Investigating the Causal Effects of Direct vs Indirect Stimulus Payments on Consumption and Saving Decisions Throughout the Covid-19 Pandemic

Zachary Jaramillo

Princeton University
Department of Economics

April 18th, 2022

Key Words: Stimulus Payments, Covid-19, CARES Act, American Rescue Plan, Prospect Theory, Marginal Propensity to Consume, Recovery Rebate Act

This paper represents my own work in correspondence with the University's Honor Code - Zachary Jaramillo

I. Abstract

The goal of this paper is to analyze the causal effects of stimulus payments made during the Covid-19 Pandemic on increases in household consumption and personal savings. Specifically, I will estimate the increases in consumption utilizing a Difference-in-Differences regression between the first and fourth quartiles of income for all three rounds of stimulus payments. The analysis leverages Affinity Solutions' consumer spending data made available by the Opportunity Insights Economic Tracker website created by Chetty, Friedman, Hendren, Stepner (2020). Overall, by conducting this research, I attempt to investigate the presence of behavioral biases described by Tversky and Kahneman's Prospect Theory in spending and saving decisions throughout the Pandemic. My main hypothesis is that increased wealth gained through the American Rescue Plan Act stimulus payments was spent at much lower rates than the previous two stimulus efforts (CARES Act and the Consolidated Appropriations Act) due to the fact many individuals received their stimulus as a tax rebate and do not view recovered losses in the same way as they do windfall gains. Overall, I find that all three stimulus payments result in increases in the savings rate and personal spending; however, it appears that all income categories move very similarly except for stimulus three which shows a significant difference between high income and low-income consumer spending as a result of the stimulus payment.

II. Introduction

The Covid-19 Worldwide Pandemic is the globe's most recent economic and health crisis. Due to initial uncertainty and widespread fear about the uncontrollable nature of the virus, many nations made the conscious decision to require mandatory lockdowns to restrict movement and help slow the spread of the disease. These lockdowns led to rapid unemployment which in turn caused many Americans to question their ability to pay for basic necessities and/or bills while being out of a job. To combat this unavoidable crisis, many national governments approved economic relief measures like the CARES Act that aimed to use transitory income either in the form of direct stimulus checks to supplement and kickstart economic growth. The main idea behind these measures and others in the past is to help fill the gaps and cover many citizens' basic needs during a time of emergency. Additionally, there is also the secondary but important governmental goal for citizens to use this extra income to boost aggregate spending and speed up the return to pre-crisis levels of monetary flow. Naturally, the question arises of how well these transitory income streams help stimulate economic growth and how much of the income is used for saving as opposed to spending. In order to help answer this question and hopefully assess the effectiveness of past stimulus checks at revitalizing the economy through increased spending, it is necessary to understand how citizens view these "windfall" incomes and the effect that mental framing plays in influencing the consumption decisions that agents are faced with after receiving their transitory payments.

The goal of this research paper is to expand on the experiments that have already been conducted on mental accounts, prospect theory, and framing changes in income as either gains or losses to hopefully show how the 2020-2021 stimulus efforts were influenced by these sorts of behavioral biases and ultimately caused deviations from the normative predictions of rational consumption smoothing. My overall hypothesis, which is partly influenced by the results of the US Census Surge Household Survey, is that the stimulus payments during the Covid-19 crisis that were rewarded through checks and thus viewed as unexpected gains were spent in much higher proportions than the last round of stimulus that was received as a rebate, as a part of the Recovery Rebate Credit, around the time that taxes were being submitted. If this is true, it would lend credence to many behavioral economists' predictions about mental accounts as well as help governments to properly decide whether to frame stimulus efforts as positive gains or income returned to citizens in the future. Hopefully, this research will produce beneficial results that can be used to quicken economic recovery during another crisis or even help bolster up private savings if that happens to be the goal of a national government during a recession or other period of historically low aggregate savings.

III. Literature Review

A. Classic Economic Theory

Before analyzing framing's role in consumption choices surrounding windfall gains, it is important to explain the classic economic thought behind typical everyday spending. According to modern, normative economic theory, it is assumed that agents are rational and possess complete, transitive, and strictly monotonic preferences. These preferences, which large parts of intermediate microeconomics courses are devoted to explaining, attempt to define how economic agents will act and choose to spend their money in situations of scarcity. In addition to these preferences with very specific characteristics, there is an added assumption that by assessing their current allocations of resources agents aim to maximize their overall utility (or happiness). From these two suppositions, many economic theories about the world are derived in order to explain natural phenomena and choices surrounding money. The most important of these theories to the discussion of windfall gains and consumption decisions are the Life-Cycle Hypothesis and Permanent Income Hypothesis. By investigating the implications of these theories, it becomes clear how normative economics predicts US citizens will spend the income received from transitory payments.

The first hypothesis, proposed by Franco Modigliani (1957), explains that agents prefer to smooth consumption over the course of their lifetime by either borrowing or saving. By doing so, individuals can transfer resources over time periods of either low or high income and ultimately create a more stable consumption pattern. In theory this is very reasonable since one would expect agents to understand that they will not be able to work forever and thus must save up some of their income during their younger, higher income-earning years in order to retire comfortably and live off this saved income. Of course, this does not always happen in the actual world due to frictions like a present focus bias where people discount future income so much that they cannot commit themself to save or perhaps other situations where individuals simply do not have enough extra income to save in the first place (a hand-to-mouth household). Additionally, this life-cycle model relies heavily on the assumption that individuals can properly use financial instruments in order to save effectively which is not often true. Despite these criticisms, there is plenty of evidence that says when people are able, they do follow some sort of life-cycle consumption patterns similar to what Modigliani (1957) proposed. Also, since so many people save for retirement, this theory seems to be backed empirically by economists like Mervyn King who suggested that up to 75% of the population adheres to this sort of life-cycle model. Overall, it can be concluded from this theory that agents are able to rationally assess their current income situation and properly decide to spend income so long as they predict to have a similar amount in the future.

In addition to the Life-Cycle consumption model, Milton Friedman (1957) Permanent Income Hypothesis attempts to explain how consumption patterns are formed while also discussing the lenses through which agents view various changes in their income. In layman's terms, Friedman (1957) proposes that economic agents regard unexpected, one-time income as temporary and thus will not alter their spending habits unless this extra income somehow changes their permanent income (hence the name). In general, agents that receive transitory income will look towards their future expectations on consumption and either use it with the same level of marginal propensity to consume/save if they believe the change in income is permanent or smooth out it's consumption over the rest of their life if they believe it, is a one-time change. One important implication of this theory is that agents will not always increase spending proportionate to the amount of windfall income they receive in a given period. In the case of stimulus checks, this means that transitory income should not affect aggregate consumption unless perhaps it is the case that it is replacing income that was recently lost due to the crisis. All in all, these two hypotheses paint a clear picture of how agents use rational expectations of the future to effectively smooth consumer spending over time. By combining these two normative theories, economists predict that in ideal situations, American citizens can perfectly assess future consumption and tend to spend income in very calculated ways. Absent from these theories however are outside behavioral factors that tend to alter consumption decisions based on how income is framed within the minds of recipients. By looking at direct critiques of these models proposed by behavioral economists, a different perspective is given to the effect of transitory incomes on individual spending which can hopefully lead to better implementation of relief payments in the future.

B. Normative/Behavioral Economic Theory

One of these popular critiques is that humans are not able to properly assess transitory changes in income like perfectly rational agents would and therefore rely on heuristics or concealed biases to make decisions about how to spend or save amounts of money that they receive as windfall gains. Most important to this discussion is Prospect Theory, developed by Amos Tversky and Daniel Kahneman (1979), which theorizes that agents view changes in income differently based on whether it is seen as an unexpected gain or a recovered loss. In each situation, individuals will place the gain in different mental accounts (a term coined by Richard Thaler) from which they then decide to spend or save at different rates. Just like the other theories above, this too appears very reasonable when proposed to an everyday person because they know that they are much more likely to go out and spend money that they received as a bonus more readily than they would if they salvaged some money back after losing a large sum in a risky investment.

Up until the recent Covid-19 global economic crisis, most of the academic literature that attempts to analyze this question about mental accounts, framing, and Prospect Theory do so on a very small scale with experiments conducted on undergraduate students that involve windfall gains in the ballpark of $20-$50. Although many of these studies do not involve amounts of money like those of direct stimulus payments, they still provide evidence that this bias is present in many individuals. Also, many of these studies have produced exciting results that seem to support the idea that individuals have far different marginal propensities to consume/save depending on the situation in which they receive an unexpected income. These findings are useful as we will implement them as a base to build off as we look at the differences between the three rounds of stimulus payments that were sent out during the COVID-19 pandemic.

In the case of several similar studies conducted by Epley, Mak, and Chen Idson (2006) on a group of Harvard undergraduates, the experimenters decided to give payments of between $25-$50[1] to every one of the lab participants and then randomly assigned them to a group that either had this income framed as "tuition rebates" or "bonus income" (later this was changed to "rebate money" and "bonus money" just to be sure there was no confounding effect caused by the difference between the use of "tuition", "income", "bonus", and "rebate"). The participants

[1] The amount changed based on the experiment but was consistent within each iteration

were then either asked to self-report the ways in which they spent this income or were simply tracked inside the laboratory setting by giving each student their own account to buy items in the lab with. Perhaps surprisingly, there were extreme variations between the two groups with the participants that received money framed as rebates typically spending between 20% to even 50% of what the other "bonus income" group would. In the case of the last experiment, which Epley et al. (2006) argue in their paper was the most precise at measuring the differences in spending since it removed many of the confounding variables of the previous experiments, out of windfall gains of $25 the "bonus" group on average spent $11.46 compared to $2.43 spent by the "rebate" group. Of course, this sounds very shocking at first, but many other studies conducted in a similar manner support this discrepancy in marginal propensity to consume. Also, it should be noted that other recent research by the Chicago Federal Reserve Bank that estimated the MPC of the first two rounds of stimulus payments has similar findings to this small experiment which implicitly says that the MPC of the "bonus" group is around 0.45 = $11.46/$25.

Moving on, Arkes et al, (1994) used a similar methodology as the paper mentioned above and ran various experiments to assess the effect of unexpected gains on individuals' MPC's and found statistically significant evidence to support Prospect Theory and Richard Thaler (1985) idea of separate mental accounts. In this paper, the researchers first polled undergraduates to see how they would spend 'hard-earned' money compared to money they won through a random radio promotion. Later, they altered the experiment to give lab participants sums of money by either telling them about it in advance by means of a phone call or giving it to them on the day of without future warning. In each case, participants were then asked to bet money on games within the lab and then in a different experiment, sent off to a basketball game so that the researchers could track their willingness to spend their newfound money. At the end of the paper after observing consistent results across all experiments, Epley et al. (2006) concluded that windfall gains appear to be spent more readily than non-windfall gains and a defining characteristic of a windfall gain seems to be its unanticipated status. Additionally, in their Playing with House Money section, the economists mention a hypothesis made by Shefrin and Thaler (1988) that points out that large amounts of money generally go in the assets account, which has a very low MPC. Overall and in conjunction with the previous paper by Eply and fellows, this research helps provide clear empirical evidence for Prospect Theory and mental framing of windfall gains which will be useful as we analyze more recent stimulus efforts and the ways in which these behavioral biases affect consumption on a larger scale.

C. Recent Literature on Stimulus Efforts

Shifting focus to recent literature, Kangli et al, (2020) used debit card spending panel data from low-income households to track how these households' spending decisions were affected by the onset of the lockdowns and then how they changed directly after a household received the extra income provided by the stimulus checks. Not surprisingly, this team found that lockdowns negatively impacted aggregate spending and then that the stimulus checks were able to effectively increase spending within the first couple weeks of an individual receiving their payments. More specifically, Kangli et al (2020) looked at how regional differences played a role in the changes in aggregate spending. By utilizing a difference-in-differences regression analysis that broke down the credit card spending on an individual basis and a regional basis, which they called a per card level and a zip code level, the research team was able to isolate spending changes in major categories such as Travel, Home, Health, Food, Entertainment, and Finance. They then took it a step further and looked at differences between zip codes that were predominantly Democratic or Republican. Among their most notable findings was the fact that

Democratic areas displayed much more volatile reactions to lockdowns and then the stimulus payments. Altogether, it is from this research paper that I decided to find similar data in order to see how regional differences played a role into the changes of consumer spending/saving between the various rounds of payments. Also, I believe that a difference-in-differences methodology will be effective when looking at changes in stimulus payment spending because it will allow for stimulus efforts to be compared to each other and then hopefully see if the last round caused a significant increase in spending just like the first two.

Finally in another recent working paper, Karger and Rajan (2021) from the Federal Reserve Bank of Chicago investigated the "Heterogeneity in the Marginal Propensity to Consume" by looking at the effect of the first two rounds of stimulus payments made in April 2020 and January 2021. They concluded that consumers who received the first round of checks had an MPC of around 46% and a similar MPC of around 39% for the second round. These results were found by looking at compiled data from a private company called Facetus that contains anonymized information about around 2.6 million card transactions that occurred around the same time the stimulus payments were received. After estimating the MPC for both the 2020 CARES Act and the subsequent Consolidated Appropriations Act, Karger and Rajan (2021) then claimed that a more targeted approach would have been able to produce similar increases in spending and debt payments while also saving nearly $50 billion. Overall, this approach is very sophisticated and relies heavily on the use of private transaction data. However, the results of the Karger and Rajan (2021) study helps to support the hypothesis that the first two rounds of stimulus payments were viewed as supplementary income as the average MPC of these two gains was around 0.40-0.45. Like I mentioned before when looking at the Epley et al. (2006) lab experiment, it is very interesting that the small-scale tests also showed a similar estimate of

MPC of stimulus recipients. In order to fully test the hypothesis that the last round of stimulus payments was viewed as rebates, one must extend the methodology and study of Karger and Rajan (2021) to recipients of the American Rescue Plan Act.

IV. Data

A. Pulse Household Survey Results: From US Census Bureau

The first task after formulating the research question was to determine if there was any evidence pointing to US citizens spending less of the third stimulus payments when compared to the first two rounds. After some initial research, I found the Household Pulse Survey conducted by the United States Census Bureau that aimed to measure how the COVID-19 pandemic affected households on both a social and economic level. As one part of their weekly survey that started at the end of April 2020, the Census Bureau would ask participants if anyone in their household had received a stimulus payment within the past seven days and then proceed to ask if that stimulus payment was "mostly spent", "mostly used to pay off debt", or "mostly saved". The results of these polls were quite surprising and seem to support the initial hypothesis that the last stimulus payments were saved at higher percentages. In the absence of data such as the Facteus and SafeGraph sources that can identify whether individuals received stimulus payments or not and how they spent them, the Household Pulse Survey provided the next best option for gauging overall trends of the effects on consumption and saving.

In order to compare the results of the Household Pulse Survey and see if there was any noticeable difference in how participants were choosing to consume their stimulus checks, I separated all of the data based on the weeks that corresponded with each round of payments. Since the Census Bureau did not include the stimulus payment section in every week of their study since there were obviously weeks in 2020 in which a significant amount of US citizens did not receive stimulus payments within the last 7 days, this process was relatively straightforward. After aggregating the results and classifying them based on each stimulus round, I then decided to take the average of each category which can be seen below. Overall, the compiled results seem to show that the second and third stimulus payments were saved nearly twice as often as the first one. This was enough evidence to motivate further research into how much less individuals decided to spend their stimulus.

Table 1. Results of Household Pulse Survey[2]

Compiled Household Pulse Survey Data (Seperated by each round of stimulus)

First Stimulus	Someone in household received a stimulus payment in the last 7 days						
Week	Mostly spent it	Mostly used it to pay off debt	Mostly saved it	Total	Mostly spent it %	Mostly used it to pay off debt %	Mostly saved it %
7	147,888,134	33,180,406	29,840,893	210,909,433	70%	16%	**14%**
8	151,352,774	31,902,848	29,675,024	212,930,646	71%	15%	**14%**
9	155,773,950	30,393,210	27,062,509	213,229,669	73%	14%	**13%**
10	157,315,763	30,512,384	24,904,189	212,732,336	74%	14%	**12%**
11	157,757,161	29,955,251	23,626,464	211,338,876	75%	14%	**11%**
12	157,754,708	29,611,749	23,295,542	210,661,999	75%	14%	**11%**
Average					73%	15%	12%

Second Stimulus	Someone in household received a stimulus payment in the last 7 days						
Week	Mostly Spent it	Mostly used it to pay off debt	Mostly saved it	Total	Mostly spent it %	Mostly used it to pay off debt %	Mostly saved it %
22	31,675,000	75,494,519	37,720,126	144,889,645	22%	52%	**26%**
23	38,172,193	75,822,216	35,296,684	149,291,093	26%	51%	**24%**
24	34,698,034	65,895,929	26,369,346	126,963,309	27%	52%	**21%**
25	31,449,682	57,734,016	21,383,702	110,567,400	28%	52%	**19%**
Average					26%	52%	22%

Third Stimulus	Someone in household received a stimulus payment in the last 7 days						
Week	Mostly Spent it	Mostly used it to pay off debt	Mostly saved it	Total	Mostly spent it %	Mostly used it to pay off debt %	Mostly saved it %
26	25,848,703	50,394,510	20,089,428	96,332,641	27%	52%	**21%**
27	27,339,395	73,675,800	46,661,689	147,676,884	19%	50%	**32%**
28	12,665,003	32,153,380	17,811,038	62,629,421	20%	51%	**28%**
29	10,071,983	23,590,909	11,456,282	45,119,174	22%	52%	**25%**
30	8,943,170	19,832,349	9,482,644	38,258,163	23%	52%	**25%**
31	7,609,404	17,639,364	7,609,502	32,858,270	23%	54%	**23%**
32	6,992,209	15,494,022	7,196,650	29,682,881	24%	52%	**24%**
33	6,602,971	14,494,714	5,956,836	27,054,521	24%	54%	**22%**
Average					23%	52%	25%

[2] Week 7 corresponds to June 11, 2020.

After looking at the results of the survey, it should be mentioned that the compiled Household Pulse Survey data illuminate an interesting shift in the spending/saving patterns of stimulus recipients as the pandemic progressed. Specifically, there is a large spike between round one and rounds 2-3 in respondents claiming that they will mostly be using their stimulus to pay off debt (an increase from around 15% to over half of respondents in the subsequent rounds). This shift suggests that the first-round payments were much more effective at stimulating consumer spending than the later ones. One possible explanation for this is that as the pandemic evolved, many Americans became more comfortable with their economic situation and began to shift focus from short-term needs such as disposable goods to longer-term financial payments like their mortgages, rent, etc. By paying down debt instead of outright using the stimulus payments to supplement lost income, the recipients show a forward-looking consumption function where they are not as worried about short-term economic uncertainty as much as before.

B. Personal Savings Estimates: From Bureau of Economic Analysis

In addition to using the Household Pulse Survey Results to gain a sense of how stimulus recipients spent and saved their money, I also decided to look at estimates of the Personal Savings rate from the Bureau of Economic Analysis. In their estimates, which are created using predictions of personal disposable income, the BEA defines the personal savings rate as "personal income less personal outlays and personal current taxes" on their website. Below, I have created a graph of the personal savings rate throughout the pandemic period. As can be seen below, increases in personal savings correspond directly with stimulus payments as noted by the three increases in the graph. Unfortunately, because these estimates are done monthly, direct increases in savings rate cannot be measured with great accuracy. Despite this, there is a clear connection between the stimulus payments and increased savings rate for all three rounds.

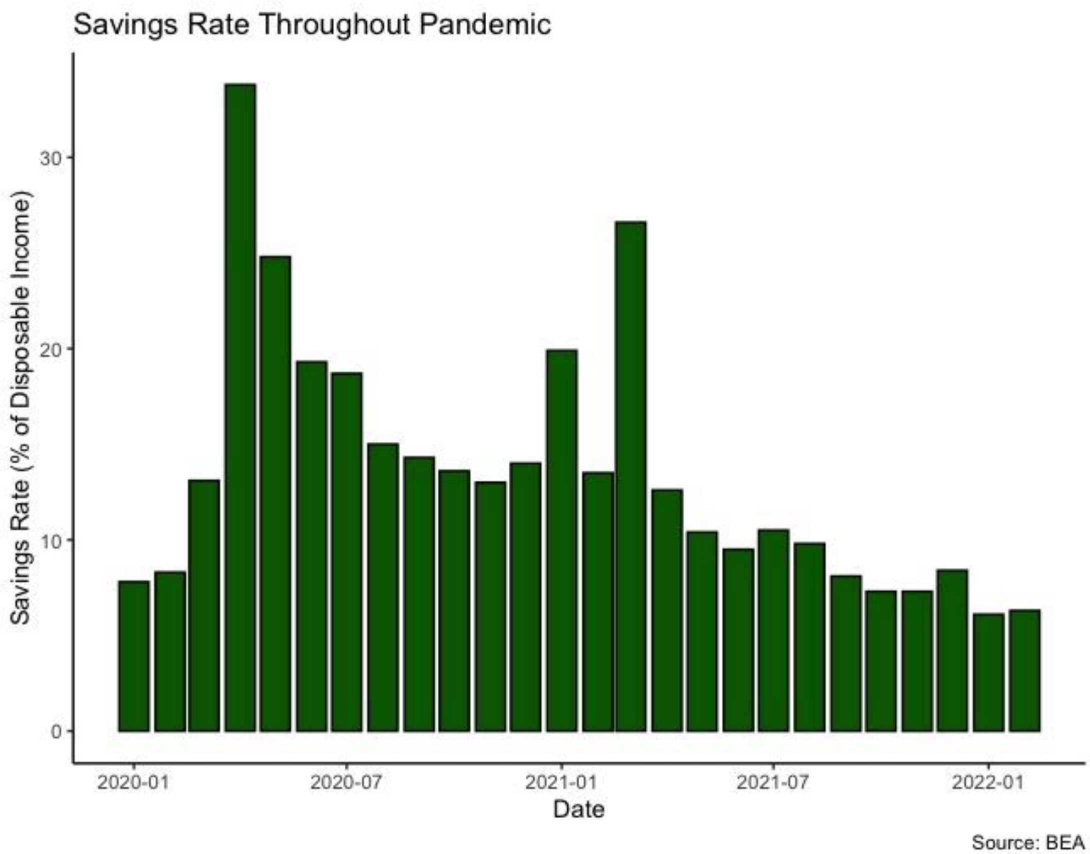


Figure 2. Personal Savings Rate

As mentioned before, there are three clear spikes in savings rate that correspond to the three rounds of payments. Interestingly, the American Recovery Act payments (stimulus 3) does seem to cause the savings rate to increase more than the Consolidation Act (stimulus 2). This seems to support the hypothesis that stimulus 3 was saved at higher rates than stimulus 2. Also, since the first stimulus payments correspond with the initial lockdowns and reduced economic activity due to uncertainty and fear, the higher savings rate for a sustained period is explained. In the appendix, figures 7a and 7b add indicators for when stimulus payments were received as well as when stimulus payments were announced. This subtlety in changes in timing will be explored later but it seems that stimulus recipients tend to spend their newfound wealth before they actually get it as they are forecasting increased wealth in the near future.

C. Consumer Spending Data: From Opportunities Insights Economic Tracker

After analyzing the compiled Household Pulse Survey Results, the next step was to look at the aggregate effects of each round of stimulus on consumer spending. In order to measure the differences between each round of stimulus, I leverage consumer spending data from the Opportunities Insights Economic Tracker created by Chetty, Friedman, Hendren, Stepner (2020). Thanks to their Opportunity Insights team, the data is simple to manipulate and presented in a very clear manner. On their website, the data is broken down into National, State, County, and Metro levels with the ability to view consumer spending in terms of daily percentage changes compared to pre-covid, January 2020. Additionally, the consumer spending data can be divided into individual industry categories such as Grocery, Retail, Transportation, Health Care, and Entertainment and Recreation and even allows for the direct comparison of low-, middle-, and high-income brackets. As part of my analysis, I will be focusing on the consumer spending estimates that aggregate all spending together to get an idea about how spending as a whole changed over time. I will also be utilizing the spending data that is broken down into the lowest 25% of national income as well as the highest 25% in order to compare changes in consumption for groups that received the stimulus payments and those that did not. Specifically, I will be using the spend_all_q# data compiled from the Affinity Solutions Inc. database that is made available by the Opportunity Insights Team on their website.

1. Is Affinity Data representative of Consumer Spending?

A very important question before doing this analysis is: How well does the Affinity data represent all consumer spending despite using mainly credit/debit card transactions? According to Chetty et al (2020), when compared to QSS and MARTS data, the Affinity data captures around 92% of spending across all represented sectors but seems to over-represent categories in which credit/debit cards are primarily used for purchases such as accommodation, food, and clothing sectors. Despite this, they say that the Affinity data is representative of total card spending which makes up around 50% of consumer spending. In their paper, they lay out some solutions to capture the other 50% of consumer spending in the forms of cash or other means by leveraging transaction data from a company by the name of CoinOut. Overall, I believe this is a great proxy for consumer spending; however, aggregated data that also adds in spending contributions from cash and other sources would be even better.

D. Data File Descriptions and Summary Statistics

Credit/debit card spending data from Affinity Solutions

- Spend_all: Spending in all merchant category codes (MCCs).
  - Spend_all_q1 : … by consumers living in ZIP codes with median income in quartile 1
  - Spend_all_q2 : … by consumers living in ZIP codes with median income in quartile 2
  - Spend_all_q3 : … by consumers living in ZIP codes with median income in quartile 3
  - Spend_all_q4 : … by consumers living in ZIP codes with median income in quartile 4

Below I have added summary statistics as well as preliminary graphs of the consumer spending data that I use in both my analyses. As mentioned above, the Affinity Data is broken down into four income brackets. As part of my analysis, I divided the data into the pandemic period as well as three separate stimulus periods which include 30 days before and after the treatment date. This treatment date initially is when each stimulus payment hits the bank accounts of recipients. Later on in the methodology section, I explain that I vary this treatment effect to explore stimulus check recipients' spending behavior before actually acquiring the windfall gain. Other summary statistics of the alternate periods can be found in the appendix section under Table 5.

Table 2. Pandemic Period Summary Statistics

Whole Pandemic Period

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
spend_all	726	0.021	0.085	-0.312	-0.003	0.029	0.078	0.216
spend_all_q1	726	0.079	0.09	-0.268	0.035	0.082	0.146	0.311
spend_all_q2	726	0.037	0.081	-0.285	0.004	0.041	0.095	0.249
spend_all_q3	726	0.021	0.085	-0.31	-0.005	0.029	0.079	0.213
spend_all_q4	726	-0.019	0.089	-0.354	-0.033	-0.004	0.035	0.159

Stimulus 1 Period

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
spend_all	61	-0.191	0.084	-0.312	-0.266	-0.197	-0.128	0.016
spend_all_q1	61	-0.122	0.089	-0.268	-0.203	-0.11	-0.043	0.032
spend_all_q2	61	-0.154	0.086	-0.285	-0.233	-0.151	-0.086	0.028
spend_all_q3	61	-0.189	0.086	-0.31	-0.266	-0.195	-0.124	0.018
spend_all_q4	61	-0.25	0.084	-0.354	-0.319	-0.267	-0.196	-0.004

Stimulus 2 Period

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
spend_all	61	0.024	0.049	-0.072	0.004	0.019	0.038	0.216
spend_all_q1	61	0.085	0.059	-0.008	0.052	0.077	0.098	0.311
spend_all_q2	61	0.041	0.053	-0.056	0.016	0.036	0.055	0.249
spend_all_q3	61	0.024	0.048	-0.07	0.004	0.02	0.038	0.213
spend_all_q4	61	-0.013	0.045	-0.108	-0.028	-0.016	-0.001	0.159

Stimulus 3 Period

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
spend_all	61	0.058	0.035	-0.011	0.036	0.066	0.074	0.13
spend_all_q1	61	0.138	0.064	0.035	0.09	0.14	0.169	0.277
spend_all_q2	61	0.08	0.044	0.004	0.048	0.084	0.103	0.174
spend_all_q3	61	0.058	0.033	-0.01	0.036	0.065	0.073	0.126
spend_all_q4	61	0.007	0.021	-0.043	-0.011	0.013	0.021	0.043

Figure 3a. Consumer Spending Broken Down by Stimulus (Round 1)

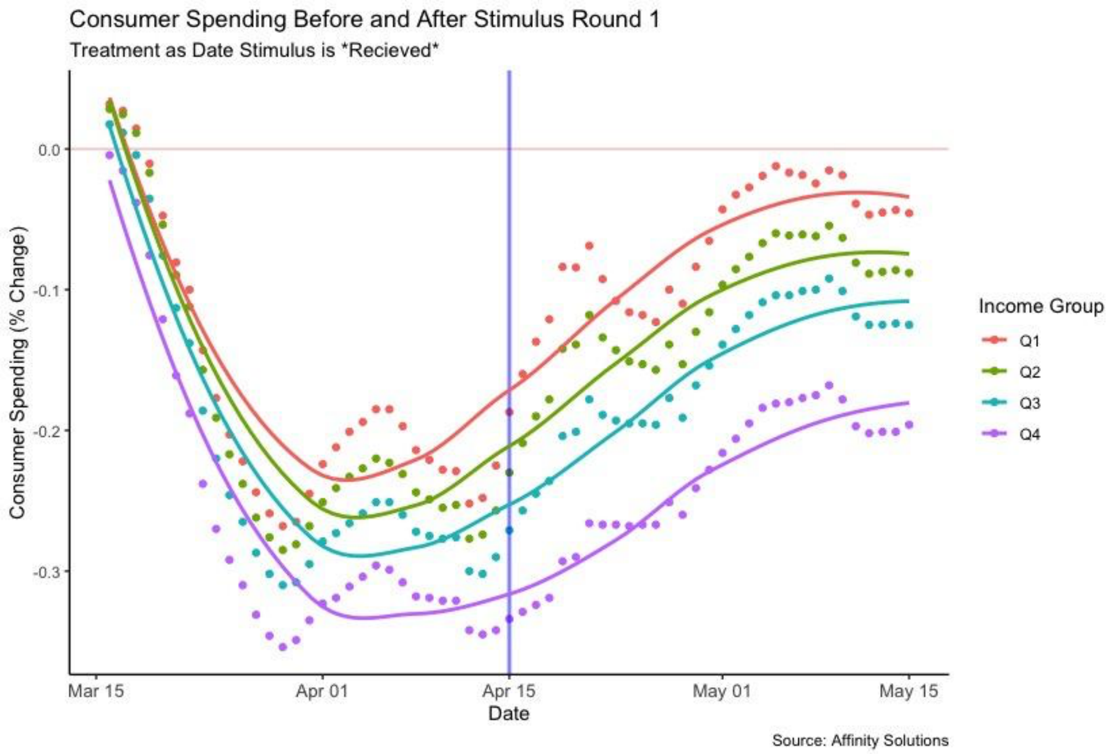


Figure 3b. Consumer Spending Broken Down by Stimulus (Round 2)

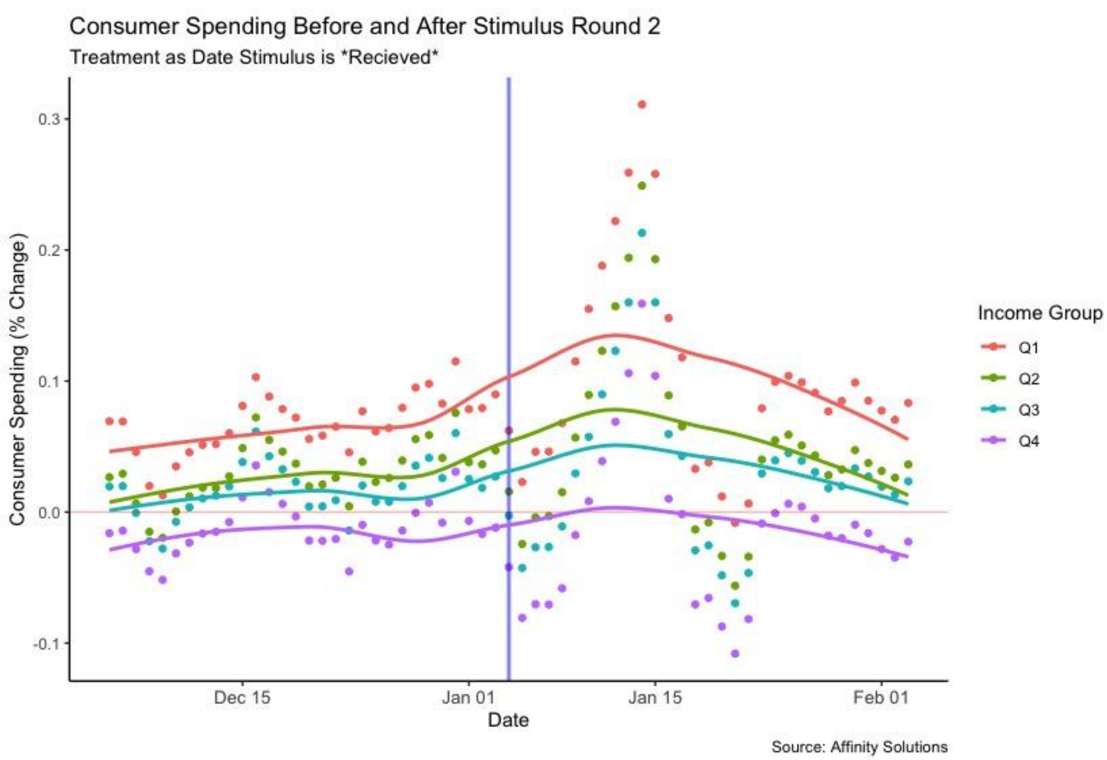
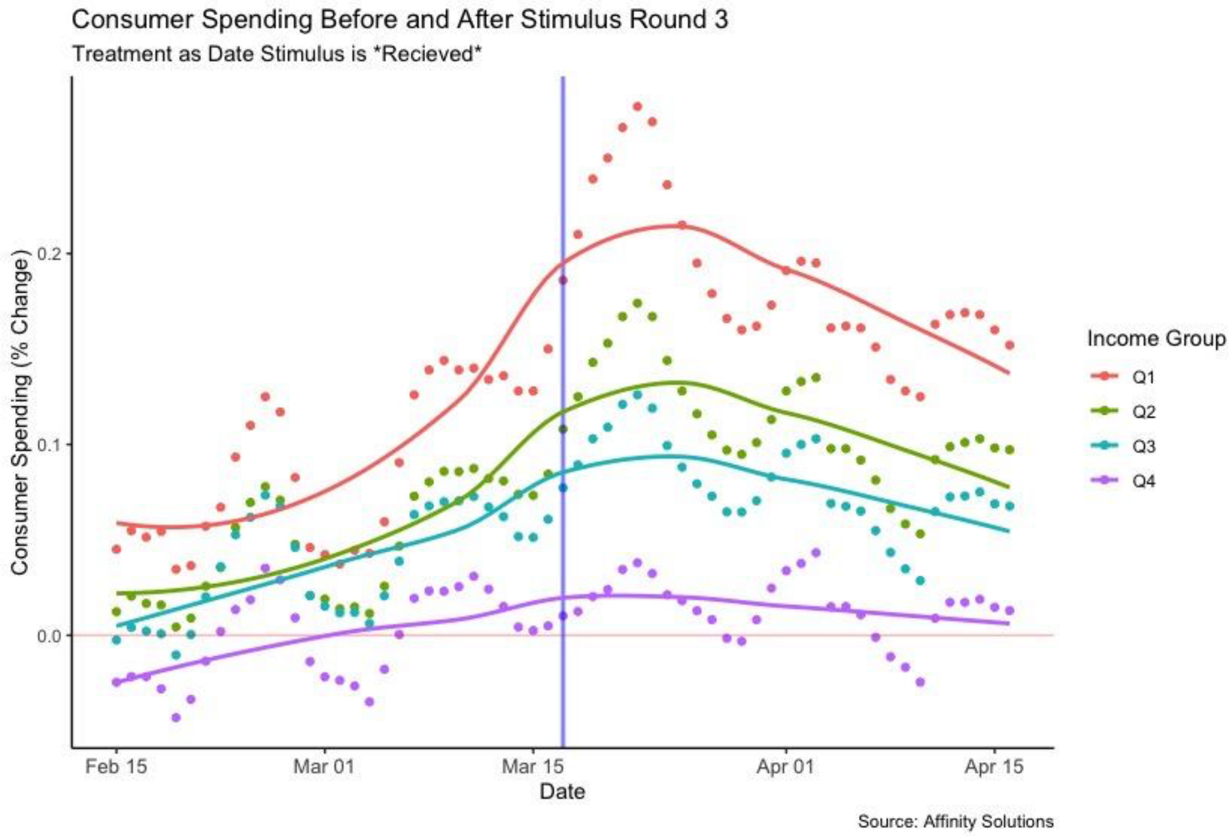


Figure 3c. Consumer Spending Broken Down by Stimulus (Round 3)



V. Methodology

A. Difference-in-Differences Analysis

When first looking at the stimulus payments and how each one specifically affects consumer spending, it was suggested to me to implement a Difference-in-Differences regression to measure the effect before and after the stimulus payments hit the hands of US citizens. A DID regression is useful in this case because there are clear treatment groups (Americans that received stimulus payments), control groups (Americans in the highest income bracket), as well as treatment times (when the stimulus payments are received for each of the three rounds). In this section, I explain my DID methodology as well as provide dates for the treatments I decide to use.

For my initial DID regressions, I decided to look at time periods before and after each stimulus payment was received in order to measure supposed changes in spending patterns caused by each round. As part of this analysis, I picked three dates corresponding to times when stimulus payments were first received. These dates are corroborated by many sources including the Chetty et al, (2020) Opportunities Insights Economic Tracker Website. These first dates came out to be “April 15, 2020”, “January 4, 2021”, and “March 17, 2021” for stimulus rounds 1, 2, and 3 respectively. These three dates marked the three treatment times that I use in my first DID regressions on each time period. As for length of time before and after treatment, I chose to look at time periods of 30 days before and 30 days after. I chose to use periods of roughly a month because I thought increases in wealth of around $500-$1000 would be spent over this period. Given the nature of the stimulus payments attempting to replace or stimulate necessary spending, it is possible that the time periods of treatment could be much shorter. This will be discussed in depth in the results and conclusion sections where I mention opportunities for future research.

$$\Delta Y_t = \alpha + \beta_1 * Time_t + \beta_2 * Treatment_t + \beta_3 * DID_t + \varepsilon_t \tag{1}$$

In the DID equation above, ΔYi is the dependent variable and measures the change in consumer spending for the low-income spenders before and after treatment. $Time$ is an indicator function when $Time_t = 1\{date \geq "Treatment\ Date"\}$ where the treatment dates are the times classified above. $Treated$ is also an indicator function $Treatment_t = 1\{ Spend =$ Spend_all_q1 } indicating the lower-income group which is the spend_all_q1 in the Affinity Data. Finally, DID measures the interaction of Time and Treated, $DID_t = Time_t * Treated_t$, its coefficient marks the change in spending between the treated and control group after the stimulus payments are received. Below in the results section are the regression outputs for the first, second, and third stimulus periods as well as the alternate treatment as announcement date.

B. Regression Discontinuity in Time Analysis

Additionally, I thought it would be beneficial to also use a Regression Discontinuity in Time analysis to measure the effect each stimulus round had on consumer spending of the low-income group. This is very similar to a Difference-in-Differences regression but does not rely on the use of a control group. In this part of my analysis, I used the same initial treatment dates as the DID regressions. This sort of analysis could be conducted on shorter time periods in order to investigate how changes in treatment length affected changes in spending. Finally, I thought that graphically this is a better representation of the supposed effect that each stimulus payment had on consumer spending.

$$\Delta Y_t = \alpha + \beta_1 * D + \beta_2 * X_t + \beta_3 * (X_{Right_t}) + \varepsilon_t \qquad \textbf{(2)}$$

In the RDiT equation above, ΔY_t is the dependent variable and is the change in consumer spending for the low-income consumers. α is the intercept value and X_t act as a control variable and denotes the periods before and after treatment where $X_t = 1\{date \geq "Treatment\ Date"\}$ X_{Right} is the interaction between D and X_t. In the RDiT equation, D is the main parameter of interest and its coefficient β_1 captures the estimated treatment effect which is the change in spending before and after the treatment dates. This coefficient will be compared to the β_3 coefficient from the DID regressions later in the results section. Overall, the RDiT analysis is meant to provide additional information and estimates above the causal effect of each stimulus payment. As well as graphically show the regression estimates of spending before and after treatments. In the results and appendix section, Figures 6a-c. and Figures 8a-c. show the results of the RDiT analysis.

C. Discussion on Treatment Times as Announcement

After looking at the initial graphs I made for each stimulus round and adding in a line for treatment date as the dates the stimulus payments began appearing in Americans' bank accounts, I noticed that it appeared that consumer spending was actually increasing before the treatment date. This got me thinking that perhaps individuals were going out and increasing their spending after forecasting future increases in wealth as a result of the stimulus payments they were going to receive. I then looked up when each stimulus payment was announced and decided to see if these dates corresponded with the increases in spending that I could see in the graphs. According to many news sources, the days that the stimulus payments were signed into law, making it official that Americans would soon begin receiving new wealth, were much earlier than the days the stimulus payments were received. This makes sense as it is a very difficult logistical problem to send millions of Americans payments all at once. As will be seen, this process improves over time and by the third stimulus payment, the difference between announcement date and the date payments are received is less than a week.

Down below I have added graphs similar to figures 3a-c with the dates of when each stimulus payments were announced as well as when they were received. As can be seen with stimulus one and two, spending appears to increase far before stimulus payments are received. After seeing this fact, I decided to split the data into three new periods including 30 days before and after the stimulus payments were announced. Using these three periods, I also conducted both the DID as well as the RDiT analysis to see if the spending increases were more significant with these new treatment dates of "March 25, 2020", "December 20, 2020", and "March 12, 2021" for stimulus 1, 2, and 3 respectively. The graphs of the new periods are shown below, and it is apparent the shapes of spending are different, especially in stimulus 2.

Figure 4a. Consumer Spending w/ Both Treatments Included (Round 1)

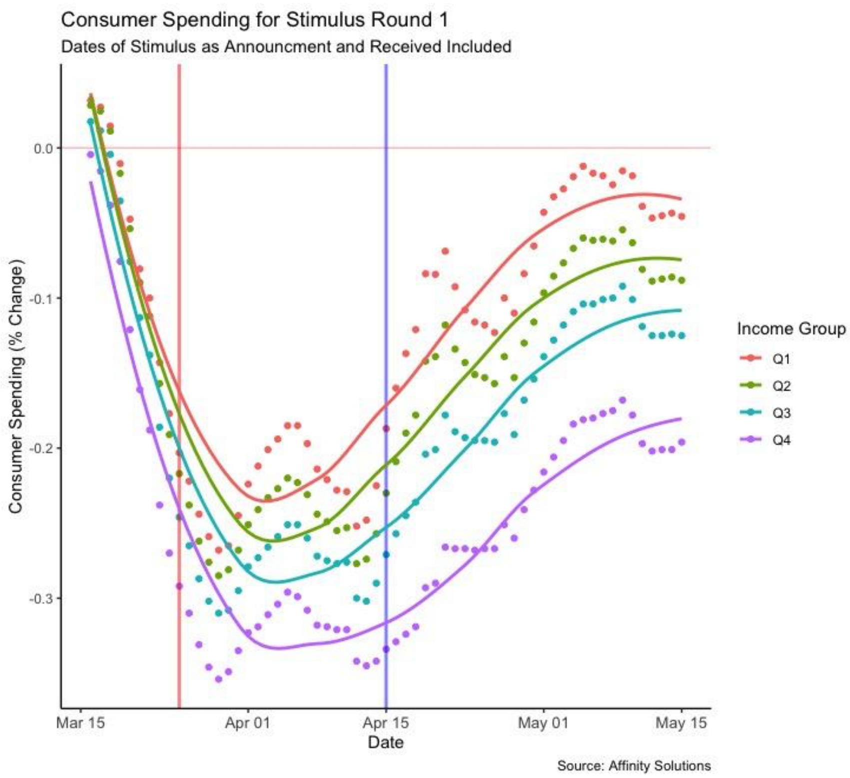


Figure 4b. Consumer Spending w/ Both Treatments Included (Round 2)

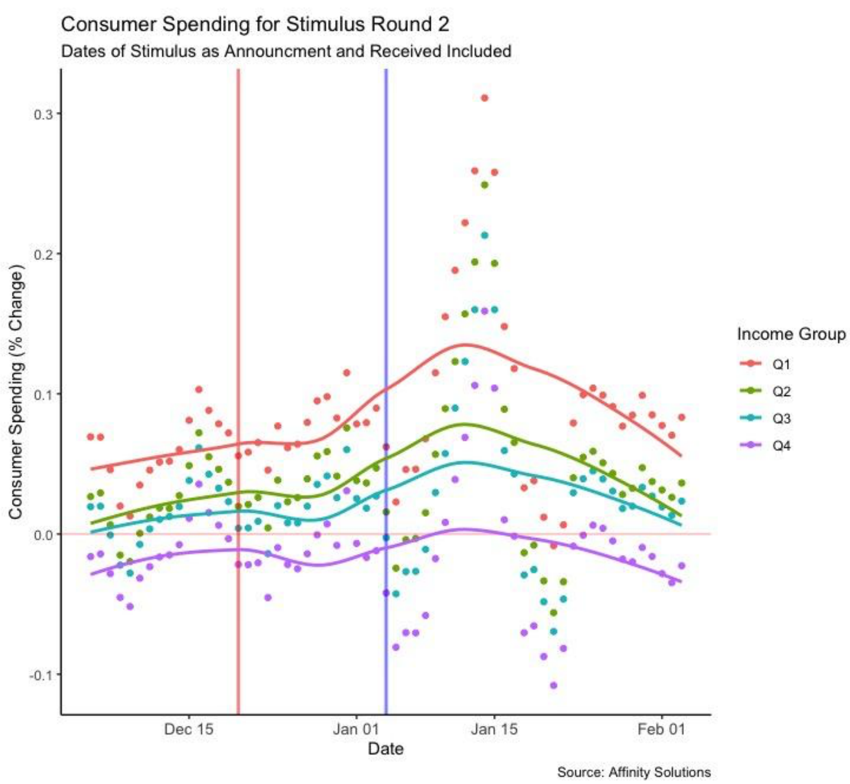
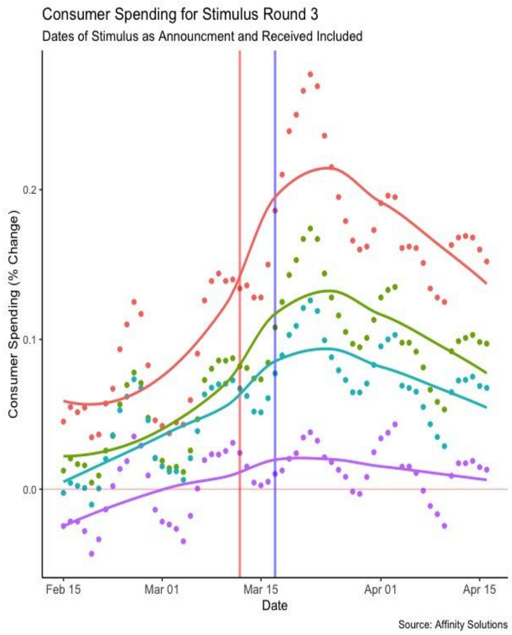


Figure 4c and Figures 5a. Consumer Spending w/ Both Treatments Included (Round 3) and Consumer Spending w/ Treatment as Announcement Date (Round 1)



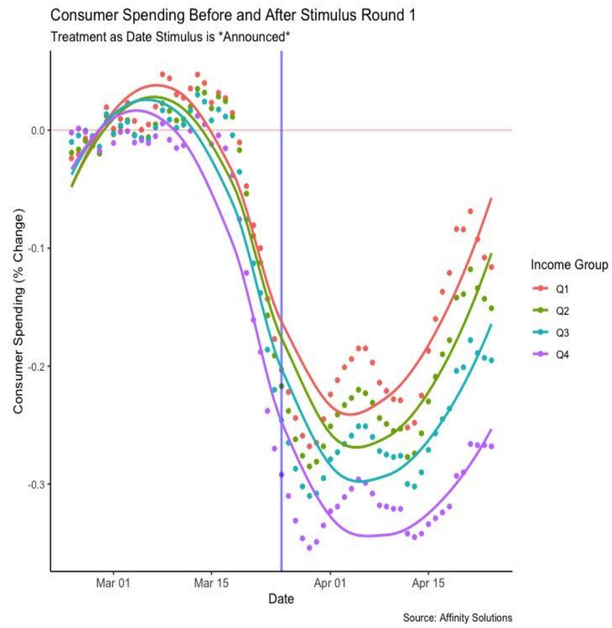
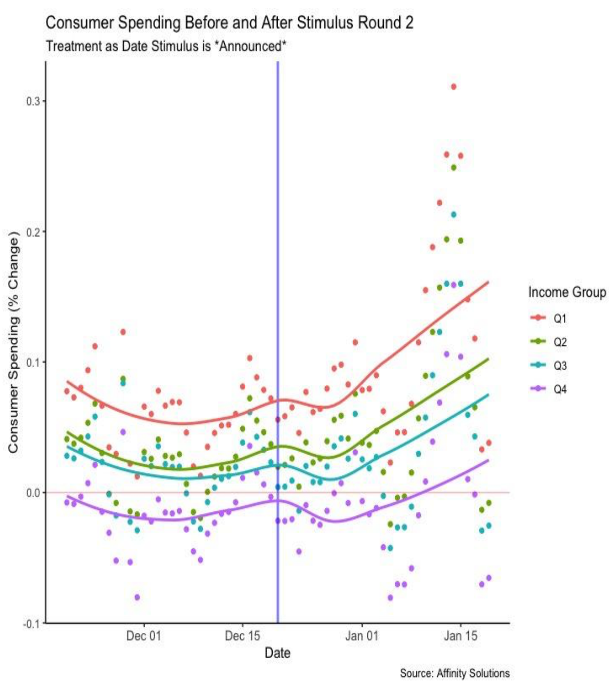
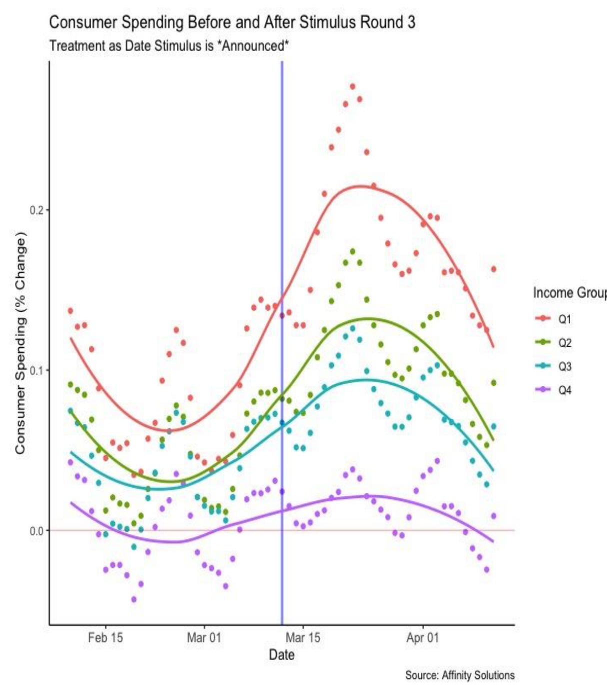


Figure 5b and Figures 5c. Consumer Spending w/ Treatment as Announcement Date (Rounds 2 and 3)





VI. Results

A. DID Results

Table 3a. DID Results (Treatment as Stimulus *Received*)

	Stimulus 1			Stimulus 2			Stimulus 3		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.26	-0.29 – -0.23	**<0.001**	-0.01	-0.03 – 0.01	0.193	-0.00	-0.01 – 0.01	0.811
treated	0.09	0.05 – 0.13	**<0.001**	0.08	0.05 – 0.11	**<0.001**	0.09	0.07 – 0.11	**<0.001**
time	0.03	-0.01 – 0.07	0.184	-0.00	-0.03 – 0.03	0.944	0.02	-0.00 – 0.03	0.056
did	0.08	0.02 – 0.13	**0.009**	0.03	-0.00 – 0.07	0.064	0.08	0.06 – 0.10	**<0.001**
Observations	122			122			122		
R^2 / R^2 adjusted	0.481 / 0.468			0.496 / 0.483			0.845 / 0.841		

Table 3b. DID Results (Treatment as Stimulus *Announced*)

	Stimulus 1			Stimulus 2			Stimulus 3		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.04	-0.06 – -0.02	**<0.001**	-0.01	-0.03 – 0.00	0.125	0.00	-0.01 – 0.01	0.898
treated	0.03	0.00 – 0.06	**0.022**	0.08	0.05 – 0.10	**<0.001**	0.09	0.07 – 0.10	**<0.001**
time	-0.27	-0.30 – -0.25	**<0.001**	0.01	-0.02 – 0.03	0.498	0.01	-0.00 – 0.03	0.135
did	0.09	0.05 – 0.13	**<0.001**	0.03	-0.00 – 0.07	0.069	0.08	0.06 – 0.11	**<0.001**
Observations	122			122			122		
R^2 / R^2 adjusted	0.831 / 0.827			0.502 / 0.489			0.828 / 0.824		

After performing the DID regressions for all three rounds of stimulus payments, we find that there was a statistically significant increase in spending for low-income Americans directly after stimuli 1 and 3 were released. For stimulus 1 specifically, the DID regression with the treatment times as the date stimulus was received has an estimated coefficient of 0.08 that is statistically significant up to the 0.01 p-level. Additionally, the DID regression with secondary treatment date of when the stimulus was signed into law has an estimated coefficient for DID of 0.09 and is also significant to the past the 0.01 p-level. These results are promising as both treatment dates have consistent estimated effects. Also, we see a large increase in the R^2 and adjusted R^2 when we move the treatment date back.

As for the last round of stimulus, both the first and second DID regressions also have highly statistically significant results and have estimated coefficients for DID of 0.08 and 0.09 respectively. This implies that the third stimulus caused an increase in consumer spending of around 9% directly after the payments were sent out. Since the two treatment dates for the last stimulus were only four days apart, it should be expected that their results would be nearly identical. We see this is true when we look at the confidence intervals for the DID coefficients and the R^2 and adjusted R^2 for both regressions. Here, just like the first stimulus payments, we see that spending is estimated to increase as a result of the last stimulus payments. This provides evidence to disprove my initial hypothesis that the last round of stimulus payments was not as effective at increasing consumer spending as the first two.

Finally, a surprising result of the two DID regressions is that they estimate no statistically significant change in consumer spending as a result of the second stimulus payments. Both treatments have estimated coefficients for DID as 0.03 but their confidence intervals contain 0.00. At least for me this was perplexing since on the Chetty et al. (2020) graph on the Economic Tracker website, the highest increase in percentage change of spending was always around the release of the second stimulus payments. However, when looking at the graphs of income brackets, it is clear that all income groups show similar increases in spending directly after the stimulus payments are announced and received. This results in the difference between the control group and treated group to be much smaller than the other rounds. The difference is most apparent when comparing stimulus round 3 to round 2 which shows almost no increase in high-income spending as a result of the last stimulus being released. This is what would be expected as the control group should not see any increased wealth as a result of the payments.

B. RDiT Results

Table 4a. RDiT Results (Treatment as Stimulus *Received*)

	Stimulus 1			Stimulus 2			Stimulus 3		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.29	-0.33 – -0.26	**<0.001**	0.09	0.05 – 0.14	**<0.001**	0.14	0.12 – 0.16	**<0.001**
D	0.16	0.11 – 0.21	**<0.001**	0.03	-0.03 – 0.09	0.275	0.10	0.07 – 0.12	**<0.001**
x	-0.01	-0.01 – -0.01	**<0.001**	0.00	-0.00 – 0.00	0.174	0.00	0.00 – 0.00	**<0.001**
x right	0.01	0.01 – 0.01	**<0.001**	-0.00	-0.01 – 0.00	0.057	-0.01	-0.01 – -0.01	**<0.001**
Observations	61			61			61		
R^2 / R^2 adjusted	0.721 / 0.706			0.140 / 0.095			0.809 / 0.799		

Table 4b. RDiT Results (Treatment as Stimulus *Announced*)

	Stimulus 1			Stimulus 2			Stimulus 3		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-0.27	-0.30 – -0.24	**<0.001**	0.08	0.05 – 0.11	**<0.001**	0.12	0.10 – 0.14	**<0.001**
D	0.12	0.04 – 0.19	**0.004**	0.01	-0.05 – 0.06	0.795	0.13	0.09 – 0.16	**<0.001**
x	-0.01	-0.01 – -0.01	**<0.001**	0.00	-0.00 – 0.00	0.442	0.00	0.00 – 0.00	**0.012**
x right	0.02	0.00 – 0.03	**0.024**	0.01	0.00 – 0.01	**0.050**	-0.01	-0.01 – -0.00	**<0.001**
Observations	61			61			61		
R^2 / R^2 adjusted	0.718 / 0.703			0.296 / 0.259			0.730 / 0.716		

As for the RDiT results, there appears to be a significant change in consumer spending as a result of the first and last stimulus payments. Just like the DID regression results, both treatment dates as the day stimulus payments are announced and when they are received point to increases in spending. Specifically, stimulus 1 has estimated coefficients for the change in spending as 0.16 and 0.12 and are both statistically significant well beyond the 0.01 p-level. When compared to the DID regressions, the estimated effect of the stimulus payments on consumer spending is larger but also has much larger CI's. Despite this, it was great to see that both ways of measuring the effect result in statistically significant estimated increases.

Likewise, the RDiT estimations also show that stimulus 3 caused statistically significant increases in spending of low-income individuals as a result of the payments being announced and released. Here, the estimated increase is 0.10 and 0.13 which are once again slightly higher than the DID regressions. Like the estimates for stimulus 1, the CIs are once again slightly larger. Still, the DID and RDiT CI's overlap and I would conclude that consumer spending did in fact increase as a result of stimulus payments 1 and 3.

As for the second round of stimulus, the RDiT estimates both show that consumer spending was not affected by either the announcement or the stimulus payments being received. This should be taken with a grain of salt however as the R^2 and adjusted R^2 of these regressions are extremely small. This means that the dependent variables in our regression are not able to explain a large amount of the variation in consumer spending for this round. My hypothesis for this difference is that stimulus 2 appears to cause the largest increase in spending but it lasts only for a short period of time then returns quickly back to pre-treatment levels. Also, like I mentioned above, all income categories move together and show similar increases in spending which points to the fact that it was some other factor that caused the increase in consumer spending. Also, it could be possible that stimulus 2 somehow resulted in increased wealth even for the highest income category. Perhaps there was something about the structure of the stimulus that allowed rich individuals to also profit from its release. This is possible as stimulus 1 seems to also show increases in all four income categories and perhaps it was not until stimulus 3 that the government was able to correctly identify those that needed to receive stimulus payments.

Overall, both types of regressions disprove my hypothesis that stimulus 3 was not able to stimulate spending as much as stimulus 1 and 2. In fact, after looking at the DID and RDiT graphs for stimulus 3, it is apparent that this stimulus was the best at causing increases in the low-income category while not affecting the high-income category. Personally, this was surprising as the Pulse Household Survey and the Personal Savings results seem to provide conflicting evidence to this conclusion; however, it is hard to deny the results of the regressions as well as the graphical representation of consumer spending. Down below I have added graphs of the RDiT analysis to show the estimated change as a result of the stimulus payments being received. Additional graphs of RDiT analysis with treatment dates as the date stimulus payments were announced can be found in the Appendix under Figures 8a-c.

Figure 6a. Consumer Spending RDiT Graph (Round 1)

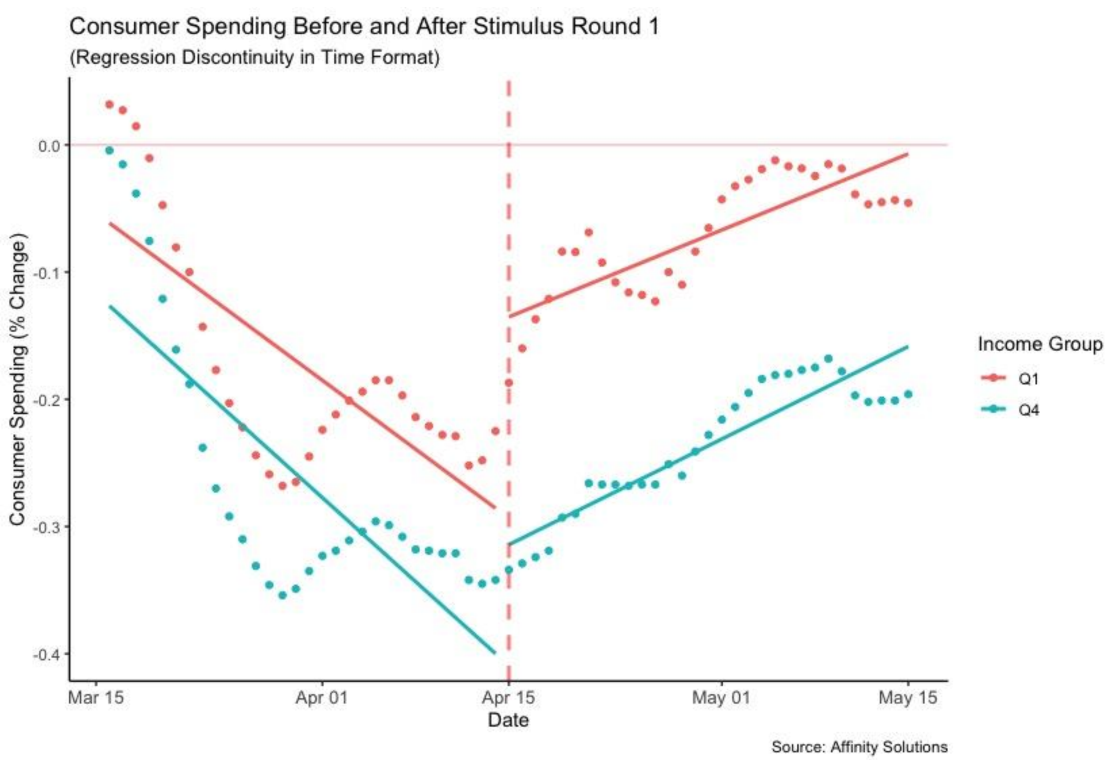


Figure 6b. Consumer Spending RDiT Graph (Round 2)

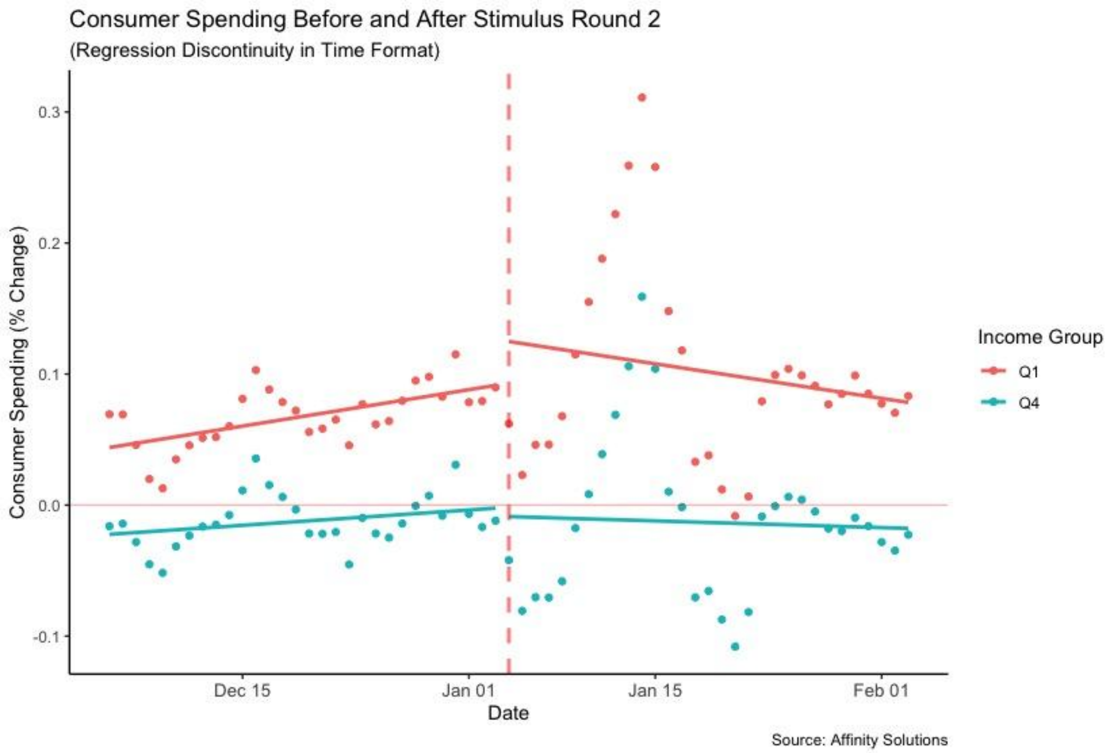
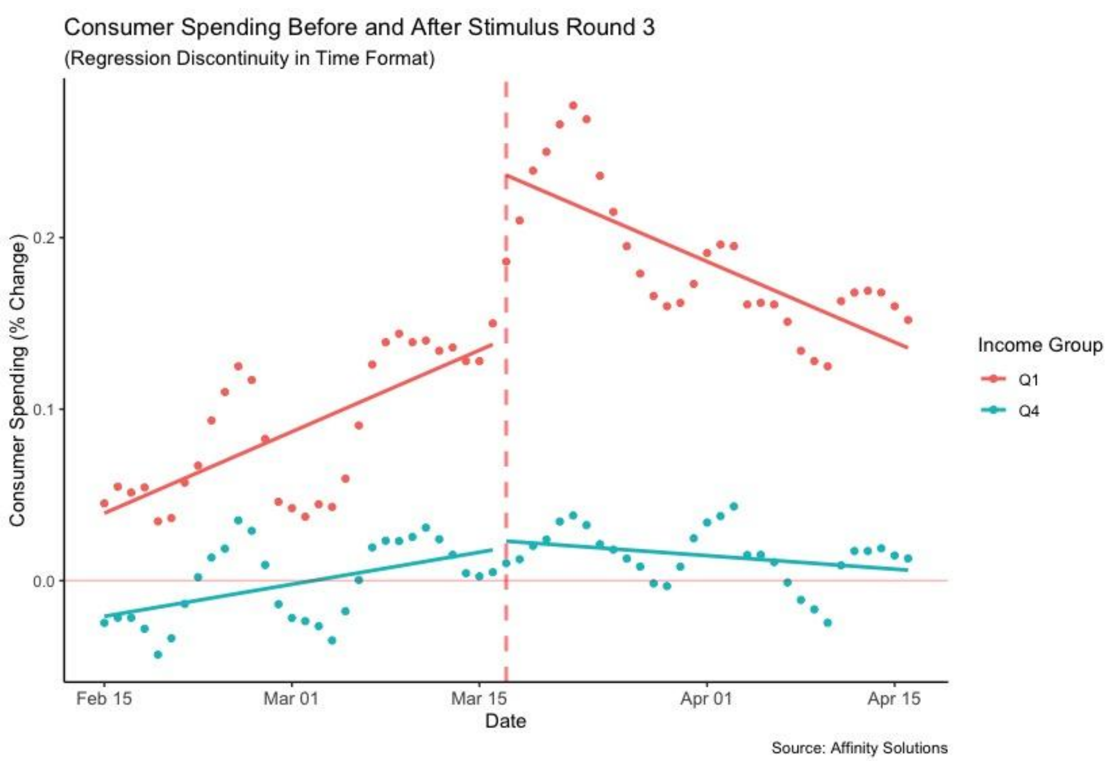


Figure 6c. Consumer Spending RDiT Graph (Round 3)



VII. Conclusion

In conclusion, it appears that the last round of stimulus paid out as a result the American Rescue Plan Act was able to stimulate consumer spending just as much as the previous stimulus rounds (The CARES Act and The Consolidated Appropriations Act). In fact, the last round of stimulus payments, despite being received in high proportions as part of the Recovery Rebate Act, caused the most apparent increase in consumer spending for low-income individuals when compared to other high-income categories. This appears to disprove my hypothesis that behavioral biases were at play and causing stimulus payments to be saved at much higher percentages than the previous rounds. In addition to those findings, it seems that Americans also started to increase consumer spending even before they had actually received their stimulus payments and that stimulus 3 was actually the most personalized and effective of the three rounds of stimulus payments. Personally, I believe that this is extremely interesting but also reasonable as many normative economic theories predict that individuals will change their consumption when they are able to predict increases in their income in the future. Finally, I think this topic of behavioral biases in spending and saving decisions need to be investigated even more in the future. As seen in my preliminary research into the topic, it is clear that the Pandemic and subsequent stimulus efforts provide the perfect large-scale experiment for the behavioral biases and the causal difference between receiving income as a windfall gain or as a tax rebate. In the future, I believe increased research could help governments correctly identify the best timing and forms of payment to help accomplish their goal of stimulating consumer spending or even perhaps of increasing savings rates in a time of need. Overall, I have been greatly satisfied with investigating the effects of each round of stimulus on spending and saving habits for Americans and would love to see more specific and professional work done in this area.

VIII. Acknowledgments

I would like to extend a special thanks to Simen Guttormsen '23 as well as Bobray Bordelon for their continued support throughout the process of writing this paper. Additionally, most of the results found in this paper could not have been found without the help of the Chetty et. al (2020) Opportunity Insights Economic Tracker website and data. Thanks to the Opportunity Insights Team I was able to find the data that I was looking for over the course of the last six months just in time to write a meaningful Junior Paper.

IX. Appendix

Figure 7a. Personal Savings Rate w/ Dates of Checks Received

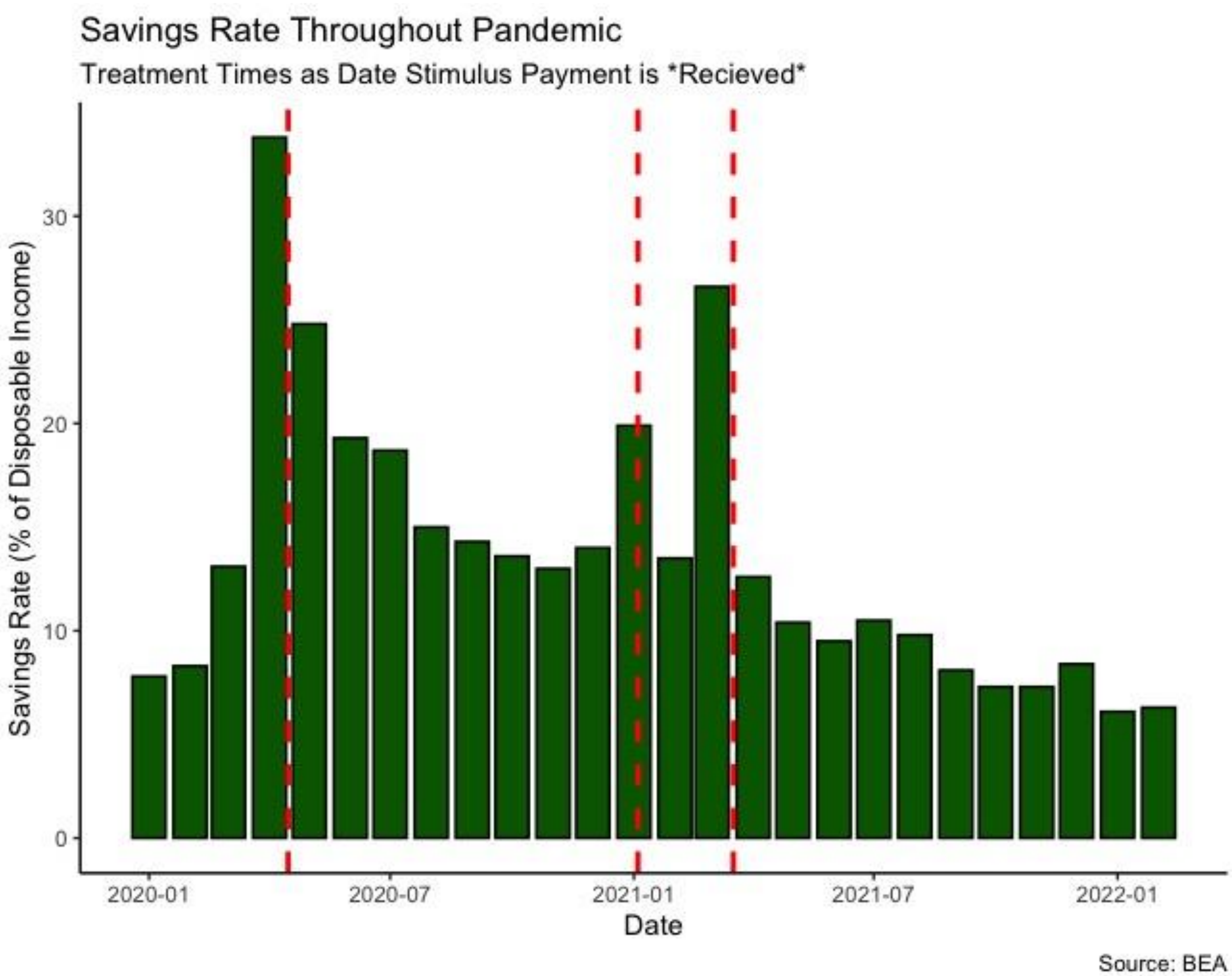


Table 7. Pandemic Period Summary Statistics (Treatment as Date Announced)

Whole Pandemic Period

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
spend_all	726	0.021	0.085	-0.312	-0.003	0.029	0.078	0.216
spend_all_q1	726	0.079	0.09	-0.268	0.035	0.082	0.146	0.311
spend_all_q2	726	0.037	0.081	-0.285	0.004	0.041	0.095	0.249
spend_all_q3	726	0.021	0.085	-0.31	-0.005	0.029	0.079	0.213
spend_all_q4	726	-0.019	0.089	-0.354	-0.033	-0.004	0.035	0.159

Stimulus 1 Period

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
spend_all	61	-0.139	0.133	-0.312	-0.266	-0.189	0.007	0.038
spend_all_q1	61	-0.099	0.108	-0.268	-0.203	-0.092	0.008	0.047
spend_all_q2	61	-0.121	0.116	-0.285	-0.233	-0.139	-0.004	0.035
spend_all_q3	61	-0.142	0.129	-0.31	-0.266	-0.189	-0.003	0.03
spend_all_q4	61	-0.179	0.149	-0.354	-0.319	-0.267	-0.011	0.012

Stimulus 2 Period

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
spend_all	61	0.027	0.048	-0.042	0	0.019	0.038	0.216
spend_all_q1	61	0.084	0.059	0.012	0.051	0.069	0.094	0.311
spend_all_q2	61	0.042	0.052	-0.024	0.015	0.031	0.055	0.249
spend_all_q3	61	0.027	0.047	-0.043	-0.001	0.02	0.038	0.213
spend_all_q4	61	-0.01	0.043	-0.081	-0.028	-0.015	0.006	0.159

Stimulus 3 Period

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
spend_all	61	0.057	0.035	-0.011	0.032	0.063	0.074	0.13
spend_all_q1	61	0.134	0.064	0.035	0.089	0.134	0.166	0.277
spend_all_q2	61	0.078	0.044	0.004	0.048	0.081	0.101	0.174
spend_all_q3	61	0.057	0.033	-0.01	0.035	0.065	0.073	0.126
spend_all_q4	61	0.007	0.022	-0.043	-0.011	0.011	0.024	0.043

Figure 7b. Personal Savings Rate w/ Dates of Checks Announced

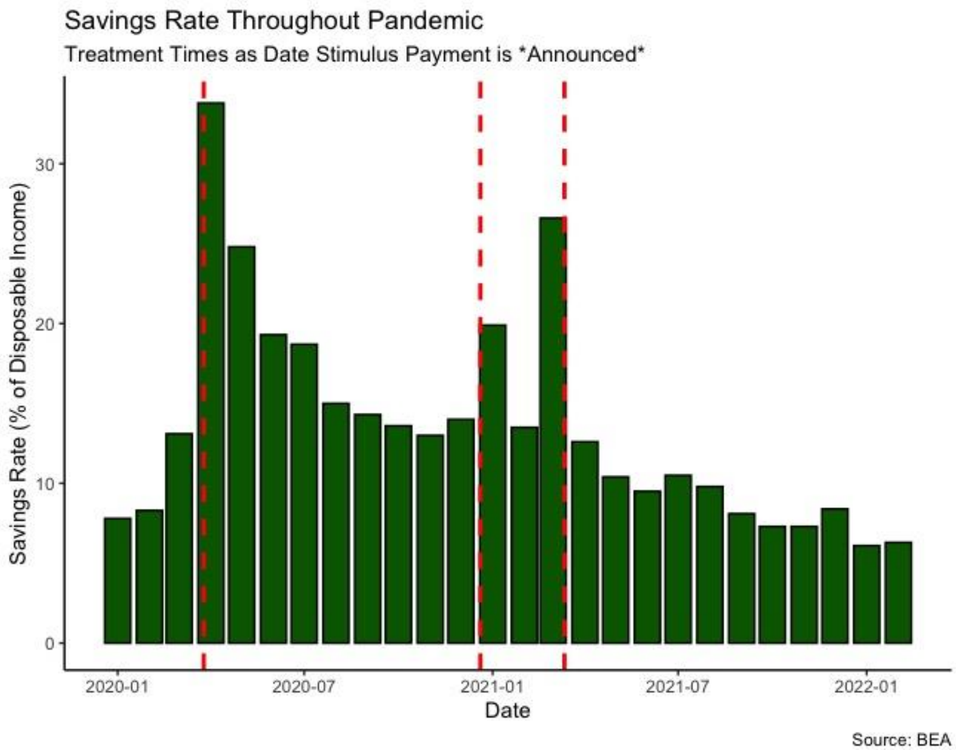


Figure 8a. Consumer Spending RDiT Graph (Round 1)

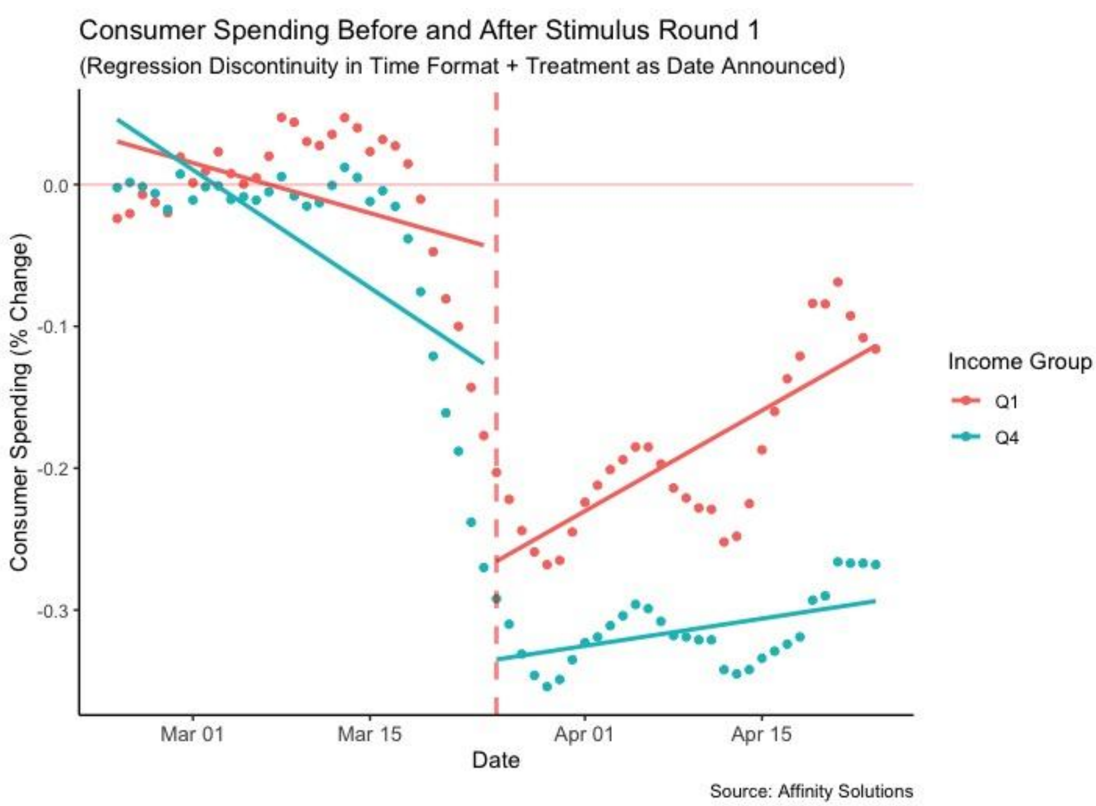


Figure 8b. Consumer Spending RDiT Graph (Round 2)

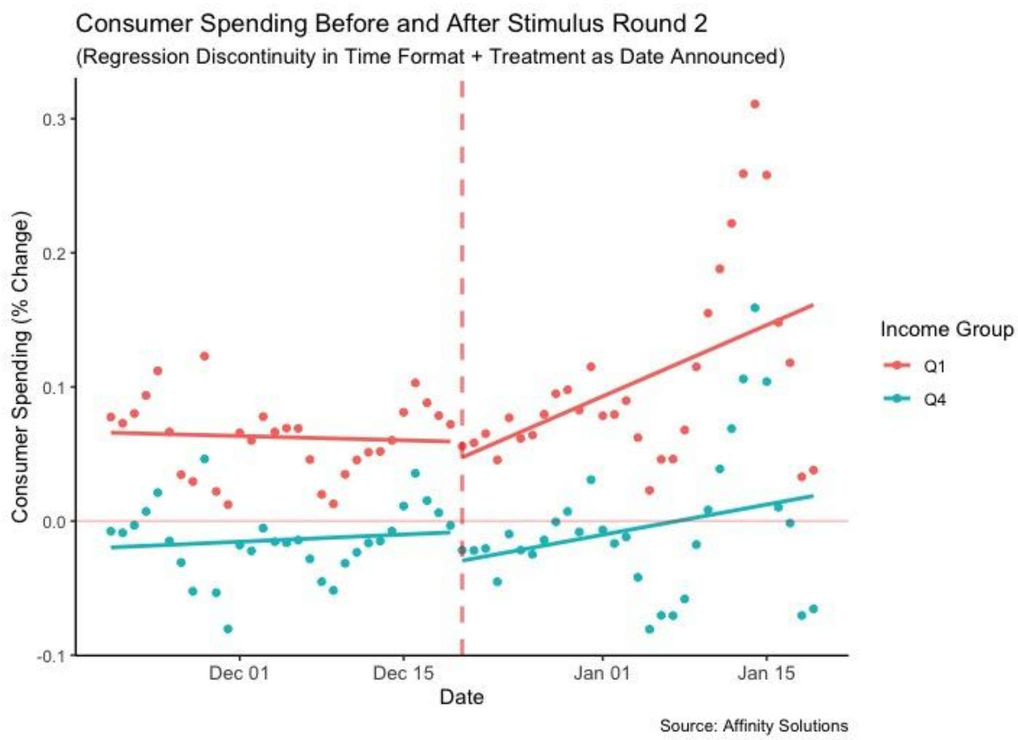
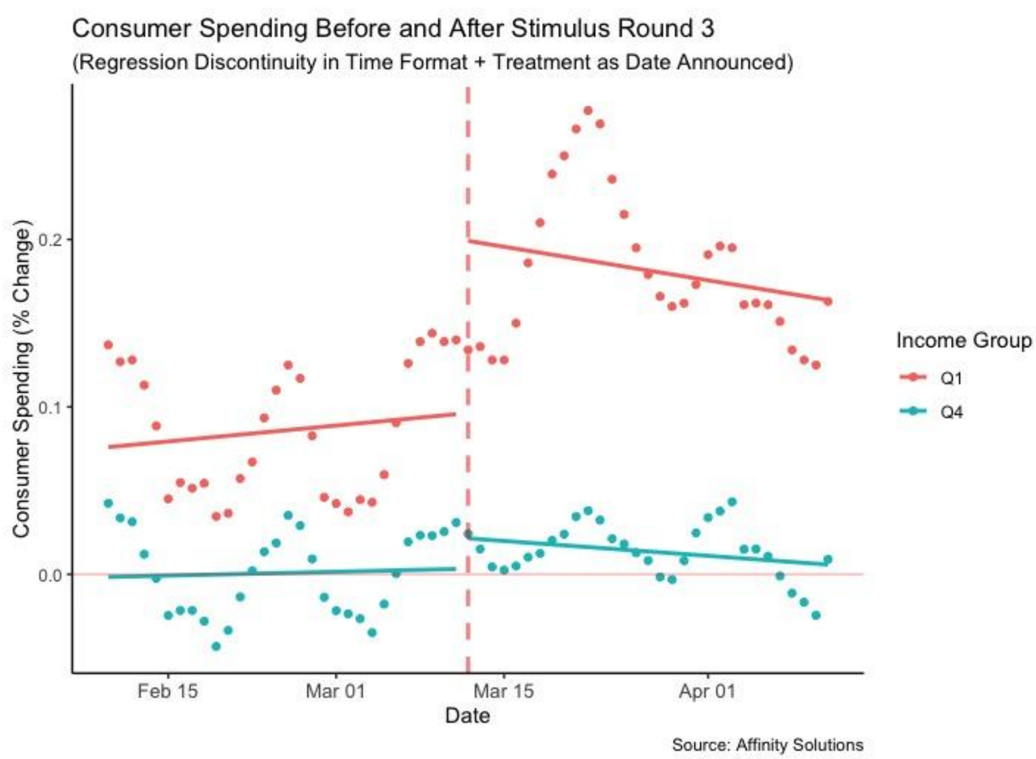


Figure 8c. Consumer Spending RDiT Graph (Round 3)



X. References

"2021 Recovery Rebate Credit - Topic A: General Information." *Internal Revenue Service*, IRS, https://www.irs.gov/newsroom/2021-recovery-rebate-credit-topic-a-general-information.

Arkes, H. R., Joyner, C. A., Pezzo, M. V., Nash, J. G., Siegel-Jacobs, K., & Stone, E. (1994). The psychology of windfall gains. Organizational Behavior and Human Decision Processes

Baker, Scott R, et al. "Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments". NBER, Sept. 2021, https://www.nber.org/system/files/working_papers/w27097/w27097.pdf.

Bureau, US Census. "Household Pulse Survey Data Tables." Census.gov, 1 Dec. 2021, https://www.census.gov/programs-surveys/household-pulse-survey/data.html.

Chetty, Raj, et al. "The Economic Impacts of Covid-19: Evidence from a New Public Database Built Using Private Sector Data." 2020, https://doi.org/10.3386/w27431.

Dunn, Abe. "Covid-19 and Recovery: Estimates from Payment Card Transactions." COVID-19 and Recovery: Estimates From Payment Card Transactions | U.S. Bureau of Economic Analysis (BEA), 30 Nov. 2021,

Epley, N., Mak, D. and Idson, L.C. (2006), Bonus of rebate?: the impact of income framing on spending and saving. J. Behav. Decis. Making, 19: 213-227. https://doi.org/10.1002/bdm.519

Epley, Nicholas & Gneezy, Ayelet. (2007). The framing of financial windfalls and implications for public policy. Journal of Socio-Economics. 36. 36-47. 10.1016/j.socec.2005.12.012.

https://www.researchgate.net/publication/222579053_The_framing_of_financial_windfalls_and_implications_for_public_policy#pfb

Friedman, Milton. “Theory of the Consumption Function.” 1957, https://doi.org/10.1515/9780691188485.

Kahneman, Daniel, and Amos Tversky. “Prospect Theory. an Analysis of Decision Making under Risk.” 1977, https://doi.org/10.21236/ada045771.

Karger, Ezra & Rajan, Aastha (2021). Heterogeneity in the Marginal Propensity to Consume: Evidence from Covid-19 Stimulus Payments. Federal Reserve Bank of Chicago

Li, Kangli et al. “Impacts of COVID-19 lockdowns and stimulus payments on low-income population's spending in the United States.” PloS one vol. 16,9 e0256407. 8 Sep. 2021, doi:10.1371/journal.pone.0256407

Measuring the Effects of the COVID-19 Pandemic on Consumer Spending https://www.bea.gov/index.php/system/files/papers/BEA-WP2020-5_0.pdf.

Modigliani, F. (1987). Life cycle, individual thrift, and the wealth of nations. American Economic Review

“National Income and Product Accounts.” *National Income and Product Accounts | U.S. Bureau of Economic Analysis (BEA)*, https://www.bea.gov/products/national-income-and-product-accounts.