How Does Household Spending Respond to an Epidemic? Consumption during the 2020 COVID-19 Pandemic*

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Abstract

Utilizing transaction-level financial data, we explore how household consumption responded to the onset of the COVID-19 pandemic. As case numbers grew and cities and states enacted shelter-in-place orders, Americans began to radically alter their typical spending across a number of major categories. In the first half of March 2020, individuals increased total spending by over 40% across a wide range of categories. This was followed by a decrease in overall spending of 25%–30% during the second half of March coinciding with the disease spreading, with only food delivery and grocery spending as major exceptions to the decline. Spending

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responded most strongly in states with active shelter-in-place orders, though individuals in all states had sizable responses. We find few differences across individuals with differing political beliefs, but households with children or low levels of liquidity saw the largest declines in spending during the latter part of March. (*JEL* D14, E21, G51)

Epidemics have plagued human societies since at least the earliest days of recorded history. This paper presents the first study of how consumption and debt respond to an outbreak using transaction-level financial data. As COVID-19 began to spread across the United States in March 2020, households were faced with drastic changes in many aspects of their lives. Large numbers of businesses were closed by government decree, and in many cities and states, Americans were advised under shelter-in-place orders to limit trips outside and their exposure to others.

While Americans adjusted their daily and work routines in response to uncertainty about the future, they also rapidly altered how and where they spent their money. This paper deploys transaction-level financial data to provide a better and more comprehensive explanation of how household spending shifted as news about the virus was disseminated and the impact of the virus in a given geographic area became more severe and far reaching.

The extent to which both individuals and the economy at large have been upended is without recent precedent. Entire industries and cities have been largely shut down, with estimates of the decline in economic activity hitting all-time records. Policy makers at all levels of government and across a wide range of institutions have been working to mitigate the economic harm on individuals and small businesses. However, the speed at which the economic dislocation is occurring has made it difficult for policy makers to properly target fiscal stimuli to individuals and credit provision to businesses. After all, little is known about how individuals change their spending habits during a pandemic on a scientific basis and across a larger number of individuals and geographies.

This paper aims to close this gap by utilizing transaction-level individual financial data to analyze the impact of the COVID-19 outbreak on the spending behavior of tens of thousands of Americans. We use transaction-level data from linked bank accounts from SaverLife that works with individuals to sustain savings habits. Transaction-level financial data is a useful tool for understanding individual financial behavior at a granular level. The context of COVID-19 allows for a high-speed, dynamic, and timely investigation of how individuals have adjusted their spending, when they began to respond to the pandemic, and which individual characteristics are associated with the fastest and strongest response.[1]

News media reported that customers emptied supermarket shelves in an effort to stockpile

[1]Researchers have previously employed a range of transaction-level individual financial data sets in their analyses to answer questions about consumption, liquidity, savings, and investment decisions. See Baker (2018), Baker and Yannelis (2017), Olafsson and Pagel (2018), Baker, Kueng, Meyer and Pagel (2020), and Meyer and Pagel (2019).

durable goods. Furthermore, as advice flowed out from federal and state governments, one common refrain was that households should prepare to mostly stay inside their homes for multiple weeks and limit trips outside. Home production is thus a source of savings that households can engage in which should also increase their spending at certain stores as opposed to others.

We find that individuals substantially changed their spending as news about the COVID-19's impact in their area spread. Overall, spending increased dramatically in an attempt to stockpile needed home goods and also in anticipation of the inability to patronize retailers. Spending increases by over 40% overall between February 26 and March 10 relative to the earlier weeks in 2020. Grocery spending remained elevated through March 31, with a 10.4% increase relative to earlier in the year. We also see an increase in card spending, which is consistent with individuals borrowing to stockpile goods. As the virus spread and more individuals stayed home, we see sharp drops in spending of about 25%–30%. These declines are most concentrated in travel, entertainment, and restaurant spending. While nearly all categories experienced large declines during this period, spending at grocery stores and on food delivery increased significantly relative to early in the year.

Restaurant spending declined by approximately one-third. The speed and timing of these increases in spending varied significantly across individuals depending on their geographic location as state and local governments reacted to outbreaks of different sizes and with different levels of urgency. The overall drop in spending is approximately twice as large in states that issued shelter-in-place orders; however, the increase in grocery spending is three times as large for states with shelter-in-place orders.

We also explore heterogeneity among partisan affiliations and demographics, which are closely tied to stated beliefs about the impacts of the new virus. Republicans generally reported less concern about the new virus. For example, an Axios Poll between March 5 and 9 found that 62% of Republicans thought that the COVID-19 risk was greatly exaggerated, whereas 31% of Democrats and 35% of Independents thought the same. A Quinnipac poll between March 5 and 8 also found that 68% of Democrats were concerned, whereas only 35% of Republicans were concerned. Barrios and Hochberg (2020) find that partisanship played a significant role in shaping risk perceptions about the new pandemic. Contrary to much of what was covered in the press, and despite lower levels of observed social distancing, we find little evidence of strong differential spending across individuals with different political beliefs.

We see significant heterogeneity along demographic characteristics, but little along individual income. Individuals with children stockpiled more, and men tended to stockpile less in early days as the virus was spreading. We find more spending in later periods by the young, consistent with reporting that younger Americans tended to not obey the shelter-in-place orders as rigidly as older Americans.

This paper joins a large literature on household consumption. Early empirical work, such as Zeldes (1989), Souleles (1999), Pistaferri (2001), Johnson, Parker and Souleles (2006), Blundell, Pistaferri and Preston (2006), and Agarwal, Liu and Souleles (2007), used survey data or studied tax rebates. Gourinchas and Parker (2002), Kaplan and Violante (2010), and Kaplan and Violante (2014) provide theoretical models of household consumption responses. Recent work uses administrative data (Fuster, Kaplan and Zafar, 2018; Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru and Yao, 2017) Baker (2018), Pagel and Vardardottir (forthcoming), and Baker and Yannelis (2017) study income shocks and consumption using financial aggregator data. Jappelli and Pistaferri (2010) review this literature. This paper is the first to study how individual spending reacts in an epidemic, a scenario with anticipated income shocks, the threat of supply chain disruption, and significant uncertainty. In February and early March, there was little direct effect of COVID-19 in the United States, but significant awareness of potential damage in the future. We see significant stockpiling and spending reactions, which is consistent with expectations playing a large role in consumption decisions.

Other studies have begun to study the impacts of the current pandemic on household spending, as well. In the United States, (Chetty, Friedman, Hendren, Stepner and Team, 2020) built a platform that aggregates daily data for consumer spending, business revenues, employment rates, and other key indicators. On household spending, we find mostly consistent results, with households reducing their consumption sharply in the middle of March, with the largest decreases found among higher income households.

Coibion, Gorodnichenko and Weber (2020a) study the causal effects of local lockdowns on consumer spending and employment using customized survey data. They find that the lockdowns not only negatively affected consumer spending and employment but also largely affected households' expectations about the economy. In addition, Alexander and Karger (2020) interrogate whether stay-at-home orders affect household spending. As expected, spending in sectors associated with mobility saw sharp decline while spending on food delivery services increased.

Several studies explore consumer spending in different countries or regions. Chronopoulos, Lukas and Wilson (2020) examine the change in household spending in the United Kingdom using high-frequency data, demonstrating that discretionary consumption dropped, while groceries and stockpiles became prevalent. Andersen, Hansen, Johannesen and Sheridan (2020a) use transaction-level consumer data to explore the response of consumer spending in Denmark. Andersen, Hansen, Johannesen and Sheridan (2020b) further investigate the pattern in Sweden and make a comparison between two countries to demonstrate the effect of restriction policies because only Denmark has enacted such policies. Chen, Qian and Wen (2020) study the response of households in China using daily transaction data. They find that the overall spending was severely affected, with categories like dining, entertainment, and travel declining the most. Chang and Meyerhoefer (2020) specifically explore the demand for online food shopping services under COVID-19 in Taiwan, finding that an increase in the number of COVID-19 cases is associated with an increase in the demand for the services.

This paper also relates to a literature on how crises affect the economy and policy responses to those crises. In the aftermath of the 2008 Great Recession, a large body of work studied how credit supply shocks (Mian and Sufi, 2011; Mian, Rao and Sufi, 2013) and securitization (Keys, Mukherjee, Seru and Vig, 2008; Keys, Seru and Vig, 2012) led to the financial crisis. Several papers also study the effect of government policies aimed at mitigating the effects of the financial crisis. (Bhutta and Keys, 2016; Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru and Yao, 2017; Ganong and Noel, 2018). This paper provides a first look at how the coronavirus affects household spending, and our findings will be key in evaluating future policy responses.

Additionally, the paper joins a growing literature in finance on the impacts of how belief heterogeneity and partisan politics affects real economic decisions. Malmendier and Nagel (2011) show the individuals who grew up in the Great Depression exhibited more risk-averse behavior relative to individuals who did not. The literature on how partisanship affects economic decisions has had mixed findings. Some papers have found large effects of partisanship on economic decision-making. For example, Kempf and Tsoutsoura (2018) explore how partisanship affects financial analysts' decisions, and Meeuwis, Parker, Schoar and Simester (2018) find large effects of the

2016 U.S. Presidential election on portfolio rebalancing. Mian, Sufi and Khoshkhou (2018) study how U.S. presidential elections affect households' consumption and savings patterns and find little effect. Baldauf, Garlappi and Yannelis (2020) study how individuals' beliefs about climate change affect home prices, and the authors find large differences when considering individuals' political affiliations.

This paper studies differences in partisan behavior in the face of a major crisis where survey evidence indicates large differences in beliefs among people belonging to different political parties, which have been attributed to statements made by policy makers.[2]

Finally, this paper joins a rapidly growing body of work studying the impact of the COVID-19 pandemic on the economy. Eichenbaum, Rebelo and Trabandt (2020), Barro, Ursua and Weng (2020), and Jones, Philippon and Venkateswaran (2020) provide macroeconomic frameworks for studying epidemics. Coibion, Gorodnichenko and Weber (2020b) document a strong impact of the epidemic on labor markets. Gormsen and Koijen (2020) study the stock price and dividend future reactions to the epidemic, and use these to back out growth expectations for a potential recession caused by the virus. In a related paper, Barrios and Hochberg (2020) find the political partisanship played a large role in shaping risk perceptions toward COVID-19. Our paper is the first to study the individual spending and debt responses to COVID-19, or any major epidemic, given that detailed high-frequency individual financial data did not exist during previous pandemics.

1 Data

1.1 Transaction data

We analyze deidentified transaction-level data from a nonprofit Fintech company called SaverLife. SaverLife encourages individuals to increase savings through targeted information and rewards. Users can sign up for an account with SaverLife and link their main bank account, including their checking, savings, and credit card accounts, via the platform. Users have two main incentives for linking accounts. First, SaverLife can provide them with information about their finances as well

[2] A NBC/Wall Street Journal Poll found more Democrats than Republicans were worried about family members contracting the virus, whereas 40% of Republicans were worried, and that twice as many Democrats thought the virus could change their lives.

as tools to aid financial decision making. Second, SaverLife offers targeted rewards and lotteries to individuals who link their accounts to achieve savings goals.

Figure 1 depicts two screenshots from the SaverLife online interface. It shows the screenshots of the main linked account as well as a screenshot of the savings and financial advice resources that the website provides.

The primary data used in this paper consists of deidentified daily data on each user's spending and income transactions from all linked checking, savings, and credit card accounts. In addition, for a large number of users, we are able to link financial transactions to demographic and geographic information. For instance, for most users, we are able to map them to a particular five-digit ZIP code. Many users self-report demographic information, such as age, education, family size, and the number of children they have. Panel A of Figure 2 indicates the number of users by U.S. ZIP code. Panel B of Figure 2 shows users' average annual income, which they self-report upon signing up with SaverLife, by ZIP code.

Using data from August 2016 to March 2020, we observe bank-account transactions for a total sample of 44,660 users. For each transaction in the data, we observe a category (such as Groceries and Supermarkets or Pharmacies), parent category names (such as ATM), and grandparent category names (such as Shopping and Food). Looking only at the sample of users who have updated their accounts reliably in March of 2020, we have complete data for 4,735 users. These users each are required to have several transactions per month in 2020 and have transacted at $1,000 in total during these 3 months of the year.

Table 1 shows summary statistics for users spending in a few select categories as well as their income at a monthly level. We can see that payroll income is relatively low for the median user of SaverLife, though many users get income from a range of other nonpayroll sources. Additionally, we can see the number of linked accounts and number of monthly transactions of users in all linked accounts. The number of total transactions and weekly observations are also noted. We run regressions at a weekly level to examine more precisely the high-frequency changes in behavior brought about by the fast-moving news about the COVID-19 outbreak and the policy responses to the outbreak.

Spending transactions are categorized into a large number of categories and subcategories. For instance, the parent category of "Shops" is decomposed into 53 unique subcategories including

"Convenience Stores," "Bookstores," "Beauty Products," 'Pets,' and "Pharmacies." For most of our analysis, we examine spending across a majority of categories, excluding spending on transfers, such as bills, mortgage, and rent. We also separately consider a number of individual categories including "Grocery Stores and Supermarkets" and "Restaurants."

1.2 Gallup daily tracking data

We predict partisanship from 2018 Gallup daily tracking data. Gallup randomly samples 1,000 Americans daily each year via landlines and cellphones. Individuals are asked questions about their political beliefs, expectations about the economy, and demographics. The sample is restricted to individuals 18 and older. We estimate a linear probability model, predicting whether a respondent identifies as a Republican using variables common to both data sets: (1) county, (2) income, (3) gender, (4) marital status, (5) presence of children in the household, (6) education, and (7) age. Older people, men, married individuals, and individuals with children are more likely to be Republicans. Identifying as a Republican is monotonically increasing in income bins.[3] The relationship between education and partisan affiliation is nonmonotonic, with individuals without a high school diploma strongly leaning Democrat, and individuals with only a high school degree, a vocational degree, or an associate's degree being most likely to identify as Republicans.

For each individual, we construct a predicted coefficient of partisan leaning, using the coefficients estimated from the Gallup data, and predicting partisan learning using demographics in the transaction data. In cases in which demographics are missing in the transaction data, we replace the predicted Republican political affiliation with the 2016 Republican vote share, using data from the MIT Election Lab. We classify individuals predicted to be in the top quartile of the highest propensity to be Republicans, and those in the bottom quartile to be Democrats. The remaining individuals in between are classified as Independents.

From a sample of over 500 users, we also obtain self-reported measure of political beliefs based on a survey that we ran in May 2020. We find that our predicted political score maps well to this self-reported measure. Figure A.1 in the appendix displays the strong relationship between our predicted political score and the self-reported political score elicited from the participants of this

[3] The Gallup data provide income in bins, rather than in a continuous fashion. We observe continuous income for the individuals in the transaction data. We standardized the income and education bins in the transaction data to match Gallup to construct out measure of predicted partisanship.

survey. Here, the scale runs from "Very Liberal" on the left to "Very Conservative" on the right. Individuals self-reporting to be "Conservative" or "Very Conservative" are 2 to 3 times as likely to be Republicans according to our predicted political beliefs score. With individual-level political scores, we can leverage the substantial range of political ideology and beliefs within a state or other geographical area. This enables us to better identify the differential impacts of political beliefs on spending relative to the local impact of COVID-19.

1.3 Social distancing data

We also collect data on the effectiveness of social distancing from unacast.com Unacast social distancing scoreboard. Unacast provides a daily updated social distancing scoreboard. The scoreboard describes the daily changes in average mobility, measured by change in average distance traveled and the change in nonessential visits using data from tracking smartphones using their GPS signals. The data are available on a daily basis and by county on their website. We use the data of average mobility, because the data on nonessential visits are less reliable as many people have relocated and moved to areas out of a city or kids have moved into parents' homes or vice versa. Therefore, Unacast reports the average distance traveled (difference in movement) as the most accurate measure in times of the pandemic. We downloaded the data from their website by day and county and merged it to our consumption data.

2 Geographic Spread of COVID-19

COVID-19 was first identified in Wuhan, China, before spreading worldwide. This new coronavirus spread very rapidly and had a mortality rate approximately ten times higher than the seasonal flu and at least twice its infection rate.[4] The first case in the United States was identified on January 21, 2020, in Washington State, and was quickly followed by cases in Chicago and Orange County, California. All early cases were linked to travel to and from Wuhan. Throughout January and February, several cases arose that were all linked to travel abroad. Community transmission was first identified in late February in California. The first COVID-19-linked death occurred on February 29, in Kirkland, Washington. In early March, the first New York case was identified, and,

[4] See the ADB study referenced by the WHO.

by the end of the month, New York would account for approximately half of all identified cases in the United States. In early and mid-March, the virus began to spread rapidly.

The federal and many state governments responded to the COVID-19 pandemic in a number of ways. The first state to declare a state of emergency was Washington, which did so on January 30. The following day the United States restricted travel from China. Initially, the President made many statements suggesting that the COVID-19 virus was under control. For example, on January 22, President Trump said that the virus was under control. On February 2nd, the President stated that "We pretty much shut it down coming in from China" (Trump, 2020). Rhetoric about the virus being under control continued throughout February, and on February 24 the President said that "the Coronavirus is very much under control in the USA."

This pattern even continued into early March, with the President saying on March 6 that "in terms of cases, it's very, very few" (House, 2020). On February 24, President Trump asked Congress for $1.25 billion in response to the pandemic. General concern and statements from policy makers changed sharply in mid-March as new cases increased rapidly. On March 11, following major outbreaks in Italy and much of Europe, President Trump announced a travel ban on most of Europe. Two days later, on March 13, President Trump declared a national emergency. Many states followed by closing schools, restaurants, and bars or issuing shelter-in-place orders.

The fact that the initial public messages about the COVID-19 pandemic were relatively mild and suggested that the panic was under control led to suggestions of a partisan divide on the dangers of the new virus. For example, a NBC/Wall Street Journal Poll between March 11 and 13 found that 68% of Democrats were worried that someone in their family could catch the virus, whereas 40% of Republicans were worried. The same poll found that 56% of Democrats thought their day-to-day lives would change because of the virus, whereas 26% of Republicans held the same view. A Pew Research Center Poll between March 10 and 16 found that 59% of Democrats and 33% of Republicans called the virus a major threat to U.S. citizens' health.

3 Financial Response to Coronavirus

While the media reported on stockpiling, whether consumption would go up or down in the early days of the COVID-19 outbreak was not ex ante obvious. Because changes in government policy and consumer behavior were so rapid during this period, we collapse our data to the weekly level and focus on changes in spending within several distinct periods of February and March 2020. We uncover some variation across individuals living in different states with policies enacted at different times, but we also point out strong common trends across states reflecting the fact that news and concerns about the virus crossed state lines.

The first period we highlight is February 26 through March 10, a period that marks when COVID-19 first began to affect life in the United States. This period marks the first deaths in the United States (February 29), some school closures as case numbers grew (e.g., schools in Seattle on March 2), and some jurisdictions declaring states of emergency (e.g., California on March 3). During this period, state and local officials were advising households to stock up on supplies in the event that a quarantine was deemed necessary, but most retail and service establishments were still open for business. As these advisories went out, reports of hoarding and shortages of consumer goods began to increase.[5] In addition, Americans were advised to return to the country if they happened to be working or traveling abroad.

In the second period, March 11 through March 17, the federal government imposed travel restrictions on European travel, and President Trump declared a national emergency under the Stafford Act (March 13). More restrictions on retail were put in place, but many households were still taking advantage of open restaurants and services before they closed. For instance, Mayor De Blasio of New York City encouraged the city's residents to patronize their favorite establishments before they were closed by government order: "If you love your neighborhood bar, go there now!" (Edition, 2020). In the final period, March 18–March 31, dozens of states began to impose shelter-in-place orders. The first shelter-in-place order was put into place in California on March 19, and a further 37 states would impose such orders by the end of March. These orders generally closely followed behind orders that severely limited retail operations, public gatherings, and entertainment offerings, and the closure of many public services. Huge numbers of retailers ceased all operations, at least temporarily, for a period of weeks.[6]

Figure 3 provides a visualization of the changes in spending during these time periods. The figure shows the percentage change in daily spending across categories, relative to a baseline of

[5] Google Trends searches for "hoarding" began steeply climbing upward in the first week of March, before peaking on March 14.

[6] CBSNEWS.com published a partial list of major retailer closures (Brooks, 2020).

January 1 through February 25, 2020. For simplicity in this figure, we combine the first two periods in the top panel. We find a sharp spike in spending between February 26 and March 17, relative to earlier weeks in 2020, as COVID-19 cases began to spike in the United States. The top panel shows evidence of stockpiling and an increase in consumer spending during the time period when it became clearer that the virus was spreading in the United States.

We find that this initial spike in spending is large and consistent across nearly all categories that we track. Even categories that may not have been a part of any "stocking up" among individuals, such as restaurant and bar spending, saw large increases in this period. This may be driven by the fact that individuals wanted to get in last meals, excursions, and shopping trips before their favorite retailers were closed by state and local governments. This behavior yielded a surge in both air and public transportation spending, increased spending at all manner of retailers, and sharp upticks in spending on food, both at home and away.

This initial spike in spending is followed by depressed levels of general spending. However, while initial spikes in spending were widespread, in later periods, there is significant heterogeneity across categories. The bottom panel shows spending between March 18 and March 31, when shelter-in-place orders were enacted in most states. The bottom panel indicates sharp declines in restaurant spending, air travel, and public transport. Food delivery spending and grocery spending significantly increase, consistent with users substituting meals at restaurants with meals at home.

3.1 Response across states

In Table 2, we examine the pattern of user spending in a regression framework, concentrating on the weekly periods mentioned above. That is, when users seemed to be increasing spending in advance of a "shelter-in-place" order and when those orders began to take effect. We estimate the following equation over individuals throughout the first 14 weeks of 2020 (January 1st through April 14th):

$$\begin{aligned} c_{it} = \alpha_i + \beta_1 \mathbb{1}[t = Feb_{26} - March_{10}]_t + \beta_2 \mathbb{1}[t = March_{11} - March_{17}]_t + \\ \beta_3 \mathbb{1}[t = March_{18} - March_{31}]_t + \varepsilon_{it}. \end{aligned}$$

c_{it} denotes spending by individual i aggregated to the weekly level t. α_i are individual fixed effects. Individual fixed effects α_i absorb time invariant user-specific factors, such as some individuals having greater average income or wealth.

We also include indicators for being in the weeks of February 26 to March 10, March 11 to March 17, and March 18 to March 31. As noted above, these periods coincide with changes in the legal and retail environment across the country and manifest themselves in differential observed patterns of behavior among individuals across the country. In the first period, households tended to be stocking up on goods across a number of categories and also still patronizing entertainment venues and restaurants. The third period, in late March, corresponds to a period in which most states began to operate under "shelter-in-place" orders, often with schools closed, nonessential businesses closed, and restaurants forced to only serve takeout food.

In each column, we present results on user spending with differing samples and types of spending. In columns 1–3, we measure user spending using a wide metric that includes services, food and restaurants, entertainment, pharmacies, personal care, and transportation. Columns 4–6 include only spending on restaurants, while the final set of columns include spending only at grocery stores and supermarkets. In addition, we vary the sample across each column. "All" represents all users in our sample. "Shelter" indicates that the sample is limited to users in states that, as of March 31, had a shelter-in-place order in place. "No Shelter" restricts to users in states without such an order. All regressions utilize user-level fixed effects and all standard errors are clustered at the user level.

Several clear patterns emerge from this analysis. Overall, we see a stark pattern consistent with the figures presented above. Users tended to stock up substantially at the end of February into the beginning of March, then begin to cut spending dramatically. We also note that the number of transactions followed a similar though less extreme pattern. That is, the number of transactions in the stocking up period increased by about 15% while spending soared by almost 50%. Thus, the *size* of transactions in the stocking up period was substantially higher than the historical average transaction size.

Comparing users that live in states that have had shelter-in-place orders put in place, we tend to see more negative coefficients in the third row for nongrocery spending (e.g., comparing columns 2 and 3 as well as columns 5 and 6. That is, users in these states tended to decrease spending across categories at a much more rapid pace. However, we see significant declines in spending, both overall and in restaurant spending, among states that did not have shelter-in-place orders in effect.[7] These common effects across states with different policy environments highlights the fact that Americans were sheltering in place voluntarily in many cases and many nationwide retailers were closing stores despite being legally allowed to operate in some locations.

In addition, we see more evidence for stocking up on groceries in states that have been put under a shelter-in-place order. Looking at columns 8 and 9, we see that grocery spending has been consistently higher among users in shelter-in-place states, likely reflecting a shift from eating at restaurants or at office cafeterias and toward eating at home.

3.2 Response by social distancing

We also link the spending decisions of individuals to the Unacast data on social distancing, which comes from cell phone records. We create bin scatters (Figure 4) relating the difference in movements to the different spending categories. On the horizontal axis, we plot the difference in movement, and, on the vertical axis, we plot the log-spending by different categories. In general, we find that across all spending categories a reduction in movement is related to a reduction in spending.[8]

The effect size, however, varies by spending category. The fewer people who move, the less they spend at restaurants, on groceries, or at retailers. We also observe a reduction in public transportation, as fewer people were traveling, and, if they did travel, they were presumably more likely to use a car. The smallest reduction is observed for credit card spending. We conjecture that the credit card still can be used for online shopping or paying for subscriptions services like Netflix or Apple TV, which individuals can use without leaving home. The data on social distancing underscore the robustness of our findings and unequivocally relates them to the shelter-in-place orders.

[7]This decline in restaurant spending is much more muted if we restrict to fast food restaurants. Coefficients for these stores are approximately half the size as for non-fast-food restaurants. This is likely driven by the fact that fast food restaurants serve a large portion of their customers via drive through and takeout.

[8]We demonstrate that the same sorts of patterns and relationships hold true in a separate set of data from SafeGraph. Figure A.2 in the appendix displays graphs using these data.

4 Heterogeneity in Response by Political Views, Demographics, and Financial Indicators

4.1 Response across political beliefs

In Table 3, we split users into two groups according to their predicted political orientation and examine how users' spending adjusted during these same periods. In particular, we utilize the Gallup polling data to map the demographic and geographic characteristics of these individuals to calculate a predicted political score. We split users into the highest and lowest quartiles that are most likely to be Republicans and Democrats, respectively. The specifications mirror those in Table 2, looking at overall spending, restaurant spending, and grocery spending across these different groups.

We see sharp increases in spending for both predicted Republicans and Democrats. Contrary to much of the discussion in the popular press and evidence from surveys suggesting that Democrats were more concerned with the virus, we actually see slightly more overall spending between February 26 and March 10 among Republicans relative to Democrats. While we see significant evidence of stockpiling for both groups, the percentage increase in grocery spending by Republicans is approximately 50% larger than the increase among Democrats.

The observed differences between predicted Republican and Democrats could be both due to differences in beliefs and differences in risk exposure. The differences in risk exposure between different partisan groups are not obvious. For example, Republicans are more likely to live in rural areas, while Democrats are more likely to live in urban areas, which are at higher risk in a contagion. On the other hand, Republicans also tend to be older, and older individuals are at higher mortality risk from COVID-19.

Figure 5 mirrors Figure 3 by decomposing the changes in spending across individuals with the highest predicted Democratic "lean" and highest predicted Republican "lean." Across both groups, we see a large rise in spending across nearly all categories and all of the displayed categories, in late February to mid-March, consistent with stockpiling behavior. Slightly larger increases occur among Democratic-leaning individuals, but the differences are generally not statistically significant.

In the bottom panel, we split the response of Republican and Democratic individuals in the second half of March. Again, we see highly similar responses overall, with spending in most categories declining substantially with the only increases coming from Food Delivery services and Grocery spending.

Figure A.3 in the appendix replicates these patterns using spending data from SafeGraph. The SafeGraph data do not contain individual-level information, so we utilize only the predicted partisan leanings based on geographic location. Here too, we generally observe similar patterns across more Republican-leaning and Democrat-leaning areas. While there are substantial differences in the *levels* of spending between these two sets of locations, the *trends* in spending surrounding the announcement of shelter-in-place policies and the actual imposition of those policies look similar.

4.2 Response across demographic and financial indicators

In Table 4, we examine how user spending responses differed across some key demographic and financial characteristics. We again perform a similar regression analysis, here interacting the weekly indicators with indicators of whether an individual possessed a demographic or financial characteristic. Notably, we include interactions for whether the user is under 30 years old, whether they have children, whether they are male, and whether they have an annual income above $40,000. Across the three panels, we again turn to looking at a wide measure of users' spending, just restaurant spending, and just spending at grocery stores and supermarkets.

In the first column, we see that younger users tended to cut back on total spending, as well as restaurant spending, by a smaller amount than older users. This coincides with reports that younger individuals were obeying the shelter-in-place orders less strictly than older Americans. In the second column, we find that individuals with children tended to have the largest declines in spending in recent days, with overall spending falling around twice as fast as among individuals without children. We also note that, in panel C, we find that individuals with children tended to increase grocery spending in the earlier weeks of the outbreak and cut spending in the later weeks, though these results are insignificant. In column 3, we see that male users tended to have more muted responses in the run-up to the crisis. That is, men generally "stocked up" less than women in the early weeks of March.

Column 4 looks at differential behavior among users with higher income. In general, here we see few differences. Users with high income tended to behave quite similarly in their patterns of spending behavior to users with lower income, at least in relative terms. To expand on this, in column 5 we also add interactions with whether the individuals had little liquidity in bank accounts in the weeks before COVID-19. In general, we find that low-liquidity individuals tend to have much larger declines in spending during the latter period in our sample relative to individuals with more liquidity.

4.3 Response across severity and perceived severity of the COVID-19 crisis

Finally, in Table 5, we perform two additional splits of the data. In particular, we examine whether individuals living in states with higher numbers of confirmed COVID-19 tests tended to spend differently from one another. We also interact with a self-reported measure of optimism about the economy that was elicited by a survey of users performed in May 2020.

In the first columns, we find that, while individuals did not engage in substantially more stocking up if they lived somewhere with a higher number of COVID-19 cases, the drop in spending was much more severe in these locations. Going from the 10th to 90th percentiles of COVID-19 deaths in a state is associated with a spending declining by about 60% more during the March 18–March 31 period. Individuals living in more severely hit states may have been not only more limited in their retail options but also more concerned about contracting the virus and limited their travel and spending.

In the second set of columns, we interact with a measure of optimism about the economy at the individual level. These individuals reported that they felt the economy was likely to return to normal in 6 months or less, compared with individuals who thought it would take 1 or more years to return to normal. Unfortunately, this survey was conducted in May 2020, after the period in the sample here. We find users who later report feeling more optimistic about the prospects for the economy tended to have spent substantially less in the run-up to the COVID-19 crisis, but did not cut spending by a significantly different amount once the shelter-in-place policies were enacted in the latter part of March 2020. It may be that these individuals did not think that COVID-19 would be a long-lasting shock and thus did not feel the need to stock up on supplies or engage in other substantial spending in the early parts of March.

5 Conclusion

This paper provides the first view of individual spending during the recent weeks of the COVID-19 outbreak in the United States. Using transaction-level individual financial data from a personal financial website, SaverLife, we illustrate how Americans' spending responded to the rise in disease cases as well as to the policy responses put in place by many city and state governments, namely, shelter-in-place orders. We show that users' spending was radically altered by these events across a wide range of categories, and that the strength of the response partly depended on how severe the outbreak was in a user's state. Spending increased over 40% in the first half of March and declined by approximately 25%–30% in the second half.

Demographic characteristics, such as age and family structure, provoked larger levels of heterogeneity in spending responses to COVID-19, whereas income did not. Moreover, we demonstrate users of all political orientation tended to follow similar patterns of spending in both the stockpiling phases and when the viral outbreak intensified.

We caution that these are very short-term responses, meant to illustrate as close to a real-time view of consumer spending as possible. In part, this paper demonstrates the utility of individual transaction-level data in providing a window into not just household finance but also aggregate trends. Additionally, we caution that our data are skewed toward younger users, who have lower risk exposure. Older individuals with very high-risk exposure may have behaved differently and cut consumption more substantially.

The COVID-19 outbreak has upended economies around the world, and we are surely just at the beginning of understanding the full impact at both individual and national levels. We anticipate large amounts of future work examining the impact of COVID-19 using individual transaction data. Questions about how households went about rearranging spending, shifted from brick and mortar to online retailers, and utilized liquidity and credit are all at the forefront. Moreover, the ability to observe individual-level income and the sources of this income may be fruitful in analyzing how individuals who faced sudden unemployment were able to substitute to new types of work and new employers. For example, disemployed retail workers might find fast employment in sectors with newly elevated demand, such as home delivery services.

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Figure 1: Platform example

Screenshots of the SaverLife app and its financial advice page. *Source*: SaverLife.

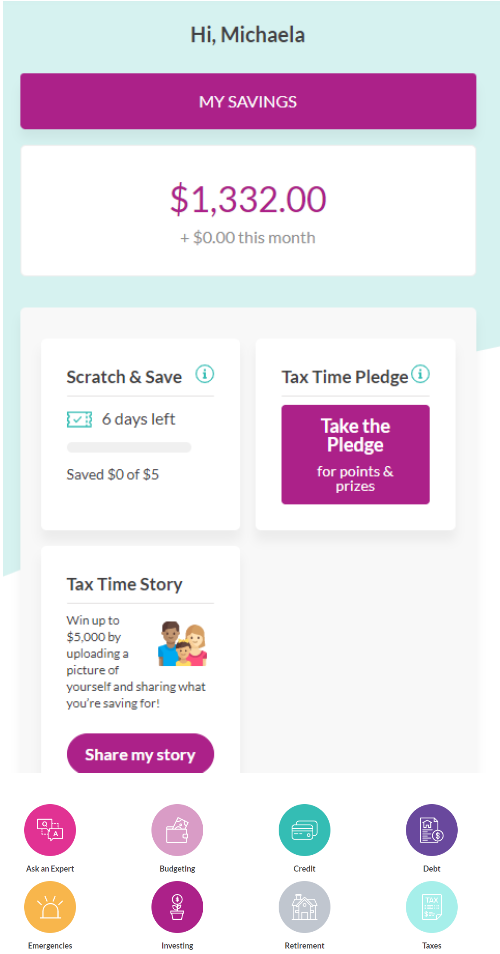
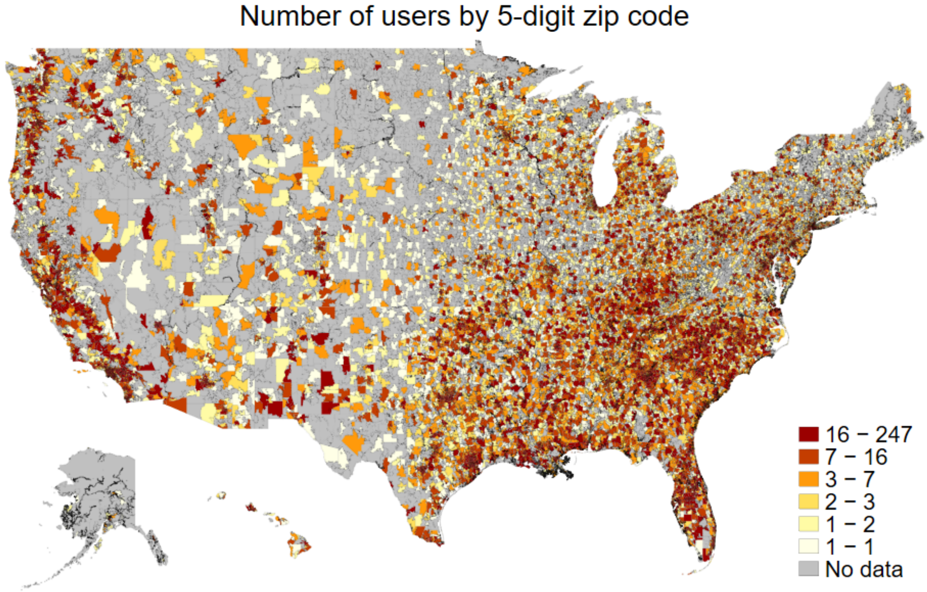


Figure 2: SaverLife users

Panel A displays the number of SaverLife users by five-digit ZIP code in the United States. Panel B shows the average annual self-reported income of users by five-digit ZIP code in the United States (in US$1,000). *Source*: SaverLife.

(A) Number of users



(B) Average user's income

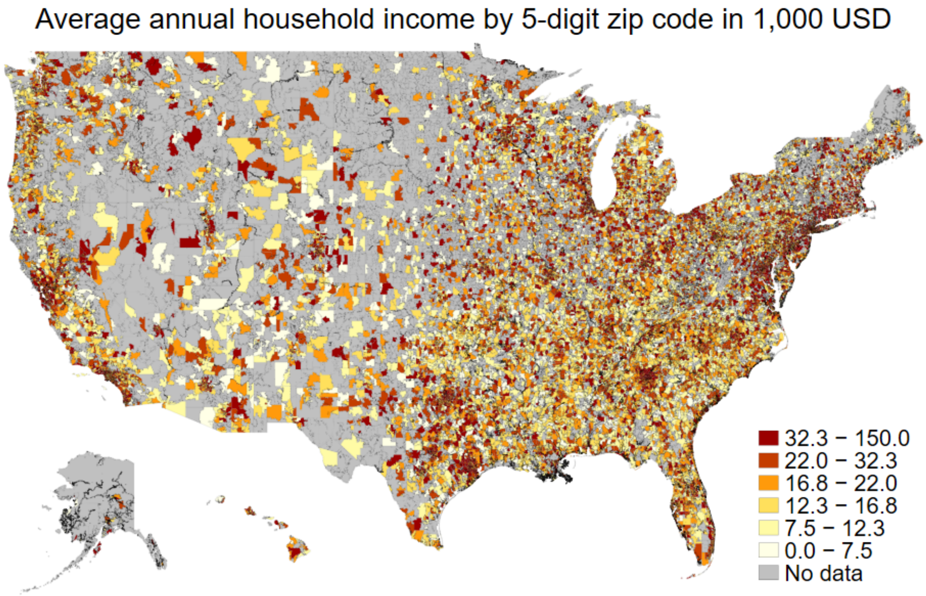
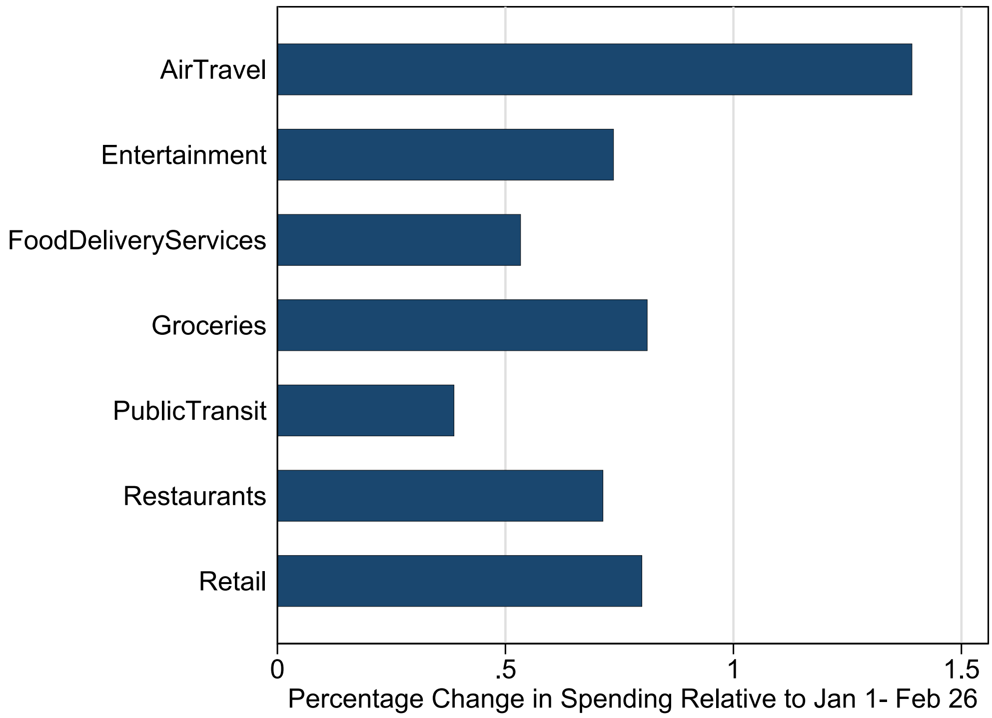


Figure 3: Spending response across categories

This figure displays the percentage change in mean daily spending across different categories, relative to spending pre-February 26. *Source*: SaverLife.

February 26–March 17



March 18–March 31

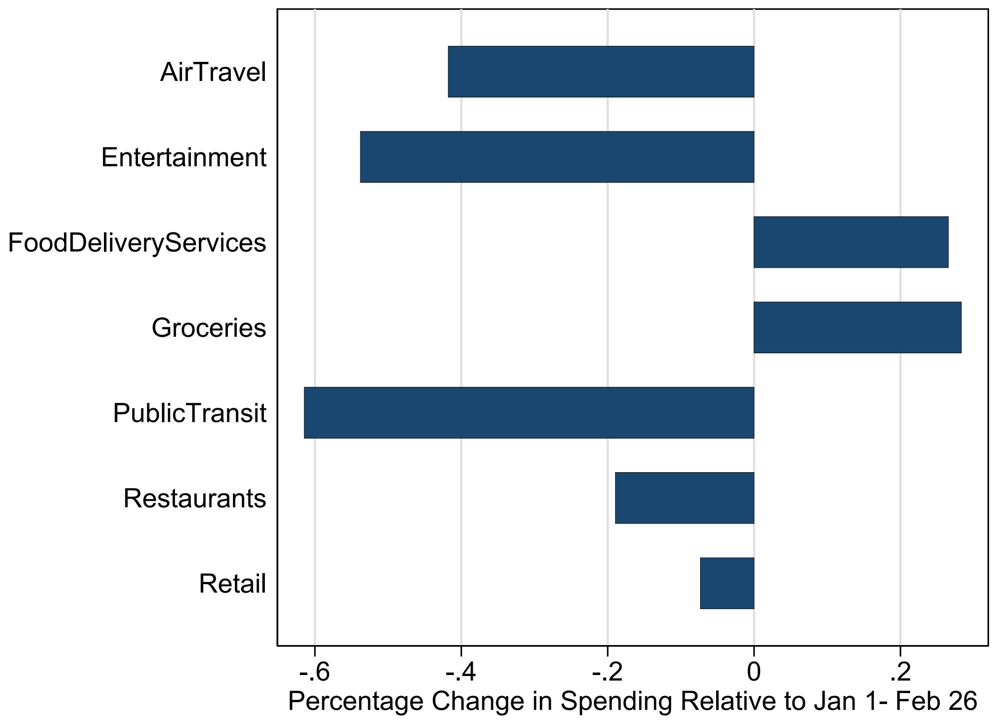
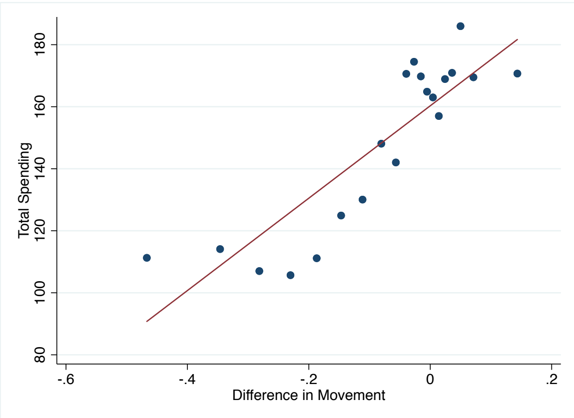


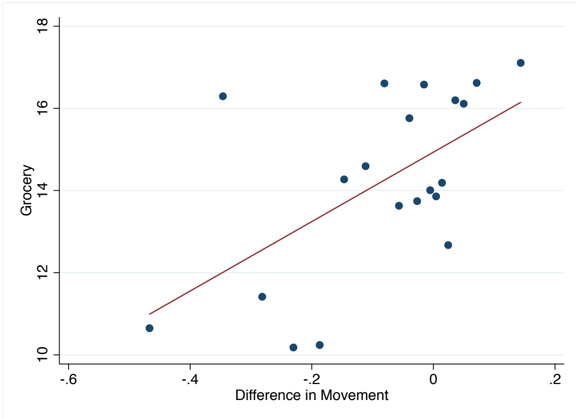
Figure 4: Spending and social distancing

This graph displays individual spending across a number of categories of spending in bins of the daily difference in movement. Spending is measured in daily dollars. *Sources*: SaverLife and Unacast.

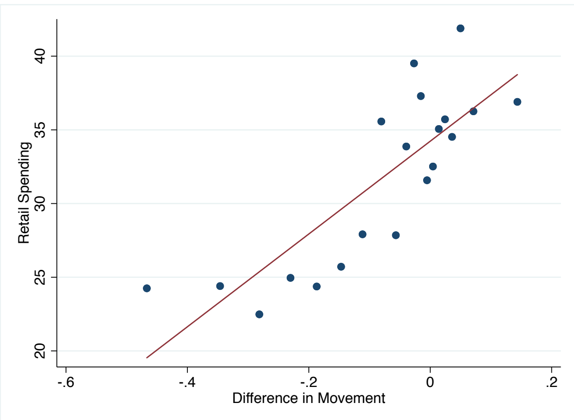
Total spending



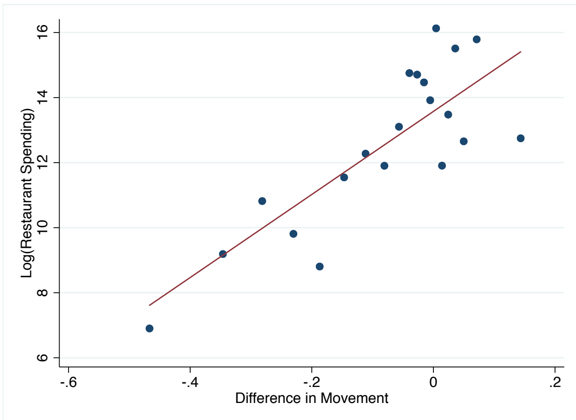
Grocery spending



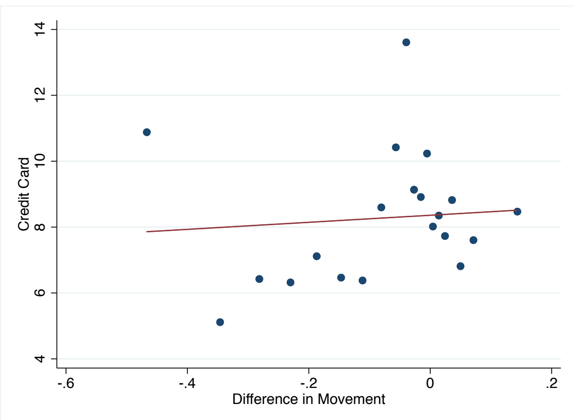
Retail spending



Restaurant spending



Credit card



Public transport

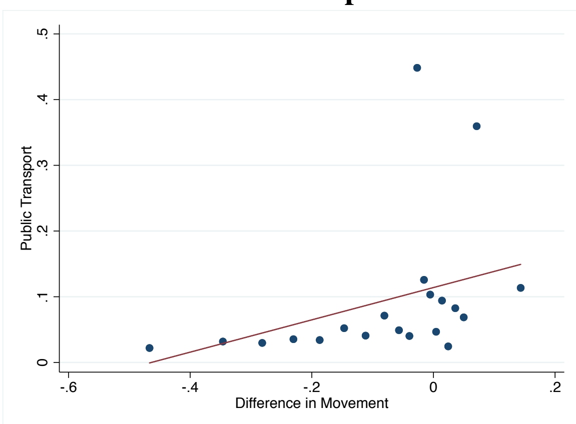
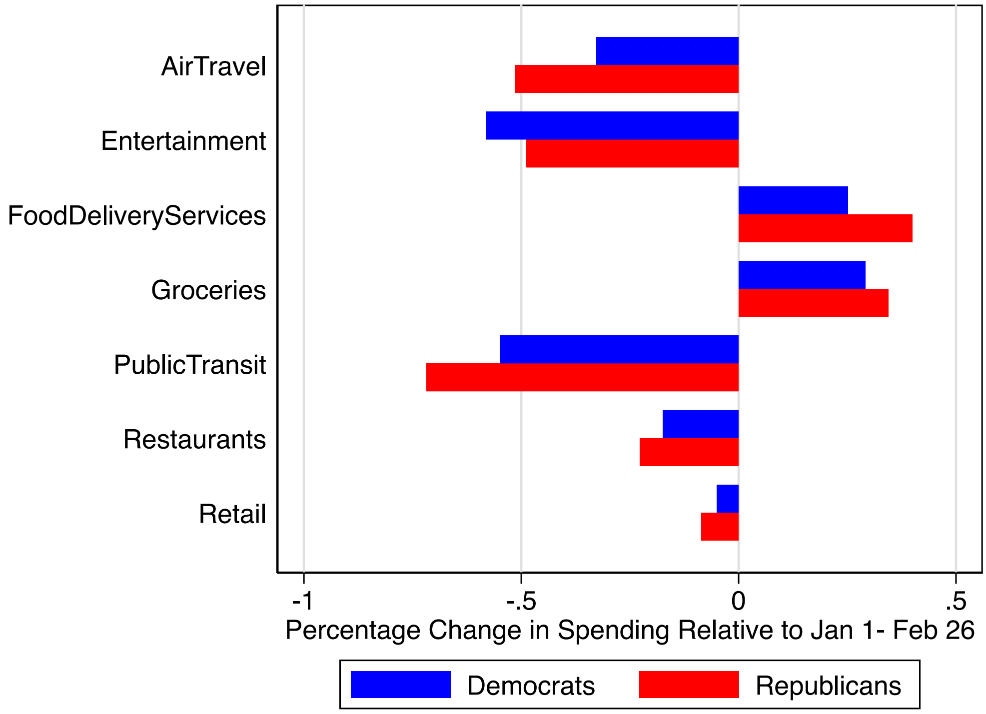


Figure 5: Spending response across categories and partisanship

This figure displays the percentage change in mean daily spending across different categories, relative to spending pre-February 26. For each category, the average response is plotted for two groups: the quartile of the sample with the highest predicted "democrat" lean and the quartile of the sample with the highest predicted "republican" lean. *Sources*: Gallup and SaverLife.

February 26–March 17



March 18–March 31

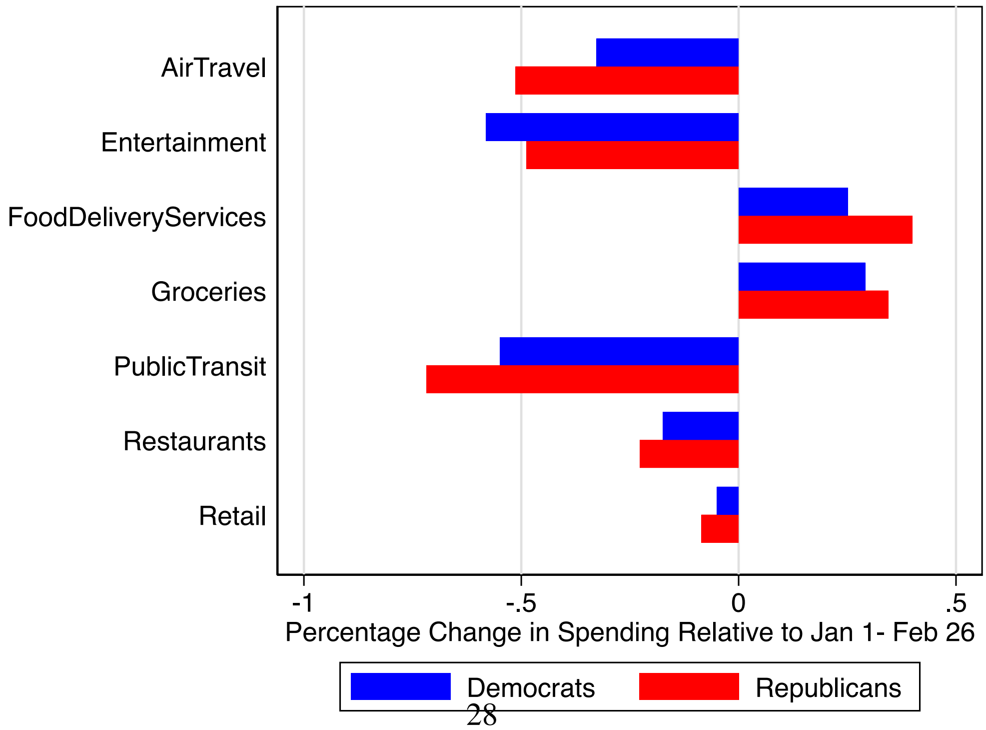


Table 1: Monthly summary statistics

This table provides summary statistics of the final sample of active users with complete data until April 14th. Data are monthly over users' entire sample histories. All statistics are in $US.

			Percentiles				
	Mean	SD	10%	25%	50%	75%	90%
Number of linked accts	2.27	2.11	1	1	2	3	4
Number of txns	72.2	64.29	14	29	59	100	146
Payroll income	$1,908.40	$1,893.53	$12.98	$522.73	$1,620.35	$3,525.95	$6,203.61
Groceries	$199.62	$374.09	$9.80	$48.01	$138.88	$351.75	$701.73
Restaurants	$186.18	$340.45	$16.32	$44.63	$124.66	$278.25	$652.35
Pharmacies	$54.10	$140.34	$4.76	$10.32	$23.64	$50.00	$140.58
Pharmacies	$54.10	$140.34	$4.76	$10.32	$23.64	$50.00	$140.58
Shopping	$109.91	$189.68	$5.57	$12.98	$34.37	$94.02	$345.06
Transaction-level obs.	3,468,339						
User-week obs.	213,122						
User-month obs.	78,590						

Table 2: Spending by week and heterogeneity by state

This table provides the results of a regression of spending on indicators for the different time periods. Dependent variables vary across columns, with columns 1–3 representing a wide metric of individual spending including services, food and restaurants, entertainment, pharmacies, personal care, and transportation. Columns 4–6 include only spending on restaurants, whereas the final set of columns include spending only at grocery stores and supermarkets. "Shelter" indicates that the sample is limited to users in states that, as of March 31, had a shelter-in-place order. "No Shelter" is restricted to users in states without such an order. 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)
Variables	All	Shelter	No shelter	All - rest	Shelter - rest	No shelter - rest	All - groc	Shelter - groc	No shelter - groc
February 26 - March 10	0.460***	0.435***	0.541***	0.360***	0.336***	0.434***	0.184***	0.222***	0.172***
	(0.0132)	(0.0153)	(0.0266)	(0.0103)	(0.0117)	(0.0212)	(0.00971)	(0.0200)	(0.0111)
March 11 - March 17	0.146***	0.115***	0.243***	0.158***	0.132***	0.238***	0.246***	0.295***	0.231***
	(0.0181)	(0.0210)	(0.0362)	(0.0140)	(0.0160)	(0.0292)	(0.0144)	(0.0165)	(0.0298)
March 18 - March 31	-0.259***	-0.307***	-0.106***	-0.226***	-0.232***	-0.207***	0.104***	0.177***	0.0809***
	(0.0159)	(0.0184)	(0.0314)	(0.0112)	(0.0127)	(0.0233)	(0.0116)	(0.0134)	(0.0236)
Observations	213,122	161,714	51,408	213,122	161,714	51,408	213,122	161,714	51,408
R^2	.415	.414	.416	.404	.404	.401	.400	.401	.396
User FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 3: Spending by week and heterogeneity by predicted political position

This table provides the results of a regression of spending on indicators for the different time periods. Dependent variables vary across columns, with columns 1–3 representing a wide metric of individual spending including services, food and restaurants, entertainment, pharmacies, personal care, and transportation. Columns 4–6 include only spending on restaurants, whereas the final set of columns include spending only at grocery stores and supermarkets. "Dem" indicates that the sample is limited to users who are predicted to be in the top quartile of most democratic leaning based on demographic and financial indicators. "Rep" indicates that the sample is limited to users who are predicted to be in the top quartile of most Republican leaning based on demographic and financial indicators. Standard errors are clustered at the user level. *$p < .1$; ** $p < .05$; *** $p < .01$. *Source*: SaverLife.

Variables	(1) All	(2) Dem	(3) Rep	(4) All - rest	(5) Dem - rest	(6) Rep - rest	(7) All - groc	(8) Dem - groc	(9) Rep - groc
February 26 - March 10	0.460***	0.449***	0.466***	0.360***	0.349***	0.362***	0.184***	0.138***	0.198***
	(0.0132)	(0.0259)	(0.0187)	(0.0103)	(0.0200)	(0.0144)	(0.00971)	(0.0184)	(0.0137)
March 11 - March 17	0.146***	0.167***	0.139***	0.158***	0.130***	0.169***	0.246***	0.265***	0.235***
	(0.0181)	(0.0357)	(0.0253)	(0.0140)	(0.0276)	(0.0196)	(0.0144)	(0.0280)	(0.0202)
March 18 - March 31	-0.259***	-0.270***	-0.240***	-0.226***	-0.258***	-0.215***	0.104***	0.129***	0.0943***
	(0.0159)	(0.0312)	(0.0224)	(0.0112)	(0.0224)	(0.0156)	(0.0116)	(0.0228)	(0.0162)
Observations	213,122	56,056	108,360	213,122	56,056	108,360	213,122	56,056	108,360
R^2	.415	.409	.414	.404	.392	.408	.400	.382	.411
User FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4: Spending response heterogeneity by demographic and financial indicators

This table provides the results of a regression of spending on indicators for the different time periods. Dependent variables vary by panel. Panel A includes a wide metric of individual spending including services, food and restaurants, entertainment, pharmacies, personal care, and transportation. Panel B includes only spending on restaurants, and panel C includes spending only at grocery stores and supermarkets. In each panel, we interact indicators for the listed periods with indicators for demographic and financial characteristics listed above the columns. Column 1 interacts with an age indicator for whether the user is under 30 years old. Column 2 interacts with an indicator for whether the user has children. Column 3 interacts with a gender indicator for whether the user identifies as male. Column 4 interacts with an income indicator for whether the user earns above $40,000 per year. Column 5 interacts with a savings indicator for whether the user had positive net savings prior to February 2020. Standard errors are clustered at the user level. *$p < .1$; ** $p < .05$; *** $p < .01$. *Source*: SaverLife.

	(Young)	(Children)	(Male)	(High income)	(Low-liquid)
			A. All spending		
February 26 - March 10	0.207***	0.423***	0.249***	0.409***	0.449***
	(0.0431)	(0.0145)	(0.0285)	(0.0127)	(0.0131)
March 18 - March 31	-0.690***	-0.309***	-0.550***	-0.364***	-0.247***
	(0.0551)	(0.0175)	(0.0366)	(0.0152)	(0.0157)
February 26 - March 10*Group	0.0922*	-0.109	-0.0533	-0.053	-0.0467
	(0.0549)	(0.0705)	(0.0630)	(0.0580)	(0.0432)
March 18 - March 31*Group	0.252***	-0.356***	-0.1	-0.099	-0.293***
	(0.0707)	(0.0829)	(0.0783)	(0.0793)	(0.0506)
Observations	137,996	164,934	144,660	213,122	213,122
R^2	.444	.414	.442	.415	.415
User FE	YES	YES	YES	YES	YES
			B. Restaurant spending		
February 26 - March 10	0.172***	0.322***	0.243***	0.258***	0.339***
	(0.0334)	(0.0113)	(0.0234)	(0.0100)	(0.0103)
March 18 - March 31	-0.417***	-0.243***	-0.358***	-0.336***	-0.232***
	(0.0357)	(0.0124)	(0.0256)	(0.0109)	(0.0113)
February 26 - March 10*Group	0.066	-0.0990*	-0.129***	-0.081	-0.0357
	(0.0444)	(0.0523)	(0.0485)	(0.0482)	(0.0336)
March 18 - March 31*Group	0.0852*	-0.122**	-0.0434	-0.110*	-0.114***
	(0.0487)	(0.0532)	(0.0525)	(0.0549)	(0.0337)
Observations	137,996	164,934	144,660	213,122	213,122
R^2	.427	.404	.424	.404	.404
User FE	YES	YES	YES	YES	YES
			C. Grocery spending		
February 26 - March 10	0.0926***	0.142***	0.122***	0.161***	0.148***
	(0.0338)	(0.0108)	(0.0231)	(0.00953)	(0.00977)
March 18 - March 31	-0.124***	0.0572***	-0.0292	0.0829***	0.0872***
	(0.0416)	(0.0130)	(0.0287)	(0.0114)	(0.0118)
February 26 - March 10*Group	0.0348	0.0492	-0.0474	-0.069	0.0270
	(0.0441)	(0.0512)	(0.0465)	(0.0476)	(0.0333)
March 18 - March 31*Group	0.181***	-0.0812	-0.05	-0.072	-0.110***
	(0.0547)	(0.0592)	(0.0555)	(0.0578)	(0.0377)
Observations	137,996	164,934	144,660	213,122	213,122
R^2	.421	.4	.422	.399	.399
User FE	YES	YES	YES	YES	YES

Table 5: Spending across varying case counts and individual outlook

This table provides the results of a regression of spending on indicators for the different time periods. ln(Cases) measures the natural log of confirmed COVID-19 cases at the state-week level. "Optimistic" is an indicator for users who completed a survey during May 2020 and believed that the economy would be back to normal within 6 months of their survey date. Standard errors are clustered at the user level. $*p < .1$; $** \ p < .05$; $*** \ p < .01$. *Source*: SaverLife.

Variables	(1) All	(2) Restaurant	(3) Groceries	(4) All	(5) Restaurant	(6) Groceries
February 26 - March 10	0.480***	0.319***	0.147***	0.446***	0.344***	0.157***
	(0.0519)	(0.0433)	(0.0419)	(0.0125)	(0.00985)	(0.00938)
March 18 - March 31	-0.194***	-0.0988***	0.0508*	-0.274***	-0.244***	0.0778***
	(0.0408)	(0.0288)	(0.0307)	(0.0150)	(0.0107)	(0.0112)
February 26 - March 10*ln(Cases)	-0.0465	0.0228	-0.0129			
	(0.0348)	(0.0283)	(0.0278)			
March 18 - March 31*ln(Cases)	-0.0252***	-0.0322***	0.000994			
	(0.00938)	(0.00680)	(0.00721)			
February 26 - March 10*Optimistic				-0.278**	-0.233**	-0.0383
				(0.138)	(0.103)	(0.116)
March 18 - March 31*Optimistic				-0.0719	0.104	-0.160
				(0.167)	(0.119)	(0.136)
Observations	213,122	213,122	213,122	213,122	213,122	213,122
R^2	.471	.453	.447	.415	.404	.399
User FE	YES	YES	YES	YES	YES	YES

A Appendix

Figure A.1: Relationship between predicted and actual political beliefs

This figure plots a binned scatterplot of predicted partisan scores against the self-reported political beliefs obtained from a survey of SaverLife users (N = 540). Self-reported political beliefs range from "Very Conservative" to "Very Liberal" with a value of zero representing "Moderate." Predicted political beliefs are based on Gallup data that have been matched to the demographic and locational data of users. *Sources*: Gallup and SaverLife.

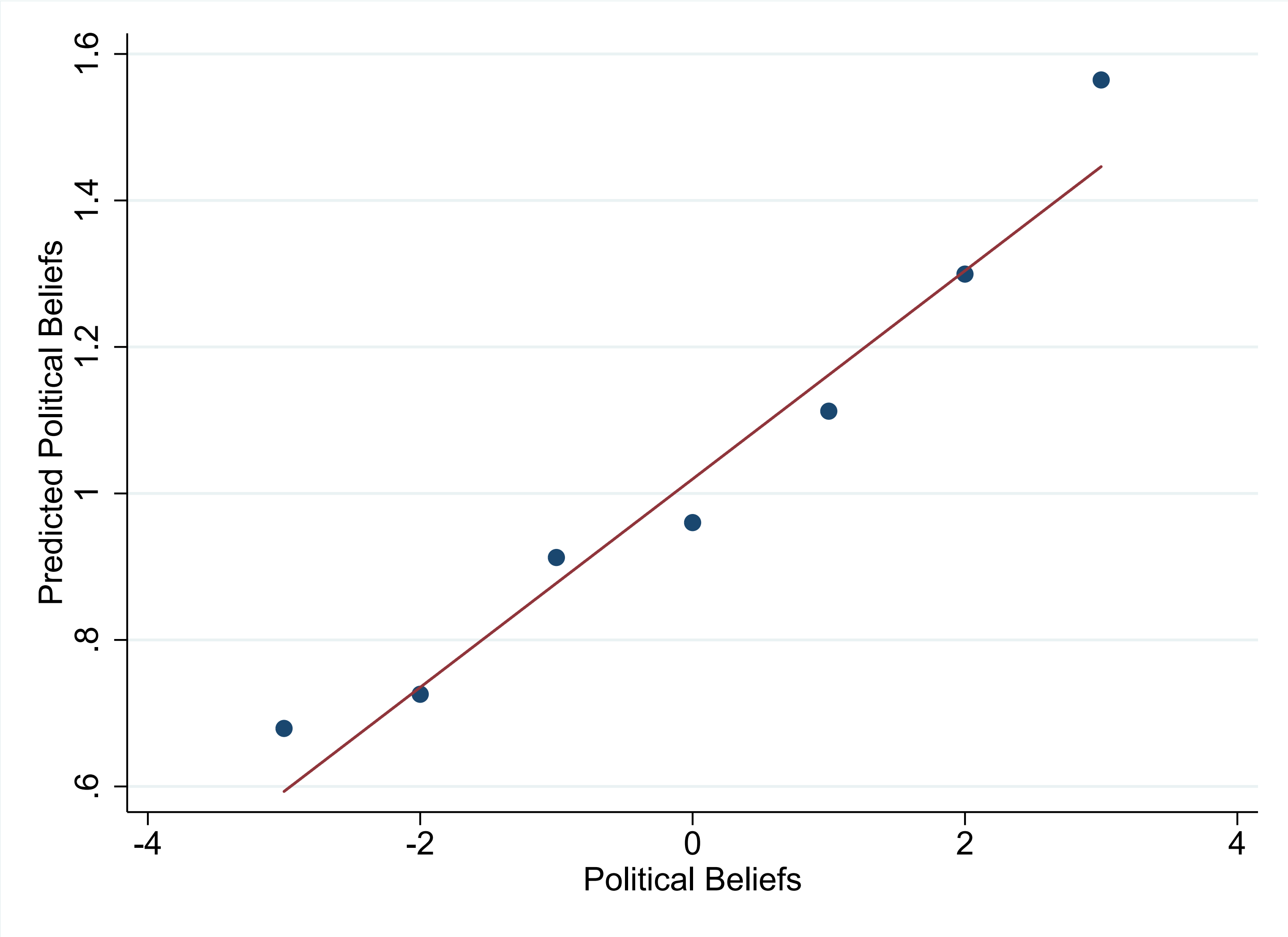


Figure A.2: Spending and social distancing: SafeGraph data

This figure plots a binned scatterplot of the drop in movement in all 50 U.S. states and Washington, DC, and the change in weekly individual spending across a number of categories in 2020, relative to the spending in the same week in 2019. Spending is measured in weekly dollars, and movement is taken as the weekly average. *Sources*: SafeGraph and Unacast.

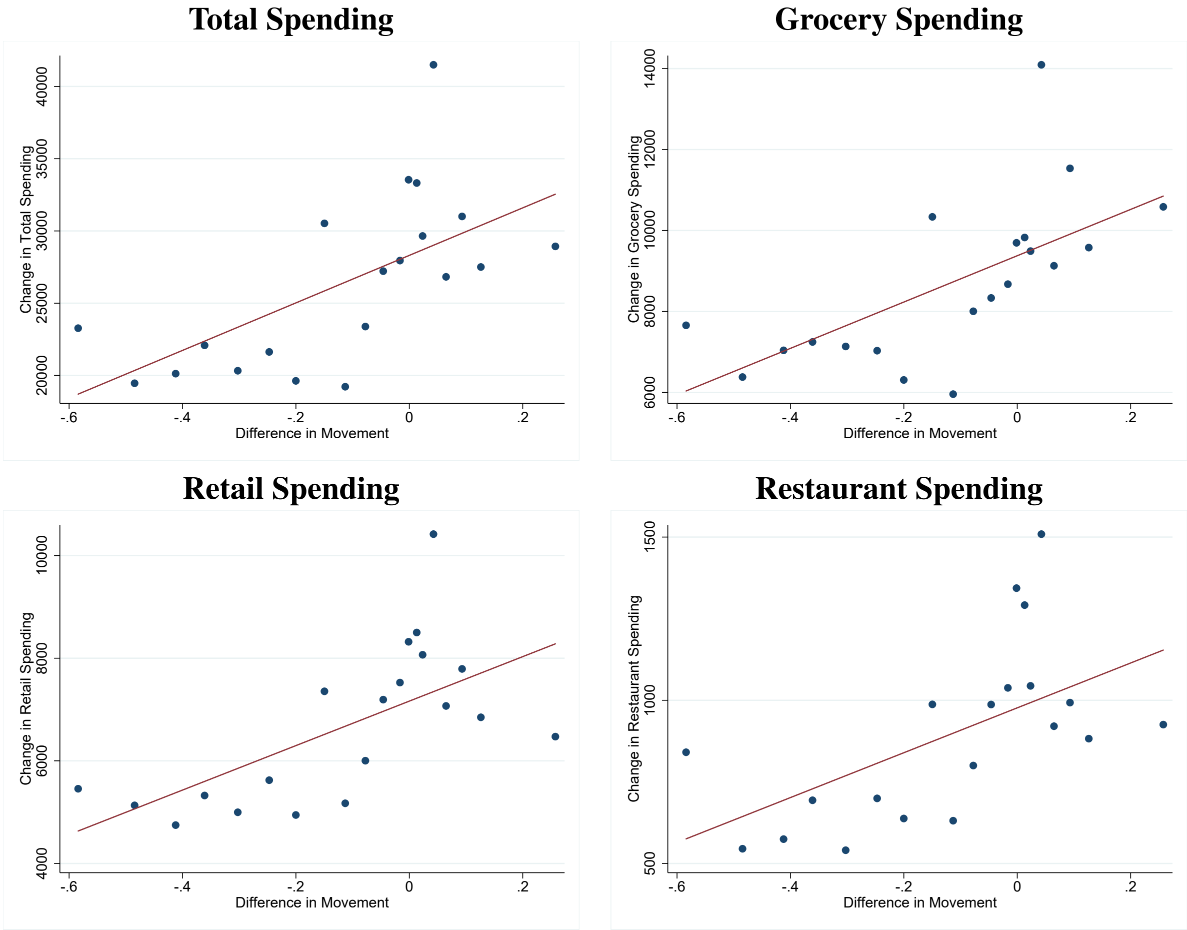


Figure A.3: Spending response across categories, by predicted partisanship: SafeGraph data

This figure displays the response of average weekly individual spending across a number of categories of spending. The figure displays the change in weekly individual spending in 2020, relative to the spending in the same week in 2019. For each category, the average user's response is plotted for three groups: the quartile of the sample with the highest "democrat" lean (quartile with the lowest Trump voter share), the quartile of the sample with the highest "republican" lean (quartile with highest Trump voter share), and "independents" who are in the middle two quartiles. Spending is measured in weekly dollars. *Source*: Safegraph.