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

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Abstract

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

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1 Introduction

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

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

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

The first CARES Act stimulus payments were made in mid-April via direct deposit from the IRS. We observe user-specific stimulus amounts as well as spending daily before and after stimulus

payments are received. We see immediate responses to the stimulus payments; within the first week, users spend about 14 cents of every dollar received in stimulus payments. In the three months following stimulus receipt, excess spending of over 25 cents per dollar is observed, with almost all of this spending occurring in the first month. The largest increases in spending are on food, 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 50% of their stimulus payments over three months, while we observe individuals with more than $1,000 in their accounts spend only about 15% of their payments.

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

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

The theory behind stimulus payments links MPCs directly to the ultimate fiscal multiplier effect, 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

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[1]SaverLife conducted our survey from mid-May to the end of July. This survey also elicited self-reported information on the receipt and use of the stimulus checks. In terms of the fiscal stimulus use, our survey results line up closely with the empirics. 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.

MPCs, and hence on fiscal multipliers.

Our study is the first to empirically explore the comprehensive spending impacts of the 2020 stimulus at an individual level. Moreover, by linking transaction and survey data, we are the first to examine more generally how expectations affect MPCs out of stimulus payments. Additionally, to our knowledge, our study is the first to look at stimulus payments using high-frequency transaction data, as such data did not exist in 2008.[2] The use of transaction data allows us to explore very short term responses across categories, minimize measurement error, and explore individual daily heterogeneity in income declines and available cash on hand.

There is an extensive literature on households' responses to tax rebates and previous stimulus payments. Using spending data from the Consumer Expenditure Survey, Johnson, Parker and Souleles (2006) and Parker, 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 (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 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 stimulus program we examine was comparatively larger than those in 2001 and 2008, with individual stimulus amounts of 2 to 4 times the size.

While previous studies have pointed out that stimulus payments have positive but heteroge-

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

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

In Section 4.3, we discuss the differences between our estimates and the previous literature that analyze past stimulus programs. While the economic setting was quite different than the previous two American recessions, our results for magnitudes of spending responses to the 2020 stimulus are generally comparable. The three main differences are: 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.

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. More broadly, our paper also links to literature on how consumption responds to income changes. For example, see Pistaferri (2001), Blundell et al. (2006), Agarwal, Liu and Souleles (2007), Jappelli and Pistaferri (2010), Aaronson, Agarwal and French (2012), Baker (2018) and Di Maggio, Kermani and Majlesi (2020).

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[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."*

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 (2020b) 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 (2021) and Allcott, Boxell, Conway, Gentzkow, Thaler and Yang (2020) show that political affiliations impact the social distancing response to the pandemic, and Coven and Gupta (2020) study disparities in COVID-19 infections and responses.[4] Chetty et al. (2020) use aggregate data to study the effects of the stimulus, and Coibion, Gorodnichenko and Weber (2020a) provide survey evidence on how households spent their stimulus payments. We join this emerging and rapidly-growing literature by providing individual-level data on comprehensive spending responses to the 2020 stimulus payments and how these responses varied across individuals' financial characteristics. The results suggesting that MPCs are much higher for low income and low liquidity households are important in designing future rounds of stimulus.

We also contribute to literature on how expectations affect households' economic behavior. A newer and growing body of recent work also shows that expectations about individual and aggregate outcomes impact behavior, studying households (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.

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[4]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).

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 concludes and suggests directions for future research.

2 Institutional Background and Empirical Strategy

2.1 2020 Household Stimulus

COVID-19, a novel coronavirus, was first identified in Wuhan, China and subsequently spread worldwide in early 2020. By some estimates, the new virus had a mortality rate that is ten times higher than the seasonal flu and has at least twice the rate of infection. The first case in the 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.[5]

Payments are made by direct deposit whenever available, or by paper check when direct deposit information was unavailable. Funds are disbursed by the IRS, and the first payments by direct deposit were made on April 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. However, given changes in banking information or addresses, many individuals were unable to receive their payments through direct deposit even when they had received prior tax refunds via direct deposit. In the case of paper checks, the order of payments across households is not random. The IRS directed to send individuals with the lowest adjusted gross income checks first in late April, and additional paper checks were sent throughout May. 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

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

and economic sentiment. $\mathbb{1}[t = k]_{it}$ is an indicator of the time period k days after receipt of the stimulus payment for individual i at time t.

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

We identify daily MPCs using the following specification:

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

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

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

where P_i is the stimulus payment an individual i is paid, D_{it} is the total number of days over which we estimate the MPC, and $Post_{it}$ is an indicator of the time-period t being after individual i receives a stimulus payment. The coefficient ζ thus captures the aggregate effect of the stimulus in the time-period in question, by scaling the average effect per day by the number of days since receipt. The resulting coefficients can be interpreted as the fraction of stimulus money spent during that period: a coefficient of 0.05 corresponds to the user spending 5% of their stimulus check during their observed post-stimulus period. Our primary estimates are calculated using a three-month post-stimulus period, though MPCs from a range of horizons are also calculated.[6]

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[6]As an example to illustrate this, imagine that a $1 transfer leads to $1 dollar of additional spending in the day immediately after receipt. Thus if we estimated the effect over one day, we would scale by 1 and $\zeta = 1$. If we estimate

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 into a large number of categories and subcategories. For 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. Across all specifications, we exclude transactions that represent transfers between accounts like transfers to savings or investment accounts.

Looking only at the sample of users who have updated their accounts reliably up until August 2020, we have complete data for 38,379 users to analyze in this paper. We require these users to have at least 2 transactions in December 2019 and more than 20 transactions adding up to at

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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.

least \$1,000 in 2020. Additionally, we drop all user-month pairs with less than 5 transactions per month. We require 5 transactions in account usage as a completeness-of-record check for bank-account data following (Ganong and Noel, 2019). We aggregate all transactions to the daily level. If a user does not have a transaction for a particular category on a given day, we fill in a zero if that user had other transactions earlier or later than that day.

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

In Table 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 (e.g. \$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. Stimulus checks for individuals in 'phase-out' would not be even numbers, meaning that we would falsely classify an individual as having not received a stimulus check. This would likely attenuate our empirical estimates somewhat, biasing our esti-

mates of the stimulus receipt downwards.

As of August, approximately 60% of users have received a stimulus payment into their linked account. The remainder of the sample may have not linked the account that they received the stimulus check in, be still waiting for a stimulus check, or maybe ineligible for one.[7] Some banks and credit unions had issues processing stimulus deposits and these deposits were still pending for a number of Americans. In addition, users may not have had direct deposit information on file with the IRS and would then need to wait for a check to be mailed. Finally, users may be ineligible for stimulus checks due to their status as a dependent, because they did not file their taxes in previous years, or because they made more than the eligible income thresholds for receipt. Of those who receive payments, two-thirds received them by April 15, with 40% of all payments occurring on April 15. 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. This measure is highly correlated with the observed stimulus payments.

Appendix A provides further details regarding payments in our sample. 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.3). We do not see any sharp breaks in spending beyond day of the week effects, suggesting that the impact of miscategorization is small and that these users did not link either their main tax or spending accounts.

3.2 Survey Data

SaverLife conducted a survey between mid-May to the end of July to elicit self-reported information on the receipt and use of the stimulus checks, expectations about personal financial situations,

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

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 sent email and text reminders. Users could take the survey on a computer or mobile device, and they were allowed to skip questions. The survey was sent to 6,060 individuals, who were longer-term active users of the platform and identified as being potentially responsive to surveys in the past. We received 1,011 unique responses, indicating a response rate of around 16.7%. The survey questions are loosely based on the Federal Reserve Bank of New York Survey of Consumer Expectations. The survey focused on the following areas:

- Expectations regarding income, the economy and benefits.

- Expectations regarding the length of the pandemic.

- Self-reported difficulties in paying bills and anxiety.

- Credit.

- Stimulus check spending.

- Political affiliation.

In the 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 would not use the check to pay past bills or would use it for future bills. Finally, 15% of users report saving most of the check amount and 45% report to save none of the

check amount.

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

4   Effects of Stimulus Payments

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

To identify the direct impacts of the stimulus check payments, we effectively compare users receiving stimulus payments to themselves before and after the event as well as to those that did not receive one on that day. Figure 4 shows estimates of β_k from the equation: $c_{it} = \alpha_i + \alpha_t + \sum_{k=-7}^{23} \beta_k \mathbb{1}[t=k]_{it} + \varepsilon_{it}$. 'Time to Payment' is equal to zero for a user on the day of receiving the stimulus check. Here, we see that users who receive stimulus checks tend to not behave differently than those that do not in the days before they receive the checks. Upon receiving the stimulus check, users dramatically increase spending relative to users who do not receive the checks. Because our sample is not representative of the nation as a whole, our main specifications re-weight our sample on several dimensions using Current Population Survey (CPS) weights: age, sex, state, and income bins.[10]

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[8]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.

[9]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.

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

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 (e.g. $36 out of a $1,200 stimulus check) more than a user who did not receive a check. In our sample, the average stimulus check size was $2,166 (median of $1,700).

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

4.1 Spending Across Categories

The remainder of the columns in Table 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 the most muted effects of the stimulus payments on durables spending. In previous recessions, spending on durables (mainly auto-related spending) was a large component of the household response to stimulus checks. At least in the short term, we find significantly different results, with durables spending contributing negligibly to the overall household response. We discuss some of these differences relative to past stimulus programs in Section 4.3. To compare our estimated coefficients to other studies using a broader sample, we also run the equivalent of the stimulus regression as done in the paper by Chetty et al. (2020) and obtain statistically indistinguishable results.[11]

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pre-trends or anticipatory spending among households who would later receive a stimulus check.

[11]In particular, we replicate the regression in their main stimulus Table 4. Exactly following their analysis, we first aggregate our data to the daily level, then express spending as the percentage change relative to the mean spending between January 4 and 31, 2020, then residualize the variable with respect to day-of-week and first-day-of-the-month

There is a sharp and immediate increase in spending following the receipt of a stimulus deposit; users show large increases in spending in the first days following the stimulus check receipt and keep spending significantly more than those who have not received checks. In Figure 5, we break down users' spending responses by categories of spending. We map our categories to roughly correspond to those reported in the Consumer Expenditure Survey: food, household goods and personal care, durables like auto-related spending, furniture, and electronics, non-durables and services.

Across all categories, we find statistically significant increases in spending following the receipt of a stimulus check. These responses are widely distributed across categories, with cumulative spending on food, household, non-durables, and durables all seeing increases in spending in the first week following. These effects are concentrated in the near term, with excess spending declining substantially following the first week.

In Figure 6, we also note the impact of the stimulus check on financial payments and transfers. In particular, we examine the impact on total transfers out of an individual's checking account, financial payments and credit card payments, and rent and mortgage payments. Most of the transfers, in the top left panel, are likely transfers to things like savings and brokerage accounts, but some may represent loan payments or transfers to external vendors, as well.[12]

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

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fixed effects, and then regress this variable on a dummy for the day being on or after April 15, 2020 restricting the regression window to April 1 to 30, 2020. We obtain a coefficient of 27.31 which is well within one standard deviation of their estimated coefficient of 25.15 for the bottom income quartile.

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

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

4.2 Robustness

In Table 3, we aggregate the daily excess spending responses across a range of horizons to provide a more thorough accounting for how the marginal propensity to consume evolves over the weeks and months after stimulus receipt. We provide estimates of spending over 5 horizons: 1-week, 2-weeks, 1-month, 2-months, and 3-months. We find that just over $0.25 of each dollar of stimulus check was spent in the three months following its arrival. About half of this spending ($0.14) was spent during the first week alone and over three quarters ($0.22) spent in the first month. We find no statistical difference in excess spending between months two and three. That is, the stimulus checks did have the effect of stimulating additional spending in the economy, but the effect was relatively short-lived and limited relative to the size of the checks.[13]

Because our sample is not representative of the nation as a whole, the previous results are reweighted by age, sex, state of residence, and income bins. In Table 4, we compare our estimates from our weighted regressions to those forgoing these user weights. Column (5) thus runs our primary MPC calculation using these user weights, finding a 3-month MPC of approximately 0.368 rather than 0.265 in column (4). In general, when not weighting our sample to match the national distribution of households, we see results approximately 50% larger in magnitudes than when weighting along these dimensions. Given our sample being younger and having lower incomes and assets than the nation as a whole, it is unsurprising that down-weighting these types of users produces a lower MPC. In this table, we also run specifications including financial payments to our measure of total spending. These include mortgages, rent, and other loan payments. These cause a slight increase in overall MPCs, as seen in columns (3) and (6).

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

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

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

4.3 Comparison to Previous Economic Stimulus Programs

Johnson, Parker and Souleles (2006) and Parker, 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 most categories of spending. Households spent approximately 14% of their stimulus checks within one week and over 20% within the first month.

Another notable difference from the stimulus programs is that we find substantially smaller impacts on durables spending and confirm this in our survey of users. Previous research has found strong responses of durables spending to large tax rebates and stimulus programs, especially on automobiles (about 90% of the estimated impact on durables spending in the 2008 stimulus program was driven by auto spending). In contrast, despite a sizable response in 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 was 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 7-9, we show the cumulative estimated MPCs from regressions of spending on an indicator of a time period being after a stimulus payment is received. Each figure contains the results of multiple regressions, with users broken down into subsamples according to a number of financial characteristics that we can observe. That is, the graphs represent the sum of daily coefficients seen in a regression as in Table 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 7 splits users by their average income in January and February 2020 (prior to the major impacts of the pandemic). We see clear evidence that users with lower levels of income tended to respond much more strongly to the receipt of a stimulus payment than those with higher levels of income. Users who had earned under $1,000 per month saw an MPC about twice as large as users who earned $5,000 a month or more.

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

In Figure 9, we examine whether a similar pattern can be seen among users who have had declines in income following the COVID 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 difference in MPCs of lower magnitude than the previous splits (and with a p-value of only 0.2 on the difference between coefficients). This smaller difference may be driven by the fact that the federal government had also made generous unemployment insurance available to nearly all workers, mitigating the potential loss of income from job loss for many lower-income households.

Tables 5 - 7 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.[14]

Table 8 shows MPCs for subgroups, based on user beliefs regarding personal unemployment, salary cuts, tax increases, government benefit cuts, stock market increases and the duration of the pandemic. More precisely, the table shows MPC estimates and interactions (ζ and ζ') from the

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

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 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.

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

7   Conclusion

This 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 the heterogeneity of MPCs in response to the stimulus payments, an important parameter both in determining multipliers and in testing between representative and heterogeneous agent models. We hope that our results inform the ongoing debate about appropriate policy measures and next steps in the face of

the COVID-19 pandemic.

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

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

More work should be done to study how targeting can be designed to have large impacts on consumption without generating significant behavioral effects. Just as unemployment benefits may increase unemployment durations (Meyer, 1990), policies targeting stimulus payments 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.
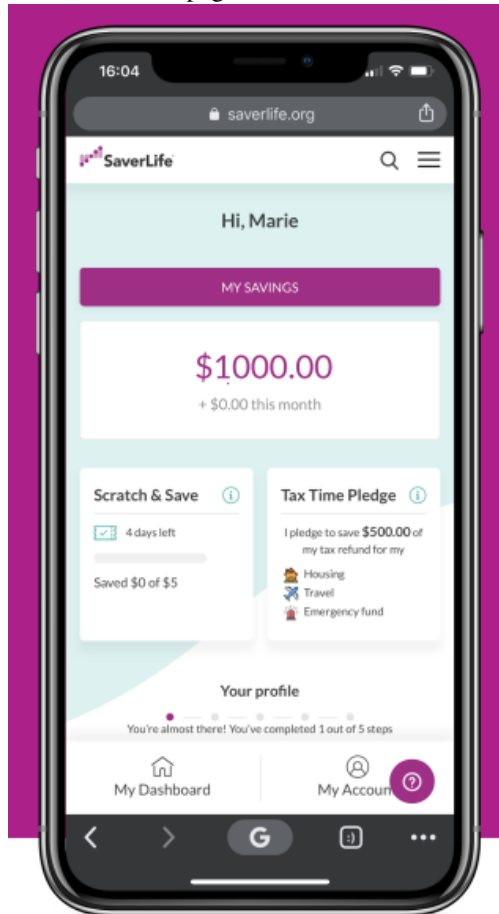
Figure 2: Daily Number of Government Payments at Stimulus Amounts

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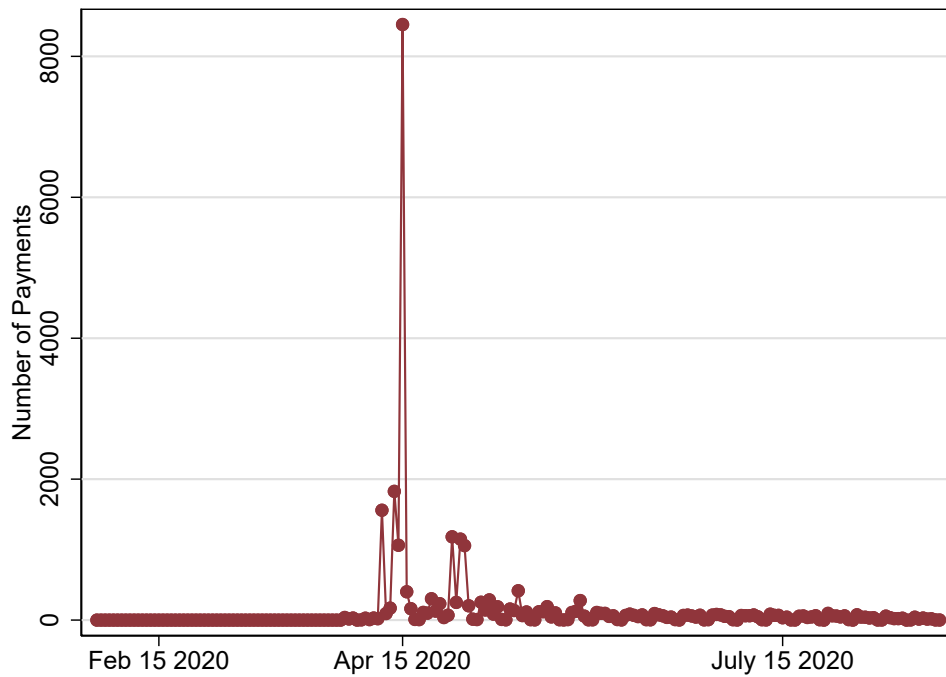
Figure 3: Mean Spending Around Receiving the Stimulus Payments - Raw Spending

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.
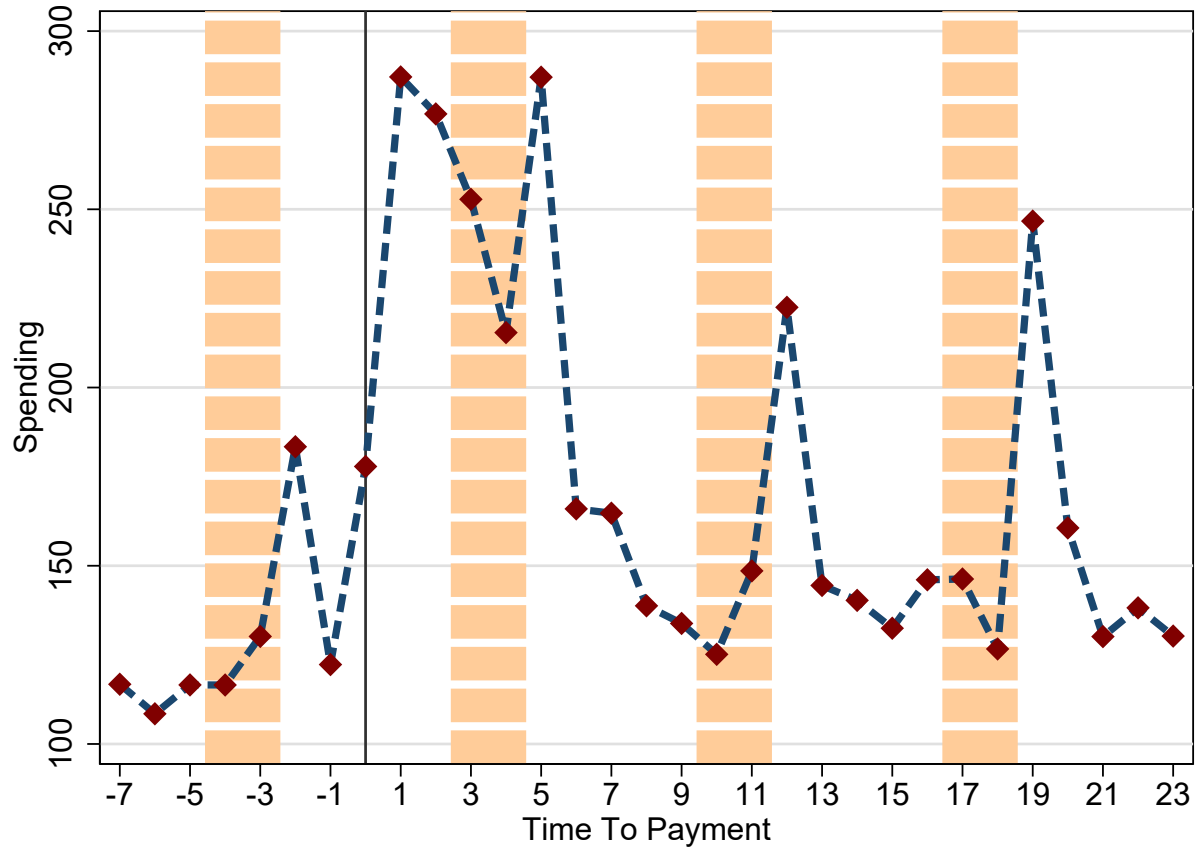
Figure 4: Spending Around Stimulus Payments - Regression Estimates

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.
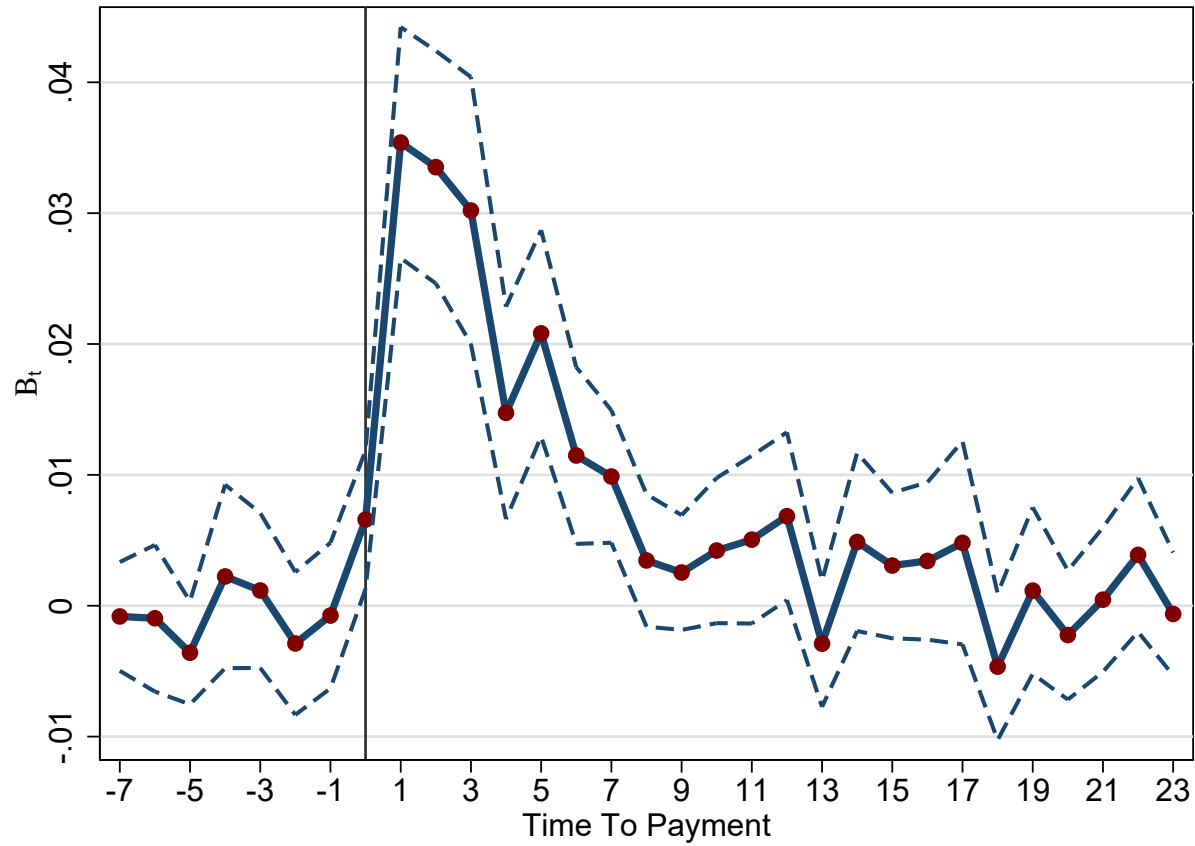
Figure 5: Spending Around Stimulus Payments by Categories

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.
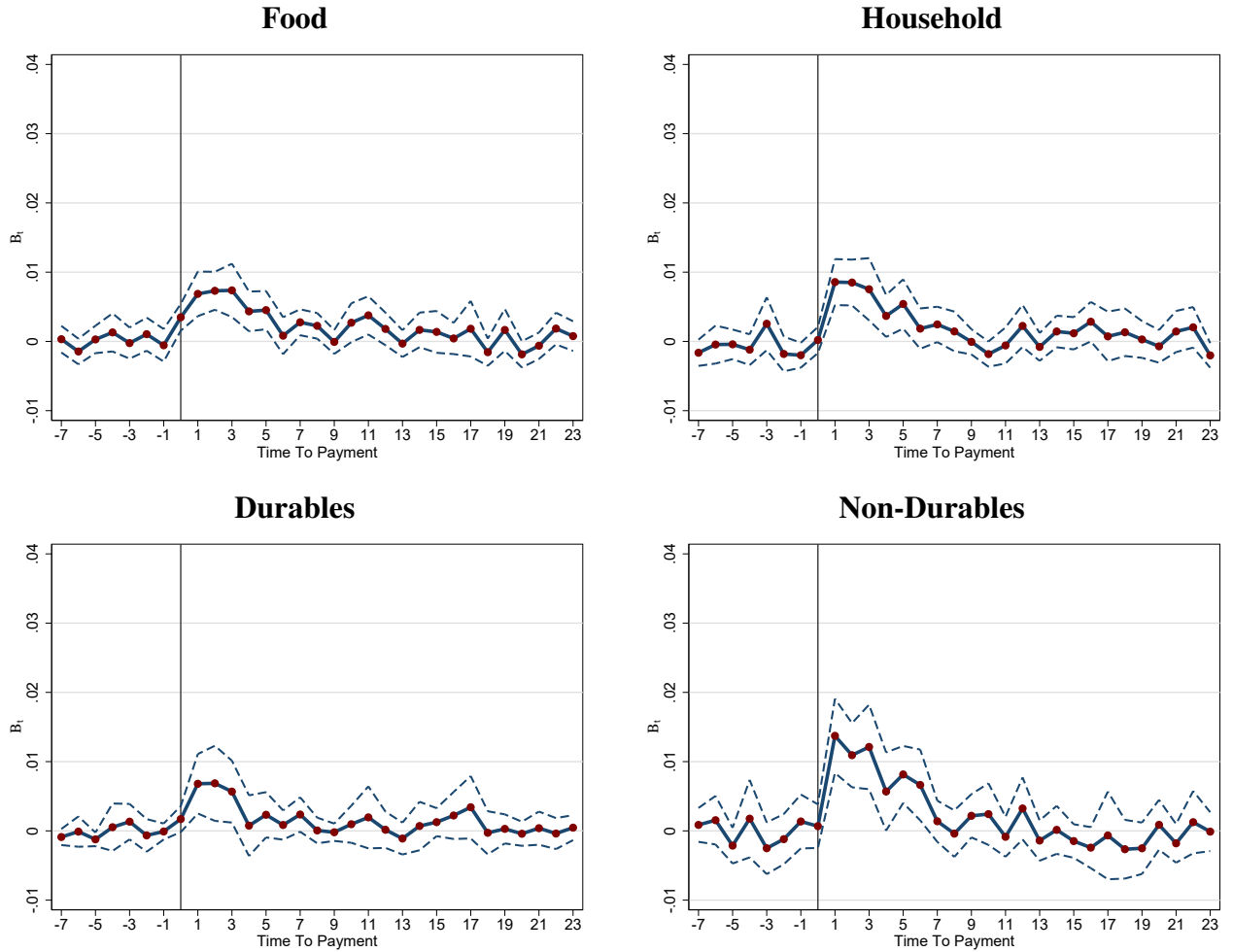
Figure 6: Payments and Transfers Around Stimulus

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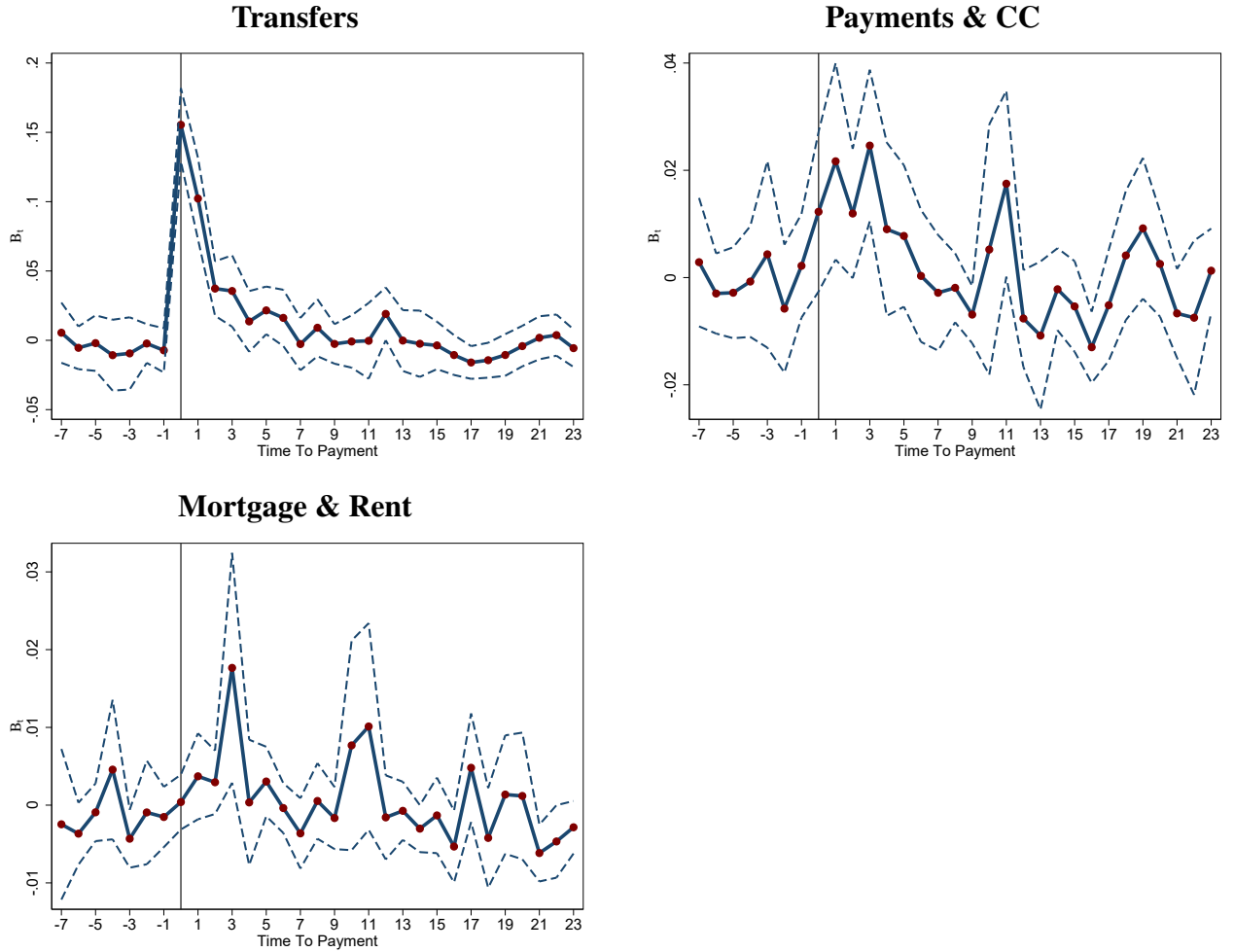
Figure 7: MPC by Income Groups

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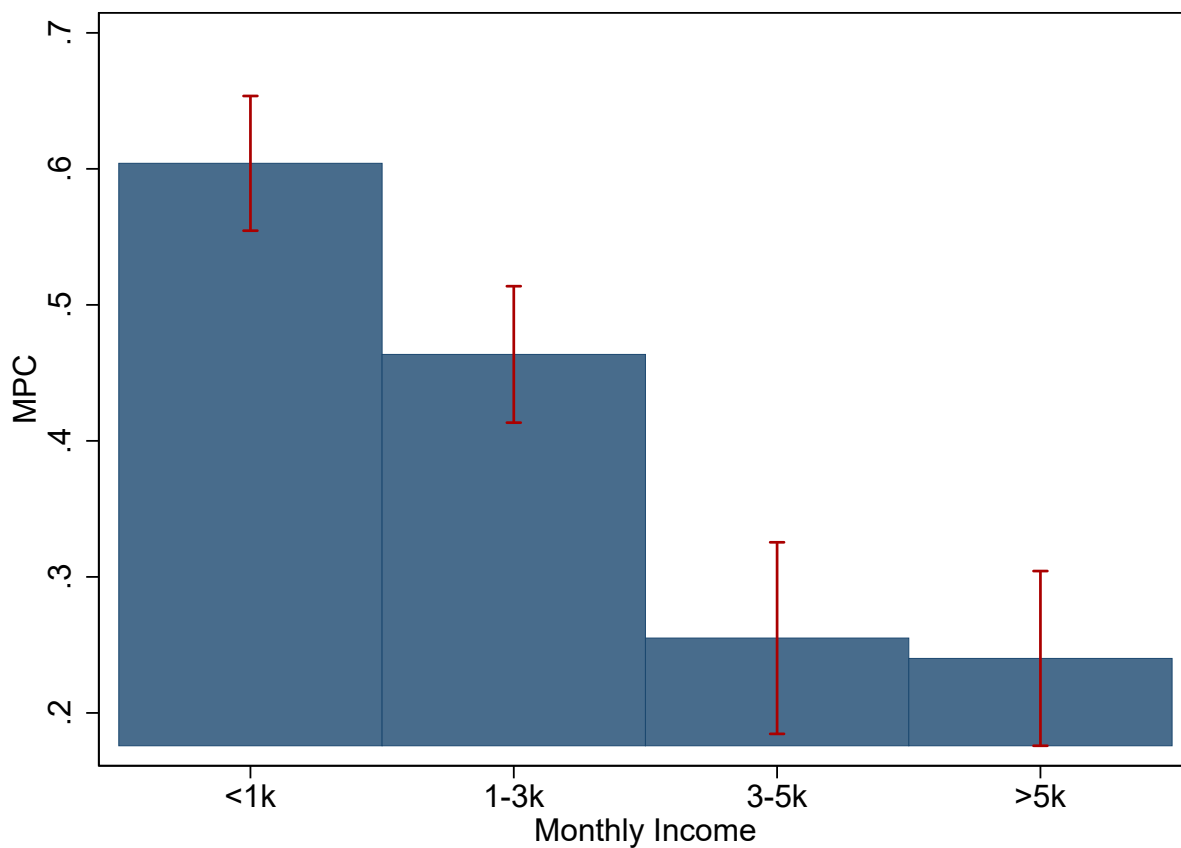
Figure 8: MPC by Liquidity

Notes: This figure shows cumulative 3-month MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. These coefficients correspond to ζ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \varepsilon_{it}$ (cumulative fraction of the stimulus check that has been spent), broken down by account balances. Date and individual fixed effects are included. The bars show point estimates, while the thin lines show 95% confidence interval. Source: SaverLife.
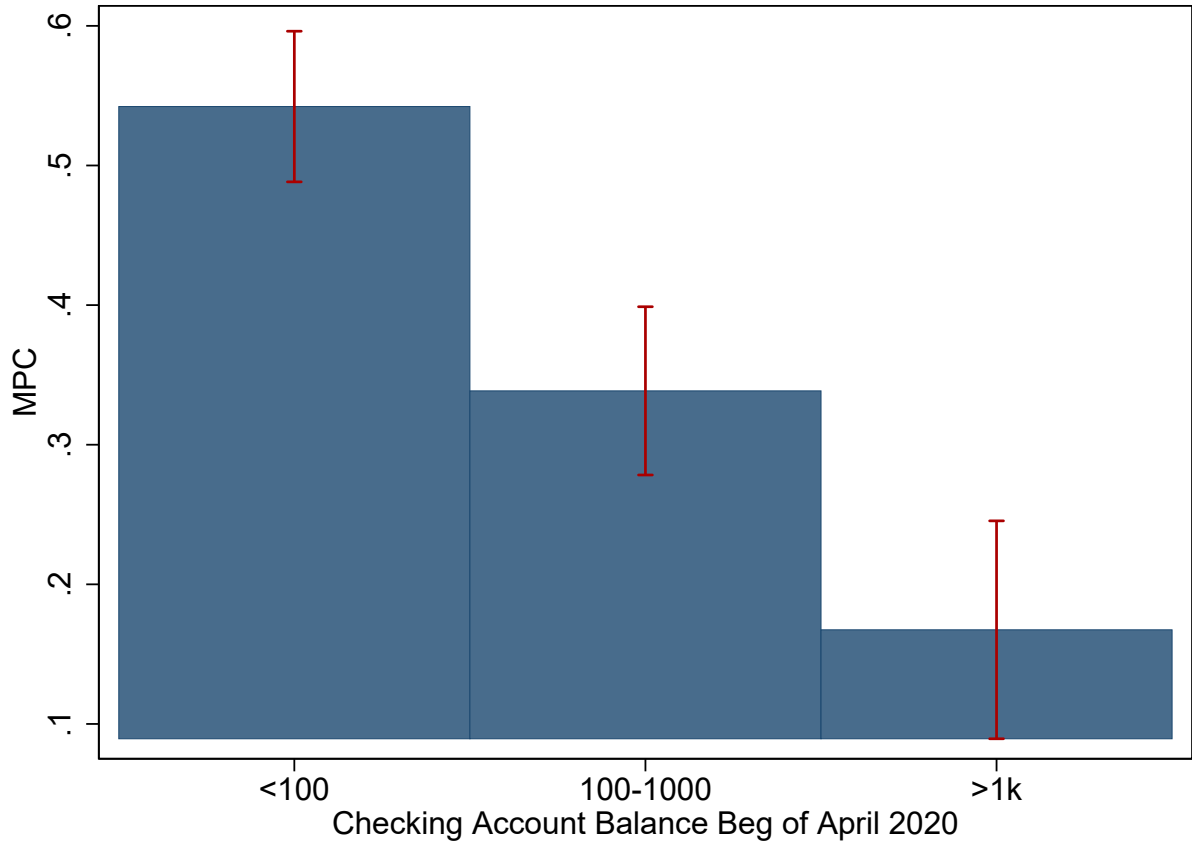
Figure 9: MPC by Drop in Income

Notes: This figure shows cumulative 3-month MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. These coefficients correspond to ζ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \varepsilon_{it}$ (cumulative fraction of the stimulus check that has been spent), broken down by the drop in income between January/February 2020 and March 2020. Date and individual fixed effects are included. The bars show point estimates, while the thin lines show 95% confidence interval. Source: SaverLife.
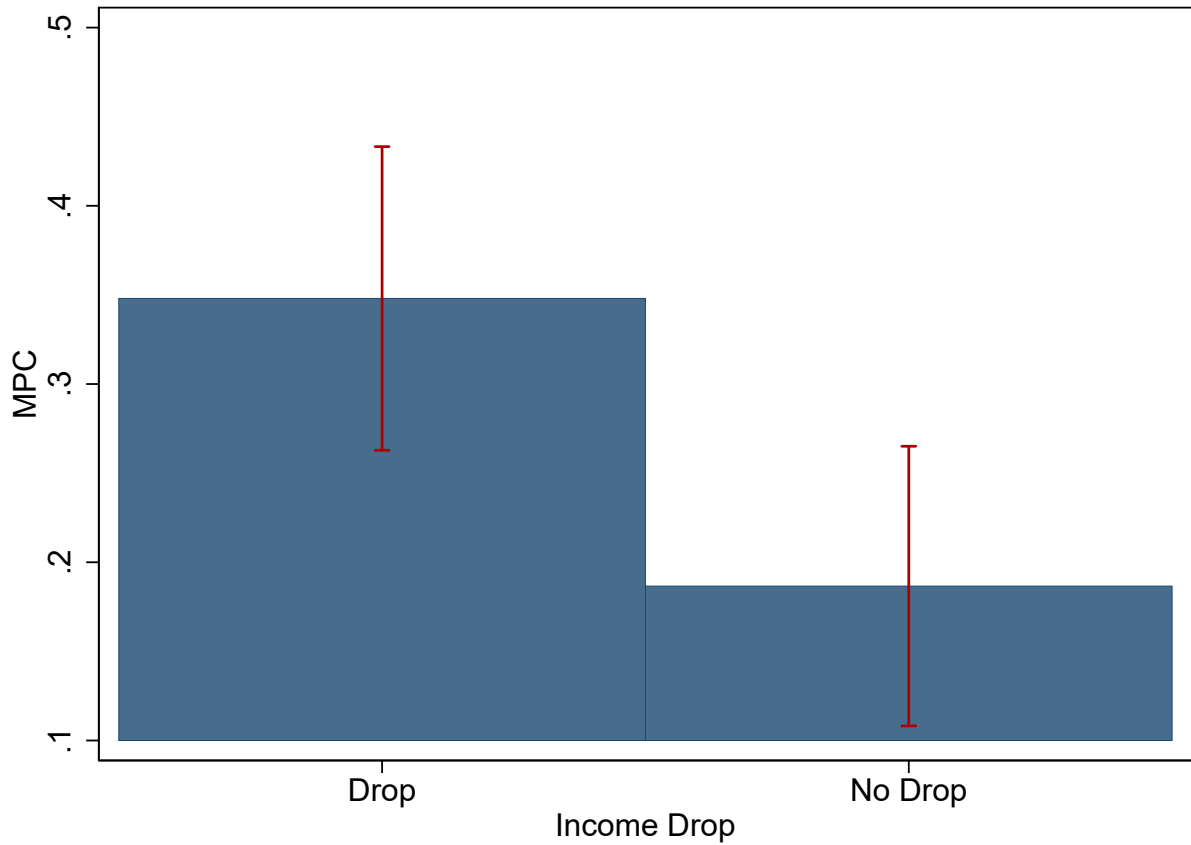
Table 1: Summary Statistics

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

Variable	# Obs.	Mean	10th	25th	Median	75th	90th
Monthly Income	254,206	2,988	140	740	2,152	4,301	6,772
Stimulus Income (Cond)	22,765	2,086	1,200	1,200	1,700	2,400	3,600
Annual Income (Self-reported)	57,378	32,009	450	9,000	25,000	45,000	80,000
Spending	254,206	2,157	25	260	1,192	3,026	5,545
Durables	254,206	46	0	0	0	11	131
Food	254,206	210	0	0	74	285	601
Household	254,206	180	0	0	58	258	522
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. For total spending, we run three specifications with varying fixed effects. We use individual by day of the month fixed effects, individual and calendar date and individual times day of month fixed effects, or individual and day of the month and individual times day of week fixed effects. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $*p < .1$, $**\ p < .05$, $***\ p < .01$. Source: SaverLife.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Total	Total	Total	Food	NonDurables	Household	Durables
Stimulus Payment	0.000882	0.00479**	0.00189	0.00585**	-0.000736	-0.00296	0.00103
	(0.00231)	(0.00230)	(0.00267)	(0.00295)	(0.00257)	(0.00221)	(0.000765)
Stimulus Payment$_{t+1}$	0.0287***	0.0310***	0.0264***	0.00586**	0.0239**	0.0132**	0.00605***
	(0.00394)	(0.00407)	(0.00472)	(0.00261)	(0.0112)	(0.00561)	(0.00210)
Stimulus Payment$_{t+2}$	0.0249***	0.0272***	0.0275***	0.00563***	0.0108***	0.00992**	0.00835**
	(0.00369)	(0.00363)	(0.00417)	(0.00167)	(0.00305)	(0.00485)	(0.00353)
Stimulus Payment$_{t+3}$	0.0263***	0.0288***	0.0175***	0.00591**	0.0221*	0.0133*	0.00714**
	(0.00539)	(0.00520)	(0.00513)	(0.00263)	(0.0132)	(0.00740)	(0.00363)
Stimulus Payment$_{t+4}$	0.0155***	0.0156***	0.0190***	0.00490**	0.00651*	0.00332	0.00123
	(0.00429)	(0.00404)	(0.00425)	(0.00193)	(0.00374)	(0.00246)	(0.00156)
Stimulus Payment$_{t+5}$	0.0244***	0.0180***	0.0256***	0.0141*	0.0117***	0.00888***	0.00340**
	(0.00505)	(0.00417)	(0.00545)	(0.00730)	(0.00414)	(0.00280)	(0.00156)
Stimulus Payment$_{t+6}$	0.00980**	0.00865**	0.0118***	0.00416	0.00640	0.0169	0.000188
	(0.00412)	(0.00426)	(0.00403)	(0.00307)	(0.00415)	(0.0143)	(0.00102)
Stimulus Payment$_{t+7}$	0.00947**	0.0129***	0.00858**	-0.000715	0.00776	0.0183	0.000367
	(0.00384)	(0.00378)	(0.00426)	(0.00140)	(0.00545)	(0.0156)	(0.000836)
Stimulus Payment$_{t+8}$	0.00751**	0.00880**	0.00522	0.00349	-0.0000900	0.00312	0.00321
	(0.00349)	(0.00348)	(0.00365)	(0.00301)	(0.00239)	(0.00312)	(0.00314)
Stimulus Payment$_{t+9}$	0.00204	0.00414*	0.00240	-0.00240**	0.00257	0.000108	-0.000683
	(0.00211)	(0.00240)	(0.00234)	(0.00106)	(0.00198)	(0.00160)	(0.000506)
Date FE	X	X	X	X	X	X	X
User FE	X	X	X	X	X	X	X
User*Day of Month FE		X					
User*Day of Week FE			X				
Observations	499945	499945	499945	499945	499945	499945	499945
R^2	0.202	0.306	0.515	0.100	0.062	0.094	0.039

Table 3: Stimulus Payments and Spending - MPC Horizons

In this table, we calculate the excess spending from the stimulus at varying time horizons. Each column regresses total spending on a post-stimulus dummy extending for the listed amount of time. Coefficients are fractions of stimulus spent within that window. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $*p < .1$, $** p < .05$, $*** p < .01$. Source: SaverLife.

	(1) Total	(2) Total	(3) Total	(4) Total	(5) Total
1-Week MPC	0.140*** (0.0124)				
2-Week MPC		0.190*** (0.0171)			
1-Month MPC			0.219*** (0.0254)		
2-Month MPC				0.286*** (0.0490)	
3-Month MPC					0.265*** (0.0757)
Date FE	X	X	X	X	X
Individual FE	X	X	X	X	X
Observations	523208	523208	523208	523208	523208
R^2	0.200	0.200	0.199	0.199	0.199

Table 4: Stimulus Payments and Spending - Robustness

These specifications mirror those in Table 2 but include two variants. In columns (2) and (5), we regression total excess spending from the stimulus on our unweighted sample of users. In columns (3) and (6) we include 'Payments' spending in the total spending which includes things like rent, mortgages, and loan payments. Standard errors are clustered at the user level. $*p < .1$, $** p < .05$, $*** p < .01$. Source: SaverLife.

	(1) Baseline	(2) Unweighted	(3) Add Payments	(4) Baseline	(5) Unweighted	(6) Add Payments
Stimulus Payment	0.000882	0.00695***	0.00577*			
	(0.00231)	(0.000835)	(0.00316)			
Stimulus Payment$_{t+1}$	0.0287***	0.0401***	0.0346***			
	(0.00394)	(0.00144)	(0.00449)			
Stimulus Payment$_{t+2}$	0.0249***	0.0353***	0.0280***			
	(0.00369)	(0.00395)	(0.00431)			
Stimulus Payment$_{t+3}$	0.0263***	0.0381***	0.0315***			
	(0.00539)	(0.00178)	(0.00563)			
Stimulus Payment$_{t+4}$	0.0155***	0.0317***	0.0197***			
	(0.00429)	(0.00155)	(0.00470)			
Stimulus Payment$_{t+5}$	0.0244***	0.0345***	0.0277***			
	(0.00505)	(0.00403)	(0.00565)			
Stimulus Payment$_{t+6}$	0.00980**	0.0115***	0.0103**			
	(0.00412)	(0.00223)	(0.00454)			
Stimulus Payment$_{t+7}$	0.00947**	0.00762***	0.00912**			
	(0.00384)	(0.00168)	(0.00372)			
Stimulus Payment$_{t+8}$	0.00751**	0.00595***	0.00860**			
	(0.00349)	(0.00101)	(0.00362)			
Stimulus Payment$_{t+9}$	0.00204	0.00407***	0.00169			
	(0.00211)	(0.000806)	(0.00259)			
Post-Stimulus*Stimulus				0.265***	0.368***	0.407***
				(0.0757)	(0.0254)	(0.0288)
Date FE	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X
Observations	499945	2115889	499945	523208	2221223	2221223
R^2	0.202	0.212	0.200	0.199	0.207	0.214

Table 5: Stimulus Payments, Spending and Income

This table shows cumulative 3-month MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. These coefficients correspond to ζ and ξ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \xi \frac{Post_{it} \times P_i}{D_{it}} \times I_i + \phi Post_{it} \times I_i + \varepsilon_{it}$. Average monthly income is approximately \$2,000, yielding a logged income value of 7.6. Columns (4) and (5) drop the interaction, and split the sample into the top and bottom quartiles of January and February monthly income. The inclusion of fixed effects is denoted beneath each specification. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. *$p < .1$, ** $p < .05$, *** $p < .01$. Source: SaverLife.

	(1) Total	(2) Total	(3) Total	(4) Low Inc	(5) High Inc
Post-Stimulus*Stimulus	2.024***	2.116***	2.126***	0.544***	0.257***
	(0.370)	(0.385)	(0.411)	(0.106)	(0.0960)
Post-Stimulus*Stimulus*ln(Inc)	-0.220***	-0.231***	-0.229***		
	(0.0456)	(0.0475)	(0.0502)		
Date FE	X	X	X	X	X
Individual FE	X	X	X	X	X
Individual X Day of Month FE		X			
Individual X Day of Week FE			X	X	X
Observations	517477	517477	517477	126317	145553
R^2	0.199	0.300	0.502	0.160	0.277

Table 6: Stimulus Payments, Spending and Liquidity

This table shows cumulative 3-month MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. These coefficients correspond to ζ and ξ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \xi \frac{Post_{it} \times P_i}{D_{it}} \times L_i + \phi Post_{it} \times L_i + \varepsilon_{it}$. The second row of columns (1) through (3) interacts with the individual's bank account balance prior to the arrival of the stimulus payment, in thousands of dollars. Columns (4) and (5) drop the interaction, and split the into the sample into the top and bottom half of account balances, with column (4) regressing over those with the lowest account balances. The inclusion of fixed effects is denoted beneath each specification. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $*p < .1$, $** p < .05$, $*** p < .01$. Source: SaverLife.

	(1) Total	(2) Total	(3) Total	(4) Low Bal	(5) High Bal
Post-Stimulus*Stimulus	0.598***	0.635***	0.551**	0.641***	0.216**
	(0.211)	(0.211)	(0.239)	(0.239)	(0.0939)
Post-Stimulus*Stimulus*Balance	-0.187***	-0.202***	-0.183**		
	(0.0618)	(0.0628)	(0.0717)		
Date FE	X	X	X	X	X
Individual FE	X	X	X	X	X
Individual X Day of Month FE		X			
Individual X Day of Week FE			X	X	X
Observations	429123	429123	429123	115080	152923
R^2	0.199	0.294	0.486	0.208	0.213

Table 7: Stimulus Payments, Spending and Income Declines

This figure shows cumulative 3-month MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. These coefficients correspond to ζ and ξ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \xi \frac{Post_{it} \times P_i}{D_{it}} \times D_i + \phi Post_{it} \times D_i + \varepsilon_{it}$. The second row of columns (1) through (3) interacts with the fraction of January and February income that an individual earned in March (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. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $*p < .1$, $** p < .05$, $*** p < .01$. Source: SaverLife.

	(1) Total	(2) Total	(3) Total	(4) Inc Drop	(5) No Drop
Post-Stimulus*Stimulus	0.248***	0.276***	0.215**	0.348***	0.187
	(0.0854)	(0.0871)	(0.0986)	(0.0940)	(0.117)
Post-Stimulus*Stimulus*Inc Drop	-0.0538	-0.0737**	-0.0269		
	(0.0352)	(0.0368)	(0.0385)		
Date FE	X	X	X	X	X
Individual FE	X	X	X	X	X
Individual X Day of Month FE		X			
Individual X Day of Week FE			X	X	X
Observations	504385	504385	504385	240924	263461
R^2	0.199	0.299	0.499	0.219	0.182

Table 8: MPCs and Expectations

This table shows cumulative 3-month MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment, and their interaction with surveyed beliefs. That is, of ζ and ζ' from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \zeta' \frac{Post_{it} \times P_i \times Belief_i}{D_{it}} + \omega \frac{Post_{it} \times Belief_i}{D_{it}} + \varepsilon_{it}$. The inclusion of fixed effects is denoted beneath each specification. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $*p < .1$, $** p < .05$, $*** p < .01$. Source: SaverLife.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						Total Spending						
Post-Stimulus X Stimulus	0.246***	0.242***	0.238***	0.229***	0.186***	0.178***	0.147***	0.142**	0.252***	0.243***	0.227***	0.219***
	(0.0704)	(0.0709)	(0.0396)	(0.0410)	(0.0486)	(0.0485)	(0.0551)	(0.0557)	(0.0590)	(0.0593)	(0.0479)	(0.0475)
Post-Stimulus X Stimulus X Stock	-0.333***	-0.335***										
	(0.114)	(0.115)										
Post-Stimulus X Stimulus X Unemployed			-0.281***	-0.276***								
			(0.0696)	(0.0725)								
Post-Stimulus X Stimulus X Salary Cut					-0.231**	-0.229**						
					(0.0957)	(0.0974)						
Post-Stimulus X Stimulus X Higher Taxes							-0.127	-0.130				
							(0.0946)	(0.0965)				
Post-Stimulus X Stimulus X Benefit Cuts									-0.255***	-0.249***		
									(0.0756)	(0.0772)		
Post-Stimulus X Stimulus X Pessimistic											-0.202***	-0.200***
											(0.0759)	(0.0767)
Date FE	X	X	X	X	X	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X	X	X	X	X	X
Individual X Day of Week FE		X		X		X		X		X		X
Observations	100064	100064	100064	100064	100064	100064	100064	100064	100064	100064	100064	100064
R^2	0.314	0.381	0.315	0.381	0.314	0.381	0.314	0.381	0.314	0.381	0.314	0.381

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.5 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.6, 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.7). 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

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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.3 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)

Table A.2: Stimulus Payments and Spending: Robustness

This table shows cumulative 3-month MPCs estimated from coefficients from regressions of spending on an indicator of a time period being after a stimulus payment, scaled by the amount of the payment over the number of days since the payment. These coefficients correspond to ζ and ξ from $c_{it} = \alpha_i + \alpha_t + \zeta \frac{Post_{it} \times P_i}{D_{it}} + \xi \frac{Post_{it} \times P_i}{D_{it}} \times I_i + \phi Post_{it} \times I_i + \varepsilon_{it}$. Column (1) shows the baseline estimate. In Columns (2) to (6), we interact the post*stimulus variable $\frac{Post_{it} \times P_i}{D_{it}}$ with an indicator for whether a user signed up to the app before April 1, 2020, is a survey respondent, particpated in the most recent savings challenge, was more rewarded for savings than the median user, or earns more than 6,500 USD per month in income. In Columns (7) and (8), we restrict the samples to users for whom we received a data update after April 1, 2020 or to users who passed additional completeness-of-records checks, namely had more than 15 days per month in which they spend in common categories and had more than 2,000 USD per month in spending and income. The inclusion of fixed effects is denoted beneath each specification. All estimates are weighted at a user level by age, sex, income, and state of residence to match CPS aggregate figures for 2019. Standard errors are clustered at the user level. $*p < .1$, $** p < .05$, $*** p < .01$. Source: SaverLife.

	(1) Baseline	(2)	(3)	(4)	(5)	(6)	(7) Recently Updated	(8) Complete Records
Post-Stimulus*Stimulus	0.265***	0.257***	0.280***	0.281***	0.285***	0.471***	0.265***	0.243**
	(0.0757)	(0.0675)	(0.0664)	(0.0854)	(0.0845)	(0.0986)	(0.0757)	(0.0972)
Early Sign-up *Post-Stimulus*Stimulus		0.0260 (0.187)						
Survey Respondent *Post-Stimulus*Stimulus			-0.161 (0.422)					
Savings Challenge Participant *Post-Stimulus*Stimulus				-0.0814 (0.127)		-0.0552 (0.163)		
Highly Rewarded Saver *Post-Stimulus*Stimulus					-0.112 (0.131)			
High-Income Individual *Post-Stimulus*Stimulus						-0.512*** (0.155)		
Savings Challenge Participant *High-Income Individual *Post-Stimulus*Stimulus						-0.0424 (0.264)		
Date FE	X	X	X	X	X	X	X	X
Individual FE	X	X	X	X	X	X	X	X
Observations	523208	523208	523208	523208	523208	523208	496682	282329
R^2	0.199	0.199	0.199	0.199	0.199	0.199	0.198	0.196

Table A.3: Comparison to Safegraph Data

This table uses consumer spending data at both an aggregated and categorical level from two data sources. The first is our sample of consumers from SaverLife. The second is from Safegraph, a data provider with access to transactions from millions of debit and other payment cards within the US. Data are aggregated to weekly levels and sample runs from January 2020 to August 2020. The inclusion of fixed effects is denoted beneath each specification. Saverlift data is aggregated based on user weights at an age, sex, income, and state of residence to match CPS aggregate figures for 2019.*$p < .1$, ** $p < .05$, *** $p < .01$. Source: SaverLife and Safegraph.

VARIABLES	(1) ln(Aggregate Safegraph Spending)	(2) ln(Categorical Safegraph Spending)
ln(Aggregate Saverlife Spending)	1.307***	
	(0.359)	
ln(Categorical Saverlife Spending)		1.043***
		(0.146)
Observations	32	160
R^2	0.307	0.561
Category FE	NO	YES

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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.
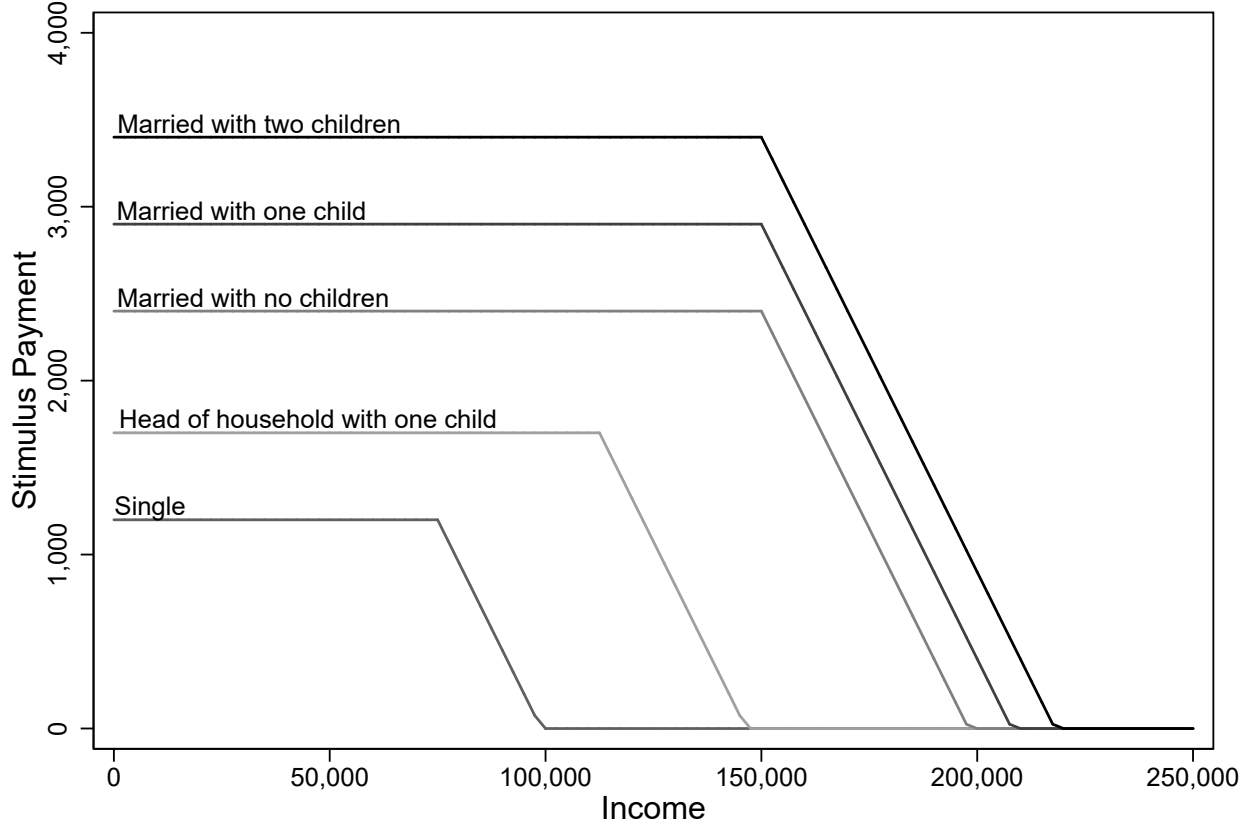
Figure A.2: Consumer Spending Comparison to Affinity Data

Notes: This figure depicts changes in consumer spending relative to January and February 2020 from two sources. The first is our sample of consumers (weighted by demographics to match US national averages) from SaverLife. The second is from Affinity Solutions, a data provider that captures credit and debit card transaction data from about 10% of the US population.
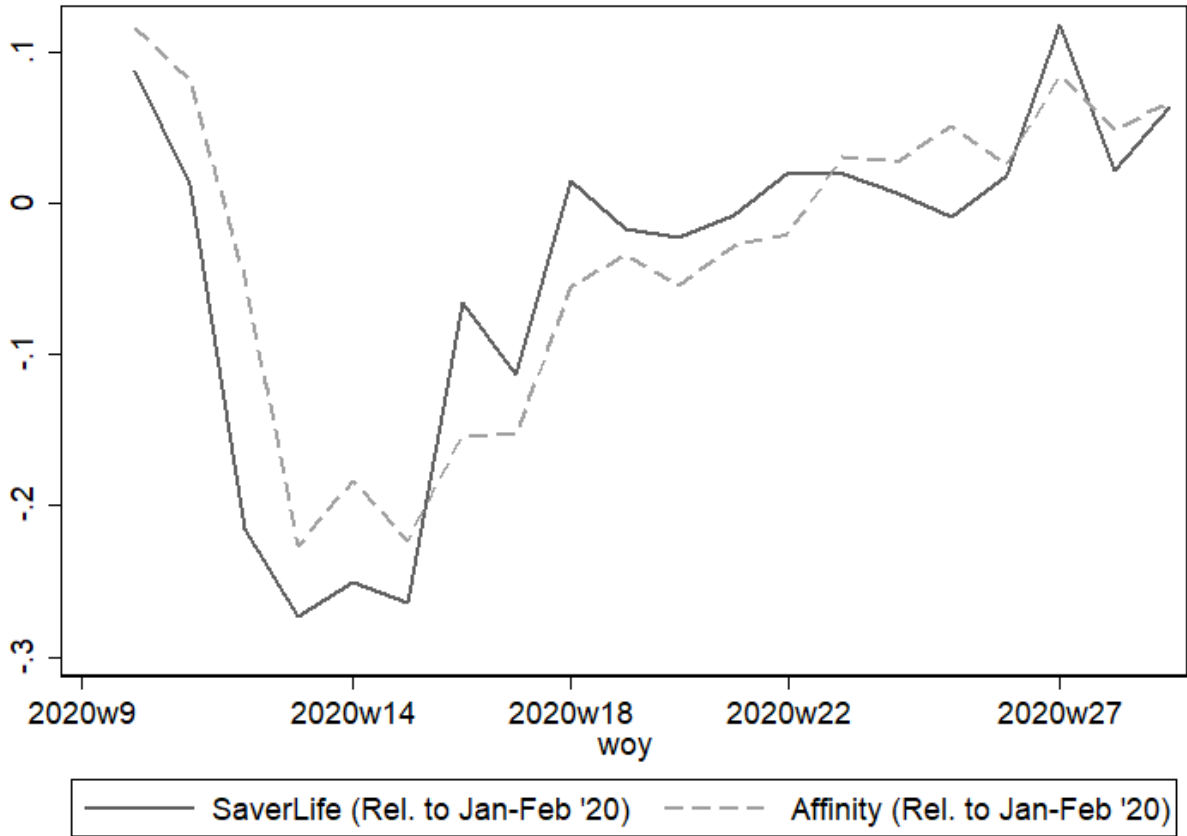
Figure A.3: Mean Spending in April for Individuals Not Receiving Payment- Raw Spending

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.
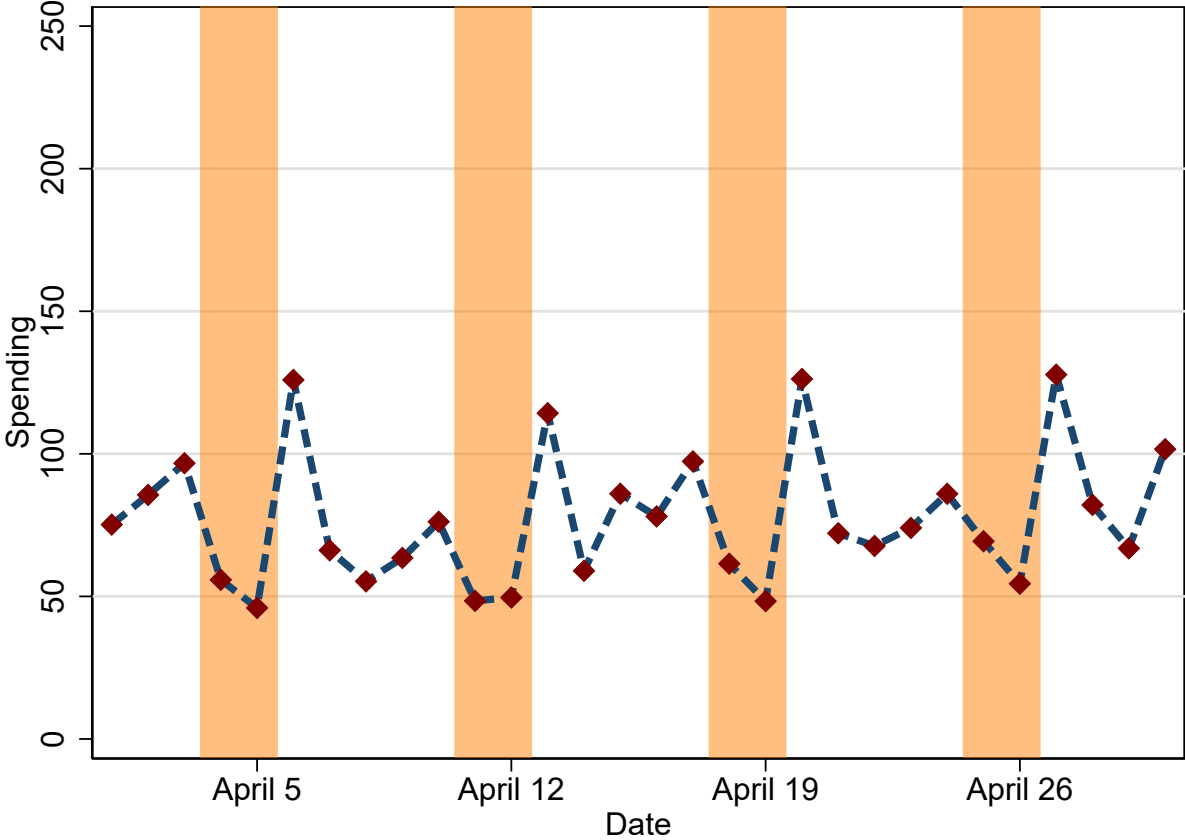
Figure A.4: Spending Around Stimulus Payments - Regression Estimates (Long Pretrends)

Notes: This figure shows a version of Figure 4 with longer pre-trends. This figure shows estimates of β_k from $c_{it} = \alpha_i + \alpha_t + \sum_{k=-23}^{23} \beta_k \mathbb{1}[t = k]_{it} + \varepsilon_{it}$. 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 A.5: 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.

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Figure A.6: 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.
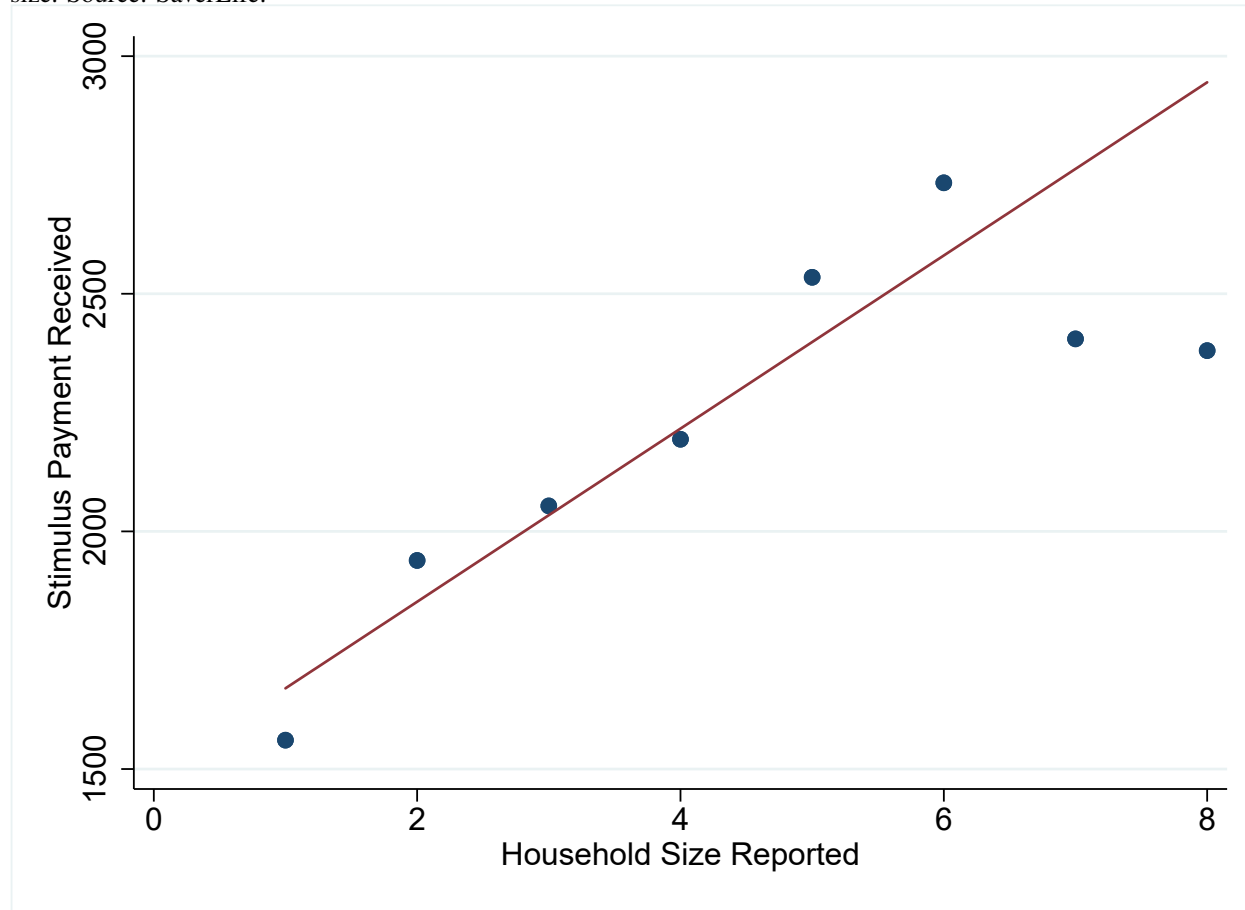
Figure A.7: Timeline of Stimulus Payouts

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

	Apr 13	Apr 20	Apr 27	May 4	May 11	May 18	May 25	Jun 1	...	Aug 28
Taxpayers (145-150 mil eligible people)										
IRS with website to collect direct deposit information			Apr 28 – May 13							
Direct deposits for all eligible individuals with direct deposit information on file	80 mil	Weekly rounds of direct deposits as information gets to IRS								
Distribution of stimulus checks		5 mil checks a week starting with the lowest income. Send to those with no direct deposit information on file by May 13								
Social security beneficiaries & SSI recipients (24-45 mil eligible people)										
Direct deposits to SSDI beneficiaries and SSI recipients				99% of all eligible						
Distribution of stimulus checks						Remainder receives stimulus by paper checks				
Total payouts										
	Mar 27 Enactment CARES Act	Apr 18 80 mil received stimulus		May 8 130 mil received stimulus		May 22 152 mil received stimulus				

B   Survey Details and Results

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.

1→ What's the likelihood of the following...

b. You will be unemployed *

Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain.

Type your answer here...

8% completed   Powered by **Typeform**

1→ What's the likelihood of the following...

c. You will have a lower salary *

Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain.

Type your answer here...

17% completed   Powered by **Typeform**

1→ What's the likelihood of the following...

d. You will pay more in taxes *

Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain.

Type your answer here...

25% completed   Powered by **Typeform**

1→ What's the likelihood of the following...

e. You will receive lower government benefits *

Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain.

Type your answer here...

33% completed   Powered by **Typeform**

2→ We are currently in an economic crisis driven by the Coronavirus outbreak. When do you think the economy will return to a more normal state (e.g. as it was in 2019)? *

A   3 months

B   6 months

C   1 year

D   More than 2 years

E   Never

42% completed   Powered by **Typeform**

3→ Did you experience any of the following over the past 2 months? Check all that apply. *

Choose as many as you like

A   Difficulty in purchasing enough food for the family

B   Difficulty in paying rent/mortgages

C   Difficulty in paying medical bills

D   Difficulty in paying for other items or services

E   Difficulty in obtaining credit or a loan

F   Anxiety or stress

50% completed   Powered by **Typeform**

60

Figure B.1: SaverLife Survey (continued)

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

1→ What's the likelihood of the following...

a. Stock prices in the U.S. stock market will be higher than they are now. *

Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain.

Type your answer here...

0% completed   Powered by **Typeform**

4→ Have you obtained a new credit card, home equity line of credit, or loan in the past 12 months? *

A No

B Yes

58% completed   Powered by **Typeform**

5→ Which one? (check all that apply)
*

Choose as many as you like

A New Credit Card

B Home Equity Line of Credit

C Bank Loan

D Other

62% completed   Powered by **Typeform**

7→ What will you use your Economic Stimulus check from the government for?

Select one answer for each of the following questions.

OK, let's go!

a. Paying past due or unpaid rent/mortgages/bills *

A Most of the check amount

B Part of the check amount

C None of the check amount

b. Paying current rent/mortgages/bills *

A Most of the check amount

B Part of the check amount

C None of the check amount

61

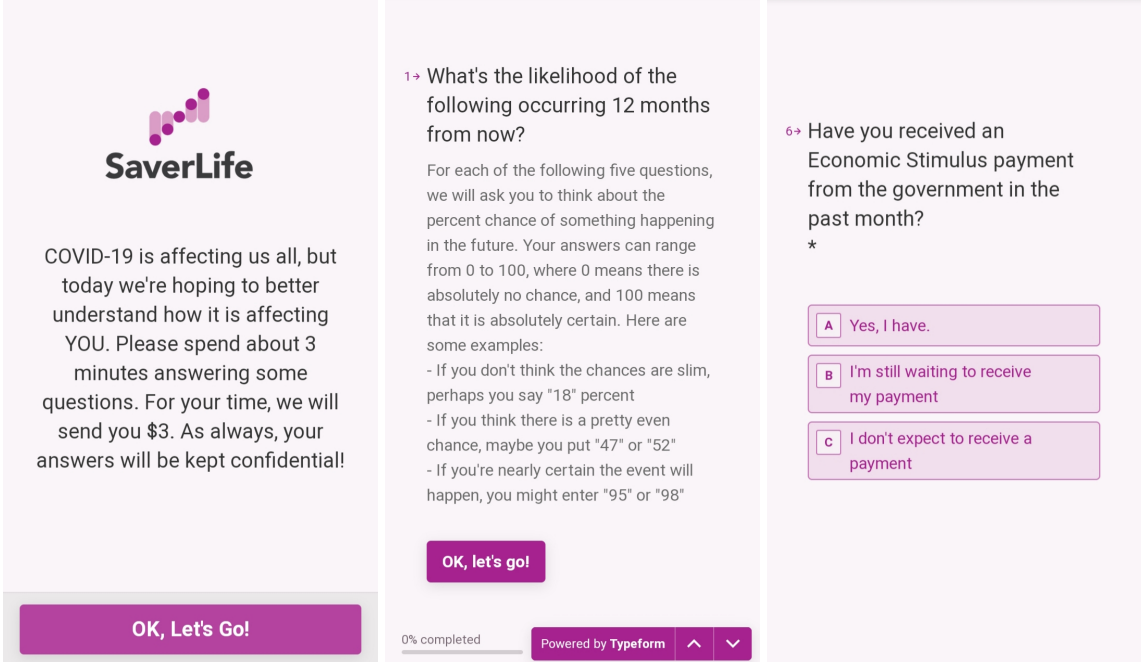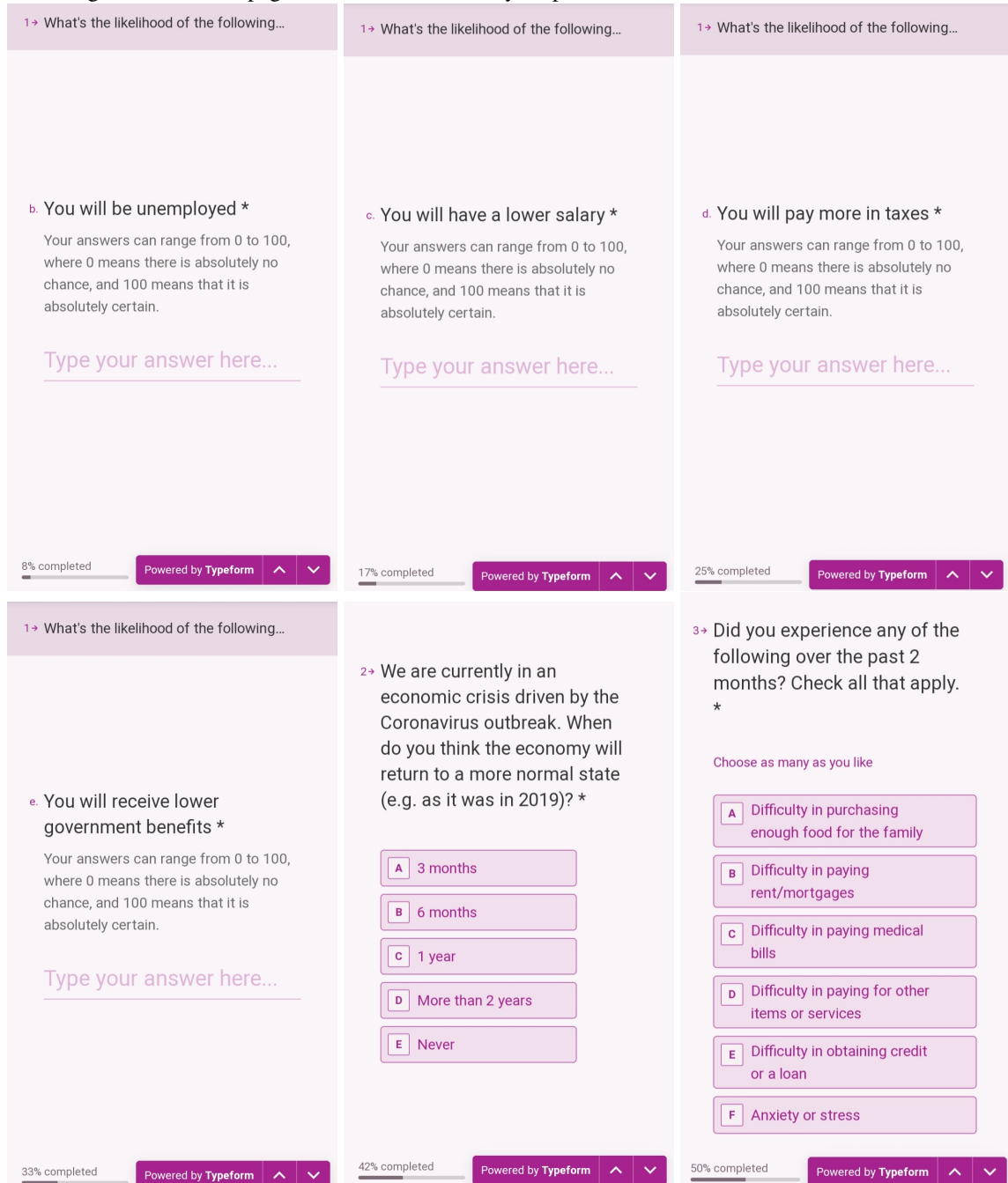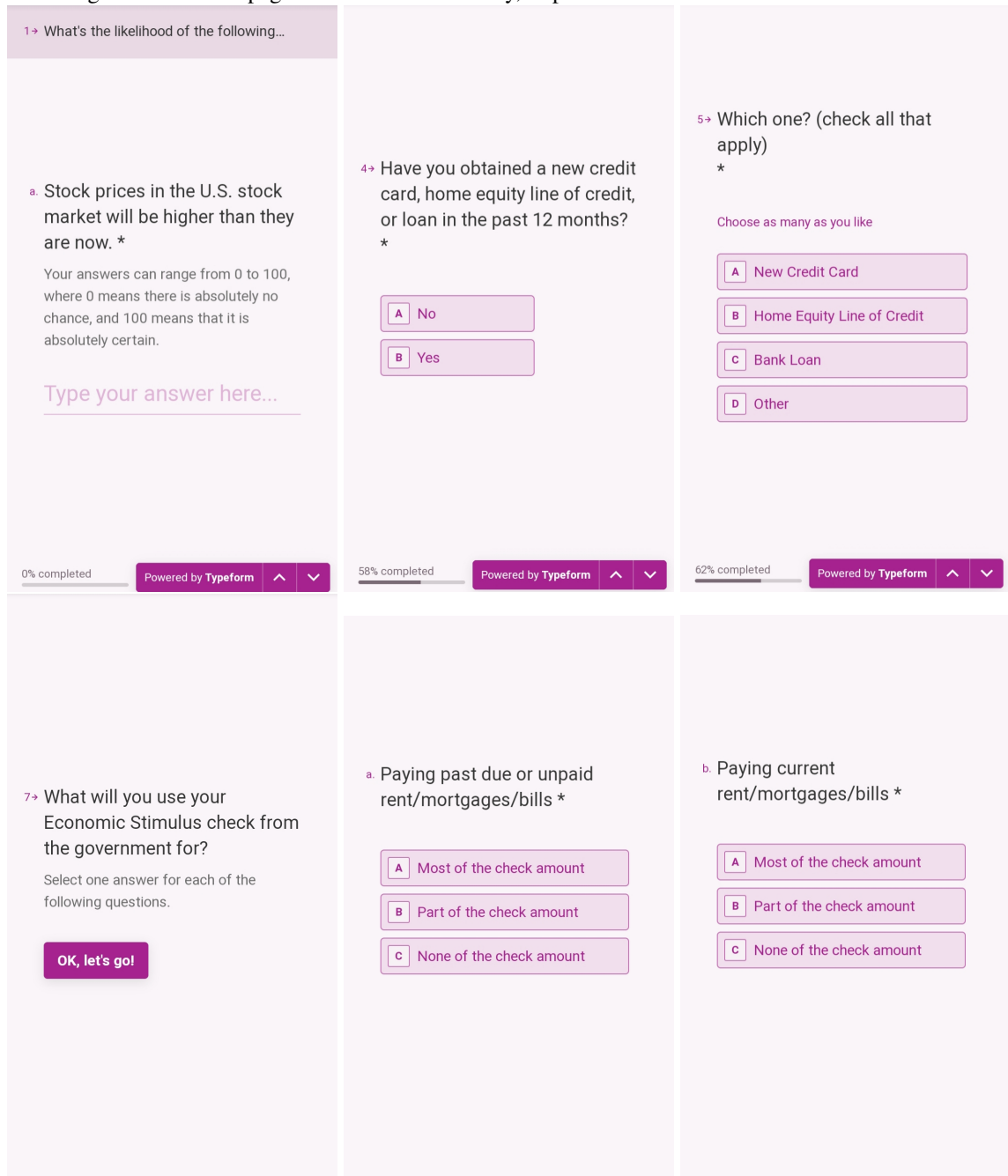**Figure B.1: SaverLife Survey** (continued)

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

c. Food or other goods to use immediately *

- **A** Most of the check amount
- **B** Part of the check amount
- **C** None of the check amount

d. Durable goods like furniture, electronics, appliances, or a car *

- **A** Most of the check amount
- **B** Part of the check amount
- **C** None of the check amount

e. Savings *

- **A** Most of the check amount
- **B** Part of the check amount
- **C** None of the check amount

8→ What is your political affiliation? *

- **A** Very Liberal
- **B** Liberal
- **C** Somewhat Liberal
- **D** Moderate
- **E** Somewhat Conservative
- **F** Conservative
- **G** Very Conservative
- **H** I prefer not to disclose

9→ Ok, that's it! Time to let us know where we should send your $3. Please type *the email address associated with your PayPal account.* *

It must be the email address you use to log in to PayPal.

somebody@example.com

10→ Great! Please confirm that your PayPal account email address is _____ by typing it in again. *

It must be the email address you use to log in to PayPal.
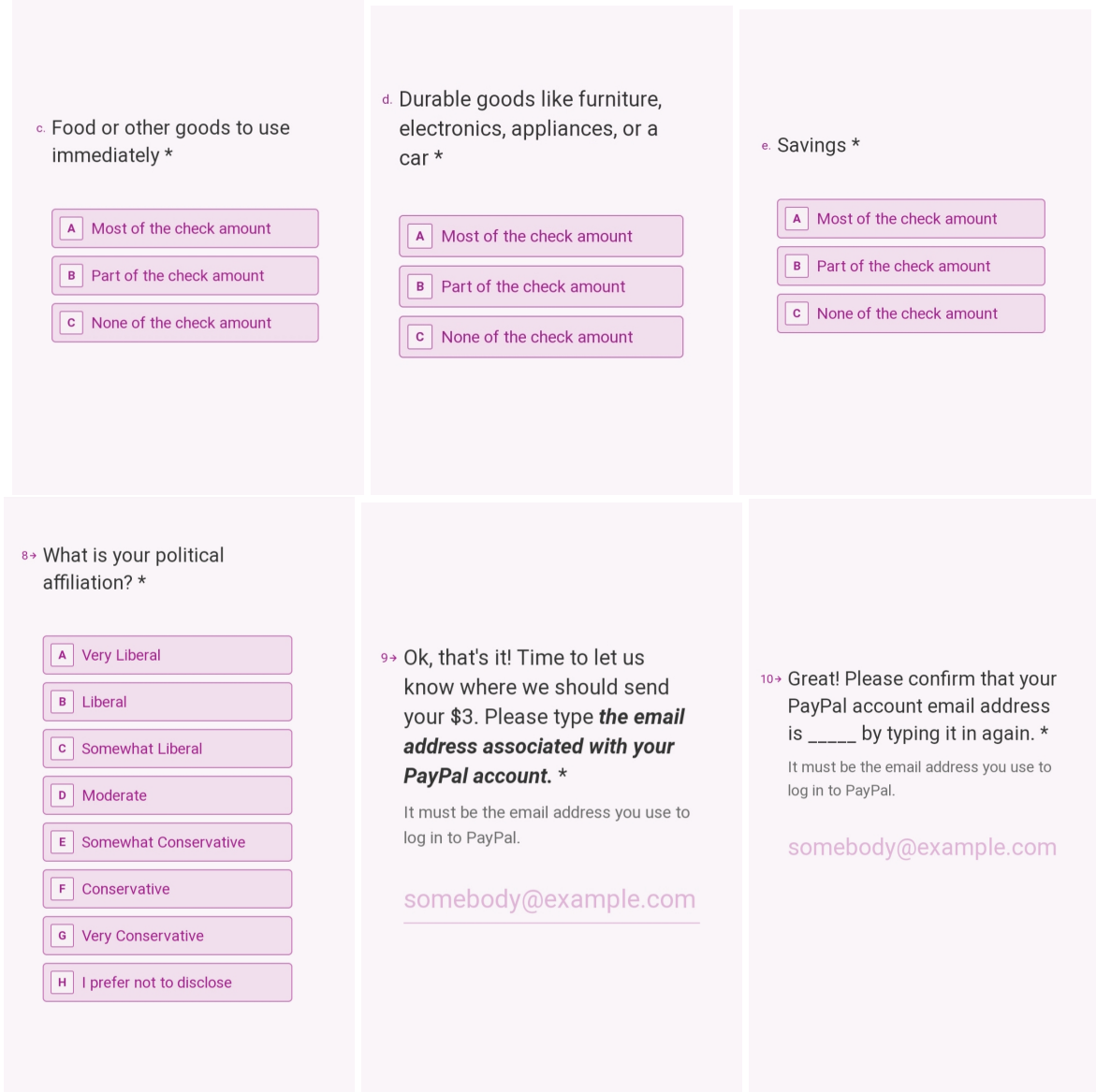
somebody@example.com

Figure B.2: SaverLife Survey Results: Stimulus Checks

Notes: This figure shows survey responses to the pandemic, financial hardship, credit, and political orientation questions.
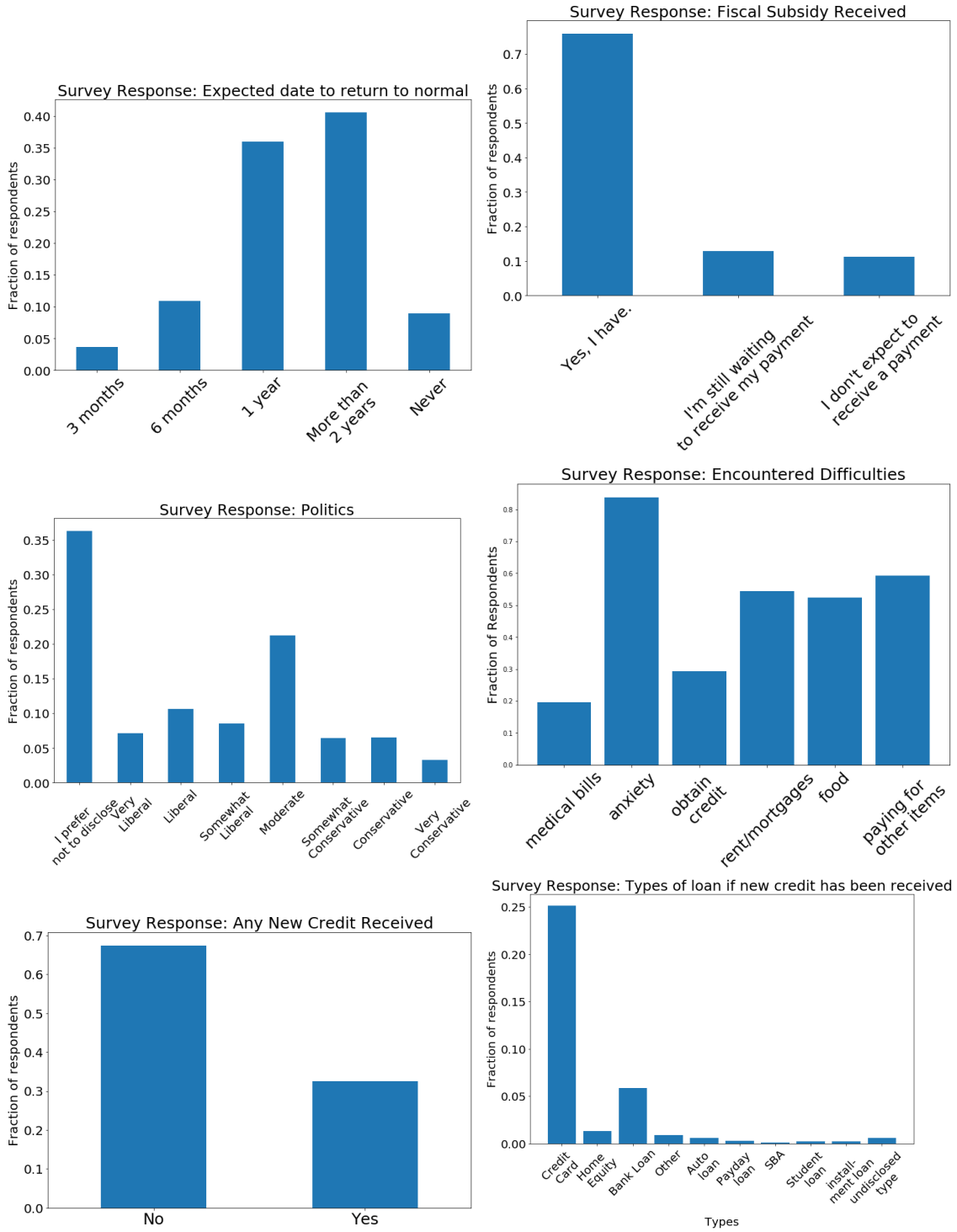
Figure B.3: SaverLife Survey Results: Stimulus Checks

Notes: This figure shows survey responses to the fiscal stimulus use questions.
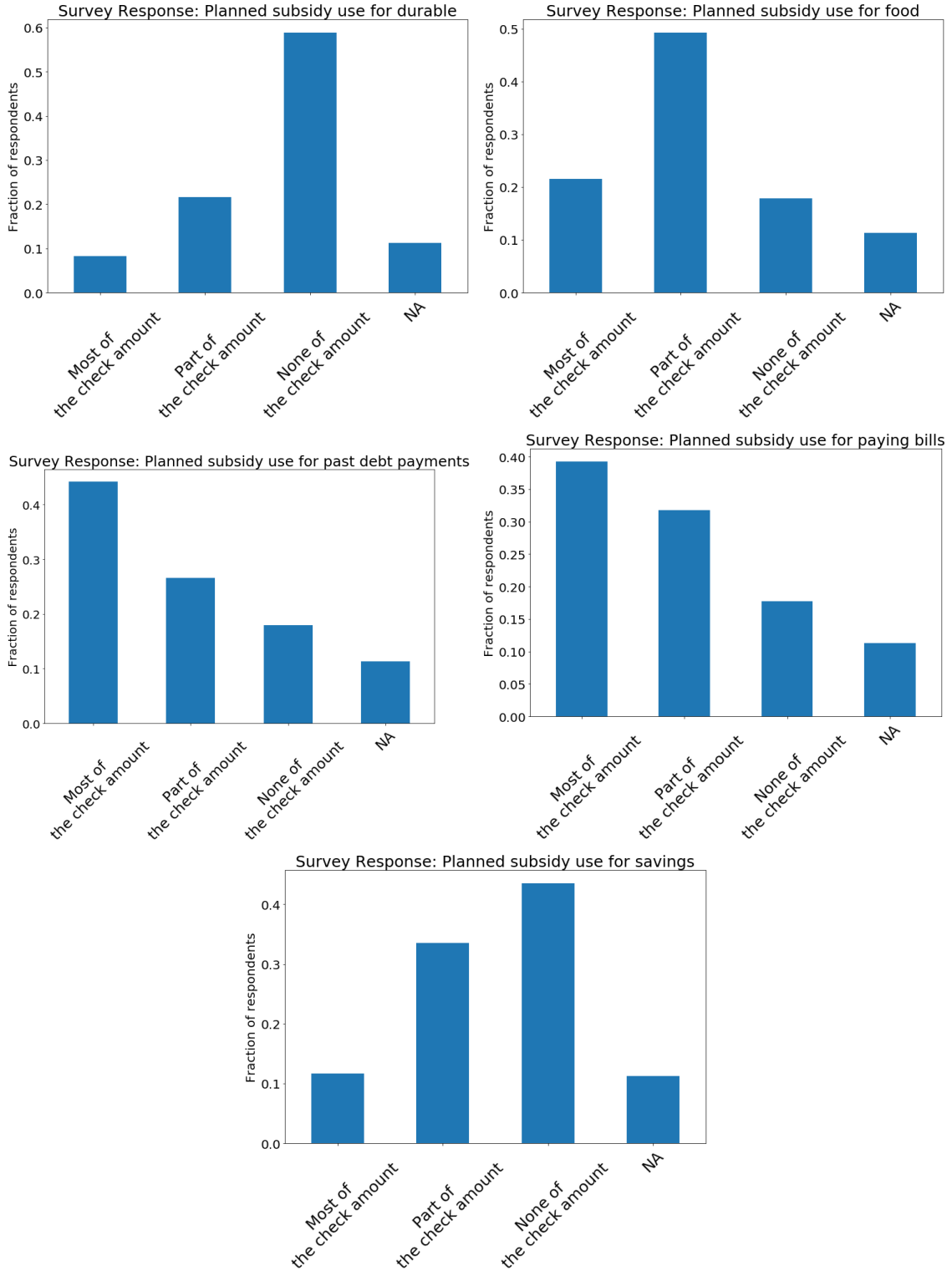
Figure B.4: SaverLife Survey Results: Expectations

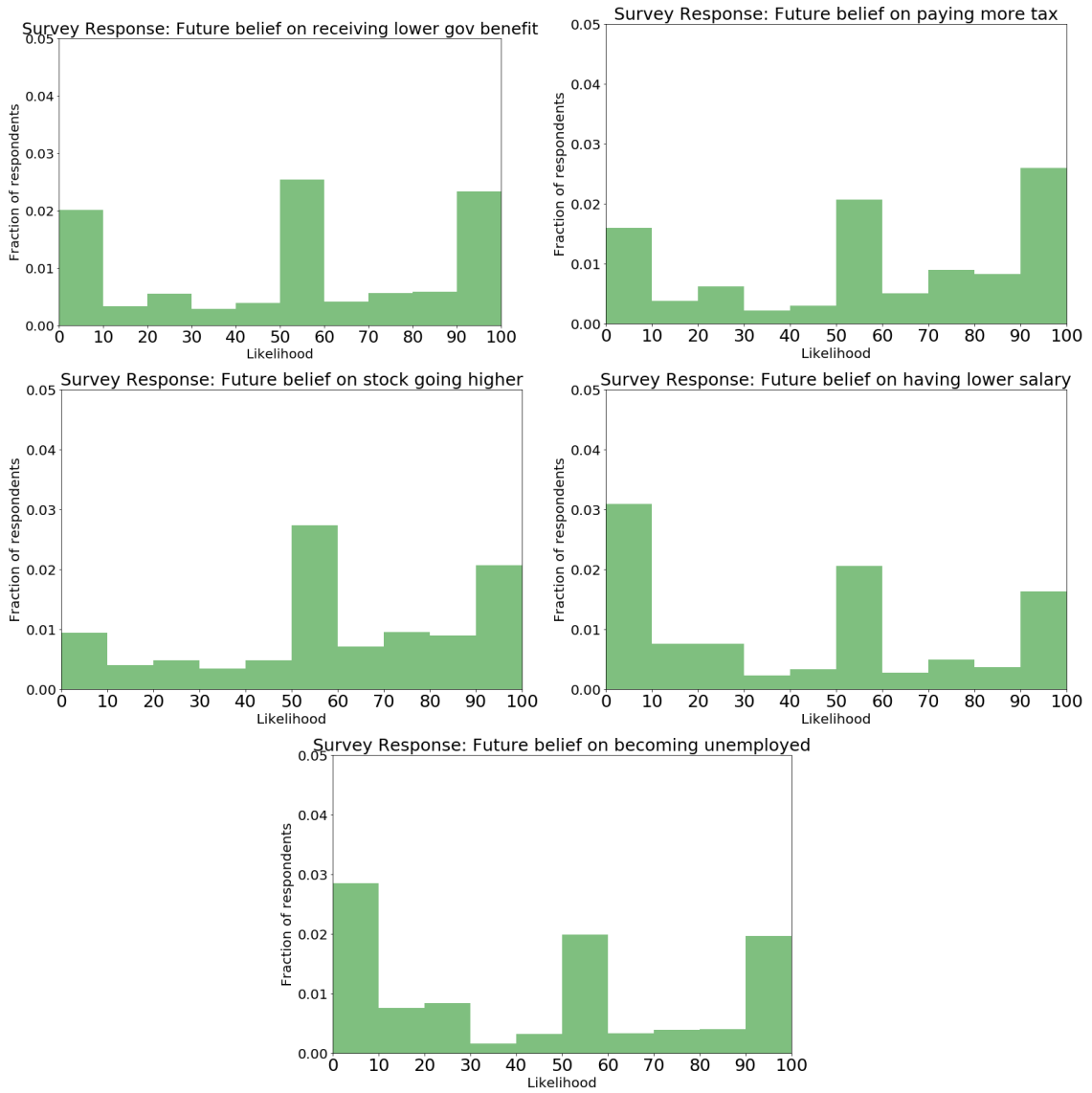Notes: This figure shows survey responses to the expectations questions.

Figure B.5: Correlation Between Survey Beliefs

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

Stock Market Inc. & Unemployed

Stock Market Inc. & Salary Cut

Tax Increase & Benefit Cut

Unemployed & Salary Cut