Evaluation of Consumption Responses to the CARES Act: The Influence of Urbanization

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Abstract

I explore consumer spending reactions to the stimulus payments from the CARES Act using high-frequency financial data and a Regression Discontinuity Design to investigate the impact of that policy. I further perform an analysis at the state level, dividing states by their level of "urbanization." I find important levels of heterogeneity in spending reactions to that policy across different states and different levels of household income. In general, I find that following the stimulus payments greater levels of urbanization are associated with smaller increases in spending. My findings highlight the importance of the geographical area for the success of the policy.
Previous literature analyzing the impact of stimulus has largely overlooked geographical differences, which have important policy implications. My results suggest an important shortcoming in fiscal policies that ignore the local environment.

[1] I owe particular thanks to my thesis advisor Professor Pablo Ottonello for his perspective, knowledge, and guidance. I would also like to thank my Honors Economics Professor, Kathryn Dominguez, for her perspective and support over the course of this project.

I Introduction

Amid the pandemic governments around the world were called to implement different monetary and fiscal policies to restore economic activity. On March 27th, 2020, President Donald Trump signed the Coronavirus Aid, Relief, and Economic Security (CARES) Act, a stimulus package meant to alleviate the ongoing economic crisis. Indeed, stimulus payments are a form of expansionary fiscal policy (they can be considered a way of decreasing taxes), and their main goal is to boost consumption and stimulate the entire economy through multiplier effects. However, the success of this policy relies deeply on households' consumption responses to the stimulus payments, which, in turn, depend on a variety of other factors.

Since the economic impact of the Covid-19 pandemic did have heterogeneous effects across the U.S. (Althoff et al. (2020)), one will expect stimulus payments to also have such effects depending on the areas in which they were implemented, as well as on the income groups that received it. Changes in consumer spending were heterogeneous across different income groups and different types of goods (see Figure 1 and Figure 2).

Figure 1:

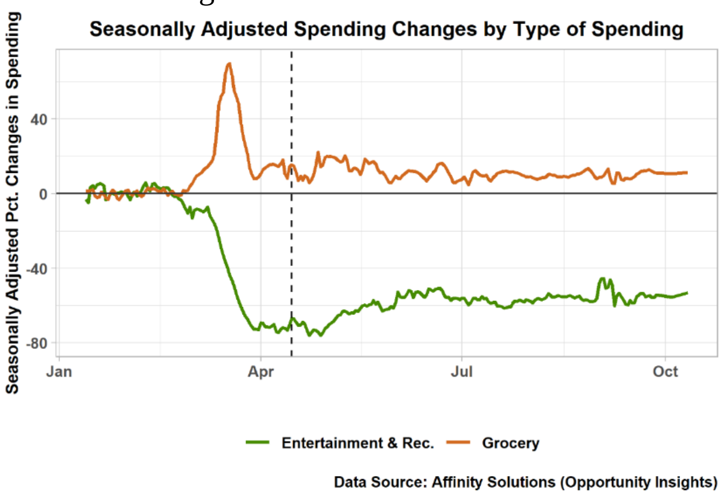
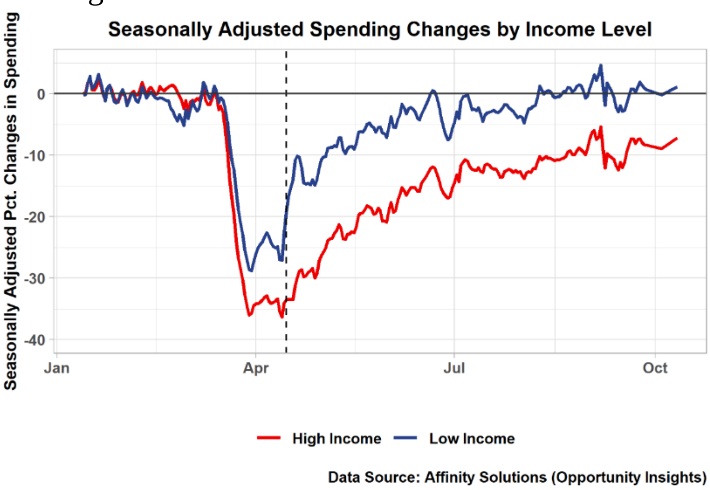


Figure 2:



Through July 2020, households received federal stimulus payments, such as unemployment insurance benefits and other types of government transfers. Even if we can find evidence that suggests that numerous low-income households spent the federal payments right away, Baker et al. (2020a) and Chetty et al. (2020) point out that other income groups planned to save the money, supporting once again the idea that cash transfers had different impacts across different income groups. These heterogeneous effects of consumer spending across income groups and good categories can be seen in Figures 3 and 4.

In this paper, I examine the effect of stimulus payments from the CARES Act on consumer spending in the US, by considering the potential heterogeneity of that policy across geographical areas and income groups. For my study, I perform several regression discontinuity analyses across different groups of states (more urbanized vs less urbanized) and across different income groups (low-income households vs high-income households). In that way, my examination takes into account the specificity of the areas in which the payments were implemented (urban vs rural states), as well as the potential difference in outcomes for lower-income and higher-income households in each different set of states. By performing this analysis, I will be able to identify the effects that the stimulus payments from the CARES Act had on different areas of the country and different income groups. Thus, identifying the areas as well as the income groups that could create potentially higher multiplier effects into the economy.

I begin my analysis by examining the response of low and high-income groups to the stimulus payments in areas of high vs low population density with an individual study of two states: California vs Maine. I use a Regression Discontinuity Design to determine the consumption response to the transfer payments, and I show that the consumption effects were significantly higher in low population density Maine than in high population density California.

I then expand this study to all fifty states by creating a measure (based on population density) that divides states into two categories: “rural” or “urban.” I estimate the individual effect that the stimulus payments had on consumer spending in each state, and I create averages of those effects in rural and in urban states. My results show that in each case the stimulus payments were followed by an immediate increase in spending. I find the largest increase in spending in low-income households in low urbanization states. Low-income households in high urbanization states and high-income households in low urbanization states had a smaller increase in spending than in the previous group, and, finally, the increase in spending was the smallest for high-income households in high urbanization states.

I argue that this difference in spending responses might be due to a more meaningful supply-side alteration in urban areas or to the fact that low-income households in urban areas experienced a greater shock to their permanent income, and thus had a smaller marginal propensity to consume (MPC). My findings suggest that the local environment has relevant implications for the implementation of fiscal policy programs.

II-Literature Review

My paper contributes to the new and expanding literature on how household spending responded to the Covid-19 crisis and on the later impact federal stimulus payments had. Indeed, multiple papers have recently analyzed the consumption response to the Covid-19 pandemic using data from banks or other financial institutions[2]. This topic has been studied by Andersen et al. 2020 (for Denmark), Baker et al. 2020a (for the U.S.), Carvalho et al. 2020 (for Spain), Chen et al. 2020 (for China), Bounie et al. 2020 (for France), among others. In the case of the U.S., Baker et al. (2020a) use data from a Non-Profit Fintech (which records spending through an app) to study the effect of the pandemic on consumption. Even though their contributions are very important to increase our understanding of the effect of the Covid-19 pandemic on consumer spending and savings, one of the problems that may arise from using data from financial apps is that users are not always a representative sample of the overall population. For this reason, I decided to base my study on the work of Chetty et al. (2020) and use the database that they construct for their study, which covers nearly 10% of debit and credit card spending in the U.S, and thus constitutes a more representative sample of the entire population. This is explained in further detail in the data section of the paper.

Furthermore, my paper also contributes to a larger literature on households' responses to previous stimulus payments and tax deductions. Johnson et al. (2006) and Parker et al. (2013) use spending data from the Consumer Expenditure Survey to investigate the tax cuts of 2001 and the stimulus payments of 2008, respectively. In both cases, the authors report positive effects on spending (in non-durable and durable goods). In another study, Broda and Parker (2014) use high-frequency data recorded by retailers and identify significant positive

[2] Considering that official economic data often has unavoidable delays with respect to recent economic events, many researchers shifted their attention to new high-frequency data sources to study the economic effects of the pandemic.

effects on spending following the stimulus payments of 2008. Among the literature on households' responses to stimulus payments, some recent papers investigate the responses of stimulus payments associated with the Covid-19 pandemic. Feldman and Heffetz (2020), Kim et al. (2020), and Kubota et al. (2020) explore stimulus payments related to the COVID-19 pandemic in Israel, South Korea, and Japan, respectively.

Additionally, Baker et al. expand their initial study on consumption responses to the pandemic in the U.S., with another paper (Baker et al. 2020b) in which they examine the heterogeneity of household reactions to the stimulus payments from the CARES Act. Using the same high-frequency transaction data as in their previous paper (Baker et al. 2020a), the authors determine that households responded quickly to the receipt of stimulus payments, with a major increase in spending during the first weeks after the receipt of the payments. In their study, Baker et al. calculate the MPC associated with the stimulus payments for different income groups and identify liquidity levels and economic expectations as some of the major sources of heterogeneity for households spending reactions to the stimulus payments. They point out that there was not a sizeable spending response for households that had large checking account balances as well as for households that expected to lose their employment or that expected benefit cuts. Chetty et al. (2020) also study the effects of the stimulus payments under the CARES Act at the national level. Chetty et al. find that stimulus payments increased consumer spending sharply for low-income households. However, they point out that just a small part of this increase in spending reached businesses that were the most touched by the pandemic, thus diminishing the impacts of this policy on employment.

Following the general idea in Baker et al.'s 2020b paper, my paper explores the heterogeneity of household reactions to the stimulus payments from the CARES Act. However, instead of focusing on liquidity levels and economic expectations, I decided to shift my attention to household income levels and the different characteristics of the geographical areas in which the policy was implemented.

That is why my paper is also related to the literature that examines the heterogeneous economic impact of the pandemic and policy responses across different regions in the U.S. Althoff et al. (2020) argue that the "remote work" shock disproportionally affected low-skill service workers in big cities. Their evidence suggests that it was because high-skill workers, which were predominantly present in large cities, began to work from home or work from a different city; thus, decreasing their spending on local consumer service businesses, and subsequently impacting low-skill service workers in those cities. Althoff et al.'s analysis highlights the need to differentiate between geographical areas and household income levels when evaluating the impact of a stimulus policy since it was shown that they had different economic reactions to the pandemic, to begin with. Another study that estimates the spending response to the CARES Act stimulus payments across, among other factors, geographical areas is the analysis conducted by Misra et al 2021. The authors find similar results as Baker et al. 2020b. Misra et al.'s evidence suggests that a large portion of the payments was spent shortly after its receipt. Furthermore, the authors also calculate MPC estimates to explore the heterogeneity of household responses to the stimulus payments. However, unlike Baker et al. 2020b, they center their analysis on geographical areas and cost of living. The authors measure MPC estimates to be much higher in densely populated urban areas with higher cost-of-living as well as in areas with more restrictions to mobility.

Finally, my results could seem to contradict Misra et al. 2021 results, since I find the largest spending effects of the stimulus payments on areas with a low level of urbanization. Nevertheless, Misra et al. 2021 calculated the MPC, which depends on the cost of living of each region, while I calculate changes in spending using seasonally adjusted data for each region. So, in some sense, the cost of living in every state is already taken into account when calculating changes in spending since it is compared with last year's spending in each of those states (more detail on that in the data section of the paper).

III-Data and Methodological Design

3.1. Background

The stimulus payment program I will focus on is the Coronavirus Aid, Relief, and Economic Security (CARES) Act which made direct payments to nearly 160 million people, and —according to the U.S. Department of Treasury — totaled $267 billion as of May 31, 2020. The CARES Act distributed those payments in the following manner: individuals earning less than $75,000 received a payment of $1,200; married couples earning less than $150,000 received a payment of $2,400, and households received an additional $500 for each dependent. The payments progressively decreased as the level of income increased and phased out entirely for households that had incomes greater than $99,000 (for single individuals without children) or $198,000 (for married couples without children). According to the Daily Treasury Statement, most of these stimulus payments were deposited on exactly April 15, 2020, while some households received payments on April 14.

According to Keynesian macroeconomic theory, this particular stabilization policy would induce "multiplier" effects in the economy by increasing demand for goods and services, and, thus, stimulating economic production. However, another important macroeconomic theory, the permanent income hypothesis, argues for a lower marginal propensity to consume (MPC) out of current income than the one the Keynesian model promotes. The permanent income hypothesis predicts consumption smoothing, supporting the idea that households would distribute their transitory changes of income (such as stimulus payments from the government) over time. In other words, the permanent income hypothesis suggests that when receiving those stimulus payments, households will be more inclined to use them for debt payments or savings.

3.2. Consumption data

The data that I use for this paper comes from a dataset constructed by Chetty et el. 2020. This is a public dataset that contains a variety of economic and public health indicators that inform the general populace, policymakers, and researchers about the real-time state of the economy and the effects of Covid-19.

This data on consumer spending is measured primarily using aggregated and anonymized consumer purchase data collected by a private company: Affinity Solutions (see Chetty et al 2020 for details). Affinity Solutions is a company that aggregates consumer credit and debit card spending information to support a variety of financial service products. The data collected by Affinity Solutions captures nearly 10% of debit and credit card spending in the U.S. Chetty et al. obtain the raw data from Affinity Solutions and, after a cleaning process, they construct daily values of the consumer spending series using a seven-day moving average of the current day and previous six days of spending. Furthermore, the data is seasonally adjusted by dividing each calendar date in 2020 value by its corresponding value from 2019. Finally, Chetty et al. index the seasonally adjusted series relative to pre-Covid-19 spending by dividing each value by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020. In other words, the final data represents the change in spending compared to January 2020 (seasonally adjusted).

Moreover, the authors disaggregate the data by types of goods, by income level (based on the ZIP code where the cardholder lives), and by region (city, county, state, and nation).

Spending data is broken down by industry by grouping merchant codes that are used by Affinity Solutions to identify the category of merchant and merchant activity. Those categories are: Apparel and General Merchandise, Entertainment and Recreation, Grocery, Health Care, Restaurants and Hotels, Transportation.

Chetty et al. link a specific consumer with the ZIP codes in which they live to break down spending data by income groups. The authors classify ZIP codes into income categories based on measurements of median household income and population from the American Community Survey (ACS). This classification is the following: high-income (median household income greater than $78,000 per year), middle-income (median household income between $46,000 per year and $78,000 per year), low-income (median household income less than $46,000 per year).

This dataset offers several advantages for studying consumption. The data on consumer spending covers nearly 10% of debit and credit card spending in the U.S. Therefore, it provides a sample of study that is more representative of the entire population than other private sector datasets (such as data from financial apps). Additionally, the use of high-frequency, up-to-date, transaction-based information about consumers' spending before and after the outbreak of Covid-19 provides a much more granular view of spending transactions.

However, even if this dataset provides a more representative sample of the entire population, the data from Affinity Solutions should only be considered representative of total card spending (but not total consumer spending in general).

3.3. Empirical Methodology

The empirical strategy that I use in this paper is very much based on the one Chetty et al. (2020) implement in their study to examine the effect of the stimulus at a national level. This strategy exploits the high-frequency dataset and the timing of the transfer payments to capture changes in spending in the days surrounding the date when the stimulus payments were made. Then, I compare outcomes for low-income and high-income households in areas of high urbanization and areas with low levels of urbanization.

I start my study by plotting a weekly moving average of spending changes relative to mean levels in January for low-income vs. high-income households. Figure 2 shows that high-income households decreased spending more than low-income households right after the start of the pandemic in March 2020. We can see that in the week ending April 13th, spending in top-income-quartile households was down by 37% relative to pre-Covid levels, as compared with 28% for bottom-income-quartile households. Then, from April 15, the date on which the stimulus payments were deposited (vertical line on the graph), onwards, spending increased steeply for people in low-income households, it increased by over 15 percentage points in a few days. Spending for high-income households also increased, but by a much smaller amount, only 7 percentage points. A conclusion that arises from this graph is that the stimulus payments had a sizeable positive effect on spending, in particular for low-income families.

To precisely estimate the causal effect of the stimulus payments, I use a regression discontinuity design with daily spending data. I use the date on which the stimulus payments were deposited, April 15, 2020, as the cutoff; and I run a regression within a window of 30 days from cutoff (15 days before and 15 days after) and then another regression within a window of 14 days from cutoff (7 days before and 7 days after) to evaluate the impact of the stimulus payments on consumer spending.

The regression equation is the following:

$$Y_t = \alpha_t + \tau D_t + \beta T + \varepsilon_t$$

where T is the independent continuous variable that represents time (measured in days) and D_t is the binary treatment variable that is equal to 1 when T crosses the threshold date (date in which the stimulus payments were received). Y_t is the dependent variable that represents the percent change in spending. α_t captures the group fixed effects to account for time-variant factors, and ε_t is the error term associated with the regression. Hence, ε_t corresponds to factors other than time to that are related with changes in spending over that given period. By construction, ε_t is not associated with the government transfer payments that occurred on April 15$^{\text{th}}$, 2020, since this date is set as the cutoff in the RDD model and should be accounted for in the regression. In other words, a key assumption of the model is that no other major events that could have influenced household spending reactions occurred during the time window of the analysis. Another major assumption of this model is that during the same time windows of the previous year (2019) household spending did not experience any major or unusual shocks (such as another major fiscal policy program). This latter assumption is important since the data that I use for the study is calculated by dividing the spending value for each calendar date in 2020 by its corresponding value from 2019. Those two assumptions are easily verifiable, and, according to my searches, they both hold.

Therefore, this experimental design allows to rigorously evaluate the impacts of the stimulus payments on spending across different income groups or geographical areas to then be able to determine what percent of this change is due to the policy and what percent is inherited from the normal change across different groups.

IV-Analysis

Even if there are multiple interesting directions this research could take (some of them might be analyzed in a future paper), I decided to focus on the impact of stimulus payments on two very different geographical areas: urban vs rural.

To extend the analysis of the effects of the CARES Act stimulus payments to a regional level, it is first necessary to clearly identify areas that had heterogenous spending reactions to the Covid-19 crisis. Althoff et al. (2020) present evidence that suggests that low-skill service workers in large cities were the group that was most impacted by the Covid-19 pandemic. In the context of the permanent income hypothesis, I could hypothesize that low skill-service workers in big cities (which according to Althoff et al.'s arguments should have experienced a greater shock to their permanent income) would either save the money from the stimulus payments or use it for debt payments. In other words, this first hypothesis states that low-skill-service workers in urban areas should have a lower spending response to the stimulus payments than low skill-service-workers in non-urban areas.

Furthermore, it is well known that metropolitan areas around the world—in particular, the biggest ones, —quickly became places with an elevated prevalence and an increased transmission risk of coronavirus. Smaller and more rural areas seemed to be less affected by the virus. According to the New York Times Covid data, in the U.S., large urban counties have the highest death rate, followed by suburbs, smaller towns, and rural areas. Big cities are, by definition, more densely populated and connected, and thus also more vulnerable to the spread of Covid-19 than smaller towns or rural areas. This higher level of vulnerability and the greater number of restrictions in place in large metropolitan areas led urban consumers to experience a more severe supply shock than consumers in rural areas. Once again, with those reasons in mind, we could reach the same hypothesis as in the previous paragraph. Urban consumers could be less responsive to the transfer payments since there exists a higher supply shock in those regions, thus it is more difficult to spend their money.

Now that I have established that urban and rural regions had different economic reactions to the Covid-19 pandemic, I can conclude that "urbanization" is a characteristic worth studying in the context of the stimulus policy. The natural next step is to define a scale that allows me to rank regions by their degree of "urbanization". For the sake of the simplicity of my model, I only associate the concept of "urbanization" with population density[3]. To measure the degree of "urbanization," I use data collected by FiveThirtyEight, an American website that focuses on opinion poll analysis, politics, and economics blogging. FiveThirtyEight uses data from the American Community Survey (ACS) to calculate the average number of people live within a five-mile radius of every census tract and then they take the natural logarithm to construct an "urbanization index." For my analysis, I use a weighted average based on each census tract's population[4], to compute this index for every state.

[3] The U.S. Census Bureau and other literature's definitions of "urbanization" are slightly more complex; however, population density stands as one of the main concepts in each of those definitions.
[4] This data can be obtained from the U.S. Census Bureau.

Figure 3:

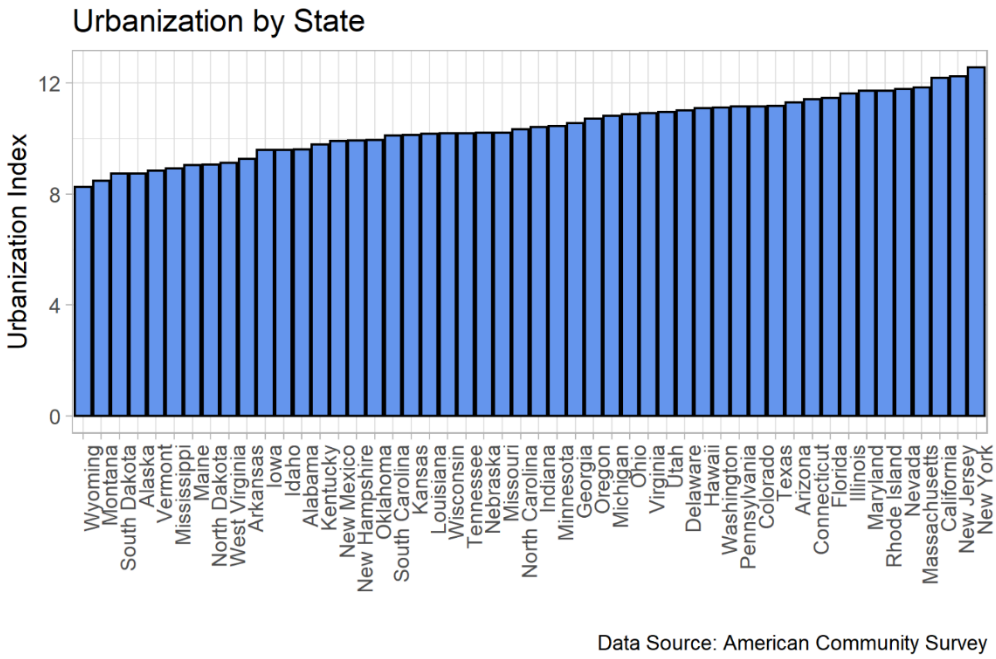


Figure 3 shows the degree of urbanization for all fifty states in ascending order. The urbanization index goes from 8.2 to 12.5 with Wyoming being the state with the least degree of urbanization, and New York being the state with the greatest level of urbanization (all the other states range in between). For my analysis, I use this figure to divide states into two categories, rural vs urban, in the following way: the 25 states with smaller urbanization levels are categorized as rural and the 25 states with higher urbanization levels are categorized as urban (see Table 1).

Table 1: Urban vs Rural States.

Low Urbanization States (Rural States)	High Urbanization States (Urban States)
Wyoming	Indiana
Montana	Minnesota
South Dakota	Georgia
Alaska	Oregon
Vermont	Michigan
Mississippi	Ohio
Maine	Virginia
North Dakota	Utah
West Virginia	Delaware
Arkansas	Hawaii
Iowa	Washington
Idaho	Pennsylvania
Alabama	Colorado
Kentucky	Texas
New Mexico	Arizona
New Hampshire	Connecticut
Oklahoma	Florida
South Carolina	Illinois
Kansas	Maryland
Louisiana	Rhode Island
Wisconsin	Nevada
Tennessee	Massachusetts
Nebraska	California
Missouri	New Jersey
North Carolina	New York

4.1. Average effect on the stimulus by income groups in two individual states (one rural and one urban)

I will start my analysis with a study of two individual states in each category (one rural and one urban), and then I will expand it to a group study (all rural states vs all urban states). The two states that I will examine first are Maine (rural, see Figure 3) and California (urban, see Figure 3). Those two states are not only diametrically opposed geographically speaking, but, according to U.S. Census Bureau[5], California is the state with the highest urban density in the country, while Maine has one of the lowest. In fact, if we used U.S. Census data to rank all states by the percentage of their population living in rural areas from greatest to least6, California would rank first, and Maine would find itself last. Then, by comparing the effect of the stimulus payments to high and low-income households in those two states, we are actually analyzing the different effects of this policy on high and low-income groups on a predominantly urban region of the country and comparing it to the effect in a predominantly rural region of the country. In other words, using these parameters, the question of whether high and low-income populations within specifically rural or urban areas responded differently to the April 15th, 2020 stimulus payments can be answered. If there is a significant difference, I will also be able to quantify the magnitude of those effects.

I conduct at the state level the same research design as the one implemented Chetty et al. implemented at the national level (see the methodology section for more details). I use the same high-frequency daily data as well as the same income group categories[7] as the ones

[5] Another source for urbanization data.
[6] This is another way to characterize rural and urban areas differently from the one my model is based on.
[7] High-income: median household income greater than $78,000 per year, and low-income: median household income less than $46,000 per year

described in the data section, but I restrict my observations to two of those two states separately.

First, to get a visual representation of the level of spending in those two states, I start by plotting the weekly moving average of spending changes relative to mean levels in January for high-income households in both states.

Figure 4:

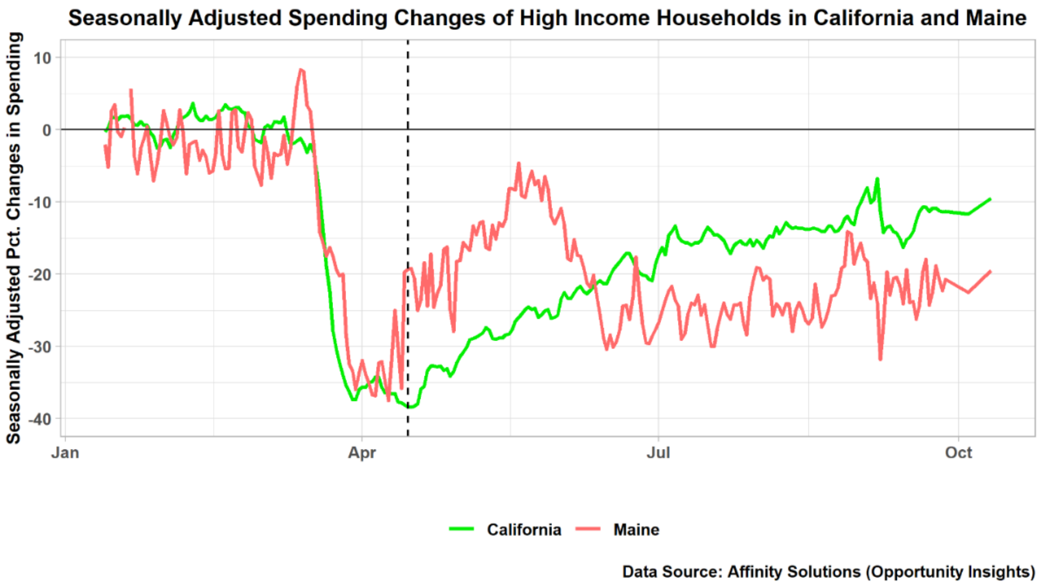


Figure 4 shows the seasonally adjusted spending changes for high-income households in California and Maine. We observe that in the week ending April 13th, spending in high-income households is down by 37% relative to pre-Covid levels in California, while for in high-income households in Maine it is down by about 35% relative to pre-Covid levels. Then, from April 15 (vertical line on the graph) onwards, spending increase at different rates for each state. For the high-income group in California, the increase is close to 5 percentage points in the span of a couple of days, while for the high-income group in Maine the increase is more than double; it rises by 11 or 12 percentage points in a few days after April 15. However, looking at the general picture (see figure 2), spending changes for high-income households in California and Maine are somewhat comparable to the national changes in spending for that income group.

I now plot the weekly moving average of spending changes relative to mean levels in January for low-income households in California and Maine.

Figure 5:

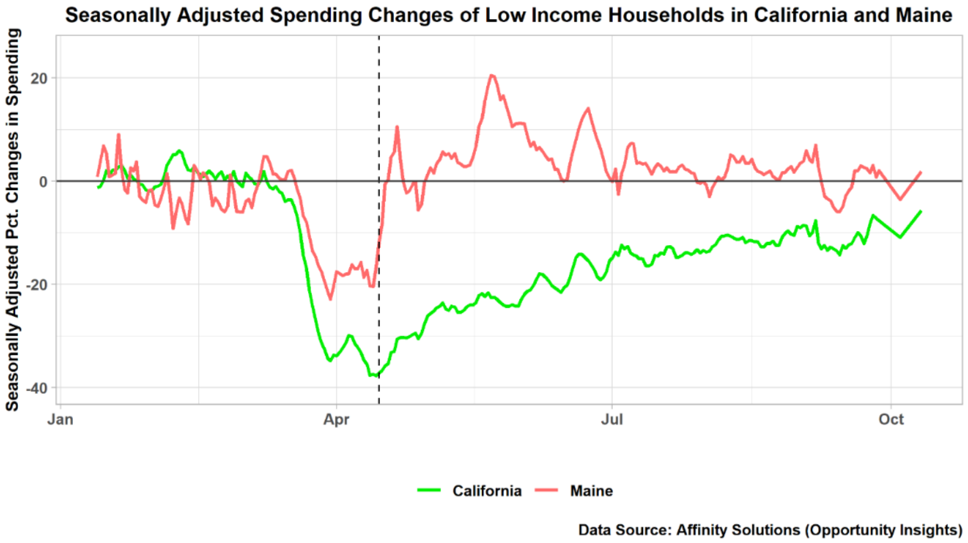


Figure 5 shows the seasonally adjusted spending changes for low-income households in those two states. We observe that in the week ending April 13th, spending for low-income households in Maine is only 20% to 22% below pre-Covid levels. This is a big difference from the California data, as well as the national level data (see Figure 2), in which the decrease is close to 30% for the same income group. From April 15 (vertical line on the graph) onwards, spending increases abruptly for the low-income group in Maine; their spending increases by almost 30 percentage points in a matter of a few days and remained above pre-pandemic levels from then onwards, with the exception of a few short periods, while for the low-income group in California the increase in spending is much more modest. In fact, it is very similar to the national average for that group; it rises by about 7 or 8 percentage points in a few days. A conclusion that arises from this graph is that, at the beginning of the pandemic, low-income households in Maine do not decrease their consumption as deeply compared to low-income households in California or the average low-income household at the national level. However, once the stimulus payments came in low-income households in Maine increase their consumption dramatically.

Looking at Figure 4 and 6 together, we can see that high-income households in California and Maine decreased spending more than low-income households right after the start of the pandemic starting in March 2020, as was the case on the national level. We also observe that in California the difference in spending between low and high-income households is much smaller than at the national level. As a matter of fact, on the same dates, in the national level data, there is a difference of 9 percentage points, in contrast to the two-percentage points difference found in California. Similarly, we realize that compared to the national level effects, the stimulus payments had a modest positive effect on spending both for low and for high-income households in California.

I now run the regression discontinuity for high and low-income groups in California at two different windows (April 1-April 30 and April 7-April 21). The results are presented in Table 2.

Table 2: Regression Discontinuity Estimates of Stimulus Payments on Spending in California

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.107	-0.035	0.104**	-0.029
	(0.064)	(0.150)	(0.043)	(0.080)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.096	0.005	0.185	0.012
Adjusted R^2	0.062	-0.085	0.154	-0.078
Residual Std. Error	2.744 (df = 26)	2.021 (df = 11)	1.827 (df = 26)	1.076 (df = 11)
F Statistic	2.770 (df = 1; 26)	0.055 (df = 1; 11)	5.914** (df = 1; 26)	0.128 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 2 shows that none of the coefficients for the low-income group seem to be statistically significant at a 1% level. According to the table, if the take the window of April 1 to April 30, the effect of the stimulus payments for the low-income group is an increase in spending by 10.7 percentage points. While, for the window of April 7 to April 21, the effect of the stimulus payments for the low-income group becomes negative, describing a decrease of 3.5 percentage points in spending for this group. The latter effect of a decrease in spending for the low-income group after the cut-off of the stimulus payments seems odd. However, as the results are not statistically significant, it would not be appropriate to overinterpret them or give them much importance.

Furthermore, Table 2 also shows that one of the coefficients for the high-income group is statistically significant at a 1% level, this is the coefficient for the April 1-April 30 window. According to the table, if we look at this first window, the stimulus payments caused an increase of 10.4 percentage points in spending for the high-income group (and this result is statistically significant). For the window of April 7-April 21, we, again, find a strange effect, a decrease of 2.7 percentage points in spending for the high-income group. However, this result not being statistically significant, so it is not worth paying much attention to it.

I now run the regression discontinuity for high and low-income groups in Maine at the same two windows (April 1-April 30 and April 7-April 21). The results are presented in Table 3.

Table 3: Regression Discontinuity Estimates of Stimulus Payments on Spending in Maine

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.914***	2.178***	0.639***	1.360***
	(0.143)	(0.363)	(0.111)	(0.352)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.611	0.766	0.560	0.576
Adjusted R^2	0.596	0.745	0.543	0.538
Residual Std. Error	6.114 (df = 26)	4.893 (df = 11)	4.748 (df = 26)	4.742 (df = 11)
F Statistic	40.855*** (df = 1; 26)	36.057*** (df = 1; 11)	33.066*** (df = 1; 26)	14.967*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 3 shows that both coefficients for the low-income group are statistically significant at a 1% level. When considering the window of April 1 to April 30, the effect of the stimulus payments for the low-income group is an increase in spending by 91.4 percentage points. In the window of April 7 to April 21, the effect of the stimulus payments for the low-income group more than doubles, there is a discontinuous increase of 217.8 percentage points in spending. Both windows' effects represent incredibly high increases in spending for low-income households in that period and they are consistent with what we observed in the plot (Figure 3).

Table 3 also shows that both coefficients for the high-income group are statistically significant at a 1% level. When considering the window of April 1 to April 30, the stimulus payments caused an increase of 63.9 percentage points in spending for the high-income group. While, in the window of April 7 to April 21, this effect increases quite a lot. The effect becomes an increase of 136 percentage points in spending for the high-income group in that period.

In conclusion, these results show that the effect of the stimulus payments was more important in Maine than in California (more important in the rural state than in the urban one). Thus, this analysis of two individual states agrees with my initial hypothesis that rural states reacted more strongly to the stimulus policy supporting the idea of a more important supply-side alteration in urban areas. Additionally, the fact that consumers in Maine reacted more strongly to the transfer payments supports the permanent income hypothesis idea that low-income households living in urban settings had more negative expectations about their future income.

4.2. Average effect on the stimulus by income groups in rural vs urban states

Now, I expand this analysis to all fifty states. Again, I start by plotting the weekly moving average of spending changes relative to mean levels in January for high-income households in the two sets of states.

Figure 6:

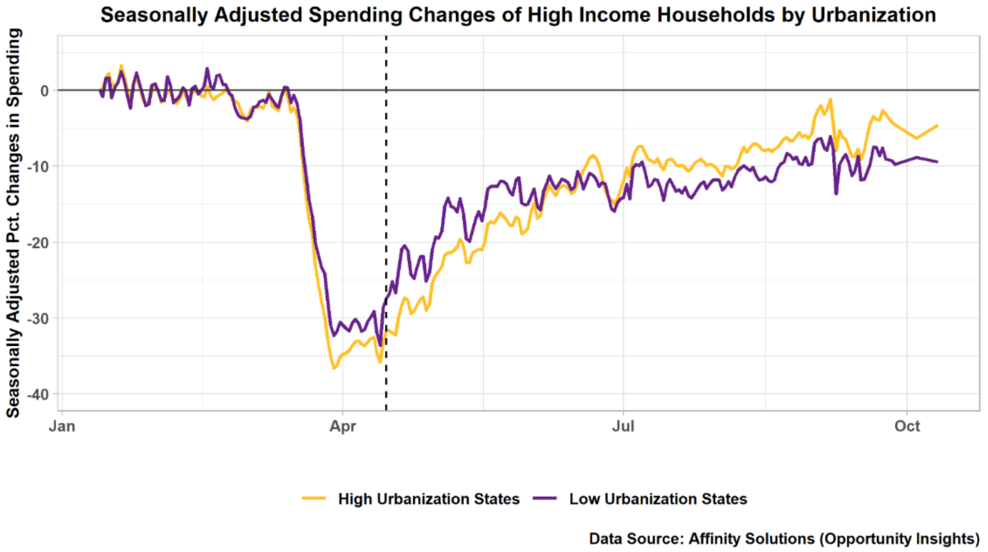


Figure 6 shows the seasonally adjusted spending changes for high income households in urban and in rural states. We observe that in the week ending April 13th, spending in high-income households is down by about 36% relative to pre-Covid levels in urban states, while for high-income households in low urbanization states it is down by about 33% relative to pre-Covid levels. Then, from April 15 (vertical line on the graph) onwards, spending increase at similar rates for both groups. For the high-income group in high-urbanization states, the increase is close to 6 percentage points in a couple of days, while for the high-income group in low-urbanization states the increase is almost double, but still only a few percentage points away, it rises by 9 or 10 percentage points in a few days after April 15. However, when compared with spending changes for high-income households in California and in Maine (see Figure 4), the changes for high-income households in the set of all rural vs all urban states are much more uniform. In both cases (urban and rural states), the variations in high-income household spending are very similar to the national spending trend for that income group.

Similarly, the changes in spending for low-income households across urban and rural states is quite uniform.

Figure 7:

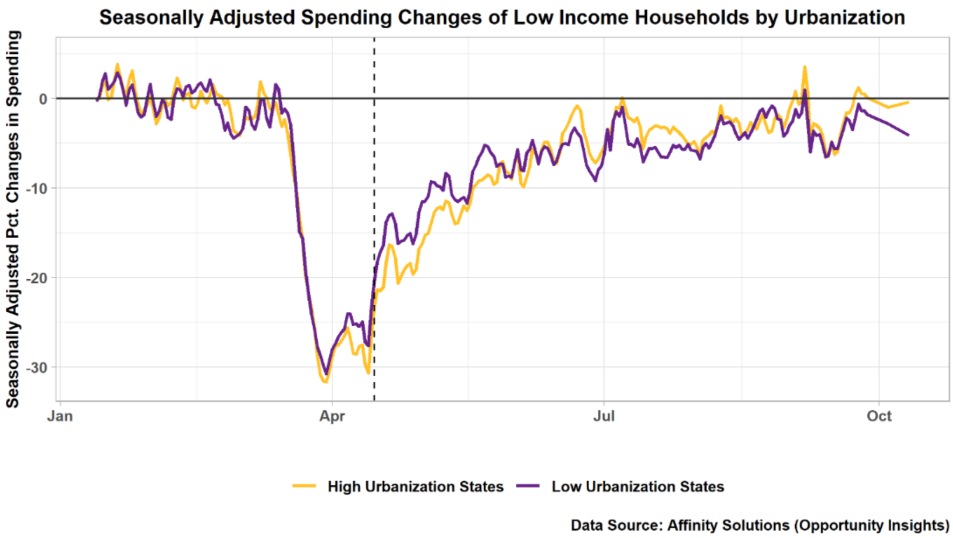


Figure 7 shows the seasonally adjusted spending changes for low-income households relative to mean levels in January in states of high urbanization vs states of low urbanization. We see that in the week ending April 13th, spending for low-income households in low urbanization states is 27% below pre-Covid levels, this number is a very close to the spending levels for high urbanization states, which at the that time were around 31% below pre-Covid levels. Both of those numbers are also very similar to the national level decrease for that income group (see Figure 2) which was about to 30%. From April 15 (vertical line on the graph) onwards, spending for the low-income group in low urbanization areas increases by 13 or 14 percentage points in a matter of a few days but remains below pre-pandemic levels from most of that year (2020). For the low-income group in high urbanization states the increase in spending is very similar to the one I just described for low urbanization states, it rises by about 14 or 15 percentage points in a few days. From this graph, we can reach some of the same conclusion as before. Unlike the previous analysis of California and Maine, this graph tells us that at the beginning of the pandemic, low-income households in low and high urbanization areas decrease their consumption in a very similar manner.

Focusing on figures 7 and 8 together, we observe that high-income households in both high and low urbanization states decreased spending more than low-income households just after the start of the pandemic in March 2020, as it was the case for the national level (see figure 2).Moreover, the fact that consumer spending, for both low and high-income groups, does not behave much differently in rural vs urban areas suggests that urbanization does not have a very important effect on pre-pandemic consumption. Nevertheless, this observation does not contradict my previous hypothesis since for both types of households (low and high-income) spending decreases more in high urbanization areas than in low urbanization areas (which is what I expected).

After this general exploration of changes in spending induced by the pandemic on rural vs urban states, I now turn my attention to the analysis of spending reactions to the transfer payments in those two different sets of states. I run regression discontinuities for every state using the same two time-windows as in the previous cases (April 1-April 30 and April 7-April 21). For every state I obtain four different RDD estimates corresponding to high and low-income households in each of the two time-windows (for example see Table 2, RDD estimates for California). Then, I take the 25 urban states and I compute the average effect for each income group and for each time window. I do the same for the 25 rural states. Table 4 presents the average effect of the stimulus payments on spending by income groups and by urbanization levels from April 1st to April 30th, and Table 5 presents the results from April 7th to April 21st. If we compare in each table the average effect of the stimulus payments across groups, we consistently find that the effect is larger in low urbanization states than in high urbanization states.

Table 4: Average RD Effect of Stimulus Payments on Spending (Window: April 1st - April 30th).

Item	Low Urbanization States (Low Income Households)	Low Urbanization States (High Income Households)	High Urbanization States (Low Income Households)	High Urbanization States (High Income Households)
Average RD Effect	**0.591**	**0.429**	**0.453**	**0.279**
Number of States	23[8]	25	25	25
Number of Observations in each State =	28	28	28	28

Table 5: Average RD Effect of Stimulus Payments on Spending (Window: April 7th - April 21st).

Item	Low Urbanization States (Low Income Households)	Low Urbanization States (High Income Households)	High Urbanization States (Low Income Households)	High Urbanization States (High Income Households)
Average RD Effect	**1.225**	**0.737**	**1.056**	**0.337**
Number of States	23[8]	25	25	25
Number of Observations in each State =	13	13	13	13

Focusing only on low-income households on Table 4, we observe that the RD effect of the policy in low urbanization areas is 0.591 that is $\frac{0.591-0.453}{0.591} \approx 0.23$ or 23% higher than the RD estimate in high urbanization areas. If we look back to our two previous hypotheses to explain this difference between urban and rural reactions to the stimulus, we can interpret this 23% variation in two different ways.

[8] Missing data for low-income households in Alaska and New-Hampshire

First, if we think of low-income consumers in general as purely demand driven, we should expect to find the same effect of the stimulus regarding the type of region in which they live. Hence, there is something happening in urban areas that is reducing by 23% the effect of this policy, and, according to our first hypothesis, that something is the more intense supply shock that urban areas experienced. In this case, the 23% represents the percentage of the stimulus that is associated with the supply-side. Similarly, in Table 5 the RD effect of the policy in low urbanization areas (again I am just focusing on low -income households) is 1.225 that is $\frac{1.225-1.056}{1.225} \approx 0.14$ or 14% higher than the RD estimate in high urbanization areas. This number could be interpreted the same way as before, and we could then estimate the percentage of the of the effect of the stimulus associated with the supply-side to be between 14 and 23%.

The large gap in consumption responses of high-income households between low and high urbanization areas observed in Tables 4 and 5 could also constitute evidence that supply-side restrictions—either because some businesses are closed or because households have large health considerations— play an important role in consumption adjustment.

To analyze this hypothesis in more depth, I examine the change in the type of consumption for households in different regions.

Figure 8:

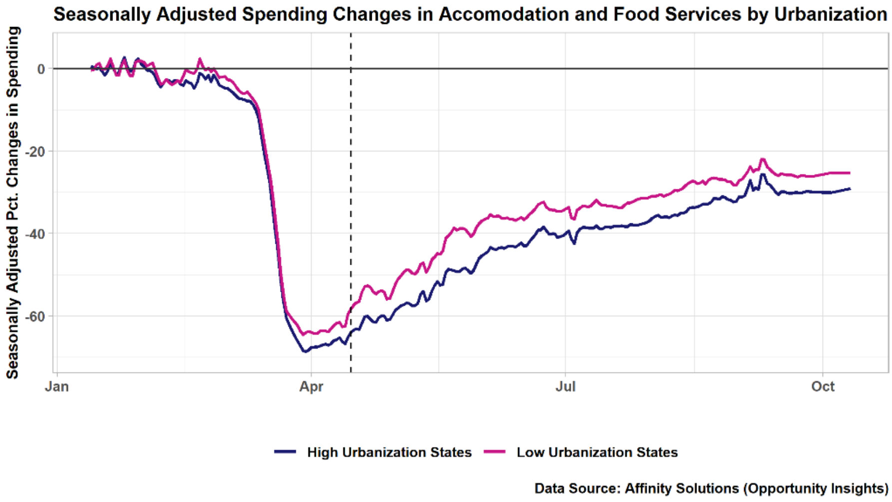


Figure 8 shows the seasonally adjusted spending changes in accommodation and food services for all households relative to mean levels in January in states of high urbanization vs states of low urbanization. According to our hypothesis, we expect to see a large increase in this consumption category for households in low-urbanization areas. Indeed, in Figure 8 we observe a significant increase in consumption in accommodation and food services for households in low urbanization areas. However, this increase seems to be proportional to the increase in consumption in the same category for households in high urbanization areas. Thus, this does not constitute enough evidence to support the idea that supply-side restrictions explain the significant difference in consumption responses between those two areas. This could then lean us toward our second hypothesis, which states that the permanent income of urban low-income households suffered the most during the pandemic, as a possible explanation for this fact. Nevertheless, our first hypothesis should not be discarded, and further analysis is needed to identify an explicit cause for the heterogeneous consumption effects that I find.

Alternatively, using our second hypothesis we can interpret those numbers in a different way. In this case, the percent difference between low-income rural and urban households' reactions to the policy would represent the percent in which low-income urban households reacted to the permanent income hypothesis. In other words, we could estimate that 14 to 23% of the effect of the stimulus for low-income households in urban areas was reduced because of the negative shock that their permanent income suffered.

Furthermore, I can also conclude that the urbanization characteristic plays a more important role on the recovery phase (after the stimulus payments were distributed) than on contraction phase (that is when consumers initially decreased their spending as a consequence of the pandemic, see Figures 7 and 8).

Another important observation from Tables 4 and 5 is that that high-income households had a relatively greater response to the stimulus payments that I expected. This can be seen particularly in areas of low urbanization where high-income households respond almost as much as the low-income households. For instance, in Table 4 we see that in low urbanization areas the average RD effect for high-income households was 0.429 compared to 0.591 for low-income households, the stimulus response was just $\frac{0.591-0.429}{0.591} \approx 0.27$ or 27% higher for low-income households than for high-income households in those areas.

Two possible— and complementary—interpretations could explain this fact. The first is that there is a significant proportion of "hand-to-mouth" households within high-income households. This idea would be consistent with the work of Kaplan and Violante (2014) and Kaplan, Violante, and Weidner (2014) that suggests that there is large group of households that are "wealthy hand-to-mouth". The second possible explanation lies on the following economic observation: the fact that low-income households' consumption responds more in low urbanization areas also creates more profits for firms that are owned by high-income households (for example, restaurants) in those areas. High-income households in low urbanization areas would then experience a non-negligible positive impact to their permanent income, and thus increase their consumption accordingly.

V-Conclusions

In this study, I analyze the causal effect of the stimulus payments to low and high-income households in high and low urbanization areas using a regression discontinuity design, with the date when the stimulus payments were made effective, April 15th, 2020, as the cutoff.

I first analyze spending responses to the stimulus payments for low and high-income groups in a predominantly urban state such as California and in a predominantly rural state such as Maine, and then I do it for all a set of rural states vs a set of urban states.

In the analysis of California and Maine, I find a big difference found between the effect of the stimulus payments for low and high-income groups in California and Maine could simply be explained by the fact that due to a lower population density in Maine, social distancing practices might not have been as hardly enforced as in more urban states such as California. For this reason, the low-income population in Maine might be able to spend their money from the stimulus payments in person more easily than the low-income population in California.

In the analysis of the stimulus payment reactions in high vs low urbanization states, I also find differences in spending across regions (again lower levels of spending in urban areas). I estimate that percentage of the of the effect of the stimulus associated with the supply-side is between 14 and 23%. Furthermore, those numbers could also be considered as the percentage of the effect of the stimulus for low-income households in urban areas that was reduced because of the negative shock that their permanent income suffered.

An interesting next step for this study would be to examine the extent to which the different consumption effects by the degree of urbanization are driven by other characteristics of the regions that are themselves correlated with urbanization. For instance, I could perform a similar study in which I control for the per capita level of income of each state and see if the heterogenous effects documented in this empirical analysis still hold.

Finally, I want to point out that there are many caveats to my analysis. First, my conclusions come with a caution advice since results are based on credit and debit card purchases from a sample that might not be the best representative sample of US population. Also, since data is aggregated to ZIP code level there are usually many limitations that apply.

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Appendix:

A.1. Replication of Chetty et al. Results:

I will begin by replicating some plots and figures from Chetty et al. 2020, in which they already studied the effects of this policy at the national level. Chetty et al. started their study by plotting a weekly moving average of spending changes relative to mean levels in January for low-income (bottom income quartile) vs. high-income (top income quartile ZIP codes) households. I replicate this figure but instead of using the bottom and top income quartiles, I divide the population into high, middle, and low-income level in the way previously explained (high-income: median household income greater than $78,000 per year; middle-income: median household income between $46,000 per year and $78,000 per year; low-income: median household income less than $46,000 per year) and use the high- and low-income level populations.

Figure 2 (in the paper) shows that high-income households decreased spending more than low-income households right after the start of the pandemic starting in March 2020. We can see that in the week ending April 13th, spending in top-income-quartile households was down by 37% relative to pre-Covid levels, as compared with 28% for bottom-income-quartile households. Then, from April 15 (vertical line on the graph) onwards, spending increased steeply for people in low-income people, it increased by over 15 percentage points in a few days. Spending for high-income households also increased, but by a much smaller amount, only 7 percentage points. A conclusion that arises from this graph is that the stimulus payments had a sizeable positive effect on spending, in particular for low-income families.

Chetty et al. plotted daily spending levels relative to baseline for low- and high-income households, respectively, for the month of April, following the regression discontinuity design previously outlined. They estimated that spending levels rose discontinuously on April 15 by 26 percentage points in low-income households, compared to 9 percentage points in high-income households. Both effects were statistically significantly different from 0, as well as from each other.

Now, I will present the regression results that I conducted trying to replicate the findings in the Chetty et al. paper. Table 1 (Appendix) shows the regressions discontinuity estimates for the low-income and high-income groups under a variety of bandwidths. As in Chetty et al. findings, both coefficients for the low-income group seem to be statistically significant at a 1% level. According to the table, if the take the window of April 1 to April 30 the effect of the stimulus payments for the low-income group is an increase of 56 percentage points in spending. In the window of April 7 to April 21, the effect of the stimulus payments for the low-income group becomes much larger, a discontinuous increase of 141.2 percentage points in spending. Comparing these numbers to the ones in the Chetty et al. table (Table 1 Appendix and the Chetty et al. table are placed next to each other in the appendix for ease of comparison), an increase of 26 percentage points and an increase of 38 percentage points (for the window of April 1-April 30 and April 7-April 21 respectively), we realize the numbers are not the same (even though they are somehow related). The difference is larger for the smaller window 141.2 percentage points vs 38 percentage points. One could explain those differences by the fact that the regressions were run for different populations. In the Chetty et al. paper, the regression was run for the bottom income quartile, while I ran it for a low-income group (households with median income less than $46,000 per year) which might represent a broader group than the bottom income quartile population, thus leading to different estimates. However, I could say that my results are somewhat consistent with Chetty et al. results given that they are of the same magnitude and sign, and they are also significant at a 1% level.

Parallelly, the results for the high-income group also present similarities to the Chetty et el. results. Table 1 (Appendix) shows that both coefficients for the high-income group are statistically significant at a 1% level. According to the table, if we look at the window of April 1 to April 30, the stimulus payments caused an increase of 23.2 percentage points in spending for the high-income group. In the window of April 7 to April 21, this effect is an increase slightly bigger, the effect becomes an increase of 25.4 percentage points in spending for the high-income group. Again, we can compare these numbers to the ones found in the Chetty et al. table, an increase of 9 percentage points and 16 percentage points (for the window of April 1 to April 30 and April 7 to April 21 respectively). Chetty et al. numbers are also a bit different from the ones I found, the difference is larger, this time, for the larger window 23 percentage points vs 9 percentage points. Once again, this difference could be explained by the fact that the regressions were run for different populations. In the Chetty et al. paper, the regression was run for the top income quartile, while I ran it for a different high-income group (households with median income greater than $78,000 per year). This might represent a broader group than the top income quartile population, thus leading to larger estimates of the effect of the stimulus payments (because a broader group, in this case, would mean a less wealthy group than the top income quartile thus their marginal propensity to consume might be higher).

Finally, one could also wonder what category of consumption has suffered the most from the pandemic, and we could ask if the stimulus payments were efficient in the way that they stimulated spending in that specific category. To answer this new question, I investigate the composition of goods and services on which individuals spent their stimulus checks. To do this, I implement a regression discontinuity design similar to the previous one, but this time I poll all individuals together instead of dividing spending into population categories (high vs low income) to maximize precision. Then I divide spending by category type. I run multiple regressions in which the dependent variable is time, and the independent variable is defined as the spending change in each category. Next, I compare my results to the ones found in the Chetty et al. paper.

Chetty et al. results show that spending on durable goods increased by 21 percentage points after the deposit of the stimulus payments and it increased even more afterward, surpassing pre-crisis levels. In contrast, spending on in-person services only increased by only 7 percentage points, and it remained more than 50% lower than pre-crisis levels.

Now, I will present the regression results that I conducted trying to replicate the findings in the Chetty et al. paper. Table 2 (Appendix) shows the regression of spending on in-person services. We observe that the coefficient is statistically significant at a 5% level. According to the table, if the take the window of April 1 to April 30 the effect of the stimulus payments will increase in-person services by 8.4 percentage points. We can compare this number to the one found in Chetty et al. regression which is an increase of 7 percentage points, and we realize that they differ by 1.4 percentage points. One could explain this small difference by a slightly different choice of goods (for example I did not include data on hair salon and spa because I did not have it but those are also in-person services which Chetty et al. did include in their regression).

A.2. Appendix Tables

Table 1: Regression Discontinuity Estimates of Stimulus Payments on Spending

	Dependent variable: Spending			
	Spending Low Income		spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.564***	1.412***	0.232***	0.254**
	(0.079)	(0.210)	(0.034)	(0.097)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.663	0.805	0.647	0.384
Adjusted R^2	0.650	0.787	0.634	0.328
Residual Std. Error	3.373 (df = 26)	2.830 (df = 11)	1.437 (df = 26)	1.311 (df = 11)
F Statistic	51.100*** (df = 1; 26)	45.293*** (df = 1; 11)	47.693*** (df = 1; 26)	6.850** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Regression Discontinuity Estimates of Stimulus Payments on Spending

	(1)	(2)	(3)	(4)
	Q1 ZIP codes	Q1 ZIP codes	Q4 ZIP codes	Q4 ZIP codes
Panel A: Impact of Stimulus Payments on Consumer Spending				
Dep. Var.:	Spending			
RD Effect of Stimulus:	0.26	0.38	0.09	0.16
	(0.07)	(0.10)	(0.04)	(0.05)
Window:	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21

Table from Chetty at al. (2020), used for comparison with Table 1 Appendix (above)

Table 2: RDD Estimates of Stimulus Payments on Spending on In-Person Services

	Dependent variable: Spending	
	Mi Results	Chetty et al. Results
	(1)	(2)
RD Effect of stimulus	0.084**	0.07*
	(0.039)	(0.04)
Observations	28	
R^2	0.151	
Adjusted R^2	0.119	
Residual Std. Error (df = 26)	1.662	
F Statistic (df = 1; 26)	4.639**	

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Only one time window is used in this table, a 30-day window (15 days before the cutoff and 15 days after the cutoff).

Table 3: Regression Discontinuity Estimates of Stimulus Payments on Spending in New York

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.736***	1.660***	0.271***	0.442***
	(0.083)	(0.233)	(0.044)	(0.134)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.753	0.822	0.596	0.497
Adjusted R^2	0.744	0.806	0.581	0.451
Residual Std. Error	3.528 (df = 26)	3.140 (df = 11)	1.867 (df = 26)	1.811 (df = 11)
F Statistic	79.456*** (df = 1; 26)	50.882*** (df = 1; 11)	38.433*** (df = 1; 26)	10.856*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 4: Regression Discontinuity Estimates of Stimulus Payments on Spending in New Jersey

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.521***	1.423***	0.254***	0.480***
	(0.078)	(0.191)	(0.043)	(0.133)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.635	0.835	0.577	0.541
Adjusted R^2	0.620	0.820	0.561	0.499
Residual Std. Error	3.315 (df = 26)	2.572 (df = 11)	1.824 (df = 26)	1.798 (df = 11)
F Statistic	45.144*** (df = 1; 26)	55.664*** (df = 1; 11)	35.453*** (df = 1; 26)	12.948*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 5: Regression Discontinuity Estimates of Stimulus Payments on Spending in California

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.107	-0.035	0.104**	-0.029
	(0.064)	(0.150)	(0.043)	(0.080)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.096	0.005	0.185	0.012
Adjusted R^2	0.062	-0.085	0.154	-0.078
Residual Std. Error	2.744 (df = 26)	2.021 (df = 11)	1.827 (df = 26)	1.076 (df = 11)
F Statistic	2.770 (df = 1; 26)	0.055 (df = 1; 11)	5.914** (df = 1; 26)	0.128 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 6: Regression Discontinuity Estimates of Stimulus Payments on Spending in Massachusetts

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.243	1.387	0.271***	0.163
	(0.262)	(0.994)	(0.036)	(0.129)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.032	0.150	0.689	0.127
Adjusted R^2	-0.005	0.073	0.677	0.047
Residual Std. Error	11.188 (df = 26)	13.416 (df = 11)	1.524 (df = 26)	1.744 (df = 11)
F Statistic	0.865 (df = 1; 26)	1.945 (df = 1; 11)	57.670*** (df = 1; 26)	1.594 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30 day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 7: Regression Discontinuity Estimates of Stimulus Payments on Spending in Nevada

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.336***	0.144	0.058	-0.194
	(0.072)	(0.157)	(0.040)	(0.124)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.455	0.071	0.073	0.182
Adjusted R^2	0.434	-0.013	0.037	0.108
Residual Std. Error	3.083 (df = 26)	2.112 (df = 11)	1.728 (df = 26)	1.672 (df = 11)
F Statistic	21.664*** (df = 1; 26)	0.846 (df = 1; 11)	2.038 (df = 1; 26)	2.450 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 8: Regression Discontinuity Estimates of Stimulus Payments on Spending in Rhode Island

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.584***	0.427*	0.489***	0.388
	(0.114)	(0.202)	(0.084)	(0.300)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.501	0.289	0.568	0.132
Adjusted R^2	0.482	0.224	0.551	0.053
Residual Std. Error	4.881 (df = 26)	2.727 (df = 11)	3.576 (df = 26)	4.047 (df = 11)
F Statistic	26.151*** (df = 1; 26)	4.462* (df = 1; 11)	34.156*** (df = 1; 26)	1.672 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 9: Regression Discontinuity Estimates of Stimulus Payments on Spending in Maryland

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.553***	2.181***	0.169***	0.132
	(0.146)	(0.376)	(0.039)	(0.136)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.355	0.754	0.418	0.079
Adjusted R^2	0.330	0.732	0.396	-0.005
Residual Std. Error	6.244 (df = 26)	5.068 (df = 11)	1.677 (df = 26)	1.833 (df = 11)
F Statistic	14.327*** (df = 1; 26)	33.711*** (df = 1; 11)	18.669*** (df = 1; 26)	0.942 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 10: Regression Discontinuity Estimates of Stimulus Payments on Spending in Illinois

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.894***	2.046***	0.316***	0.445***
	(0.130)	(0.329)	(0.029)	(0.092)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.646	0.778	0.819	0.681
Adjusted R^2	0.632	0.758	0.812	0.652
Residual Std. Error	5.550 (df = 26)	4.441 (df = 11)	1.244 (df = 26)	1.240 (df = 11)
F Statistic	47.366*** (df = 1; 26)	38.646*** (df = 1; 11)	117.679*** (df = 1; 26)	23.454*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 11: Regression Discontinuity Estimates of Stimulus Payments on Spending in Florida

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.575***	1.781***	0.131**	0.502**
	(0.111)	(0.280)	(0.053)	(0.172)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.508	0.786	0.187	0.435
Adjusted R^2	0.489	0.767	0.156	0.383
Residual Std. Error	4.743 (df = 26)	3.776 (df = 11)	2.282 (df = 26)	2.326 (df = 11)
F Statistic	26.813*** (df = 1; 26)	40.492*** (df = 1; 11)	5.989** (df = 1; 26)	8.464** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 12: Regression Discontinuity Estimates of Stimulus Payments on Spending in Connecticut

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.403***	0.926***	0.235***	0.386**
	(0.114)	(0.138)	(0.041)	(0.133)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.324	0.805	0.558	0.434
Adjusted R^2	0.298	0.787	0.541	0.383
Residual Std. Error	4.876 (df = 26)	1.856 (df = 11)	1.749 (df = 26)	1.793 (df = 11)
F Statistic	12.480*** (df = 1; 26)	45.348*** (df = 1; 11)	32.858*** (df = 1; 26)	8.450** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 13: Regression Discontinuity Estimates of Stimulus Payments on Spending in Arizona

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.161**	0.408**	0.123**	0.231
	(0.064)	(0.179)	(0.050)	(0.140)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.197	0.322	0.191	0.197
Adjusted R^2	0.166	0.260	0.160	0.124
Residual Std. Error	2.715 (df = 26)	2.409 (df = 11)	2.123 (df = 26)	1.895 (df = 11)
F Statistic	6.386** (df = 1; 26)	5.215** (df = 1; 11)	6.136** (df = 1; 26)	2.699 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 14: Regression Discontinuity Estimates of Stimulus Payments on Spending in Texas

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.621***	1.519***	0.293***	0.409***
	(0.078)	(0.168)	(0.035)	(0.093)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.707	0.882	0.731	0.637
Adjusted R^2	0.695	0.871	0.720	0.604
Residual Std. Error	3.352 (df = 26)	2.264 (df = 11)	1.492 (df = 26)	1.255 (df = 11)
F Statistic	62.664*** (df = 1; 26)	81.972*** (df = 1; 11)	70.476*** (df = 1; 26)	19.297*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 15: Regression Discontinuity Estimates of Stimulus Payments on Spending in Colorado

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.601***	0.292**	0.295***	-0.025
	(0.048)	(0.102)	(0.034)	(0.090)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.860	0.425	0.742	0.007
Adjusted R^2	0.854	0.372	0.732	-0.083
Residual Std. Error	2.036 (df = 26)	1.381 (df = 11)	1.461 (df = 26)	1.218 (df = 11)
F Statistic	159.188*** (df = 1; 26)	8.119** (df = 1; 11)	74.606*** (df = 1; 26)	0.078 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 16: Regression Discontinuity Estimates of Stimulus Payments on Spending in Pennsylvania

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.434**	1.973***	0.270***	0.223
	(0.159)	(0.324)	(0.041)	(0.150)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.222	0.771	0.622	0.168
Adjusted R^2	0.192	0.750	0.607	0.092
Residual Std. Error	6.800 (df = 26)	4.372 (df = 11)	1.766 (df = 26)	2.021 (df = 11)
F Statistic	7.434** (df = 1; 26)	37.053*** (df = 1; 11)	42.749*** (df = 1; 26)	2.218 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 17: Regression Discontinuity Estimates of Stimulus Payments on Spending in Washington

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.366***	1.397***	0.390***	0.481***
	(0.100)	(0.210)	(0.034)	(0.099)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.339	0.800	0.834	0.683
Adjusted R^2	0.313	0.782	0.827	0.655
Residual Std. Error	4.290 (df = 26)	2.839 (df = 11)	1.460 (df = 26)	1.331 (df = 11)
F Statistic	13.315*** (df = 1; 26)	44.089*** (df = 1; 11)	130.478*** (df = 1; 26)	23.749*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 18: Regression Discontinuity Estimates of Stimulus Payments on Spending in Hawaii

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.177	-0.345	0.579***	1.377***
	(0.144)	(0.319)	(0.087)	(0.200)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.055	0.096	0.631	0.812
Adjusted R^2	0.018	0.014	0.617	0.795
Residual Std. Error	6.162 (df = 26)	4.309 (df = 11)	3.711 (df = 26)	2.695 (df = 11)
F Statistic	1.509 (df = 1; 26)	1.165 (df = 1; 11)	44.407*** (df = 1; 26)	47.548*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 19: Regression Discontinuity Estimates of Stimulus Payments on Spending in Delaware

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	-0.952**	-0.667	-0.059	-0.140
	(0.359)	(0.841)	(0.055)	(0.132)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.213	0.054	0.043	0.092
Adjusted R^2	0.183	-0.032	0.006	0.009
Residual Std. Error	15.342 (df = 26)	11.347 (df = 11)	2.330 (df = 26)	1.787 (df = 11)
F Statistic	7.032** (df = 1; 26)	0.630 (df = 1; 11)	1.173 (df = 1; 26)	1.110 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 20: Regression Discontinuity Estimates of Stimulus Payments on Spending in Utah

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.416***	0.682***	0.283***	-0.202*
	(0.033)	(0.093)	(0.047)	(0.104)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.856	0.829	0.577	0.257
Adjusted R^2	0.850	0.814	0.561	0.189
Residual Std. Error	1.431 (df = 26)	1.258 (df = 11)	2.028 (df = 26)	1.400 (df = 11)
F Statistic	154.592*** (df = 1; 26)	53.443*** (df = 1; 11)	35.537*** (df = 1; 26)	3.796* (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 21: Regression Discontinuity Estimates of Stimulus Payments on Spending in Virginia

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.756***	1.806***	0.172***	0.077
	(0.109)	(0.297)	(0.049)	(0.118)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.647	0.771	0.323	0.038
Adjusted R^2	0.634	0.750	0.297	-0.050
Residual Std. Error	4.678 (df = 26)	4.007 (df = 11)	2.089 (df = 26)	1.596 (df = 11)
F Statistic	47.708*** (df = 1; 26)	36.970*** (df = 1; 11)	12.382*** (df = 1; 26)	0.429 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 22: Regression Discontinuity Estimates of Stimulus Payments on Spending in Ohio

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.755***	1.659***	0.307***	0.647***
	(0.089)	(0.215)	(0.045)	(0.141)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.733	0.844	0.644	0.655
Adjusted R^2	0.723	0.830	0.630	0.624
Residual Std. Error	3.816 (df = 26)	2.897 (df = 11)	1.915 (df = 26)	1.908 (df = 11)
F Statistic	71.473*** (df = 1; 26)	59.715*** (df = 1; 11)	46.967*** (df = 1; 26)	20.919*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 23: Regression Discontinuity Estimates of Stimulus Payments on Spending in Michigan

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.843***	1.448***	0.451***	0.588***
	(0.075)	(0.221)	(0.044)	(0.162)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.828	0.796	0.803	0.544
Adjusted R^2	0.822	0.778	0.795	0.502
Residual Std. Error	3.216 (df = 26)	2.979 (df = 11)	1.873 (df = 26)	2.191 (df = 11)
F Statistic	125.436*** (df = 1; 26)	42.991*** (df = 1; 11)	105.790*** (df = 1; 26)	13.109*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 24: Regression Discontinuity Estimates of Stimulus Payments on Spending in Oregon

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.219***	0.172	0.356***	0.667***
	(0.036)	(0.112)	(0.089)	(0.186)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.593	0.176	0.380	0.539
Adjusted R^2	0.577	0.101	0.357	0.497
Residual Std. Error	1.523 (df = 26)	1.516 (df = 11)	3.807 (df = 26)	2.510 (df = 11)
F Statistic	37.830*** (df = 1; 26)	2.342 (df = 1; 11)	15.968*** (df = 1; 26)	12.853*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 25: Regression Discontinuity Estimates of Stimulus Payments on Spending in Georgia

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.494***	1.269***	0.138***	0.160
	(0.079)	(0.199)	(0.044)	(0.102)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.601	0.787	0.270	0.182
Adjusted R^2	0.586	0.768	0.242	0.108
Residual Std. Error	3.375 (df = 26)	2.686 (df = 11)	1.902 (df = 26)	1.382 (df = 11)
F Statistic	39.219*** (df = 1; 26)	40.640*** (df = 1; 11)	9.601*** (df = 1; 26)	2.454 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 26: Regression Discontinuity Estimates of Stimulus Payments on Spending in Minnesota

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.602***	0.826***	0.548***	0.462***
	(0.042)	(0.107)	(0.032)	(0.111)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.887	0.844	0.917	0.613
Adjusted R^2	0.883	0.830	0.913	0.578
Residual Std. Error	1.798 (df = 26)	1.442 (df = 11)	1.386 (df = 26)	1.493 (df = 11)
F Statistic	204.988*** (df = 1; 26)	59.738*** (df = 1; 11)	285.610*** (df = 1; 26)	17.428*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 26: Regression Discontinuity Estimates of Stimulus Payments on Spending in Minnesota

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.602***	0.826***	0.548***	0.462***
	(0.042)	(0.107)	(0.032)	(0.111)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.887	0.844	0.917	0.613
Adjusted R^2	0.883	0.830	0.913	0.578
Residual Std. Error	1.798 (df = 26)	1.442 (df = 11)	1.386 (df = 26)	1.493 (df = 11)
F Statistic	204.988*** (df = 1; 26)	59.738*** (df = 1; 11)	285.610*** (df = 1; 26)	17.428*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 27: Regression Discontinuity Estimates of Stimulus Payments on Spending in Indiana

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.883***	2.011***	0.533***	0.748***
	(0.106)	(0.243)	(0.059)	(0.147)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.726	0.862	0.758	0.701
Adjusted R^2	0.715	0.850	0.749	0.674
Residual Std. Error	4.550 (df = 26)	3.272 (df = 11)	2.527 (df = 26)	1.988 (df = 11)
F Statistic	68.744*** (df = 1; 26)	68.735*** (df = 1; 11)	81.377*** (df = 1; 26)	25.758*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 28: Regression Discontinuity Estimates of Stimulus Payments on Spending in North Carolina

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.044	0.102	0.063	-0.196
	(0.036)	(0.135)	(0.052)	(0.155)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.056	0.050	0.052	0.127
Adjusted R^2	0.020	-0.037	0.016	0.047
Residual Std. Error	1.526 (df = 26)	1.818 (df = 11)	2.242 (df = 26)	2.088 (df = 11)
F Statistic	1.539 (df = 1; 26)	0.575 (df = 1; 11)	1.441 (df = 1; 26)	1.597 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 29: Regression Discontinuity Estimates of Stimulus Payments on Spending in Missouri

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.555***	1.398***	0.455***	0.102
	(0.073)	(0.183)	(0.086)	(0.136)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.692	0.842	0.517	0.048
Adjusted R^2	0.680	0.827	0.498	-0.038
Residual Std. Error	3.100 (df = 26)	2.468 (df = 11)	3.687 (df = 26)	1.836 (df = 11)
F Statistic	58.475*** (df = 1; 26)	58.421*** (df = 1; 11)	27.820*** (df = 1; 26)	0.558 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 30: Regression Discontinuity Estimates of Stimulus Payments on Spending in Nebraska

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.652***	1.347***	0.290***	0.396**
	(0.095)	(0.242)	(0.049)	(0.152)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.645	0.738	0.575	0.381
Adjusted R^2	0.632	0.714	0.559	0.325
Residual Std. Error	4.051 (df = 26)	3.267 (df = 11)	2.087 (df = 26)	2.054 (df = 11)
F Statistic	47.328*** (df = 1; 26)	30.932*** (df = 1; 11)	35.180*** (df = 1; 26)	6.768** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 31: Regression Discontinuity Estimates of Stimulus Payments on Spending in Tennessee

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	1.015***	3.267***	0.307***	0.363**
	(0.183)	(0.358)	(0.042)	(0.135)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.543	0.884	0.675	0.396
Adjusted R^2	0.525	0.873	0.662	0.341
Residual Std. Error	7.808 (df = 26)	4.824 (df = 11)	1.787 (df = 26)	1.824 (df = 11)
F Statistic	30.874*** (df = 1; 26)	83.478*** (df = 1; 11)	53.930*** (df = 1; 26)	7.215** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 32: Regression Discontinuity Estimates of Stimulus Payments on Spending in Wisconsin

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.516***	1.246***	0.400***	1.264***
	(0.077)	(0.149)	(0.080)	(0.240)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.631	0.865	0.489	0.717
Adjusted R^2	0.617	0.852	0.469	0.691
Residual Std. Error	3.307 (df = 26)	2.004 (df = 11)	3.434 (df = 26)	3.235 (df = 11)
F Statistic	44.418*** (df = 1; 26)	70.354*** (df = 1; 11)	24.842*** (df = 1; 26)	27.803*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 33: Regression Discontinuity Estimates of Stimulus Payments on Spending in Louisiana

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.634***	0.954***	0.747***	1.279***
	(0.081)	(0.252)	(0.125)	(0.398)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.699	0.566	0.577	0.484
Adjusted R^2	0.688	0.526	0.560	0.437
Residual Std. Error	3.482 (df = 26)	3.402 (df = 11)	5.362 (df = 26)	5.375 (df = 11)
F Statistic	60.485*** (df = 1; 26)	14.328*** (df = 1; 11)	35.418*** (df = 1; 26)	10.309*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 34: Regression Discontinuity Estimates of Stimulus Payments on Spending in Kansas

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.584***	1.272***	0.516***	0.322*
	(0.080)	(0.112)	(0.052)	(0.174)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.673	0.921	0.792	0.237
Adjusted R^2	0.661	0.914	0.784	0.168
Residual Std. Error	3.410 (df = 26)	1.511 (df = 11)	2.218 (df = 26)	2.351 (df = 11)
F Statistic	53.560*** (df = 1; 26)	128.897*** (df = 1; 11)	98.940*** (df = 1; 26)	3.415* (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 35: Regression Discontinuity Estimates of Stimulus Payments on Spending in South Carolina

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.421***	0.803**	0.211***	-0.078
	(0.094)	(0.332)	(0.071)	(0.184)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.436	0.347	0.252	0.016
Adjusted R^2	0.415	0.287	0.223	-0.073
Residual Std. Error	4.013 (df = 26)	4.483 (df = 11)	3.049 (df = 26)	2.482 (df = 11)
F Statistic	20.118*** (df = 1; 26)	5.834** (df = 1; 11)	8.762*** (df = 1; 26)	0.180 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 36: Regression Discontinuity Estimates of Stimulus Payments on Spending in Oklahoma

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.644***	1.007***	0.610***	0.816***
	(0.065)	(0.173)	(0.061)	(0.113)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.790	0.756	0.792	0.826
Adjusted R^2	0.782	0.734	0.784	0.810
Residual Std. Error	2.786 (df = 26)	2.327 (df = 11)	2.617 (df = 26)	1.526 (df = 11)
F Statistic	97.593*** (df = 1; 26)	34.085*** (df = 1; 11)	99.238*** (df = 1; 26)	52.097*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 37: Regression Discontinuity Estimates of Stimulus Payments on Spending in New Hampshire

	Dependent variable: Spending	
	Spending High Income	
	(1)	(2)
RD Effect of stimulus	0.428***	0.772***
	(0.044)	(0.118)
Window	April 1 - April 30	April 7 - April 21
Observations	28	13
R^2	0.782	0.795
Adjusted R^2	0.773	0.777
Residual Std. Error	1.894 (df = 26)	1.593 (df = 11)
F Statistic	93.119*** (df = 1; 26)	42.756*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 38: Regression Discontinuity Estimates of Stimulus Payments on Spending in New Mexico

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.266***	-0.040	0.451***	0.648**
	(0.067)	(0.165)	(0.108)	(0.250)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.375	0.005	0.402	0.380
Adjusted R^2	0.351	-0.085	0.379	0.323
Residual Std. Error	2.883 (df = 26)	2.227 (df = 11)	4.614 (df = 26)	3.370 (df = 11)
F Statistic	15.603*** (df = 1; 26)	0.057 (df = 1; 11)	17.486*** (df = 1; 26)	6.735** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 39: Regression Discontinuity Estimates of Stimulus Payments on Spending in Kentucky

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	1.185***	2.005***	0.262***	0.664***
	(0.126)	(0.327)	(0.063)	(0.189)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.774	0.774	0.398	0.529
Adjusted R^2	0.765	0.754	0.375	0.486
Residual Std. Error	5.376 (df = 26)	4.406 (df = 11)	2.697 (df = 26)	2.548 (df = 11)
F Statistic	88.826*** (df = 1; 26)	37.714*** (df = 1; 11)	17.207*** (df = 1; 26)	12.351*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 40: Regression Discontinuity Estimates of Stimulus Payments on Spending in Alabama

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.622***	1.385***	0.016	0.100
	(0.107)	(0.323)	(0.057)	(0.213)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.564	0.626	0.003	0.020
Adjusted R^2	0.548	0.592	-0.035	-0.070
Residual Std. Error	4.577 (df = 26)	4.359 (df = 11)	2.445 (df = 26)	2.878 (df = 11)
F Statistic	33.691*** (df = 1; 26)	18.389*** (df = 1; 11)	0.080 (df = 1; 26)	0.220 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 41: Regression Discontinuity Estimates of Stimulus Payments on Spending in Idaho

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.764***	1.020***	0.531***	-0.431
	(0.063)	(0.177)	(0.156)	(0.496)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.848	0.751	0.308	0.064
Adjusted R^2	0.842	0.728	0.282	-0.021
Residual Std. Error	2.711 (df = 26)	2.390 (df = 11)	6.665 (df = 26)	6.685 (df = 11)
F Statistic	145.242*** (df = 1; 26)	33.159*** (df = 1; 11)	11.585*** (df = 1; 26)	0.758 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 42: Regression Discontinuity Estimates of Stimulus Payments on Spending in Iowa

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.520***	0.941***	0.336***	0.318*
	(0.081)	(0.231)	(0.059)	(0.162)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.614	0.601	0.554	0.260
Adjusted R^2	0.599	0.565	0.537	0.192
Residual Std. Error	3.456 (df = 26)	3.115 (df = 11)	2.529 (df = 26)	2.182 (df = 11)
F Statistic	41.315*** (df = 1; 26)	16.599*** (df = 1; 11)	32.306*** (df = 1; 26)	3.855* (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 43: Regression Discontinuity Estimates of Stimulus Payments on Spending in Arkansas

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.827***	2.261***	0.438***	0.420
	(0.123)	(0.278)	(0.109)	(0.418)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.633	0.858	0.382	0.084
Adjusted R^2	0.619	0.845	0.358	0.001
Residual Std. Error	5.273 (df = 26)	3.745 (df = 11)	4.675 (df = 26)	5.639 (df = 11)
F Statistic	44.907*** (df = 1; 26)	66.379*** (df = 1; 11)	16.043*** (df = 1; 26)	1.008 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 44: Regression Discontinuity Estimates of Stimulus Payments on Spending in West Virginia

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.935***	2.303***	0.658***	1.659***
	(0.135)	(0.335)	(0.138)	(0.350)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.647	0.811	0.466	0.671
Adjusted R^2	0.634	0.794	0.446	0.641
Residual Std. Error	5.786 (df = 26)	4.518 (df = 11)	5.903 (df = 26)	4.725 (df = 11)
F Statistic	47.732*** (df = 1; 26)	47.271*** (df = 1; 11)	22.693*** (df = 1; 26)	22.443*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 45: Regression Discontinuity Estimates of Stimulus Payments on Spending in North Dakota

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	1.118***	2.176***	0.860***	1.429***
	(0.131)	(0.259)	(0.072)	(0.124)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.737	0.865	0.846	0.923
Adjusted R^2	0.727	0.853	0.840	0.916
Residual Std. Error	5.599 (df = 26)	3.490 (df = 11)	3.073 (df = 26)	1.679 (df = 11)
F Statistic	72.851*** (df = 1; 26)	70.739*** (df = 1; 11)	143.163*** (df = 1; 26)	131.750*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 46: Regression Discontinuity Estimates of Stimulus Payments on Spending in Maine

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.914***	2.178***	0.639***	1.360***
	(0.143)	(0.363)	(0.111)	(0.352)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.611	0.766	0.560	0.576
Adjusted R^2	0.596	0.745	0.543	0.538
Residual Std. Error	6.114 (df = 26)	4.893 (df = 11)	4.748 (df = 26)	4.742 (df = 11)
F Statistic	40.855*** (df = 1; 26)	36.057*** (df = 1; 11)	33.066*** (df = 1; 26)	14.967*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 47: Regression Discontinuity Estimates of Stimulus Payments on Spending in Mississippi

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.441***	1.426***	0.336***	0.063
	(0.115)	(0.392)	(0.110)	(0.150)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.363	0.545	0.264	0.016
Adjusted R^2	0.338	0.504	0.236	-0.074
Residual Std. Error	4.902 (df = 26)	5.295 (df = 11)	4.694 (df = 26)	2.026 (df = 11)
F Statistic	14.799*** (df = 1; 26)	13.195*** (df = 1; 11)	9.350*** (df = 1; 26)	0.174 (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 48: Regression Discontinuity Estimates of Stimulus Payments on Spending in Vermont

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	-0.013	-0.711***	1.128***	2.426***
	(0.090)	(0.175)	(0.192)	(0.436)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.001	0.601	0.570	0.738
Adjusted R^2	-0.038	0.564	0.553	0.714
Residual Std. Error	3.840 (df = 26)	2.357 (df = 11)	8.218 (df = 26)	5.878 (df = 11)
F Statistic	0.020 (df = 1; 26)	16.554*** (df = 1; 11)	34.411*** (df = 1; 26)	31.015*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 49: Regression Discontinuity Estimates of Stimulus Payments on Spending in Alaska

	Dependent variable: Spending	
	Spending High Income	
	(1)	(2)
RD Effect of stimulus	0.296***	0.338**
	(0.041)	(0.139)
Window	April 1 - April 30	April 7 - April 21
Observations	28	13
R^2	0.670	0.352
Adjusted R^2	0.658	0.293
Residual Std. Error	1.742 (df = 26)	1.869 (df = 11)
F Statistic	52.852*** (df = 1; 26)	5.966** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses. The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 50: Regression Discontinuity Estimates of Stimulus Payments on Spending in South Dakota

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	-0.059	0.185	0.160	1.360***
	(0.127)	(0.349)	(0.124)	(0.350)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.008	0.025	0.060	0.578
Adjusted R^2	-0.030	-0.064	0.024	0.540
Residual Std. Error	5.433 (df = 26)	4.706 (df = 11)	5.301 (df = 26)	4.723 (df = 11)
F Statistic	0.214 (df = 1; 26)	0.282 (df = 1; 11)	1.660 (df = 1; 26)	15.087*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 51: Regression Discontinuity Estimates of Stimulus Payments on Spending in Montana

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.413***	0.673***	0.383	2.004*
	(0.062)	(0.139)	(0.436)	(1.038)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.631	0.679	0.029	0.253
Adjusted R^2	0.617	0.650	-0.009	0.185
Residual Std. Error	2.643 (df = 26)	1.881 (df = 11)	18.633 (df = 26)	14.006 (df = 11)
F Statistic	44.556*** (df = 1; 26)	23.270*** (df = 1; 11)	0.770 (df = 1; 26)	3.727* (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).

Table 52: Regression Discontinuity Estimates of Stimulus Payments on Spending in Wyoming

	Dependent variable: Spending			
	Spending Low Income		Spending High Income	
	(1)	(2)	(3)	(4)
RD Effect of stimulus	0.606***	0.976***	0.214*	1.017***
	(0.085)	(0.167)	(0.116)	(0.302)
Window	April 1 - April 30	April 7 - April 21	April 1 - April 30	April 7 - April 21
Observations	28	13	28	13
R^2	0.660	0.755	0.116	0.508
Adjusted R^2	0.647	0.733	0.082	0.463
Residual Std. Error	3.647 (df = 26)	2.260 (df = 11)	4.947 (df = 26)	4.071 (df = 11)
F Statistic	50.420*** (df = 1; 26)	33.961*** (df = 1; 11)	3.414* (df = 1; 26)	11.357*** (df = 1; 11)

*p<0.1; **p<0.05; ***p<0.01

Note: The unit of observation is changes in spending (as decimals). Those percentage changes are seasonally adjusted (each calendar date in 2020 value is divided by its corresponding value from 2019) and represent changes in spending compared to January 2020 (each value is divided by the mean of the seasonally adjusted average spending level in the first four complete weeks of 2020). Standard errors are in parentheses.
The date on which the stimulus payments were deposited, April 15, 2020, is used as the cutoff. Columns 1 and 3 correspond to the evaluation of the policy on a 30-day window (15 days before the cutoff and 15 days after the cutoff). Columns 2 and 4 correspond to the evaluation of the policy on a 14-day window (7 days before the cutoff and 7 days after the cutoff).