25.15 for the bottom income quartile.

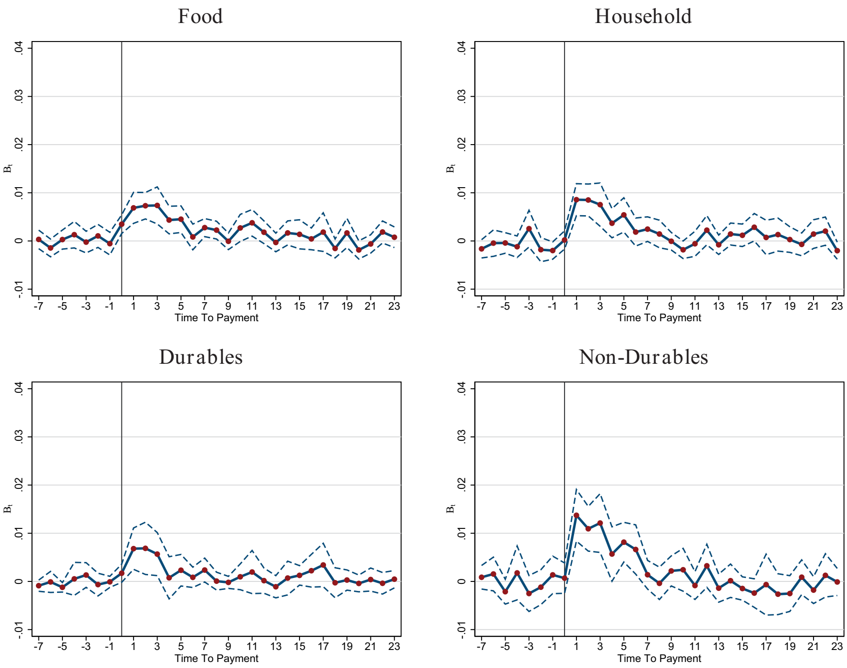

Figure 5. Spending around stimulus payments by categories.
Notes: This figure shows estimates of β_k from $c_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{23} \beta_k \mathbb{1}[\mathrm{t}=\mathrm{k}]_{\mathrm{it}} + \varepsilon_{\mathrm{it}}$, broken down by spending categories. The solid line shows point estimates of β_k, while the dashed lines show the 95% confidence interval. Standard errors are clustered at the user level. Time to payment is equal to zero on the day of receiving the stimulus check.
Source: SaverLife.

savings and brokerage accounts, but some may represent loan payments or transfers to external vendors, as well.[12]

As with other categories of spending, we find that financial payments and transfers surge substantially upon receipt of the 2020 stimulus payments. Households increase their paying down of credit cards and also increase payments on mortgages, rent, and other loan products. Many of these credit card and loan products were subject to a temporary forbearance enacted by governments or financial institutions. For instance, many financial institutions allowed delays of mortgage payments and most federal student loans were similarly eligible for delayed payments. While we cannot observe in detail the types of loan products that consumers were paying down in our data, these results suggest that many consumers were not fully taking advantage of such delayed payment programs but actually accelerated debt payments following the stimulus checks' arrival.

12 We separately test whether transfers to equity investment accounts increased in the wake of stimulus checks' arrival. A majority of transfers to equity accounts in our sample went to the FinTech firm, Robinhood. We see economically small effects on the number of such transfers, with individual transfers being rare and averaging less than $100.

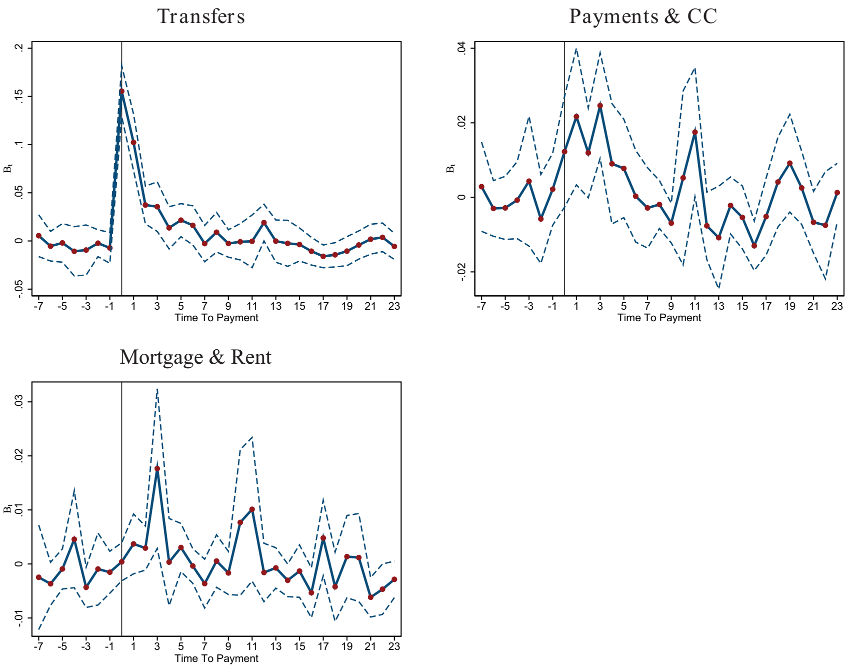

Figure 6. Payments and transfers around stimulus.

Notes: This figure shows estimates of β_k from $c_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{23} \beta_k \mathbb{1}[t=k]_{it} + \varepsilon_{it}$, broken down by payment categories. The solid line shows point estimates of β_k, while the dashed lines show the 95% confidence interval. Standard errors are clustered at the user level. Date and individual times day-of-week fixed effects are included. Time to payment is equal to zero on the day of receiving the stimulus check.

Source: SaverLife.

The increase in debt payments that we observe mirrors findings from surveys of consumers regarding how they might spend their stimulus checks. For instance, Coibion, Gorodnichenko, and Weber (2020a) and Sahm *et al.* (2020) both find that substantial portions of consumers reported planning to devote significant portions of their stimulus checks to the payment of current and past due bills and other debt.

4.2 Robustness

In Table III, we aggregate the daily excess spending responses across a range of horizons to provide a more thorough accounting for how the marginal propensity to consume evolves over the weeks and months after stimulus receipt. We provide estimates of spending over five horizons: 1-week, 2-weeks, 1-month, 2-months, and 3-months. We find that just over \$0.25 of each dollar of stimulus check was spent in 3 months following its arrival. About half of this spending (\$0.14) was spent during the first week alone and over three quarters (\$0.22) spent in the first month. We find no statistical difference in excess spending between Months 2 and 3. That is, the stimulus checks did have the effect of stimulating

Table III. Stimulus payments and spending—MPC horizons

In this table, we calculate the excess spending from the stimulus at varying time horizons. Each column regresses total spending on a post-stimulus dummy extending for the listed amount of time. Coefficients are fractions of stimulus spent within that window. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: SaverLife.

	(1) Total	(2) Total	(3) Total	(4) Total	(5) Total
1-week MPC	0.140***				
	(0.0124)				
2-week MPC		0.190***			
		(0.0171)			
1-month MPC			0.219***		
			(0.0254)		
2-month MPC				0.286***	
				(0.0490)	
3-month MPC					0.265***
					(0.0757)
Date FE	X	X	X	X	X
Individual FE	X	X	X	X	X
Observations	523,208	523,208	523,208	523,208	523,208
R^2	0.200	0.200	0.199	0.199	0.199

additional spending in the economy, but the effect was relatively short-lived and limited relative to the size of the checks.[13]

Because our sample is not representative of the nation as a whole, the previous results are reweighted by age, sex, state of residence, and income bins. In Table IV, we compare our estimates from our weighted regressions to those forgoing these user weights. Column (5) thus runs our primary MPC calculation using these user weights, finding a 3-month MPC of approximately 0.368 rather than 0.265 in Column (4). In general, when not weighting our sample to match the national distribution of households, we see results approximately 50% larger in magnitudes than when weighting along these dimensions. Given our sample being younger and having lower incomes and assets than the nation as a whole, it is unsurprising that down-weighting these types of users produces a lower MPC. In this table, we also run specifications including financial payments to our measure of total

13 Given limited spending out of stimulus checks, much of the lasting impact of these checks was simply in increasing household balance sheets. This was also noted in Kim *et al.* (2021), where the authors documented large increases in bank account balances for both households and businesses following the large government interventions of the CARES Act.

Table IV. Stimulus payments and spending—robustness

These specifications mirror those in Table II but include two variants. In Columns (2) and (5), we regression total excess spending from the stimulus on our unweighted sample of users. In Columns (3) and (6), we include "Payments" spending in the total spending which includes things like rent, mortgages, and loan payments. Standard errors are clustered at the user level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: SaverLife.

	(1) Baseline	(2) Unweighted	(3) Add payments	(4) Baseline	(5) Unweighted	(6) Add payments
Stimulus payment	0.000882	0.00695***	0.00577*			
	(0.00231)	(0.000835)	(0.00316)			
Stimulus payment$_{t+1}$	0.0287***	0.0401***	0.0346***			
	(0.00394)	(0.00144)	(0.00449)			
Stimulus payment$_{t+2}$	0.0249***	0.0353***	0.0280***			
	(0.00369)	(0.00395)	(0.00431)			
Stimulus payment$_{t+3}$	0.0263***	0.0381***	0.0315***			
	(0.00539)	(0.00178)	(0.00563)			
Stimulus payment$_{t+4}$	0.0155***	0.0317***	0.0197***			
	(0.00429)	(0.00155)	(0.00470)			
Stimulus payment$_{t+5}$	0.0244***	0.0345***	0.0277***			
	(0.00505)	(0.00403)	(0.00565)			
Stimulus payment$_{t+6}$	0.00980**	0.0115***	0.0103**			
	(0.00412)	(0.00223)	(0.00454)			

(continued)

Table IV. Continued

	(1) Baseline	(2) Unweighted	(3) Add payments	(4) Baseline	(5) Unweighted	(6) Add payments
Stimulus payment$_{t+7}$	0.00947**	0.00762***	0.00912**			
	(0.00384)	(0.00168)	(0.00372)			
Stimulus payment$_{t+8}$	0.00751**	0.00595***	0.00860**			
	(0.00349)	(0.00101)	(0.00362)			
Stimulus payment$_{t+9}$	0.00204	0.00407***	0.00169			
	(0.00211)	(0.000806)	(0.00259)			
Post-stimulus × Stimulus				0.265***	0.368***	0.407***
				(0.0757)	(0.0254)	(0.0288)
Date FE	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X
Observations	499,945	2,115,889	499,945	523,208	2,221,223	2,221,223
R^2	0.202	0.212	0.200	0.199	0.207	0.214

spending. These include mortgages, rent, and other loan payments. These cause a slight increase in overall MPCs, as seen in Columns (3) and (6).

To further address selection concerns, we perform a number of additional robustness checks in Supplementary Appendix Table A.2. We interact the post-stimulus variable with several binary indicator variables that may be indicative of differences in inherent savings motives within individuals. Users that joined more recently, have interacted with the app more, or have participated in recent savings challenges all might have differential impacts from the stimulus check's arrival. We include additional interactions with whether the user signed up prior to March 2019, whether they responded to any surveys from the app, whether they participated in savings challenges, and whether they were rewarded for completing savings challenges.

We do not find significant interaction effects in the spending responses which reassures us that we may be able to extrapolate our results despite the selection on savings motives. We also note that the selection into the app, in particular, savings motives and a taste for savings challenges and financial advice, maybe biasing our results for high-income groups more so than for low-income groups. Though those who participated in the savings challenges are fairly evenly distributed over all income groups, we provide a sample split looking specifically at high-income individuals that participate in savings challenges.

4.3 Comparison to Previous Economic Stimulus Programs

Johnson, Parker, and Souleles (2006) and Parker *et al.* (2013) examine the response of households to economic stimulus programs during the previous two recessions (2001 and 2008). These programs were similar in nature to the stimulus program in 2020 but were smaller in magnitude ($300–600 rather than $1,200 checks).

In these previous stimulus programs, households also tended to respond strongly to the receipt of their checks. For instance, in 2008, Parker *et al.* (2013) estimated that households spent approximately 12–30% of their stimulus payments on nondurables and services and a total of 50–90% of their checks on total additional spending (including durables) in the 6 months following receipt. In 2001, approximately 20–40% of stimulus checks were spent on nondurables and services in the 6 months following receipt.

In one paper examining the high-frequency responses (Broda and Parker, 2014), the authors are able to use Nielsen Homescan data to examine weekly spending responses to the 2008 stimulus payments. They find that a household's spending on covered goods increased by approximately 10% in the week that it received a payment. While these authors were not able to examine the timing of all types of spending due to data limitations, we demonstrate that households respond extremely quickly to receiving stimulus checks across most categories of spending. Households spent approximately 14% of their stimulus checks within one week and over 20% within the first month.

Another notable difference from the stimulus programs is that we find substantially smaller impacts on durables spending and confirm this in our survey of users. Previous research has found strong responses of durables spending to large tax rebates and stimulus programs, especially on automobiles (about 90% of the estimated impact on durables spending in the 2008 stimulus program was driven by auto spending). In contrast, despite a sizable response in nondurables and service spending, we see little immediate impact on durables. In part, this discrepancy with past recessions may be driven by the fact that automobile use and spending were highly depressed, with many cities and states being under shelter-in-place orders and car use being restricted. Similarly, as these orders hinder home purchases, professional appliance installment and spending on home furnishings may be lower as well.

Finally, across both 2001 and 2008, Parker *et al.* (2013) note that lower-income households tend to respond more, and that households with either larger declines in net worth or households with lower levels of assets also tend 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 from actual account balances arguably suffers from much less measurement error than the measures used in previous research on stimulus checks, giving additional confidence in our estimates.

5. Income, Liquidity, and Drops in Income

The 2020 CARES Act stimulus payments were sent to taxpayers with minimal 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 eligible for 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 II, 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 January and February 2020 (prior to the major impacts of the pandemic). 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 earned under \$1,000 per month saw an MPC about twice as large as users who earned \$5,000 a month or more.

We also split our sample of users according to their accounts' balances at the beginning of April, before any stimulus payments were made. We separate users into groups according to account balances, from under \$100 to over \$1,000. Figure 8 displays dramatic differences across these groups of users. Users with the highest balances in their bank accounts tend to have 3-month MPCs on the order of 0.15 while those who had under \$100 have MPCs of above 0.5.

In Figure 9, we examine whether a similar pattern can be seen among users who have had declines in income following the COVID-19 outbreak. For each user, we measure the change in income received in March 2020 relative to how much was received, on average, in January and February 2020. We split users into those who had a decline in monthly income and those who saw no decline in income (or had an increase). Here we see a

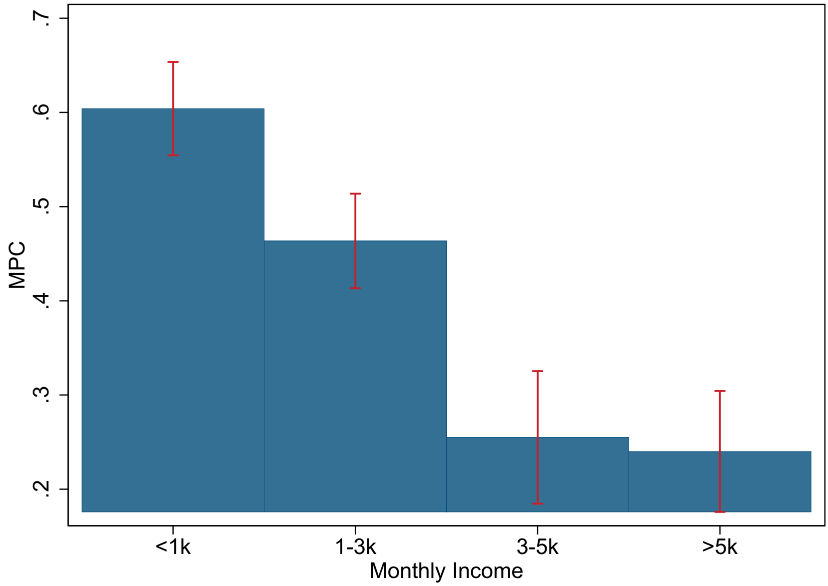

Figure 7. MPC by income groups.

Notes: This figure shows cumulative 3-month 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. These coefficients correspond to ζ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \varepsilon_{it}$ (cumulative fraction of the stimulus check that has been spent), broken down by monthly income groups. Date and individual fixed effects are included. The bars show point estimates, while the thin lines show the 95% confidence interval.

Source: SaverLife.

difference in MPCs of lower magnitude than the previous splits (and with a p-value of only 0.2 on the difference between coefficients). This smaller difference may be driven by the fact that the federal government had also made generous unemployment insurance available to nearly all workers, mitigating the potential loss of income from job loss for many lower-income households.

Tables V–VII 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 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.

6. Expectations and Stimulus Responses

In this section, we explore how household beliefs impact the response to stimulus payments. Household beliefs may impact MPCs in a number of ways. First, if households anticipate income declines in the future, they may save more to smooth consumption. Second, if households believe that taxes or government benefits may change as a result of current fiscal policy or economic conditions, they will also change consumption decisions.

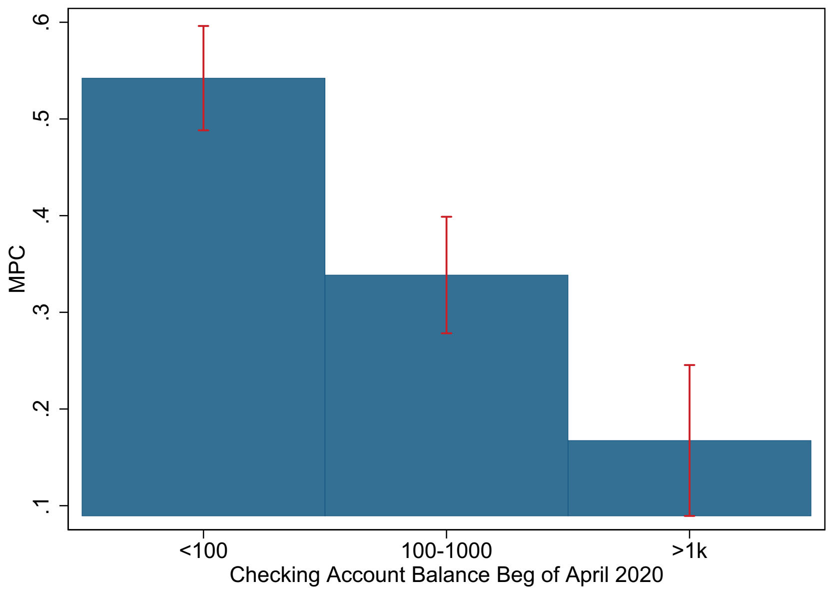

Figure 8. MPC by liquidity.
Notes: This figure shows cumulative 3-month MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. These coefficients correspond to ζ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \varepsilon_{it}$ (cumulative fraction of the stimulus check that has been spent), broken down by account balances. Date and individual fixed effects are included. The bars show point estimates, while the thin lines show 95% confidence interval.
Source: SaverLife.

For example, households anticipating benefit cuts may increase current savings levels. Finally, beliefs about future macroeconomic conditions may also impact household decision-making. On the one hand, if individuals believe that macroeconomic conditions will improve, they may believe that their own incomes or benefits may increase, and increase consumption today. On the other hand, individuals may also expect higher asset returns and invest more out of current resources.

We surveyed over 1,000 users in our sample and asked them about their beliefs regarding personal unemployment, income, government benefits and taxes, as well as expectations about the stock market and the duration of the pandemic. We discuss the survey, which was conducted via mobile device or email, in more detail in Section 3.2. We interact these surveyed beliefs with stimulus receipt and explore how beliefs impact MPCs.[14]

14 Survey respondents are similar to the full sample in most respects. We test balance on educational attainment, household size, marital status, income, bank balances, total spending, and distribution of spending across categories. Survey respondents are not significantly different on any demographic dimension, but have somewhat higher total income and spending (about 10% higher in each case). Conditional on levels of spending, the distribution of spending across categories (durables, food, nondurables, household goods and services, and financial payments) is the same for both survey respondents and the full sample.

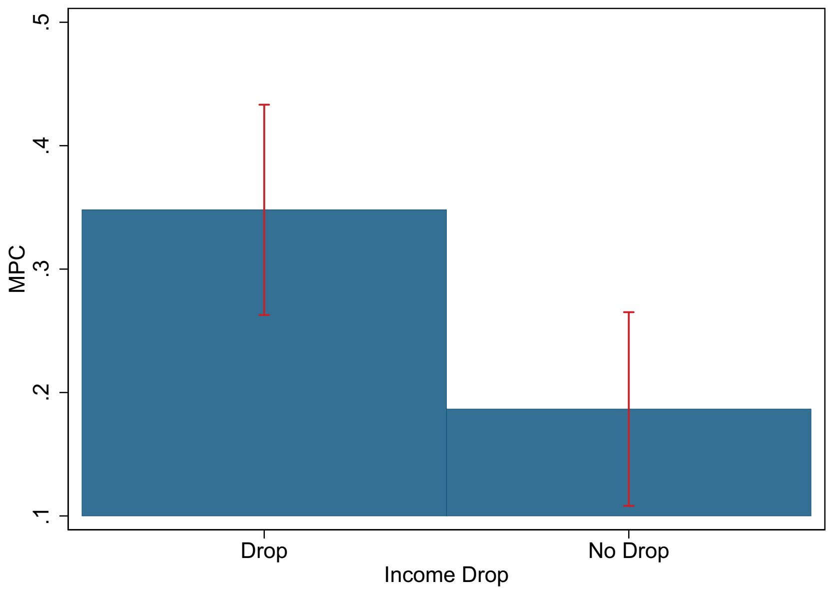

Figure 9. MPC by drop in income.

Notes: This figure shows cumulative 3-month 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. These coefficients correspond to ζ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \varepsilon_{it}$ (cumulative fraction of the stimulus check that has been spent), broken down by the drop in income between January/February 2020 and March 2020. Date and individual fixed effects are included. The bars show point estimates, while the thin lines show 95% confidence interval.
Source: SaverLife.

Table VIII shows MPCs for subgroups, based on user beliefs regarding personal unemployment, salary cuts, tax increases, government benefit cuts, stock market increases and the duration of the pandemic. More precisely, the table shows MPC estimates and interactions (ζ and ζ') from the specification:

$$c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \zeta' \frac{Post_{it} \times P_i \times Belief_i}{D_{it}} + \omega \frac{Post_{it} \times Belief_i}{D_{it}} + \varepsilon_{it} \tag{4}$$

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. $Belief_i$ is the probability that an individual believes that an event will occur. The coefficient ζ can be interpreted as the aggregate effect of the stimulus in the time period in question for individuals who do not believe that the mentioned event will occur. The sum of the coefficients ζ and ζ' can be interpreted as the aggregate effect of the stimulus in the time period in question for individuals who believe that the mentioned event will occur.

Table V. Stimulus payments, spending, and income

This table shows cumulative 3-month 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. These coefficients correspond to ζ and ξ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \xi \frac{Post_{it} \times P_i}{D_{it}} \times I_i + \phi Post_{it} \times I_i + \varepsilon_{it}$. Average monthly income is approximately \$2,000, yielding a logged income value of 7.6. Columns (4) and (5) drop the interaction, and split the sample into the top and bottom quartiles of January and February monthly income. The inclusion of fixed effects is denoted beneath each specification. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: SaverLife.

	(1) Total	(2) Total	(3) Total	(4) Low Inc	(5) High Inc
Post-stimulus × Stimulus	2.024***	2.116***	2.126***	0.544***	0.257***
	(0.370)	(0.385)	(0.411)	(0.106)	(0.0960)
Post-stimulus × Stimulus × ln(Inc)	−0.220***	−0.231***	−0.229***		
	(0.0456)	(0.0475)	(0.0502)		
Date FE	X	X	X	X	X
Individual FE	X	X	X	X	X
Individual × Day-of-month FE		X			
Individual × Day-of-week FE			X	X	X
Observations	517,477	517,477	517,477	126,317	145,553
R^2	0.199	0.300	0.502	0.160	0.277

Individuals who believe that they will be more likely to face unemployment or salary cuts see slightly smaller MPCs, consistent with higher savings in this group. The effect is much larger for individuals more likely to believe that they will be unemployed, relative to individuals who believe that they will face salary cuts. We see smaller point estimates for MPCs for individuals who expect tax increases or government benefit cuts, but the effect sizes are much larger and statistically significant for government benefit cuts. This may be consistent with the fact that our sample disproportionately includes lower-income individuals who pay little in taxes, and receive significant government transfers. Overall, our estimates indicate that beliefs and expectations about personal and aggregate events play an important role in shaping household responses to stimulus payments.

7. Conclusion

This article studies the impact of the 2020 CARES Act stimulus payments on household spending using detailed high-frequency transaction data. We utilize this dataset to explore the 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 hope that our results inform the ongoing debate about appropriate policy measures and next steps in the face of the COVID-19 pandemic.

Table VI. Stimulus payments, spending, and liquidity

This table shows cumulative 3-month 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. These coefficients correspond to ζ and ξ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \xi \frac{Post_{it} \times P_i}{D_{it}} \times L_i + \phi Post_{it} \times L_i + \varepsilon_{it}$. The second row of Columns (1) through (3) 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 into the sample into the top and bottom half of account balances, with Column (4) regressing over those with the lowest account balances. The inclusion of fixed effects is denoted beneath each specification. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: SaverLife.

	(1) Total	(2) Total	(3) Total	(4) Low Bal	(5) High Bal
Post-stimulus × Stimulus	0.598***	0.635***	0.551**	0.641***	0.216**
	(0.211)	(0.211)	(0.239)	(0.239)	(0.0939)
Post-stimulus × Stimulus × Balance	−0.187***	−0.202***	−0.183**		
	(0.0618)	(0.0628)	(0.0717)		
Date FE	X	X	X	X	X
Individual FE	X	X	X	X	X
Individual × Day-of-month FE		X			
Individual × Day-of-week FE			X	X	X
Observations	429,123	429,123	429,123	115,080	152,923
R^2	0.199	0.294	0.486	0.208	0.213

We find immediate consumption responses to fiscal stimulus payments; excess spending in the first week totaled about \$0.15 for each dollar of stimulus. These responses are concentrated in the first weeks after receipt. After two months, there was little additional spending out of these stimulus payments, with excess spending plateauing at about \$0.25–\$0.30.

We also find significant heterogeneity across individuals. Income levels and liquidity play important roles in determining MPCs, with liquidity being the strongest predictor of MPC heterogeneity. We find substantial responses for households with low levels of liquidity and small responses to stimulus payments for households with high levels of account balances or high incomes. The results will potentially be important for policy-makers in terms of designing future rounds of stimulus if the 2020 crisis persists. Our results suggest that the effects of stimulus are much larger when targeted to households with low levels of liquidity.

More work should be done to study how targeting can be designed to have large impacts on consumption without generating significant behavioral effects. Just as unemployment benefits may increase unemployment durations (Meyer, 1990), policies targeting stimulus payments toward households with low levels of liquidity could discourage liquid savings.

Table VII. Stimulus payments, spending, and income declines

This figure shows cumulative 3-month 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. These coefficients correspond to ζ and ξ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \xi \frac{Post_{it} \times P_i}{D_{it}} \times D_i + \phi Post_{it} \times D_i + \varepsilon_{it}$. The second row of Columns (1) through (3) interacts with the fraction of January and February income that an individual earned in March (i.e., a lower value means a larger decline in income). Columns (4) and (5) drop the interaction, and split the sample by whether a household had an income drop in March relative to January and February. The inclusion of fixed effects is denoted beneath each specification. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: SaverLife.

	(1) Total	(2) Total	(3) Total	(4) Inc drop	(5) No drop
Post-stimulus × Stimulus	0.248***	0.276***	0.215**	0.348***	0.187
	(0.0854)	(0.0871)	(0.0986)	(0.0940)	(0.117)
Post-stimulus × Stimulus × Inc drop	−0.0538	−0.0737**	−0.0269		
	(0.0352)	(0.0368)	(0.0385)		
Date FE	X	X	X	X	X
Individual FE	X	X	X	X	X
Individual × Day-of-month FE		X			
Individual × Day-of-week FE			X	X	X
Observations	504,385	504,385	504,385	240,924	263,461
R^2	0.199	0.299	0.499	0.219	0.182

Supplementary Material

Supplementary data are available at *Review of Finance* online.

Data Availability

This article is a part of an ongoing data-sharing relationship with a financial service provider. The data include (de-identified) information regarding individual clients' financial account positions, transaction activities, and some demographic statistics. All raw data are proprietary and belong to the bank; thus, we cannot share the raw data with other researchers who are not approved by the data protection contract. However, several researchers are currently using these data and have published papers using the data. Despite this restricted access, we are committed to helping interested researchers replicate my results and check their robustness (e.g., by obtaining program files from interested researchers, running the programs, and reporting the results).

Table VIII. MPCs and expectations

This table shows cumulative 3-month 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, and their interaction with surveyed beliefs. That is, of ζ and ζ' from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \zeta' \frac{Post_{it} \times P_i \times Belief_i}{D_{it}} + \omega \frac{Post_{it} \times Belief_i}{D_{it}} + \varepsilon_{it}$. The inclusion of fixed effects is denoted beneath each specification. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Source: SaverLife.

	(1) Total Spending	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post-stimulus × Stimulus	0.246***	0.242***	0.238***	0.229***	0.186***	0.178***	0.147***	0.142**	0.252***	0.243***	0.227***	0.219***
	(0.0704)	(0.0709)	(0.0396)	(0.0410)	(0.0486)	(0.0485)	(0.0551)	(0.0557)	(0.0590)	(0.0593)	(0.0479)	(0.0475)
Post-stimulus × Stimulus × Stock	−0.333***	−0.335***										
	(0.114)	(0.115)										
Post-stimulus × Stimulus × Unemployed			−0.281***	−0.276***								
			(0.0696)	(0.0725)								
Post-stimulus × Stimulus × Salary cut					−0.231**	−0.229**						
					(0.0957)	(0.0974)						
Post-stimulus × Stimulus × Higher taxes							−0.127	−0.130				
							(0.0946)	(0.0965)				
Post-stimulus × Stimulus × Benefit cuts									−0.255***	−0.249***		
									(0.0756)	(0.0772)		
Post-stimulus × Stimulus × Pessimistic											−0.202***	−0.200***
											(0.0759)	(0.0767)
Date FE	X	X	X	X	X	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X	X	X	X	X	X
Individual × Day-of-week FE		X		X		X		X		X		X
Observations	100,064	100,064	100,064	100,064	100,064	100,064	100,064	100,064	100,064	100,064	100,064	100,064
R^2	0.314	0.381	0.315	0.381	0.314	0.381	0.314	0.381	0.314	0.381	0.314	0.381

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