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Scott R. Baker, R. A. Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis
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ABSTRACT

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Scott R. Baker
Kellogg School of Management
Northwestern University
2211 Campus Drive
Evanston, IL 60208
and NBER
s-baker@kellogg.northwestern.edu

R. A. Farrokhnia
Columbia Graduate School of Business
3022 Broadway
New York, NY 10027
farrokhnia@gsb.columbia.edu

Steffen Meyer
University of Southern Denmark
Campusvej 55
5230 Odense M
Denmark
stme@sam.sdu.dk

Michaela Pagel
Columbia Business School
3022 Broadway
Uris Hall
New York, NY 10027
and NBER
mpagel@columbia.edu

Constantine Yannelis
Booth School of Business
University of Chicago
5807 S. Woodlawn Avenue
Chicago, IL 60637
and NBER
constantine.yannelis@chicagobooth.edu

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Scott R. Baker[†] R.A. Farrokhnia[‡] Steffen Meyer[§]
Michaela Pagel[¶] Constantine Yannelis[‖]

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Abstract

The 2020 CARES Act directed large cash payments to households. We analyze households' spending responses using high-frequency transaction data from a Fintech non-profit, exploring heterogeneity by income levels, recent income declines, and liquidity as well as linked survey responses about economic expectations. Households respond rapidly to the receipt of stimulus payments, with spending increasing by \$0.25-\$0.40 per dollar of stimulus during the first weeks. Households with lower incomes, greater income drops, and lower levels of liquidity display stronger responses highlighting the importance of targeting. Liquidity plays the most important role, with no significant spending response for households with large checking account balances. Households that expect employment losses and benefit cuts display weaker responses to the stimulus. Relative to the effects of previous economic stimulus programs in 2001 and 2008, we see faster effects, smaller increases in durables spending, larger increases in spending on food, and substantial increases in payments like rents, mortgages, and credit cards reflecting a short-term debt overhang. We formally show that these differences can make direct payments less effective in stimulating aggregate consumption.

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[†]Northwestern University, Kellogg, NBER; s-baker@kellogg.northwestern.edu

[‡]Columbia Business School, Columbia Engineering School; farrokhnia@gsb.columbia.edu

[§]University of Southern Denmark (SDU) and Danish Finance Institute (DFI); stme@sam.sdu.dk

[¶]Columbia Business School, NBER, and CEPR; mpagel@columbia.edu

[‖]University of Chicago Booth School of Business, NBER; constantine.yannelis@chicagobooth.edu

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, i.e., by increasing households' consumption which then translates in to more production and employment. The effectiveness of these payments relies on households' marginal propensities to consume, or MPCs, out of these stimulus payments which, in turn, may depend on household's expectations (Barro, 1989).

In this paper, we estimate households' MPC in response to the 2020 CARES Act stimulus payments using data from a non-profit Fintech firm, SaverLife. We explore how these MPCs vary with household financial characteristics, such as income, income declines, and cash on hand. We also describe how household MPCs vary across categories of consumption and how these categorical responses differ from those seen in previous recessions. Furthermore, this paper links transaction data to user survey data in order to study how expectations impact household responses to stimulus payments. Understanding these MPCs is key to targeting policies to households where effects will be largest, as well as distinguishing between different models of household consumption behavior.

MPCs are important to both policy and economic theory as they determine fiscal multipliers in a wide class of models. More specifically, heterogeneity in MPCs impacts which households are most responsive to stimulus payments. In turn, targeting 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 during the 2020 contraction, with highly liquid households showing no response to stimulus payments. Even among households with higher levels of income, low levels of liquidity are associated with high MPCs.

We explore responses to stimulus payments and individual heterogeneity in MPCs by using high frequency transaction data from SaverLife, a non-profit financial technology firm. Similar to many other Fintech firms, idividuals can link their accounts to the service to track their finances. We have access to de-identified bank account transactions and balances data from August 2016 to August 2020 for these users. 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. The sample consists primarily of lower- and middle-income households, and we are able to link the bank account transactions data to survey data about economic expectations.

We use this detailed data to look at the CARES Act stimulus payments distributed in April and May 2020. The first stimulus payments were made in mid April via direct deposit from the IRS, and we can observe the user-specific stimulus amounts as well as spending daily before and after stimulus payments are made. We see sharp and immediate responses to the stimulus payments; within ten days, users spend over 20 cents of every dollar received in stimulus payments. The largest increases in spending are on food, non-durables, 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 40% of their stimulus payments within the first month, while we observe a statistically insignificant response of only 11 cents for individuals with more than \$4,000 in their accounts.

These heterogeneity results are important in terms of targeting stimulus policies towards groups most impacted by them. The theory behind stimulus payments links MPCs directly to the ultimate fiscal multiplier effect, i.e., 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.

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), referred to as Ricardian equivalence.

Discussions about Ricardian equivalence have driven vigorous debates about the efficacy of fiscal stimulus (Barsky, Mankiw and Zeldes, 1986). 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 expectations about employment and government benefit cuts play an important role in determining MPCs. Households that anticipate unemployment or benefit cuts save a significantly larger fraction of their stimulus checks.

We then show in a macroeconomic model with multiple sectors that non-targeted fiscal stimulus payments in environments like the 2020 COVID-19 epidemic may be less effective than the payments in response to the 2001 and 2008 economic downturns. Reflecting the current situation, we map out a three sector model in which one sector employing lower wage agents is shut down while a second low-wage essential sector remains operational alongside a higher-wage sector that can largely work from home.

Due to the shut down of one low wage sector, those poorer and higher MPC agents are largely excluded from benefiting from additional spending induced by stimulus payments, thereby reducing the fiscal multiplier effect. We also see that agents in the lower wage sectors tend to accumulate more debt by borrowing from the higher wage sector. Agents end up using the stimulus payments to repay debt to high wage individuals who have the lowest MPCs out of income. In short, workers will spend their stimulus payment on mortgages and loan repayments as well as non-durable essentials which implies that the cash flows immediately to agents with lower MPCs. This tends to make fiscal stimulus less effective overall. This model thus confirms our empirical results.

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, Souleles, Johnson and McClelland (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 non-durable 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

[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 nicely with the empirics. 60% of individuals 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.

(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.

In Section 4.1, we discuss some of the differences between our estimates and the previous literature that analyze past stimulus programs. The existing studies exploit the differences in timing of the arrival of the payment to infer causal effects. Our results are generally comparable. However, the three main differences are: 1) during the 2020 stimulus, households spend much of their stimulus checks in a shorter period of time, 2) they spend more on food and non-durables than on durable consumption like furniture, electronics, or cars, and 3) they repay credit cards, rent, mortgages, and other overdue bills. Additionally, our study is the first to empirically explore, by linking transaction and survey data, how expectations affect MPCs out of stimulus payments, long a focus of the theory literature.

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 but low liquidity are an important driver of the magnitude of the response. 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.

In this paper, 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 pandemic has the potential to have large initial effects on income and liquidity, but potentially comparatively less on future income and wealth.

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

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 different economic circumstances. 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]

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, 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 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.

This paper 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, e.g. 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 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 Paycheck Protection Program (PPP) on employment. Barrios and Hochberg (2020) and Allcott, Boxell, Conway, Gentzkow, Thaler and Yang (2020) show that political affiliations im-

[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."*

pact the social distancing response to the pandemic, and Coven and Gupta (2020) study disparities in COVID-19 infections and responses.

Our related paper, Baker, Farrokhnia, Meyer, Pagel and Yannelis (2020b), studies household consumption during the onset of the pandemic in the United States using a smaller sample drawn from the same data source. Carvalho, Garcia, Hansen, Ortiz, Rodrigo, Mora and Ruiz (2020), Andersen, Hansen, Johannesen and Sheridan (2020), Bounie, Camara and Galbraith (2020), Chen, Qian and Wen (2020) perform similar analyses as the one in this paper using transaction-level data from the Spain, Denmark, France, and China. Dunn, Hood and Driessen (2020) uses transaction-level data from the US provided by merchants rather than individual-level data and find similar results to Baker, Farrokhnia, Meyer, Pagel and Yannelis (2020b). We join this emerging and rapidly-growing literature by providing early evidence on how households responded to the crisis and on the details of the impacts of federal stimulus policy. The results suggesting that MPCs are much higher for low liquidity households are important in designing future rounds of stimulus, as the effects of the epidemic will persist over the next months.

We also join a literature on how expectations affect household's economic behavior. Macroeconomic models since the 1980s have noted that government budget deficits may in the short-term affect household's expectations about future taxes, and implicitly transfers (Barro, 1989). A newer and growing body of recent work also shows that expectations about individual and aggregate outcomes impact behavior, studying households (Giglio, Maggiori, Stroebel and Utkus, 2019; Kuchler and Zafar, 2019; Armona, Fuster and Zafar, 2019; D'Acunto, Hoang and Weber, 2020; Manski, 2004) and firms (Landier and Thesmar, 2020; Landier, Ma and Thesmar, 2017; Bouchaud, Krueger, Landier and Thesmar, 2019; Gennaioli, Ma and Shleifer, 2016). 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 paper 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 paper 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 presents a simple model to explain how fiscal multiplier effects may differ from prior stimulus programs. Section 8 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 which is ten times higher than the seasonal flu and has at least twice the rate of infection. The first case in the United States 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 non-essential businesses.

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 17. For an overview of amounts by household, see 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.[4]

[4]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

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 9th. The IRS expected that direct deposits would largely be completed by April 15th. 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 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 70-80% of taxpayers use direct deposit to receive their tax refunds, though 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. 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 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

and particularly among our sample which is skewed towards lower income households.

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.[5]

[5] 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.

3 Data

3.1 Transaction Data

In this paper, we utilize de-identified transaction-level data from SaverLife, a non-profit fin-tech helping working families meet financial goals. As with a number of other personal 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 towards lower income individuals, given that the non-profit 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. 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 August 2020. We observe 90,844 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 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. Spending transactions are categorized into a large number of categories and subcategories. For the purposes of this paper, 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, non-durables and services, and payments including check spending, loans, mortgages, and rent. 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 May 2020, we have complete data for 38,379 users to analyze in this paper. We require these users to have at least 2 transactions in December 2019, at least 5 transactions per month in each month of 2020, and more than 20 transactions adding up to at least $1,000 in total per user. We require 5 transactions in account usage as a completeness-of-record check for bank-account data following (Ganong and Noel, 2019).

In Table 1, 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.

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

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 may be ineligible for one.[6] 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 eligible income thresholds for receipt. Of those who

[6] We note that the completeness-of-record checks we employ following (Ganong and Noel, 2019) are relatively weak. 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. When we look at the spending behavior of non-stimulus-check recipients around the time when they likely would have received a check, we do not see a spending response (see Figure A.5) suggesting that these users did not link either their main tax or spending accounts.

receive payments, two-thirds received them by April 15, with 40% of all payments occurring on April 15. 92% of those who received payments in our sample 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. 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. Our measure matches up reasonably well with the received stimulus payments.

Appendix A provides further details regarding payments in our sample. Payments line up closely with self-reported household size. Because of our 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. We conduct a placebo exercise in the appendix, and look at spending around April for households that do not receive a check (see Figure A.5). We do not see any sharp breaks in spending beyond day of the week effects, suggesting that the impact of mis-categorization is small.

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 to $10 for participation. If individuals did not respond initially, they were sendt 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 off of 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 online appendix, we report raw survey responses and questions. Figure B.1 shows the survey instrument on a smartphone, and lists all questions in the survey and Figures B.2 to B.4 show the raw averages of the survey responses. In 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. 30% of users reported they had difficulty obtaining credit and 70% received new credit primarily through a new credit card. Our users are relatively pessimistic about the lasting effects of the pandemic.

In Figure B.3, we can see that our empirical results in terms of the fiscal stimulus use line up with the survey data. 60% of individuals report to not use the check amount for durables consumption and 50% of the users are using part of the check amount for food spending. Additionally, only 15% of users said they will not use the check to pay past bills or will 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 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. [7]

[7] 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.

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.[8] Mean daily spending rises to about \$250 for the week 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 to users who do not receive the checks.

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 for the entirety of the post-check period that we observe. The relative difference in spending declines during weekends, mostly driven by the fact that observed levels of spending tend to be depressed during these days for reasons described above.

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, 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 cumulative spending on food, household, non-durables, and payments each increasing by approximately

[8] There are substantial intra-week 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.

\$75-\$150 in the week 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 2 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 (eg. \$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. 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. Overall, for each dollar of stimulus received, households in our sample spent approximately \$0.35 more in the month following the stimulus.

The remainder of the columns in Table 2 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 non-durables and payments. We find 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 4.1.

Because our sample is not representative of the nation as a whole, we also perform a similar analysis while re-weighting our sample on several dimensions using Current Population Survey

(CPS) weights. We show results of this approach in Table 3, we compare our estimates from our unweighted regressions to those using user weights defined on age, sex, state, and income bins. Column (4) thus runs our primary MPC calculation using these user weights, finding an MPC of approximately 0.266 rather than 0.369 in column (3). In general, when weighting our sample to match the national distribution of households more closely, we see qualitatively similar results approximately 30% lower in magnitudes 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 somewhat lower MPC.

4.1 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 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, 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 non-durables and services in the six 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 ten percent 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 multiple categories of spending. 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.

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 non-durables 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 is 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, Souleles, Johnson and McClelland (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 6-8, 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 2, 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 6 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 multiple groups according to account balances, from under $10 to over $4,000. Figure 7 displays dramatic differences across these groups of users. Users with the highest balances in their bank accounts tend not to have MPCs on the order of 0.1 while those who had under $100 have MPCs of 0.4 or above.

In Figure 8, we examine whether a similar pattern can be seen among users who have had declines in income following the COVID 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 significant difference in MPCs, but of lower magnitude than the previous splits. Households that saw income declines had an MPC of just over 0.4 while those with no decline in income registered MPCs of about 0.33. 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 4 - 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 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. 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.

Figure 9 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. The 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 (ζ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \varepsilon_{it}$). Each bars show individuals above and below the median of the sample in terms of their expectations.

The top row shows splits by employment outcomes. The left panel splits the sample by individual beliefs about whether they will become unemployed over the next year. The right panel splits the sample by individual beliefs regarding whether they will face a salary cut over the next year. 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.

The middle panel shows splits by outcomes related to government spending– taxes and benefits, which relates to the classic theory of Ricardian equivalence. The left panel splits the sample by individual beliefs about tax increases, while the right panel splits the sample by individual beliefs about government benefit cuts. We see smaller MPCs for individuals who expect tax increases or government benefit cuts, but the effect sizes are much larger 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.

The bottom panel splits the sample by expectations regarding whether the stock market will rise in the next year and whether the duration of the pandemic will last more than two years. Perhaps surprisingly, we find much smaller MPCs for individuals who expect the stock market to rise. One potential mechanism is that individuals who believe that the stock market will rise choose to invest rather than spend. We see little difference for individuals who think that the crisis will be over within two years, relative to those who think that it will last longer.

Table 7 quantifies this graphical evidence, interacting expectations with stimulus receipt. More precisely, the table shows MPC estimates and interactions (ζ and ζ') from the specification:

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

where as before 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 7 indicates that beliefs that individuals will be unemployed, government benefits will be cut, the pandemic will last longer and stock markets will rise are significantly associated with smaller MPCs. Beliefs about salary cuts or tax increases do not see a statistically significant association with MPCs, but the coefficients are negative and this relationship may reflect a lack of power or the fact that the individuals in our sample pay little in taxes. 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 Modeling the Effectiveness of Fiscal Stimulus Payments

In Figure 10, we note the impact of the stimulus check on financial payments. In particular, we examine the impact on total financial payments as well as payments on several subsets of payments such as credit card payments as well as rent and mortgage payments. Rent payments are not always able to be accurately identified due to the number of users who utilize checks or online transfer tools like Chase QuickPay, Zelle, or Venmo to pay their rent. Such payments will still be accurately captured by the 'Total Financial Payments' category.

We find that financial payments surge substantially upon receipt of the 2020 stimulus payments. Marginal spending on total financial payments totals about one third of total MPC out of the stimulus payments. We argue that our empirical findings imply that the fiscal stimulus payments may be less effective in stimulating aggregate consumption in the 2020 environment relative to previous downturns.

We now present a simple model that outlines two reasons, consistent with our empirical findings, that the fiscal stimulus in 2020 may be less effective in actually stimulating the economy than the 2001 or 2008 payments. The basic reason for this lack of effectiveness is that sectors of the economy employing workers with the lowest levels of liquidity are shut down, leading to lower fiscal multipliers.

Suppose that we have three types of sectors and workers employed by those sectors. First, we have a sector that we call groceries and necessities. Here, we refer to large firms that sell groceries and basic household supplies that are both essential and non-durable (moderate depreciation). For instance, large supermarkets or stores such as Target, Walmart, and CVS. At the same time, the grocery and necessity sector is moderately labor intensive. This sector is not shut down in response to an epidemic.

In turn, we have a second sector, called restaurants and hospitality, that produces non-durable consumption which depreciates immediately and is more labor intensive than the first sector. Being less essential to households, the second sector is shut down in response to the crisis.

Finally, we have a third sector of the economy. This sector is broader, and encompasses durables production as well as many white-collar services like banking and tech. This sector can avoid being locked down through employing safety measures in production or by working remotely. This sector pays higher wages than in sectors 1 and 2. Consequently, the corporations in sectors 1 and 2 are owned by the workers in sector 3. We assume that workers in sector 1 and 2 borrow (for example, rent, mortgages, or financial lending) from workers in sector 3.

The effectiveness of fiscal stimulus rests on the idea that stimulus checks induce extra spending by recipients. For example, workers in sector 3 spend in sector 2 and generate income for workers in that sector that is then spent again. Thus, if the MPC out of a stimulus payment is 0.8, then out of a \$100 payment, \$80 is consumed, generating \$80 of income for another worker. That worker then again consumes \$64 which generates income for another worker, and so on. In the classic Keynesian framework the equation for the fiscal multiplier is given by $1/(1 - MPC)$. The more cash arrives with agents that have high MPCs, the higher the fiscal multiplier.

In our framework, there are two reasons why fiscal stimulus is less effective in this environment relative to the 2001 and 2008 recessions. First, in a lockdown induced by an epidemic, neither group of workers can spend in sector 2. At the same time, workers in sector 2 are the poorest and have the highest MPCs. Second, workers in sectors 1 and 2 (who are poorer) use the stimulus payment to pay down debt held by sector 3 workers. Therefore, the excess spending from the stimulus flows to workers that have a lower MPC.

More formally, we have a three-period model inspired by Guerrieri, Lorenzoni, Straub and Werning (2020) and consider an economy with three sectors. All sector s agents' preferences are represented by the utility function:

$$\sum_{t=0}^{3} \beta^t U(c_t^s) \tag{5}$$

where c_t^s is consumption and $U(c) = c^{1-\sigma}/(1-\sigma)$ is a standard power utility function. Each agent is endowed with $\bar{n}_t^s > 0$ units of labor which are supplied inelastically but they can only work in their own sector. Competitive firms in each sector s produce the final good from labor using the linear technology:

$$Y_t^s = \bar{n}_t^s. \tag{6}$$

Each agent maximizes utility subject to:

$$c_t^s + a_t^s \leq w_t^s \bar{n}_t^s + (1 + r_{t-1}) a_{t-1}^s. \tag{7}$$

As the initial condition, we assume that agents in sectors 1 and 2 borrow from agents in sector 3, such that $a_1^1 < 0$, $a_1^2 < 0$, and $a_1^1 + a_1^2 = -a_1^3$. Given the economy is frictionless, agents choose their consumption to satisfy their Euler equation:

$$U'(c_t^s) = \beta(1 + r_t) U'(c_{t+1}^s). \tag{8}$$

Because preferences are homothetic, we can think of all agents in each sector as just being represented by one agent. In turn, each agent can consume consumption goods from any sector, denoted by c_t^{ss}. The consumption composite, c_t^s, over the three sectors' consumption goods equals $f_c(c_t^{s1}, c_t^{s2}, c_t^{s3})$ and relative goods prices meeting the composite constraint $p_t c_t^s = p_t^1 c_t^{s1} + p_t^2 c_t^{s2} + p_t^3 c_t^{s3}$ adjust to ensure full employment in each sector. Additionally, we assume that $\frac{\partial f_c}{c_t^{s1}}|_{c_t^{s1} \to 0} = \infty$ whereas $\frac{\partial f_c}{c_t^{s2}}|_{c_t^{s2} \to 0}$ and $\frac{\partial f_c}{c_t^{s3}}|_{c_t^{s3} \to 0}$ approach finite numbers, which implies that consumption purchased in sector 1 is necessary, whereas it is not necessary when it comes from sectors 2 and 3. Finally, the goods market clearing condition has to hold in each period:

$$c_t^{1s} + c_t^{2s} + c_t^{3s} = \bar{n}_t^s. \tag{9}$$

Suppose the central bank implements a fixed rate $1 + r_0 = 1/\beta$ and the economy starts from a state in which each agent consumes his or her labor income in composite consumption $c_1^s = w_1^s \bar{n}_1^s$ and does not accumulate or decumlate their debt or savings. In turn, in period 2, an unexpected shock hits that restricts agents working in sector 2 in periods 2 and 3, i.e., $w_2^2 = w_3^2 = 0$, and the government promises a stimulus payment S in period 3. Then agents in sector 2 allocate consumption in periods 2 and all the following periods according to their Euler equation and budget constraints.

$$U'(c_2^2) = U'(c_3^2),\ c_2^2 + a_2^2 \leq 1/\beta a_1^2, \text{ and } c_3^2 = S + 1/\beta a_2^2. \tag{10}$$

In turn, we obtain:

$$c_2^2 = c_3^2 = \frac{S + 1/\beta^2 a_1^2}{1 + 1/\beta} \text{ and } a_2^2 = 1/\beta a_1^2 - \frac{S + 1/\beta^2 a_1^2}{1 + 1/\beta}. \tag{11}$$

Agents in sector 1 allocate consumption in periods 2 and 3 according to their Euler equation and budget constraints in the same manner and we obtain:

$$c_2^1 = c_3^1 = \frac{S + w_3^1 \bar{n}_3^1 + 1/\beta(w_2^1 \bar{n}_2^1 + 1/\beta a_1^1)}{1 + 1/\beta} \text{ and} \tag{12}$$

$$a_2^1 = w_2^1 \bar{n}_2^1 + 1/\beta a_1^1 - \frac{S + w_3^1 \bar{n}_3^1 + 1/\beta(w_2^1 \bar{n}_2^1 + 1/\beta a_1^1)}{1 + 1/\beta}. \tag{13}$$

Consumption for agents in sector 3 follows the above straightforwardly.

Proposition 1. *The MPC out of income (or fiscal stimulus payments) is larger for agents in sector 2 than for agents in sectors 1 or 3.*

Proof. Compare MPCs, i.e., how much out of income (or fiscal stimulus payments) are consumed:

$$\frac{\partial c_2^2}{\partial S} = \frac{\partial c_3^2}{\partial S} = \frac{\partial(\frac{S+1/\beta^2 a_1^2}{(1+1/\beta)})}{\partial S} = \frac{1}{1+1/\beta} > \frac{\partial c_2^1}{\partial(S + w_2^1 \bar{n}_2^1 + w_3^1 \bar{n}_3^1)}$$

$$\text{as } \frac{\partial(\frac{S + w_2^1 \bar{n}_2^1 + w_3^1 \bar{n}_3^1 + (1/\beta - 1) w_2^1 \bar{n}_2^1 + 1/\beta^2 a_1^1}{1+1/\beta})}{\partial(S + w_2^1 \bar{n}_2^1 + w_3^1 \bar{n}_3^1)} = \frac{1}{1+1/\beta} + \underbrace{\frac{\partial(\frac{(1/\beta-1)}{1+1/\beta} w_2^1 \bar{n}_2^1)}{\partial(S + w_2^1 \bar{n}_2^1 + w_3^1 \bar{n}_3^1)}}_{<0} \text{ and } \frac{(1/\beta - 1)}{1+1/\beta} < 0.$$

This argument extends straightforwardly to the comparison of agents in sectors 2 and 3. □

Proposition 2. *The marginal propensity to repay debt out of income (or fiscal stimulus payments) is larger for agents in sector 2 than for agents in sector 1.*

Proof. Compare the propensity to repay mortgages, i.e., how much out of income (or fiscal stimulus payments) are used to repay debt:

$$\frac{\partial(-a_2^2)}{\partial S} = \frac{\partial(-1/\beta a_1^2 + \frac{S+1/\beta^2 a_1^2}{(1+1/\beta)})}{\partial S} = \frac{1}{1+1/\beta} > \frac{\partial(-a_2^1)}{\partial(S + w_2^1 \bar{n}_2^1 + w_3^1 \bar{n}_3^1)}$$

$$\text{as } \frac{\partial(-w_2^1\bar{n}_2^1 - 1/\beta a_1^1 + \frac{S+w_2^1\bar{n}_2^1+w_3^1\bar{n}_3^1+(1/\beta-1)w_2^1\bar{n}_2^1}{1+1/\beta})}{\partial(S+w_2^1\bar{n}_2^1+w_3^1\bar{n}_3^1)} = \frac{1}{1+1/\beta} + \underbrace{\frac{\partial(-w_2^1\bar{n}_2^1 + \frac{(1/\beta-1)}{1+1/\beta}w_2^1\bar{n}_2^1)}{\partial(S+w_2^1\bar{n}_2^1+w_3^1\bar{n}_3^1)}}_{<0}.$$

$\square$

If we now compare this economy to one in which sector 2 would not shut down, there are three differences that each diminish the amount of consumption induced by the stimulus payment S. First, agents in all sectors cannot consume in sector 2, thereby foregoing increases in employment and income in that sector. Secondly, sector 2 agents are the poorest agents with the highest MPC out of their income, so declines in their income disproportionately decrease the fiscal multiplier. Finally, agents in sector 2 choose to accumulate more debt in period 2 planning to repay it with their stimulus payment. In turn, the stimulus payment goes to agents in sector 3 that have lower MPCs out of the stimulus payment.

In summary, in this economy, workers in sectors 1 and 2 will spend their stimulus payment on mortgages and loan repayments as well as non-durable necessary consumption (sector 1). As shown above, this means that the fiscal stimulus payments flow to households with less high MPCs and directly decreases the fiscal multiplier, i.e., $1/(1 - MPC)$, making fiscal stimulus less effective.

8 Conclusion

This paper 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 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.

We find large consumption responses to fiscal stimulus payments and 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 no response to stimulus payments for households with high levels of account balances or cash on hand. 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 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 SaverLife website. The top panel shows the app's landing page and the bottom panel illustrates the offered financial advice pages. Source: SaverLife.

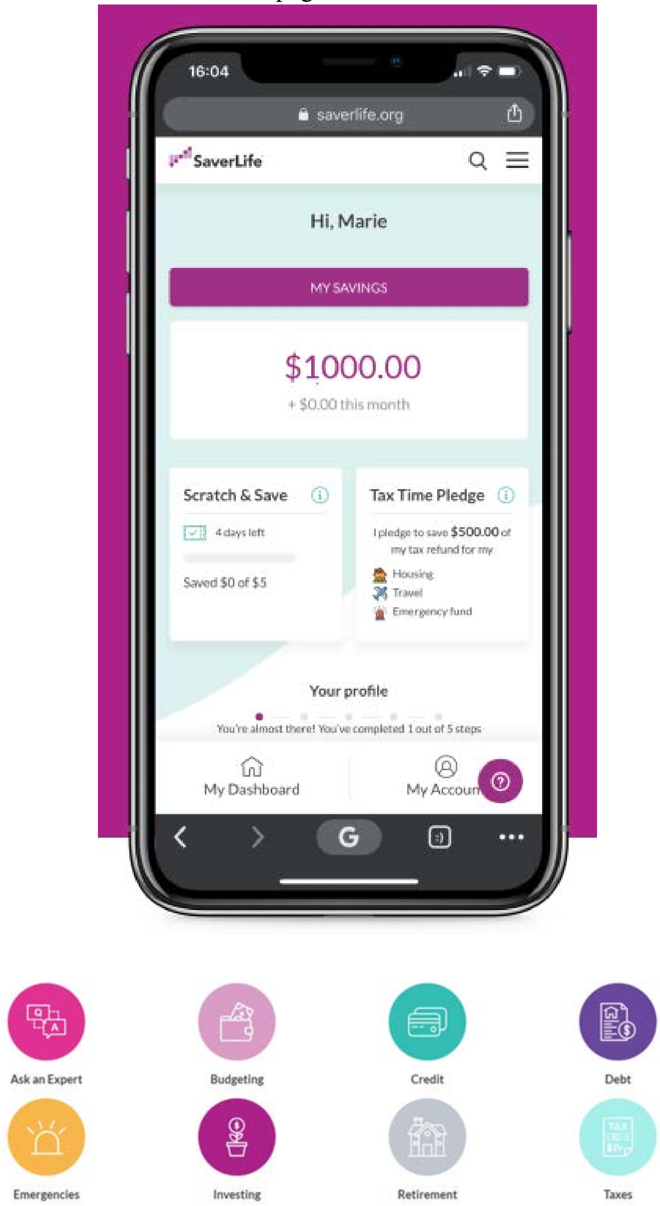


Figure 2: Daily Number of Government Payments at Stimulus Amounts

Notes: This figure shows the number of payments users receive that match the amounts of the 2020 government stimulus payment by day 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.

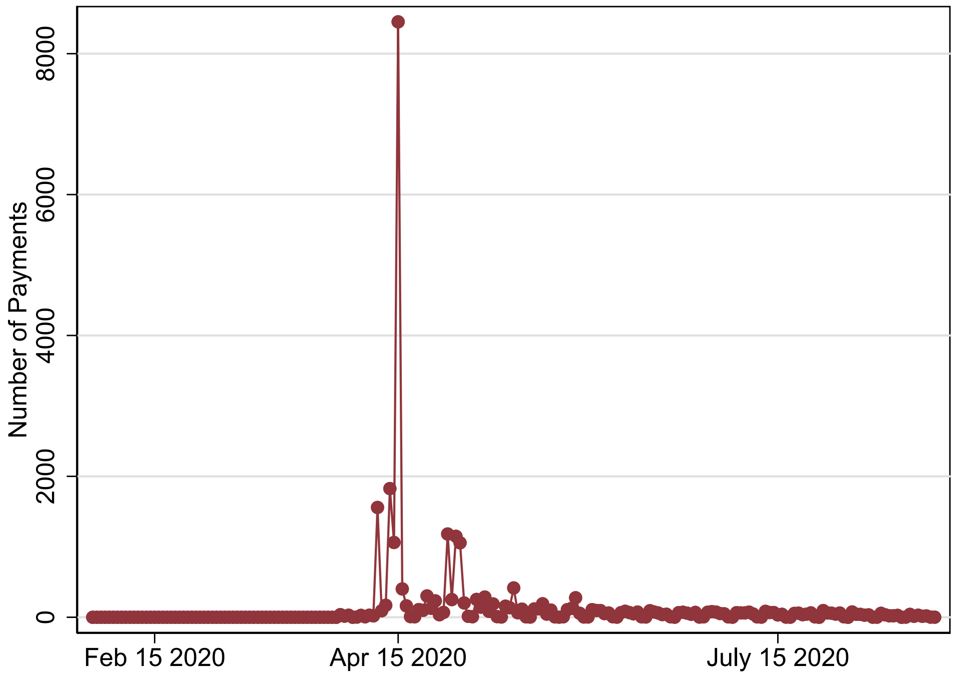


Figure 3: Mean Spending Around Receiving the Stimulus Payments - Raw Spending

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 (0). Shaded days represent weekends for the majority of stimulus-recipients who receive their payment on Wednesday April 15th. Source: SaverLife.

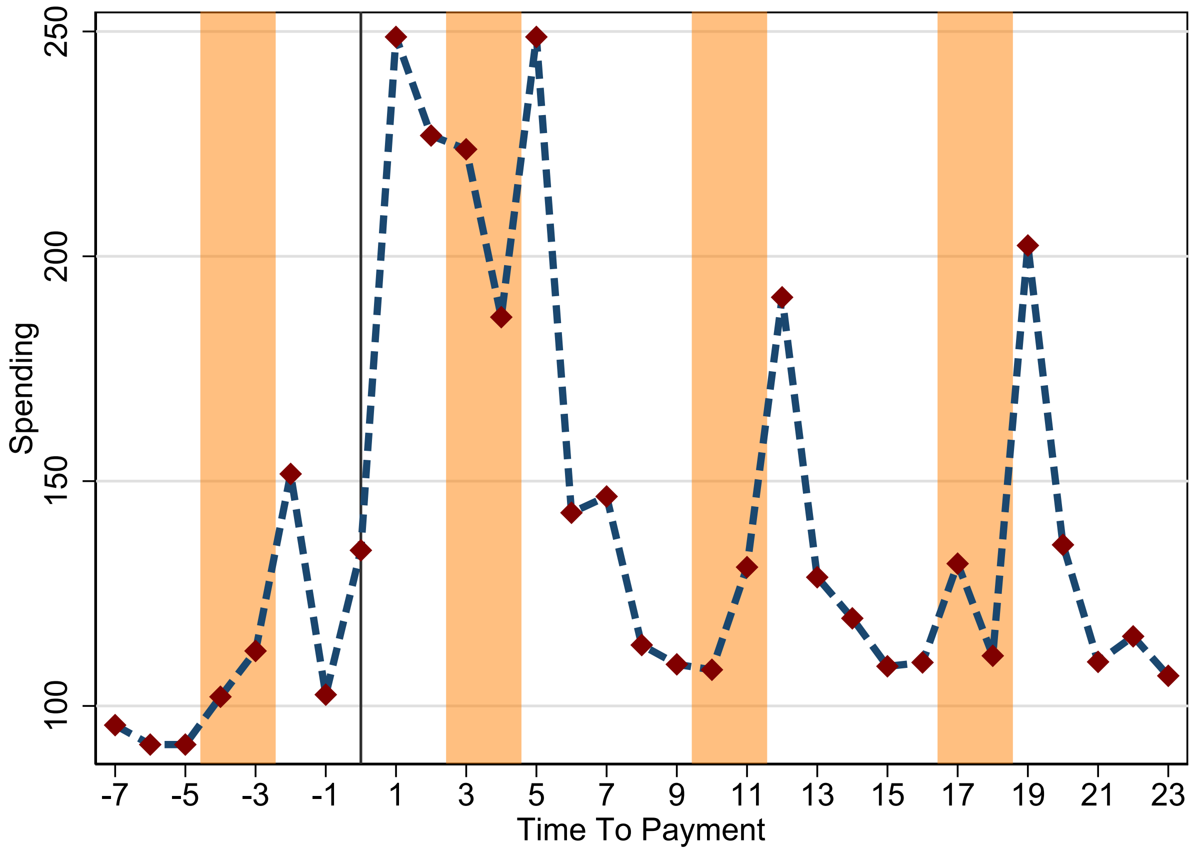


Figure 4: Spending Around Stimulus Payments - Regression Estimates

Notes: This figure shows estimates of β_k from $c_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{23} \beta_k \mathbb{1}[t = k]_{it} + \varepsilon_{it}$. 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.

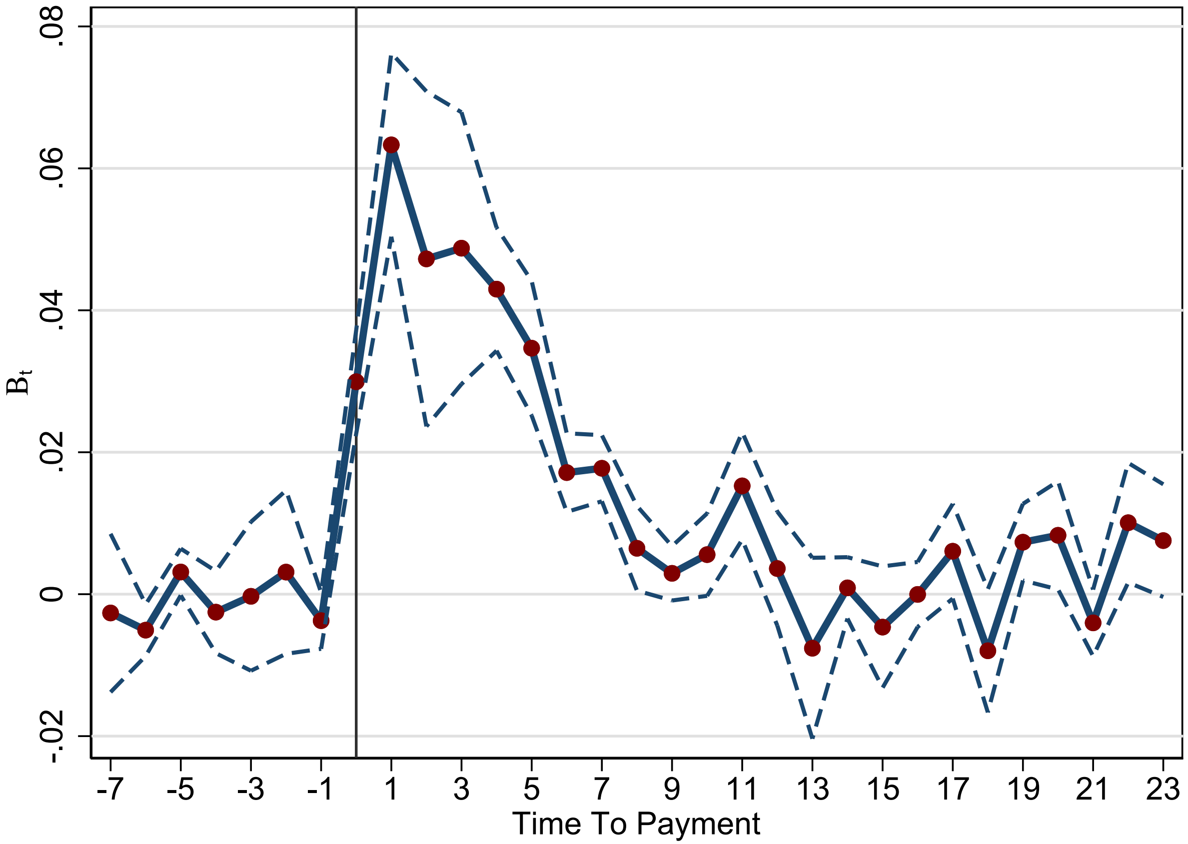


Figure 5: Spending Around Stimulus Payments by Categories

Notes: This figure shows estimates of β_k from $c_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{23} \beta_k \mathbb{1}[t = k]_{it} + \varepsilon_{it}$, 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.

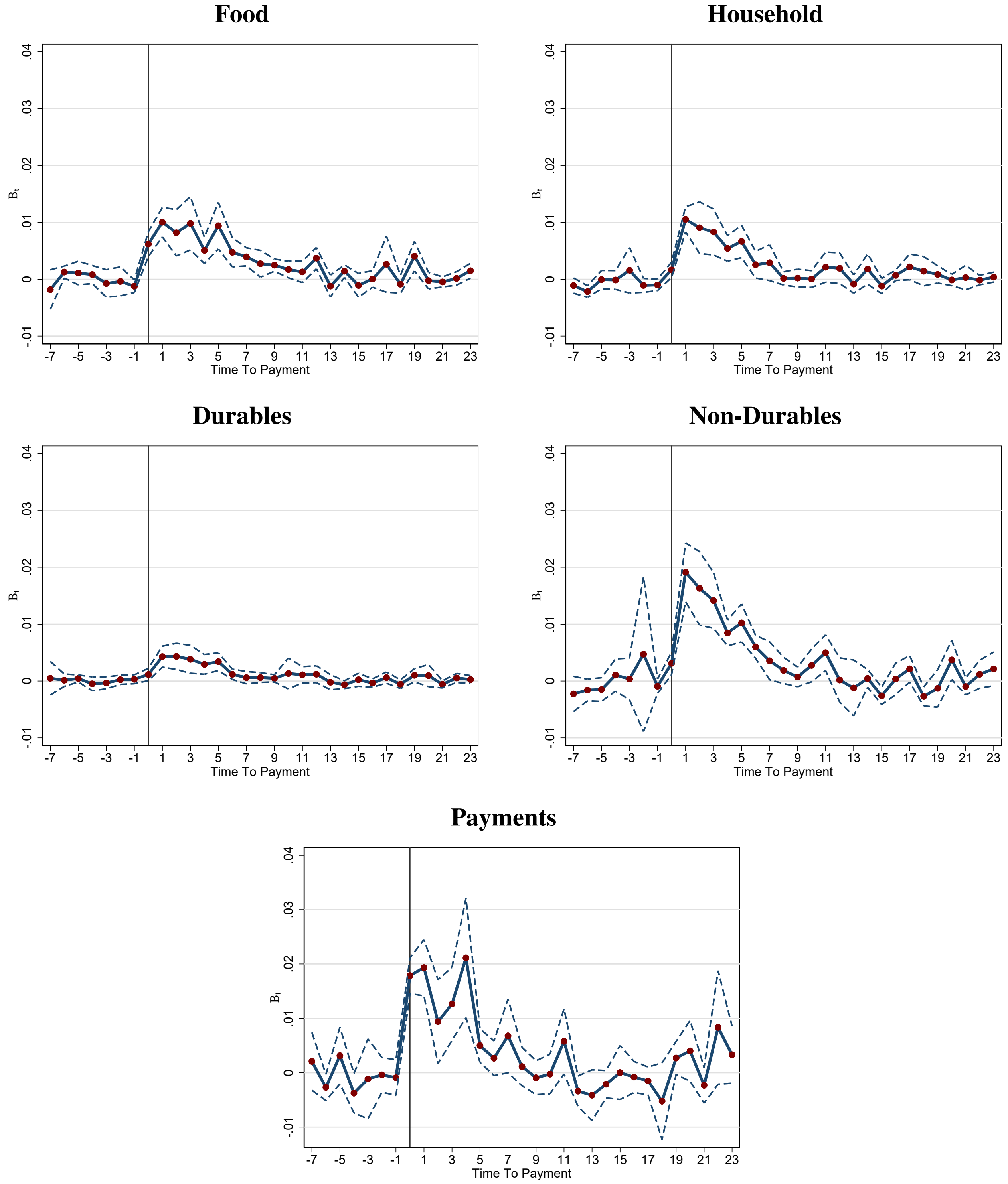


Figure 6: MPC by Income Groups

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. 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.

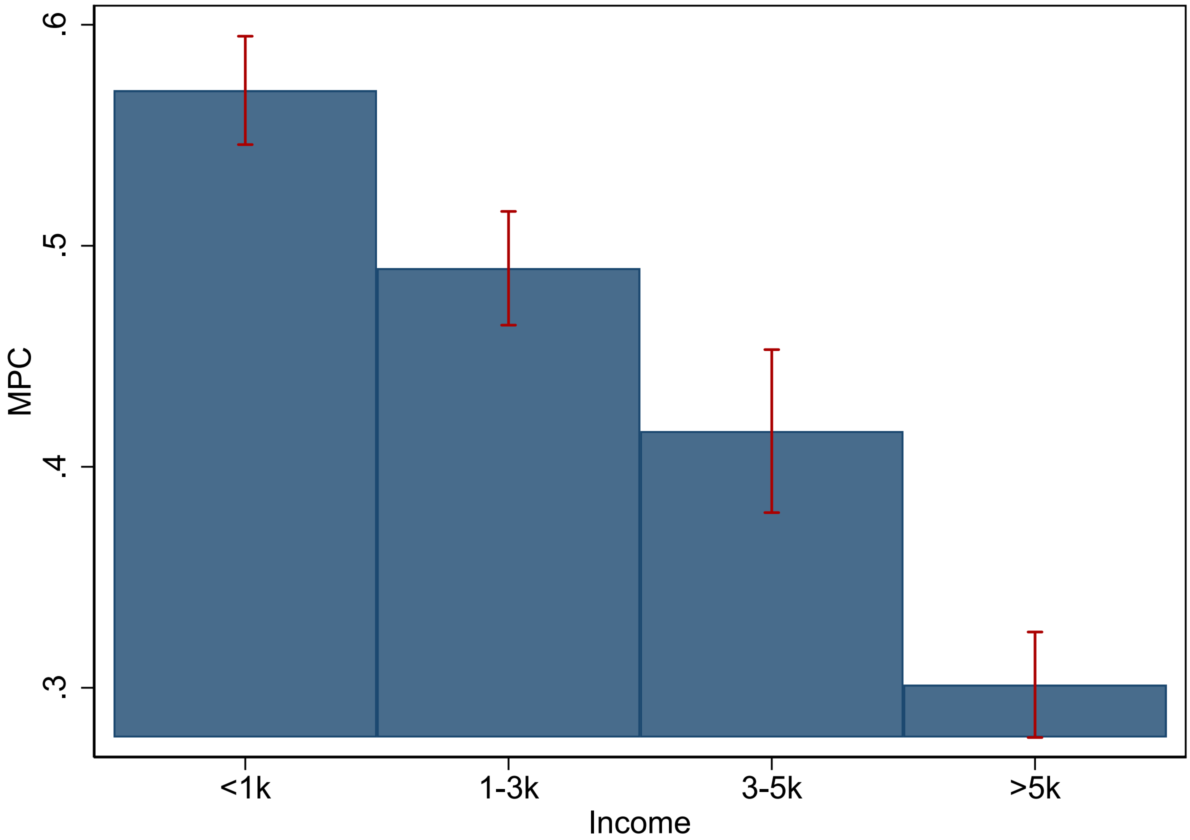


Figure 7: MPC by Liquidity

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. 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.

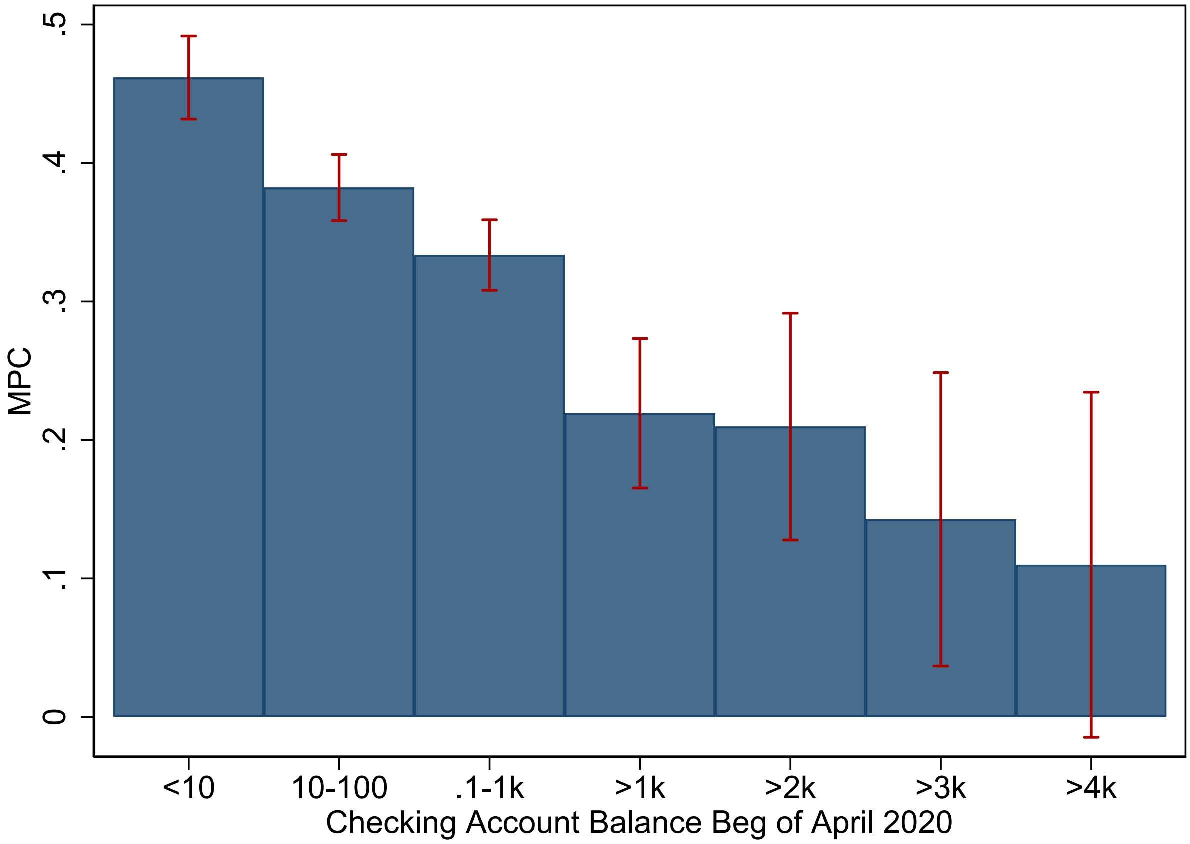


Figure 8: MPC by Drop in Income

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. 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.

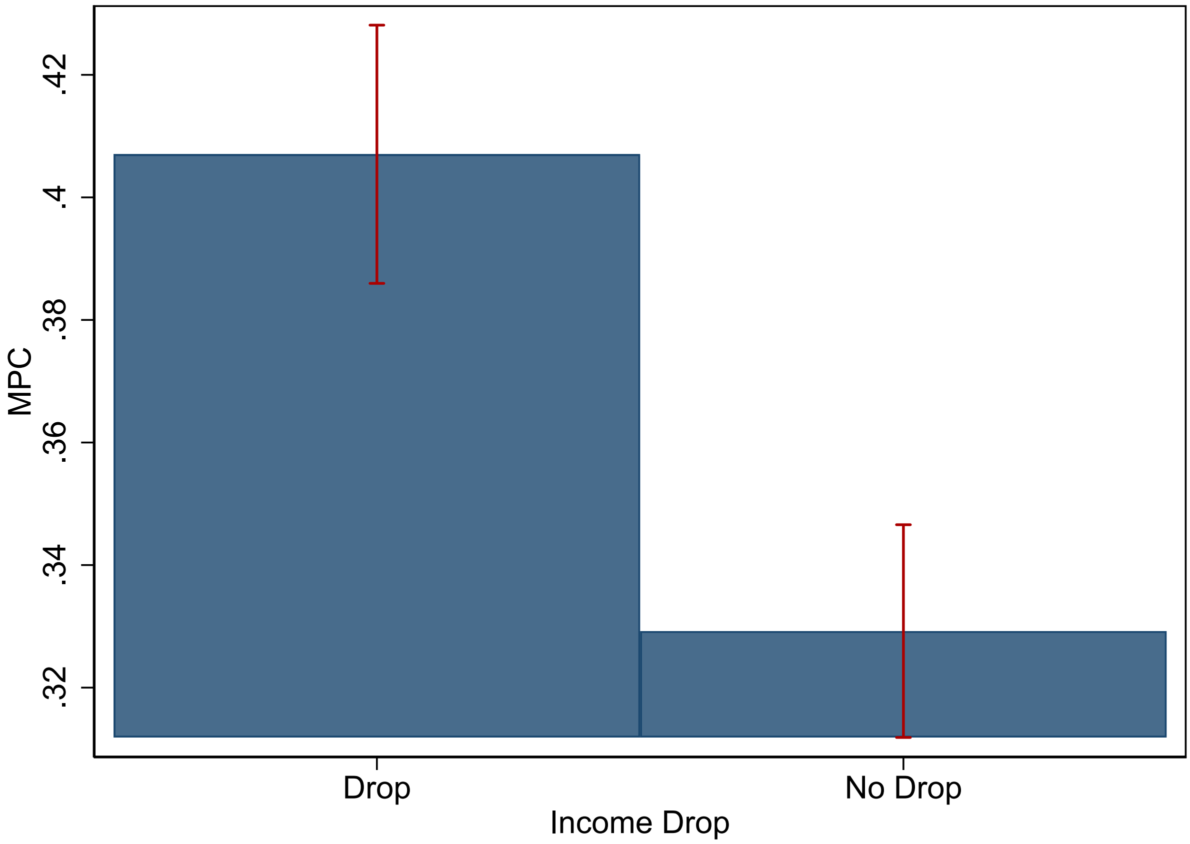


Figure 9: MPCs and Beliefs

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. 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 surveyed beliefs. Date and individual fixed effects are included. The bars show point estimates, while the thin lines show 95% confidence interval. Source: SaverLife.

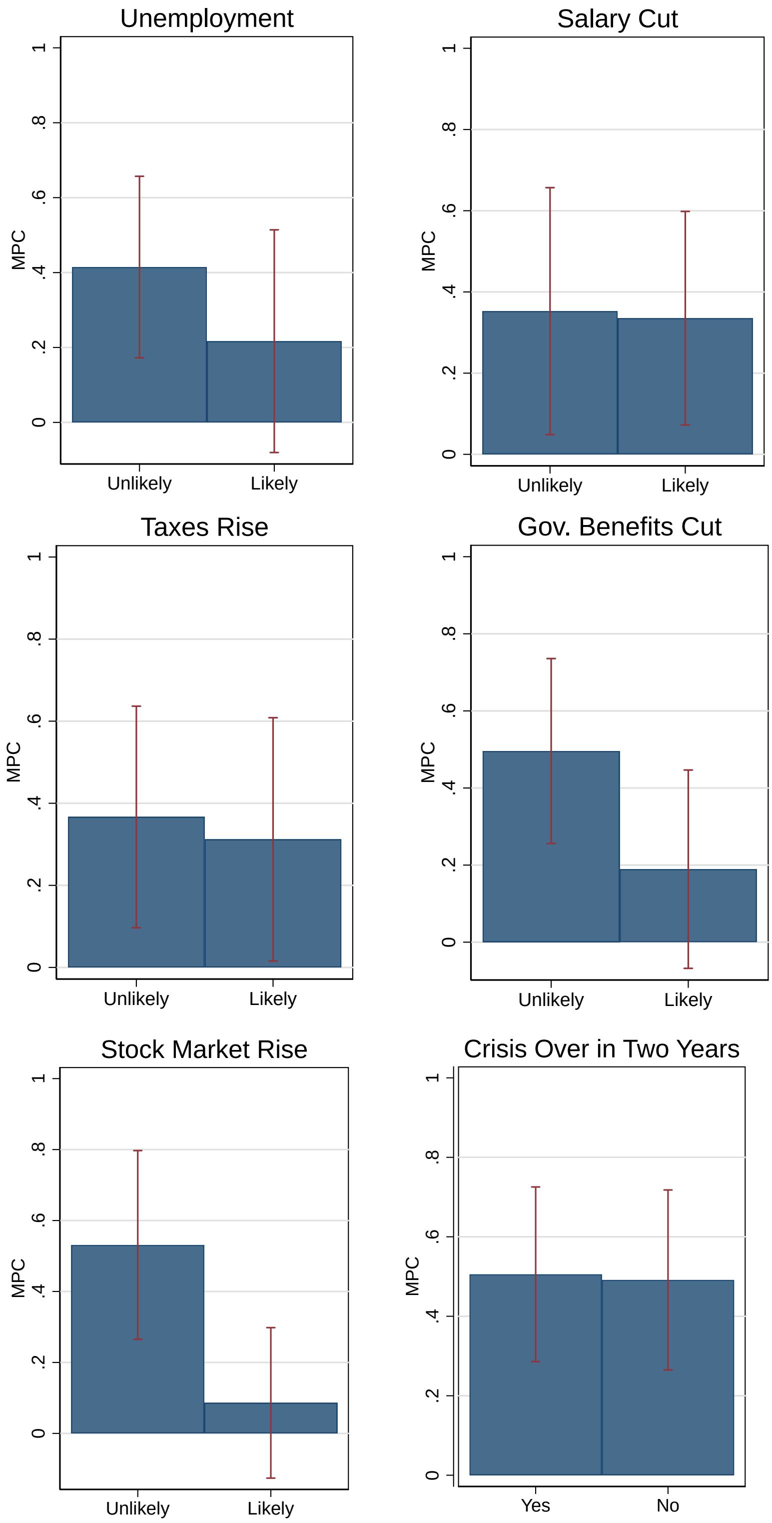


Figure 10: Payment Spending Around Stimulus

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.

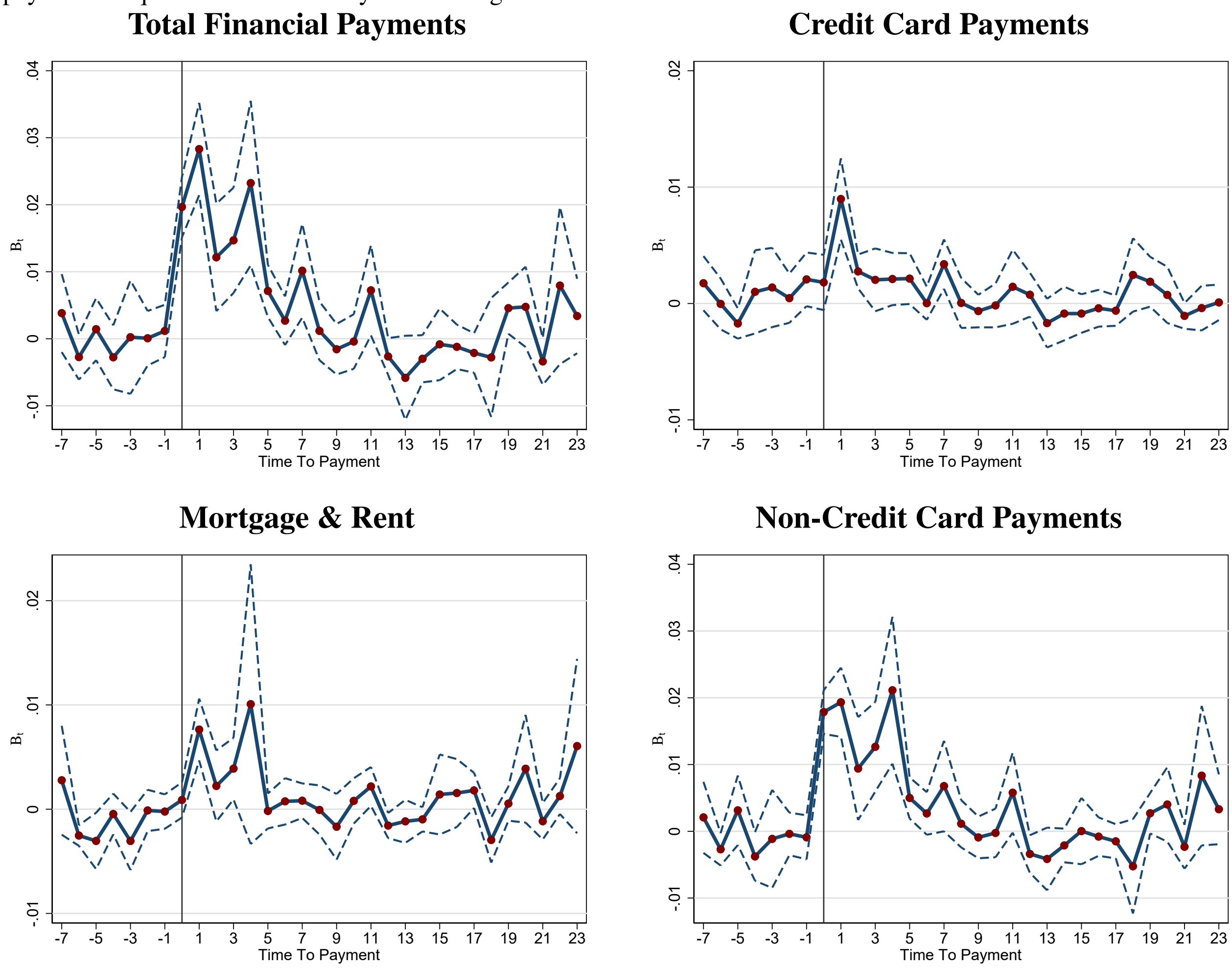


Table 1: Summary Statistics

Notes: Summary statistics for spending and income represent user-month observations. Stimulus Income (Cond) refers to the distribution of stimulus income conditional on receiving a stimulus payment. Income (self-reported) refers to annual income self-reported upon account opening. The balance in the beginning of April 2020 is the mean amount in users' checking accounts in the first week of April 2020.

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)	23,208	2,166	1,200	1,200	1,700	2,700	3,900
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
Non-Durables	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

Table 2: 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. We run separate regressions for overall spending, food, non-durables, household items, durables and payments. 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. 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	0.0139***	0.0187***	0.0138***	0.00599***	0.00260***	0.00136**	0.00141***	0.0202***
	(0.00117)	(0.00136)	(0.00139)	(0.00115)	(0.000800)	(0.000600)	(0.000401)	(0.00180)
Stimulus Payment$_{t+1}$	0.0513***	0.0546***	0.0465***	0.0108***	0.0260***	0.0121***	0.00489***	0.0257***
	(0.00164)	(0.00169)	(0.00187)	(0.00115)	(0.00192)	(0.00119)	(0.000692)	(0.00247)
Stimulus Payment$_{t+2}$	0.0437***	0.0446***	0.0433***	0.00847***	0.0183***	0.0107***	0.00471***	0.0140***
	(0.00526)	(0.00572)	(0.00562)	(0.00158)	(0.00267)	(0.00146)	(0.000988)	(0.00241)
Stimulus Payment$_{t+3}$	0.0454***	0.0500***	0.0447***	0.0123***	0.0183***	0.0111***	0.00506***	0.0185***
	(0.00194)	(0.00195)	(0.00219)	(0.00167)	(0.00180)	(0.00138)	(0.00102)	(0.00265)
Stimulus Payment$_{t+4}$	0.0356***	0.0339***	0.0355***	0.0112***	0.0124***	0.00910***	0.00448***	0.0182***
	(0.00166)	(0.00166)	(0.00190)	(0.00133)	(0.00125)	(0.00145)	(0.000918)	(0.00388)
Stimulus Payment$_{t+5}$	0.0379***	0.0274***	0.0380***	0.0142***	0.0145***	0.0100***	0.00460***	0.0103***
	(0.00469)	(0.00377)	(0.00554)	(0.00238)	(0.00184)	(0.00122)	(0.000841)	(0.00183)
Stimulus Payment$_{t+6}$	0.0132***	0.0123***	0.0123***	0.00377***	0.00586***	0.00343**	0.00177***	0.00424*
	(0.00255)	(0.00234)	(0.00287)	(0.00108)	(0.00182)	(0.00149)	(0.000571)	(0.00238)
Stimulus Payment$_{t+7}$	0.00961***	0.0144***	0.0107***	0.00147**	0.00369**	0.00322**	0.00134**	0.0100
	(0.00123)	(0.00155)	(0.00166)	(0.000651)	(0.00170)	(0.00161)	(0.000624)	(0.00655)
Stimulus Payment$_{t+8}$	0.00690***	0.0106***	0.0103***	0.00190	0.00233**	0.000102	0.000982**	0.00141
	(0.00112)	(0.00115)	(0.00138)	(0.00136)	(0.000940)	(0.000567)	(0.000451)	(0.00190)
Stimulus Payment$_{t+9}$	0.00484***	0.00673***	0.00656***	0.00104	0.000245	-0.0000469	-0.0000648	-0.000711
	(0.000888)	(0.000947)	(0.00113)	(0.000772)	(0.000856)	(0.000499)	(0.000282)	(0.00174)
Date FE	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**
User FE	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**
User*Day of Month FE		**X**						
User*Day of Week FE			**X**					
Observations	2115889	2115889	2115889	2115889	2115889	2115889	2115889	2115889
R^2	0.218	0.325	0.539	0.144	0.094	0.102	0.044	0.136

Table 3: Stimulus Payments and Spending - Weighted Estimates

Columns 1 and 2 show regressions of overall spending on lags of indicators for receiving a stimulus payment. Columns 3 and 4 calculate 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. These coefficients correspond to ζ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \varepsilon_{it}$. Columns 1 and 3 are unweighted, while columns 2 and 4 are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. *$p < .1$, ** $p < .05$, *** $p < .01$. Source: SaverLife.

	(1) Unweighted	(2) Weighted	(3) Unweighted	(4) Weighted
Stimulus Payment	0.0139***	0.00452*		
	(0.00117)	(0.00273)		
Stimulus Payment$_{t+1}$	0.0513***	0.0346***		
	(0.00164)	(0.00448)		
Stimulus Payment$_{t+2}$	0.0437***	0.0280***		
	(0.00526)	(0.00430)		
Stimulus Payment$_{t+3}$	0.0454***	0.0315***		
	(0.00194)	(0.00563)		
Stimulus Payment$_{t+4}$	0.0356***	0.0197***		
	(0.00166)	(0.00469)		
Stimulus Payment$_{t+5}$	0.0379***	0.0275***		
	(0.00469)	(0.00574)		
Stimulus Payment$_{t+6}$	0.0132***	0.0104**		
	(0.00255)	(0.00455)		
Stimulus Payment$_{t+7}$	0.00961***	0.00914**		
	(0.00123)	(0.00373)		
Stimulus Payment$_{t+8}$	0.00690***	0.00861**		
	(0.00112)	(0.00363)		
Post-Stimulus*Stimulus			0.369***	0.266***
			(0.0240)	(0.0318)
Date FE	**X**	**X**	**X**	**X**
Individual FE	**X**	**X**	**X**	**X**
Observations	2,115,889	499,945	2,221,223	523,208
R^2	0.218	0.200	0.215	0.198

Table 4: Stimulus Payments, Spending and Income

This table 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. 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 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)
	All Users	All Users	All Users	Low Inc	High Inc
Post-Stimulus*Stimulus	1.088***	1.128***	0.979***	0.571***	0.325***
	(0.0858)	(0.0919)	(0.0996)	(0.0273)	(0.0296)
Post-Stimulus*Stimulus*ln(Inc)	-0.0861***	-0.0897***	-0.0725***		
	(0.0115)	(0.0123)	(0.0131)		
Date FE	**X**	**X**	**X**	**X**	**X**
Individual FE	**X**	**X**	**X**	**X**	**X**
Individual X Day of Month FE		**X**			
Individual X Day of Week FE			**X**	**X**	**X**
Observations	2170873	2170873	2170873	992884	1177989
R^2	0.216	0.319	0.528	0.169	0.206

Table 5: Stimulus Payments, Spending and Liquidity

This table 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. 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) - (7) drop the interaction, and split the into quartiles of account balances, with column (4) regressing over those with the lowest account balances. 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)	(6)	(7)
	All Users	All Users	All Users	Q1 Bal	Q2 Bal	Q3 Bal	Q4 Bal
Post-Stimulus*Stimulus	0.613***	0.647***	0.585***	0.468***	0.376***	0.378***	0.256***
	(0.0473)	(0.0495)	(0.0479)	(0.0259)	(0.0919)	(0.0274)	(0.0225)
Post-Stimulus*Stimulus*Balance	-0.133***	-0.147***	-0.119***				
	(0.0109)	(0.0110)	(0.0120)				
Date FE	**X**	**X**	**X**	**X**	**X**	**X**	**X**
Individual FE	**X**	**X**	**X**	**X**	**X**	**X**	**X**
Individual X Day of Month FE		**X**					
Individual X Day of Week FE			**X**	**X**	**X**	**X**	**X**
Observations	1726158	1726158	1726158	431582	431572	431491	431513
R^2	0.205	0.303	0.503	0.185	0.205	0.216	0.216

Table 6: 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. 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 (ie. 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. Standard errors are clustered at the user level. $*p < .1$, ** $p < .05$, *** $p < .01$. Source: SaverLife.

	(1) All Users	(2) All Users	(3) All Users	(4) Income Drop	(5) No Drop
Post-Stimulus*Stimulus	0.366***	0.375***	0.365***	0.407***	0.329***
	(0.0203)	(0.0211)	(0.0217)	(0.0181)	(0.0355)
Post-Stimulus*Stimulus*Inc Drop	-0.0230***	-0.0259***	-0.0222**		
	(0.00858)	(0.00900)	(0.00927)		
Date FE	**X**	**X**	**X**	**X**	**X**
Individual FE	**X**	**X**	**X**	**X**	**X**
Individual X Day of Month FE		**X**			
Individual X Day of Week FE			**X**	**X**	**X**
Observations	2096864	2096864	2096864	979426	1117438
R^2	0.214	0.315	0.522	0.226	0.206

Table 7: MPCs and Expectations

This table 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, 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. Standard errors are clustered at the user level. $^{*}p < .1$, $^{**}p < .05$, $^{***}p < .01$. Source: SaverLife.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Total Spending											
Post-Stimulus X Stimulus	0.367***	0.356***	0.385***	0.371***	0.329***	0.315***	0.321***	0.309***	0.438***	0.421***	0.417***	0.404***
	(0.0762)	(0.0760)	(0.0509)	(0.0515)	(0.0529)	(0.0529)	(0.0603)	(0.0598)	(0.0577)	(0.0572)	(0.0550)	(0.0549)
Post-Stimulus X Stimulus X Stock	-0.263**	-0.252*										
	(0.128)	(0.130)										
Post-Stimulus X Stimulus X Unemployed			-0.293***	-0.278***								
			(0.0778)	(0.0812)								
Post-Stimulus X Stimulus X Salary Cut					-0.156	-0.139						
					(0.110)	(0.115)						
Post-Stimulus X Stimulus X Higher Taxes							-0.163*	-0.148				
							(0.0974)	(0.0996)				
Post-Stimulus X Stimulus X Benefit Cuts									-0.363***	-0.344***		
									(0.0837)	(0.0859)		
Post-Stimulus X Stimulus X Pessimistic											-0.258***	-0.249***
											(0.0717)	(0.0725)
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 X Day of Week FE		X		X		X		X		X		X
Observations	238360	238360	238360	238360	238360	238360	238360	238360	238360	238360	238360	238360
R^2	0.308	0.373	0.308	0.373	0.308	0.373	0.308	0.373	0.308	0.373	0.308	0.373

A Details on the CARES Act

The COVID-19 pandemic and the subsequent policy responses had a large impact on the US economy. To combat the adverse consequences, Congress passed the Coronavirus Aid, Relief and Economic Security Act (CARES Act) which was passed on March 25, 2020 and signed into law on March 27, 2020. The CARES Act is the third act in a sequence of responses to the outbreak of the coronavirus by Congress. The first act was focused on spurring coronavirus vaccine research and development (Coronavirus Preparedness and Response Supplemental Appropriations Act, March 6, 2020) with a volume of \$8.2 billion. The second act was a package of approximately \$104 billion in paid sick leave and unemployment benefits for workers and families (the Families First Coronavirus Response Act, March 18, 2020).

The CARES Act was a \$2.2 trillion economic stimulus package and is by far the largest part in this sequence of responses to the pandemic up to that point. The act splits up into \$500 billion support for companies in distress, \$350 billion in loans for small businesses, and over \$300 billion in stimulus payments for most American workers. The rebate provides a direct payment, which is treated as a refundable tax credit against 2020 personal income taxes. Thus, the rebates would not be counted as taxable income for recipients, as the rebate is a credit against tax liability and is refundable for taxpayers with no tax liability to offset. Figure A.2 shows an example of a letter sent out announcing stimulus payments.

All individuals were eligible for the stimulus if they had a valid social security number and if they were not depending on someone else. Individuals must have filed tax returns in 2018 or 2019. Individuals who did not need to file tax returns because their income was below \$12,200 (\$24,400 for married couples) were eligible but needed to register through a website at the Internal Revenue Service. Recipients of social security benefits did not need to register but were also eligible.

Single individuals received up to \$1,200, while those who filed jointly received \$2,400. Those with children under 17 received an add-on of \$500 per child. The tax rebate phased out for higher levels of income. The payment was declined by 5 percent of the amount of adjusted gross income. The phase-out started at \$75,000 for singles or at \$150,000 for married couples. For households heads with dependents (e.g. one person with a child) the phase-out began at an income of \$112,500.

Due to the phase-out provisions, singles (couples) above \$99,000 (\$198,000) did not qualify for a rebate. In Figure A.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.

The House Ways & Means Committee, using information from the IRS, estimates that 171 million people were eligible for receiving rebate payments under the CARES Act. The 171 million people split up into 145-150 million taxpayers who file returns and are were eligible for the stimulus, 20-30 million Social Security beneficiaries and SSI recipients who do not file returns, 15 million non-filers below the filing threshold, 6 million veterans, and 500-600,000 from the Railroad Retirement Board.

In comparison to previous stimulus payments in 2001 or 2008, the IRS did not communicate an exact schedule for sending out the stimulus payments. An approximate schedule for the payments can still be made based on the information available (see Table A.1 and Figure A.4). Taxpayers received the first payments, using direct deposit information from the tax filings from 2018 or 2019, during the week of April 13. The House Ways & Means Committee estimates that during this first week, over 80 million Americans received payments in their bank accounts. During the following weeks the IRS continued weekly rounds of direct deposits to those who provided direct deposit information through the website of the IRS. All taxpayers who had not registered their bank account information by May 13 received their stimulus payment as paper checks. The issuing and mailing of paper checks started in the week of April 20. The checks were sent out at a rate of 5 million checks per week.

During the end of April and beginning of May, Social Security retirement, survivor and disability insurance (SSDI) beneficiaries who did not file tax returns in 2018 or 2019 received their payments via direct transfer (nearly 100% of Social Security beneficiaries). Adult Supplemental Security Income (SSI) recipients received their payments by early May, in the same way, they received their normal benefits (see AARP).

Banks such as the Bank of America and Wells Fargo allowed customers to deposit their checks using mobile solutions to make the stimulus available during the physical lockdown period and to reduce delays. Wells Fargo also allowed non-customers to cash checks with no fees charged. As of May 8, 2020 CNN reported that more than 130 million eligible households had already received their stimulus payment. This lines up closely with the fraction receiving payments in our sample.

In addition to the economic stimulus package, the CARES Act made two additional provisions that are relevant. People who filed for unemployment or were partly unemployed due to the coronavirus received an additional $600 per week on top of their state benefits, until July 31. Whether a person is entitled to the extra money depends on whether an individual qualifies for state or other federal unemployment benefits. The extra $600 also applies to self-employed, part-time workers and gig-workers. Individuals receive their extra unemployment benefits with their state or federal benefits.

The CARES Act suspends minimum distributions from Individual Retirement Accounts (IRAs), 401(k)s, 403(b)s, 457(b)s, and inherited retirement accounts for 2020. It also waives the 10% tax penalty for early distributions of up to $100,000 retroactively by January 1, 2020 if an individual, their spouse, or dependent others is hit by negative consequences of the COVID-19 pandemic.

Figure A.5 presents a placebo exercise. We show spending for individuals in April who did not observe receiving a stimulus check. There is no sharp uptick in spending beyond day of the week effects, consistent with there not being significant measurement error in our sample.

Table A.1: The Timing of the CARES Act Stimulus Payments of 2020

Notes: The table is based on information from The House Ways & Means Committee. The table displays payments disbursed by end of week dates (Fridays). Payments received counts the number of individuals.

Payments by electronic funds transfer		*Payments by check*		*Payments received*
Taxpayer group	Date funds transferred by	Taxpayer group (if no bank account information available)	Date checks received by	Direct deposit and check (cumul.)
Direct deposit information on file	Apr 17			80 mil.
Registered direct deposit information with IRS until Apr 17	Apr 24	$<$ 10k gross income	Apr 24	
Registered direct deposit information with IRS until Apr 24	May 1	10k - 20k gross income	May 1	
Registered direct deposit information with IRS until May 1	May 8	20k - 30k gross income	May 8	130 mil.
Registered direct deposit information with IRS until May 13	May 15	30k - 40k gross income	May 15	
Website for registering direct deposit information closed on May 13		40k - 50k gross income	May 22	152 mil.
		50k - 60k gross income	May 29	
		60k - 70k gross income	Jun 05	
		Further increments of 10k (= 5 mil. checks)	Weekly until August 28	171 mil. (expected)

Figure A.1: CARES Act Economic Relief

Notes: This figure shows the expected stimulus payment for different household compositions and income levels. Source: Coronavirus Aid, Relief and Economic Security Act.

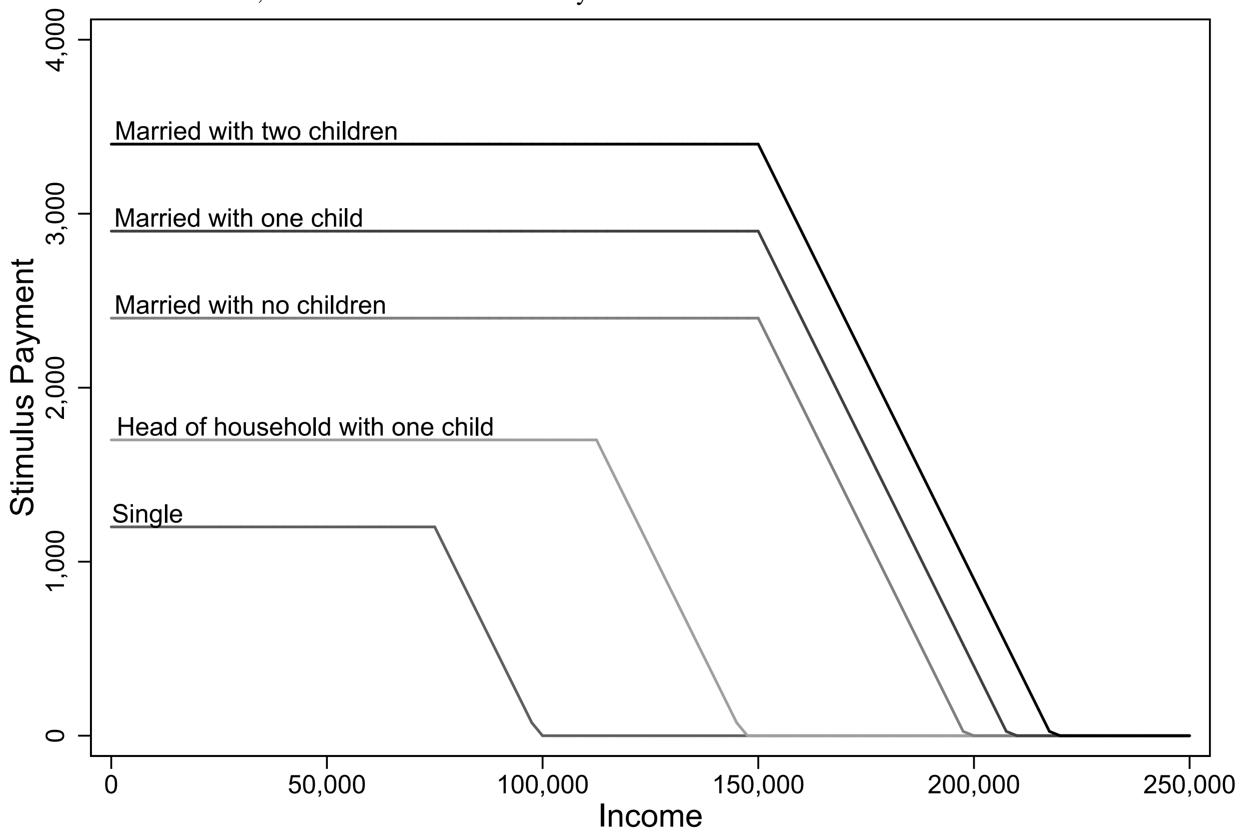
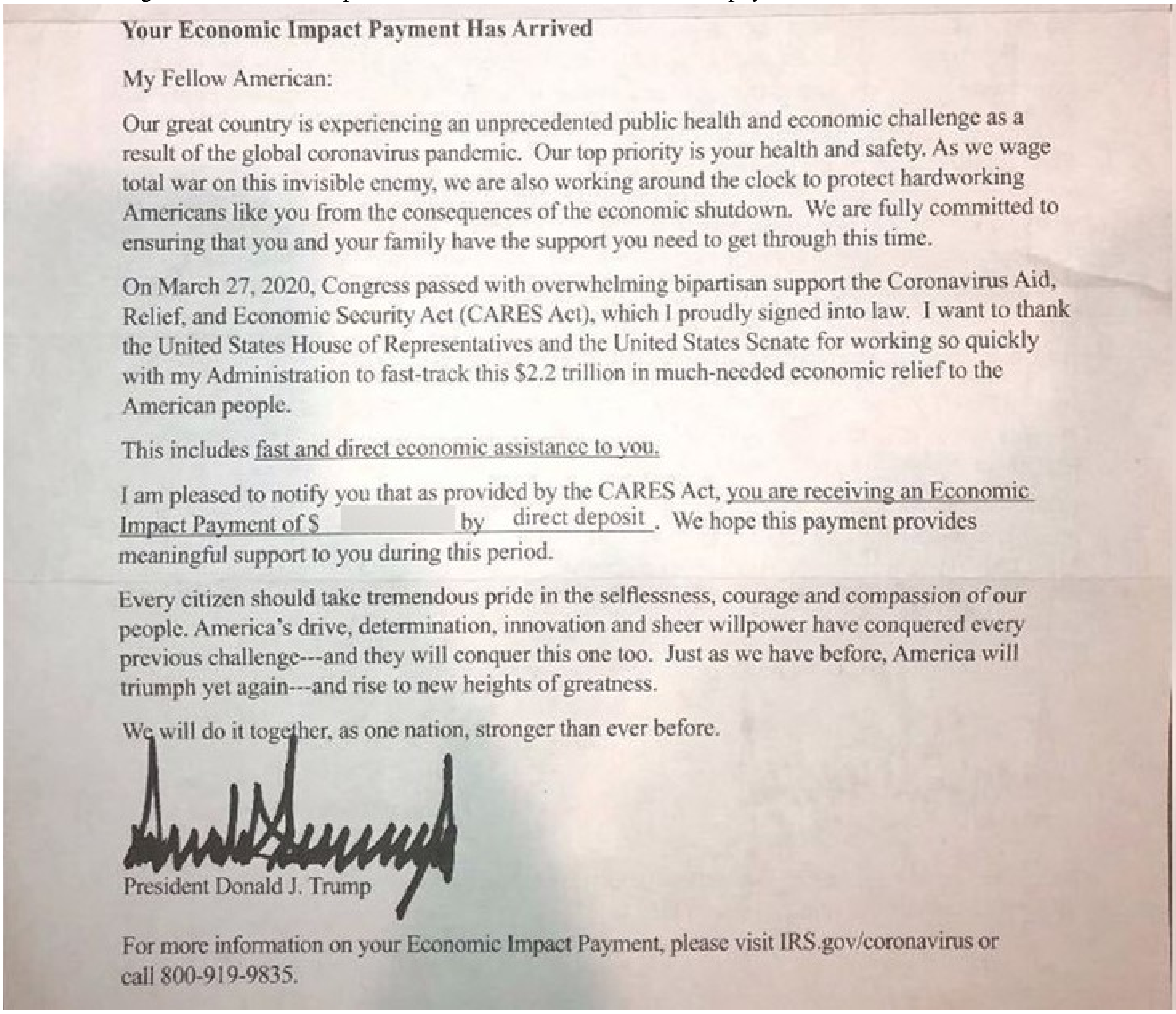


Figure A.2: Example of Notification Letter for Direct Deposit Transfer

Notes: This figure shows an example of a notification letter for stimulus payments.



Your Economic Impact Payment Has Arrived

My Fellow American:

Our great country is experiencing an unprecedented public health and economic challenge as a result of the global coronavirus pandemic. Our top priority is your health and safety. As we wage total war on this invisible enemy, we are also working around the clock to protect hardworking Americans like you from the consequences of the economic shutdown. We are fully committed to ensuring that you and your family have the support you need to get through this time.

On March 27, 2020, Congress passed with overwhelming bipartisan support the Coronavirus Aid, Relief, and Economic Security Act (CARES Act), which I proudly signed into law. I want to thank the United States House of Representatives and the United States Senate for working so quickly with my Administration to fast-track this $2.2 trillion in much-needed economic relief to the American people.

This includes fast and direct economic assistance to you.

I am pleased to notify you that as provided by the CARES Act, you are receiving an Economic Impact Payment of $ by direct deposit. We hope this payment provides meaningful support to you during this period.

Every citizen should take tremendous pride in the selflessness, courage and compassion of our people. America's drive, determination, innovation and sheer willpower have conquered every previous challenge---and they will conquer this one too. Just as we have before, America will triumph yet again---and rise to new heights of greatness.

We will do it together, as one nation, stronger than ever before.

President Donald J. Trump

For more information on your Economic Impact Payment, please visit IRS.gov/coronavirus or call 800-919-9835.

Figure A.3: Stimulus Amount Received by Household Size

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

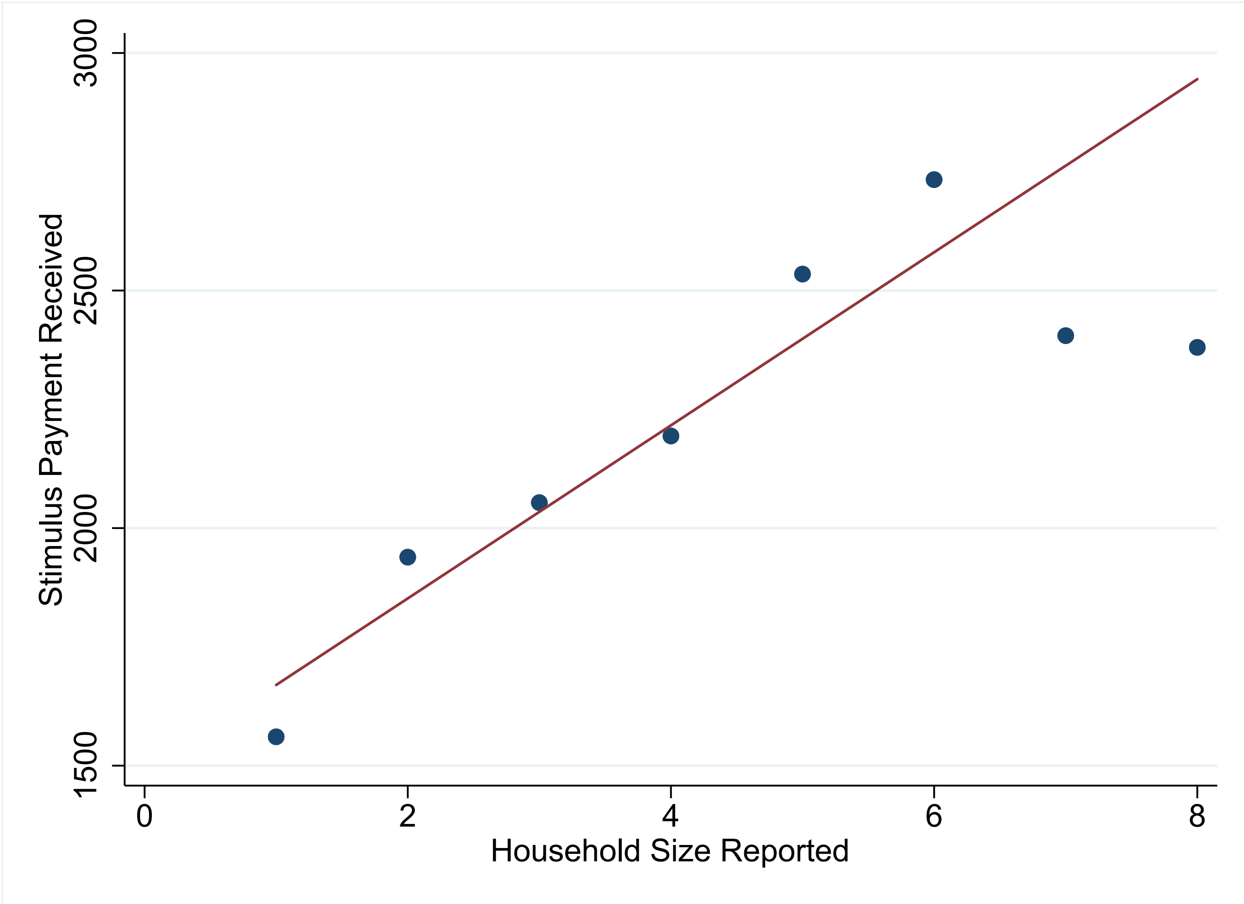


Figure A.4: Timeline of stimulus payouts

Notes: The figure presents a timeline of stimulus payments to different households. Source: House Ways & Means Committee.

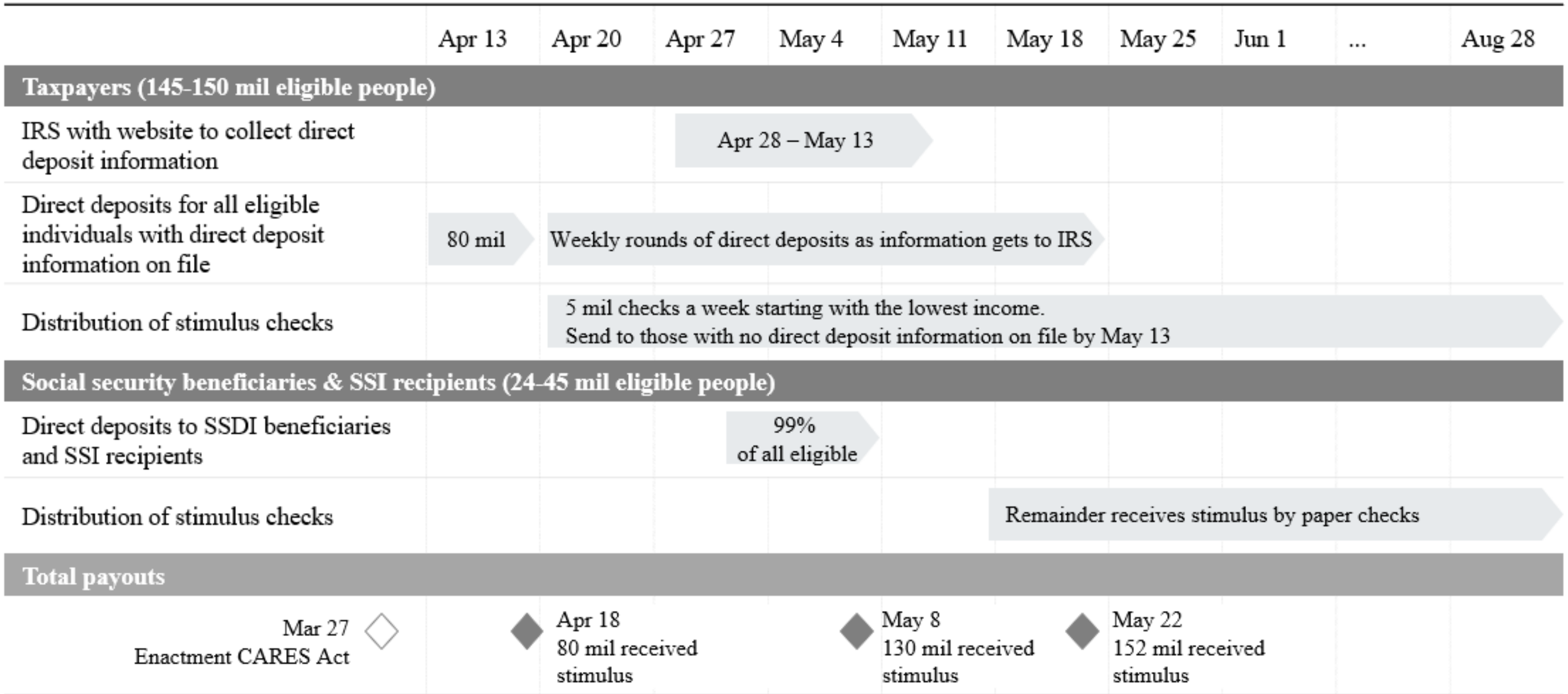
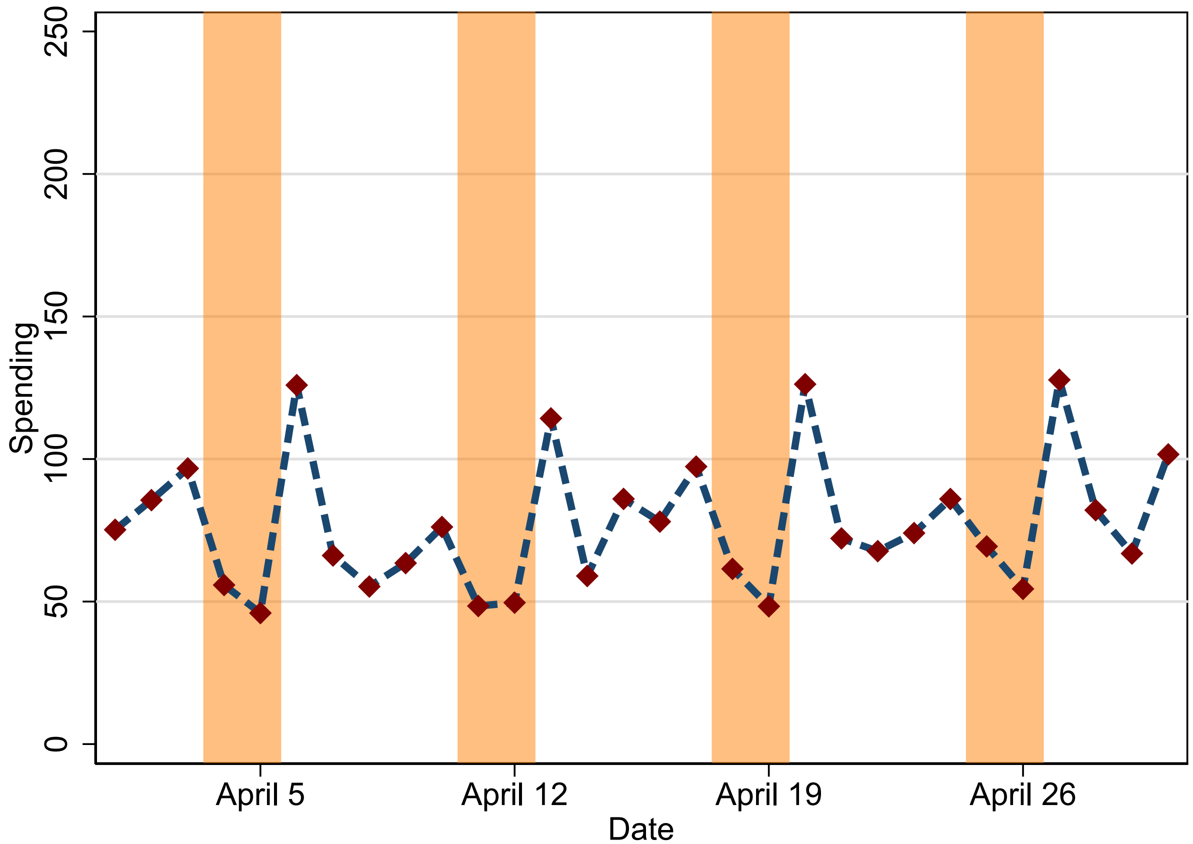


Figure A.5: Mean Spending in April for Individuals Not Receiving Payment- Raw Spending

Notes: This figure shows mean daily spending in April for individuals who did not receive payments in that month. Sample includes only users who do not receive a stimulus payment during our sample period. The vertical axis measures spending in dollars, and the horizontal axis shows the date. 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.



B Survey Results and Screenshots

Figure B.1: SaverLife Survey

Notes: This figure shows each page of the SaverLife survey, as presented on a mobile device.

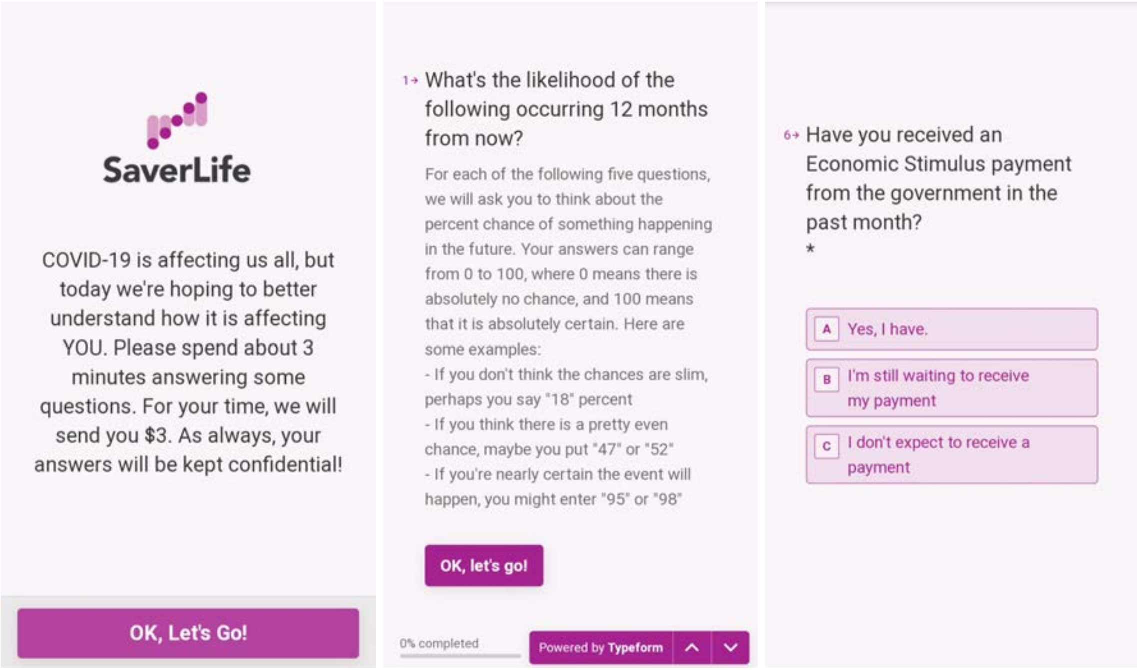


Figure B.1: SaverLife Survey (continued)

Notes: This figure shows each page of the SaverLife survey, as presented on a mobile device.

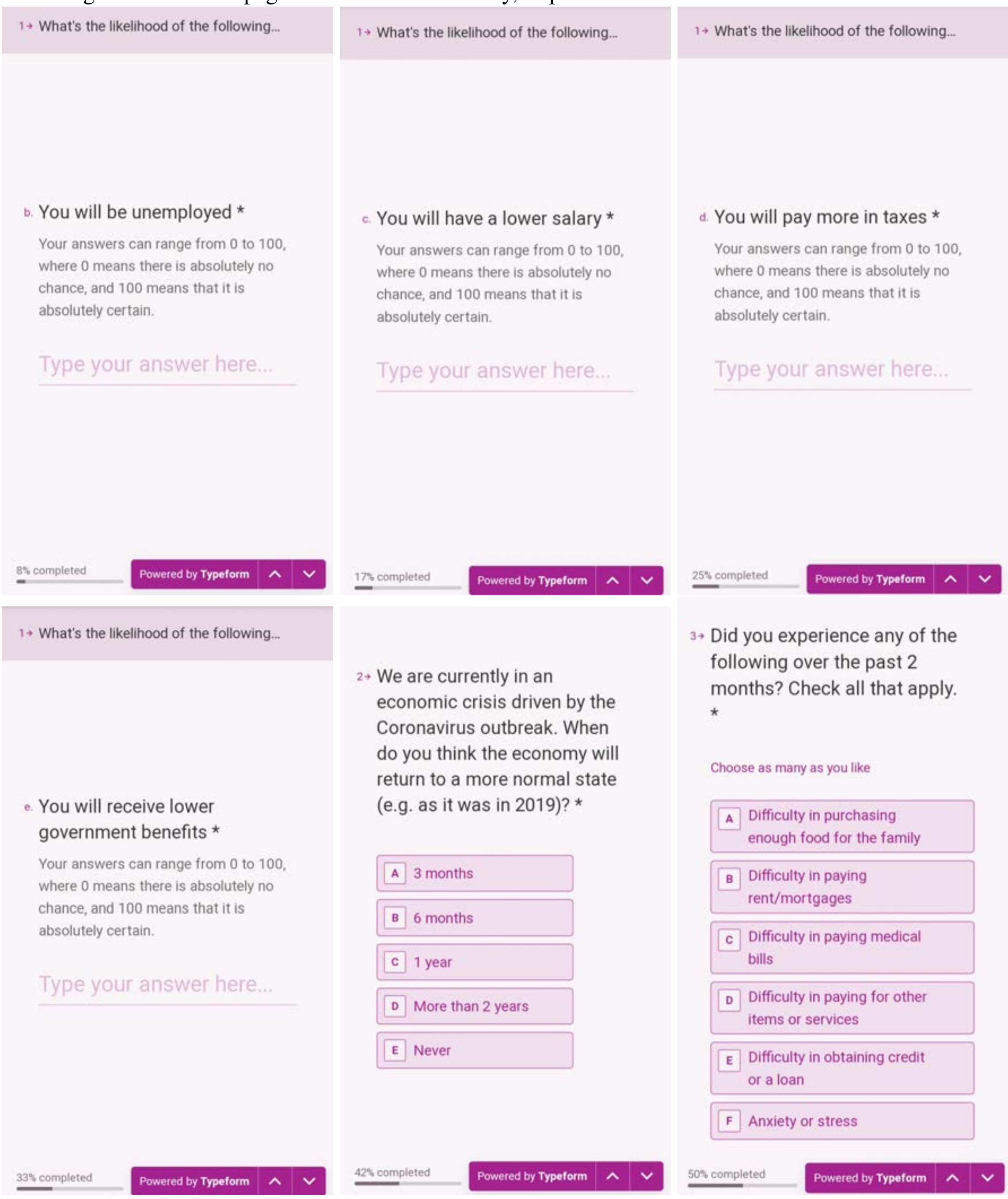


Figure B.1: SaverLife Survey (continued)

Notes: This figure shows each page of the SaverLife survey, as presented on a mobile device.

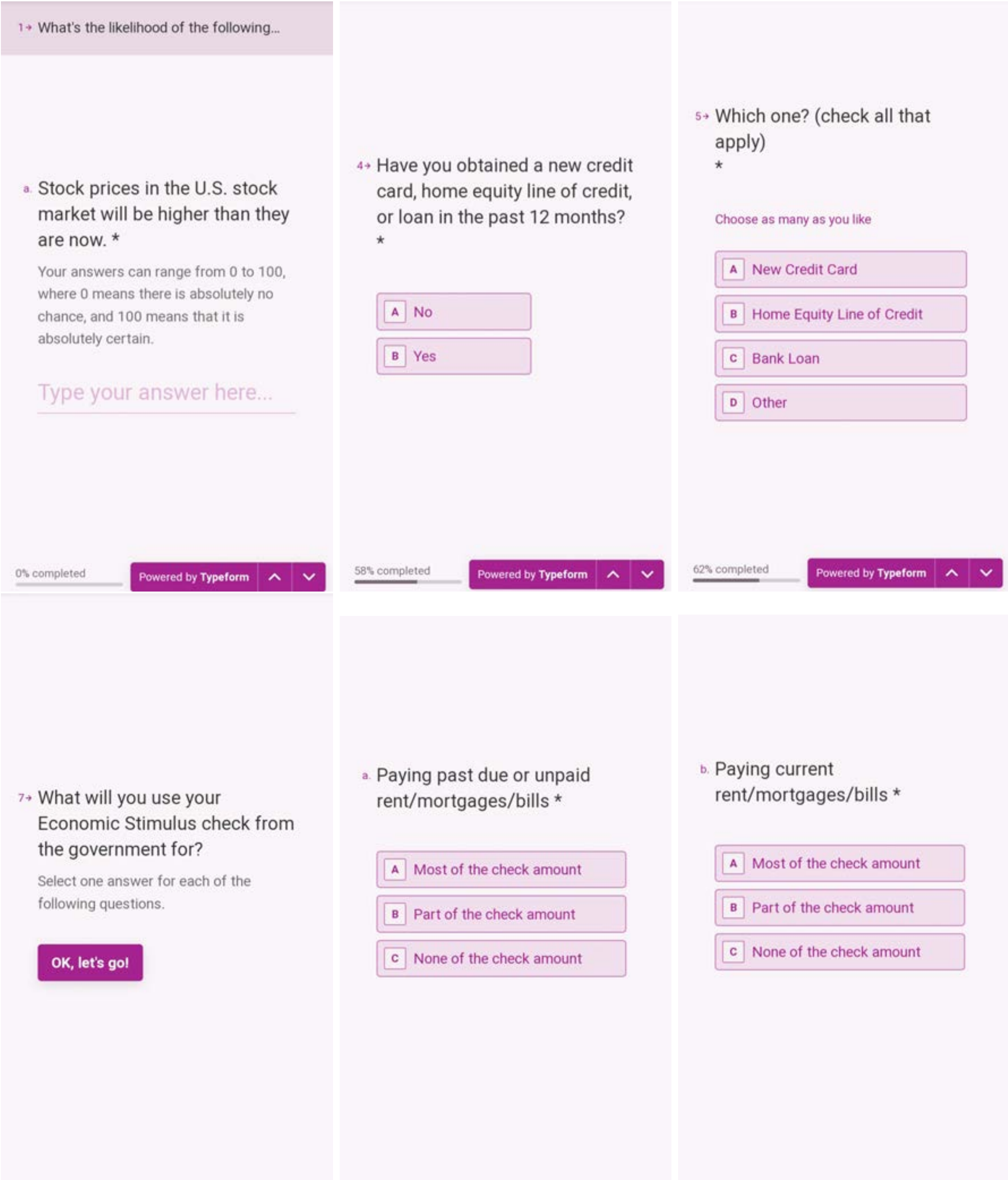


Figure B.1: SaverLife Survey (continued)

Notes: This figure shows each page of the SaverLife survey, as presented on a mobile device.

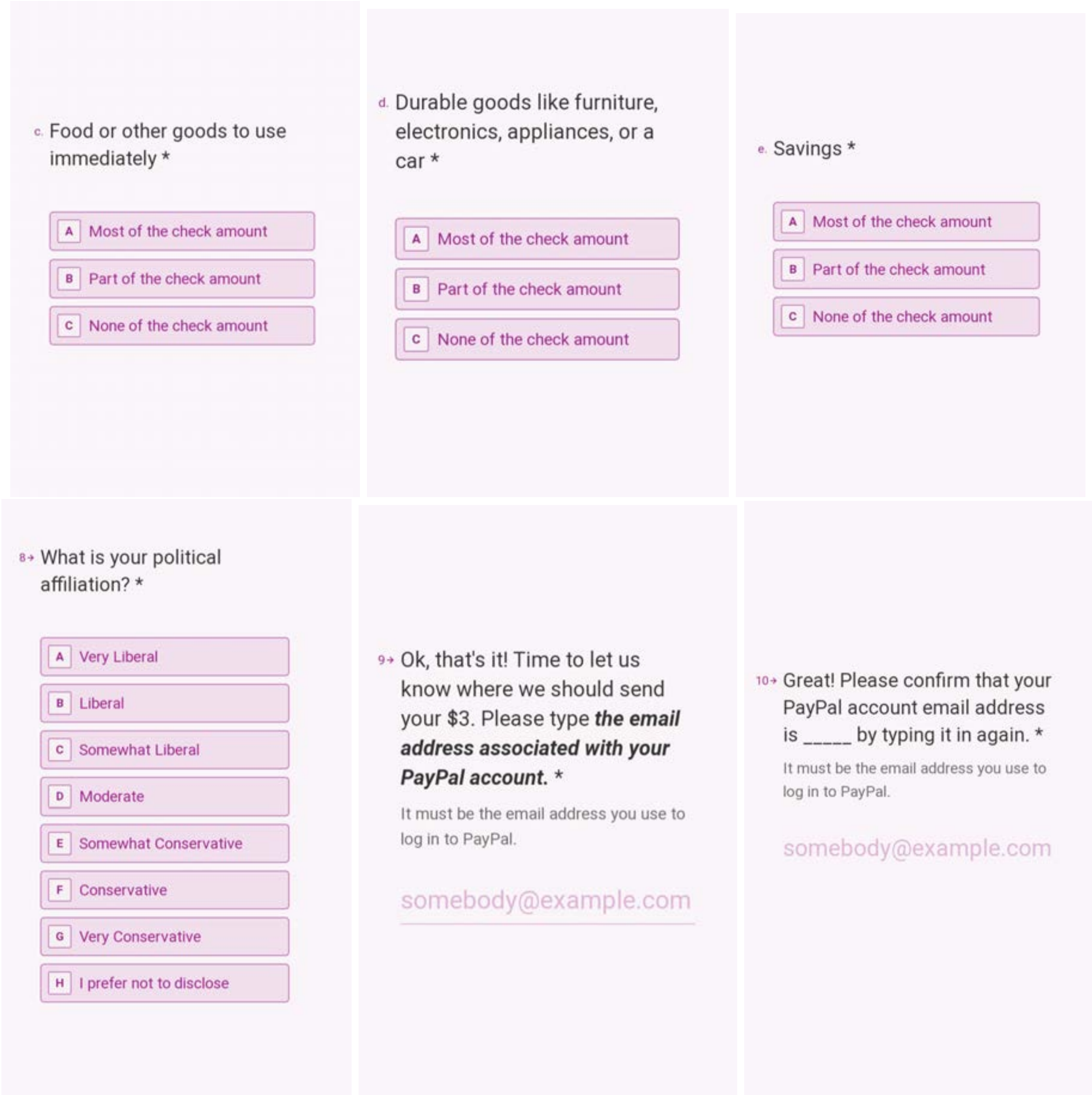


Figure B.2: SaverLife Survey Results: Stimulus Checks

Notes: This figure shows survey responses to the pandemic, financial hardship, credit, and political orientation questions.

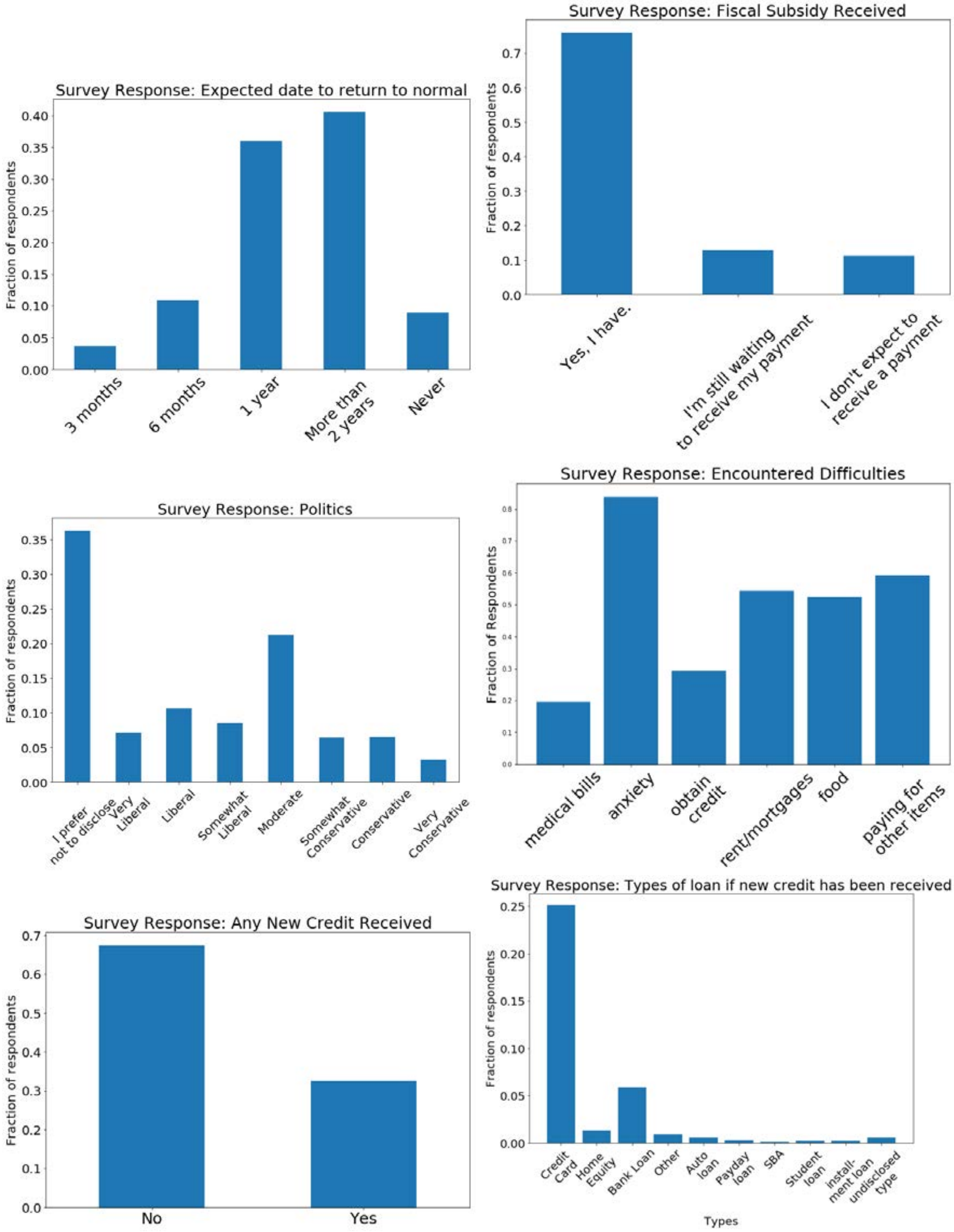


Figure B.3: SaverLife Survey Results: Stimulus Checks

Notes: This figure shows survey responses to the fiscal stimulus use questions.

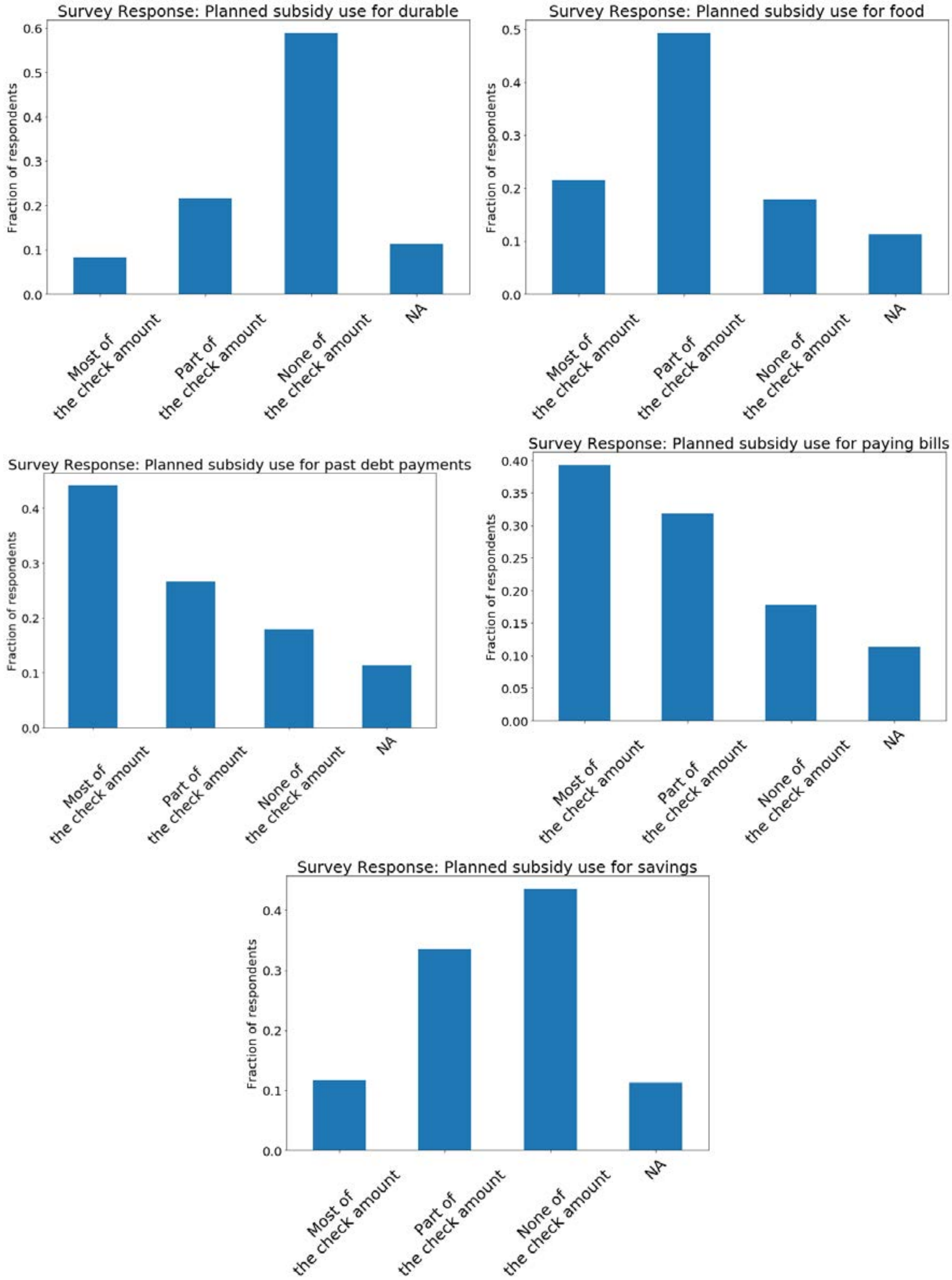


Figure B.4: SaverLife Survey Results: Expectations

Notes: This figure shows survey responses to the expectations questions.

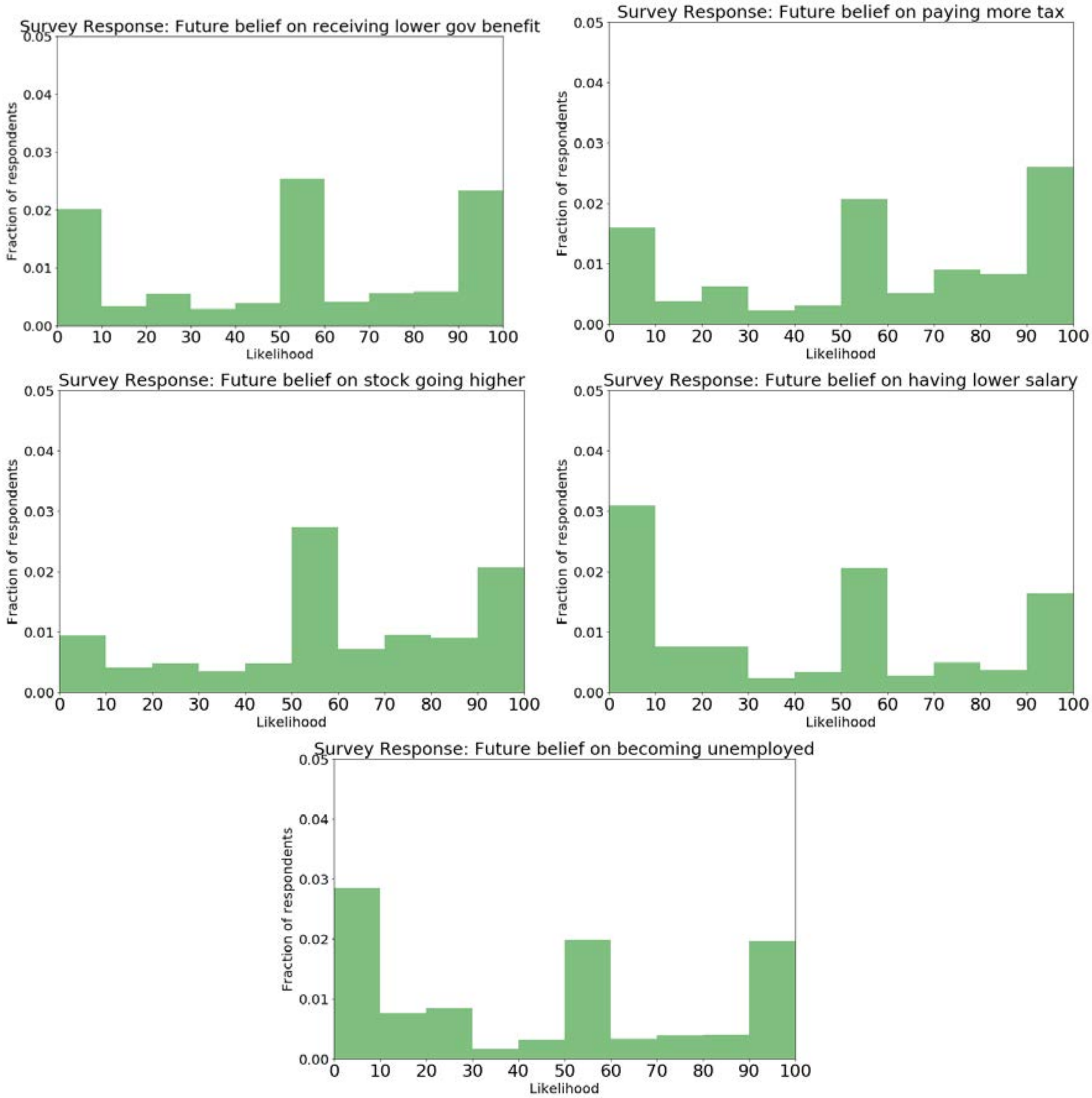


Figure B.5: Correlation Between Survey Beliefs

Notes: This figure shows binned scatter plots between reported survey beliefs. Source: SaverLife.