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Initial Impacts of the Pandemic on Consumer Behavior: Evidence from Linked Income, Spending, and Savings Data

ABSTRACT We use US household-level bank account data to investigate the heterogeneous effects of the pandemic on spending and savings. Households across the income distribution all cut spending from March to early April. Since mid-April, spending has rebounded most rapidly for low-income households. We find large increases in liquid asset balances for households throughout the income distribution. However, lower-income households contribute disproportionately to the aggregate increase in balances, relative to their prepandemic shares. Taken together, our results suggest that spending declines

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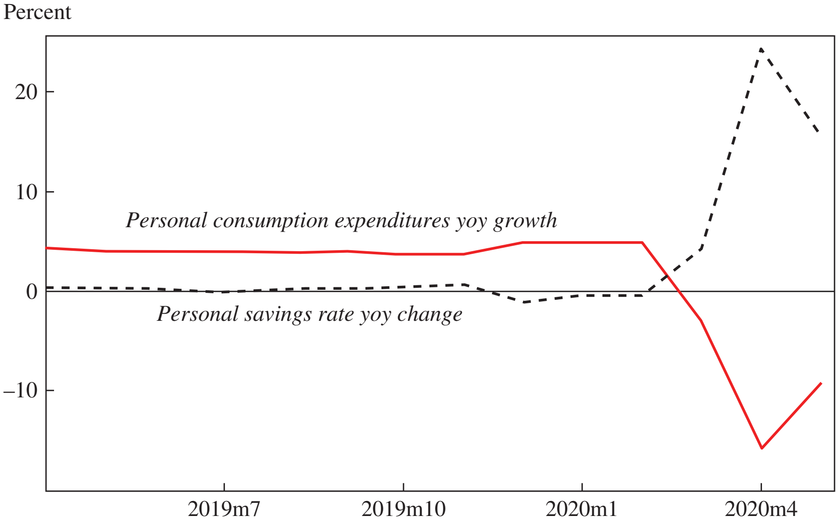
Figure 1. Aggregate Consumption and Savings



Source: BEA.
Note: Year-over-year growth calculated from monthly Bureau of Economic Analysis data.

in the initial months of the recession were primarily caused by direct effects of the pandemic, rather than resulting from labor market disruptions. The sizable growth in liquid assets we observe for low-income households suggests that stimulus and insurance programs during this period likely played an important role in limiting the effects of labor market disruptions on spending.

The COVID-19 pandemic led to a large and immediate decline in US aggregate spending and an increase in aggregate private savings (see figure 1). In this paper, we use anonymized bank account information of millions of Chase customers to measure the microeconomic dynamics underlying these aggregate patterns. Specifically, we use our household-level account data to explore how spending and savings over the initial months of the pandemic vary with household-specific demographic characteristics, such as prepandemic income and industry of employment.

Measuring and understanding the link between income, spending, and savings is useful for understanding the causes and dynamics of this recession. For instance, the relationship between individual income, spending, and savings can shed light on the role of supply factors (such as shutdowns and reducing activities with high infection risk) versus demand factors (such as Keynesian spillovers across sectors as unemployed workers reduce spending). Understanding these factors can be informative about the effectiveness of different stimulus policies for targeting different households and businesses. Many data sets have already been used to study the dynamics of geographic level spending during the pandemic, but aggregated relationships may or may not be identical to those at the individual household level at which economic behavior is ultimately determined.[1] Our paper provides an initial step in analyzing these household-level dynamics.[2]

Focusing first on aggregate results, we find that overall spending fell over 35 percent in the second half of March. In April, spending began to increase from its nadir, but it remained substantially depressed through the end of our sample on May 30. Declines in nonessential spending accounted for most of the declines in spending.[3] Amongst nonessential categories, declines were particularly large for restaurants, hotel accommodations, and clothing and department stores. Amongst essential categories, declines were most dramatic for health care, ground transportation, and fuel. Reassuringly, these patterns are similar to those found using other aggregate sources of spending data.[4] However, this also implies that these results do not rely on the unique features of our micro data, so they are not the main contribution of our paper.

We next turn to results which *do* rely on our micro data linking household-level observables on income, spending, and savings. First, we find that during the initial stages of the pandemic in March, there are extremely large declines in spending for all quartiles of the prepandemic income distribution.[5] Spending by the top quartile of the income distribution falls

1. See, for example, Chetty and others (2020).

2. To be clear, our current analysis does not run regressions at the household level, but it does crucially rely on individual household data to define groups and outcomes of interest. We also focus for now on sorting households by prepandemic characteristics like income level, rather than by changes during the pandemic.

3. We define these categories precisely later, but loosely speaking nonessential stores are those which are subject to government restrictions as a result of the pandemic.

4. See, for example, EarnestResearch, Where States Stand: Measuring the Reopenings One Step at a Time, https://www.earnestresearch.com/where-states-stand-measuring-the-reopening-one-step-at-a-time/; Baker and others (2020); Opportunity Insights Economic Tracker, https://tracktherecovery.org/, accessed June 15, 2020; Facteus, Insights on Changing Consumer Behavior FIRST Report, https://www.facteus.com/reports/first-report, accessed June 15, 2020; and Karger and Rajan (2020).

by modestly more than any other quartile (in percentage terms). However, this difference is small relative to the broad decline in spending by all income groups. Beginning in mid-April when aggregate spending begins to recover, substantial differences by income emerge: spending recovers much more rapidly for low-income households than for high-income households so that large differences arise by the end of May. We show that these relationships between income and spending over the pandemic hold both in general, as well as within narrow geographic areas like zip codes.[6]

Second, we explore differences in spending by individuals' industry of employment. This variation is interesting because industries vary substantially in both their exposure to labor market disruptions and in average income levels. Exploiting joint variation in industry of employment and household income is thus helpful for better understanding the source of heterogeneity in spending patterns. We find that spending cuts are pervasive, with declines for workers in all industries of employment. Consistent with the patterns we find by income, workers in industries with low average pay initially cut spending slightly less and then have spending which recovers more rapidly. For example, grocery store workers have the smallest declines in spending and the most rapid rebound, while white-collar professional workers' spending is recovering more slowly. We then further split workers within given industries of employment by their individual prepandemic income levels. We find that income levels appear to matter more for spending than industry of employment. For example, low-income workers in all industries have rapid increases in spending in mid-April, while these increases are muted for high-income workers.

Finally, we turn to evidence on the distribution of household savings over the pandemic to provide further insight into the effects of changing income and spending on household liquidity. To the best of our knowledge, we are the first paper to explore these distributional effects. Aggregate savings have increased substantially over the last two months. Information on the underlying distribution of increases is useful for understanding the sources and consequences of this increase. There are several forces during the pandemic that likely affected aggregate savings rates: (1) as discussed above, spending has fallen. This decline is most dramatic at the top of the

5. As we discuss more in section II, since our data arise from bank account information, we undersample the very lowest income households, but the sample is otherwise broadly representative.

6. High- and low-income people live in different locations, which might have different exposure to the pandemic. Using within zip code variation shows that income-spend relationships are not driven by confounding effects of physical location.

income distribution, which will tend to boost savings for these households; (2) massive increases in unemployment have reduced labor income, and these effects are especially concentrated on low-income workers. This will tend to reduce savings for low-income households; (3) stimulus and social insurance programs like Economic Impact Payments (EIPs) and expanded unemployment insurance (UI) provide transfers which represent a larger share of income for low- than high-income households. This will tend to increase liquidity and savings by low-income households; (4) delayed tax filing dates may increase short-term savings if those who owe money delay filing more often than those who are owed refunds.

Consistent with aggregate savings data, we find a large initial increase in savings during the pandemic. By the end of May 2020, average liquid balances are 36 percent higher than at the same point in 2019. While increases in liquid balances are pervasive throughout the income distribution, we find that lower-income households contribute disproportionately to the aggregate increase in balances, relative to their initial prepandemic shares. That is, liquid balances at the end of May are slightly more equally distributed over the income distribution than liquid balances in February. However, in dollar terms, high-income households contribute most to the aggregate increase in savings.

Taken together, our results suggest several conclusions. First, labor market disruptions were unlikely to be a primary factor driving initial spending declines during the recession. Overall declines in spending were much larger than what could be explained by the rise in unemployment in this recession, given historical relationships. Furthermore, spending actually declines by less for households with greater exposure to labor market disruptions. This does not mean that labor market disruptions have no effects on spending or that demand spillovers are unimportant, but it does suggest that at least in these initial months of the recession, the direct effects of the pandemic are the primary factor driving spending.

Second, the composition of typical spending is important for understanding spending declines. Aggregate spending declines by more in nonessential sectors which are more exposed to shutdowns and health risk. Furthermore, spending declines more for high-income households, who tend to consume more of these nonessential goods in normal times.

Third, various stimulus and social insurance programs like EIPs and expanded UI likely played a sizable role in helping to stabilize spending and liquid balances, especially for low-income households. Since fiscal stimulus was ramped up at the same time that many states began to reopen, it is difficult to disentangle general reopening effects from effects of this fiscal stimulus by looking just at aggregate spending. However, stimulus checks and expanded UI benefits represent a larger share of monthly income for low-income workers than for high-income workers, and would thus naturally explain the more rapid recovery in spending we observe for low-income workers. Finally, expanded transfers could also explain the disproportionate increase in savings that we observe for lower-income households. It is important to note that many of these transfer programs are likely temporary; the EIPs are a one-off stimulus, while the expanded component of UI benefits is slated to end in late July 2020. Households may be less likely to immediately consume, and more likely to save, these payments because they are nonpermanent.

It is important to emphasize that our evidence for now focuses on time-series patterns for relatively aggregated household groups, and so we do not provide any causal evidence on the strength of any particular channels driving spending decisions. Thus, our evidence is suggestive rather than conclusive on this front. The early patterns we find in this paper may also change as the pandemic progresses and new policy decisions are made. Future work exploring even more detailed household-level results as this recession progresses will hopefully shed further light on the economic consequences of this pandemic and associated policy responses.

I. Data Description

Our analysis of spending and checking account balances is based on the universe of transactions from Chase checking accounts, debit cards, and credit cards through May 30, 2020. Our main measure of total spending includes all debit and credit card purchases as well as cash withdrawals. In robustness checks in the online appendix we show that our conclusions are similar if we add paper checks to our measure of total spending.[7] While we observe credit, debit, cash, and check transactions, we are still working to process electronic checking account transactions such as ACH payments, and so this type of spending is not included in our analysis. For all checking accounts, we also observe checking account balances.

7. We do not include paper checks in our main analysis for two reasons. First, we do not know whether the checks reflect spending, debt payments, or transfers. Second, due to delays in depositing and processing checks, there is a lag between when the check was used and when it appears as a withdrawal in the bank account. Hence, it is hard to interpret the patterns of paper check outflows at the high frequency we use in this analysis.

Table 1. Income Distribution and Credit Card Spending

	Income quartiles			
	Quartile cutoffs ($)	*Mean income ($)*	*Sample with Chase credit card (%)*	*Avg. weekly credit card spend ($)*
Quartile 1	12,000–27,707	20,948	30	205
Quartile 2	27,707–41,255	34,185	36	228
Quartile 3	41,255–63,462	50,927	46	329
Quartile 4	63,462 +	108,914	57	639
N	5,014,672			

Source: JPMorgan Chase Institute.

We impose income and activity screens in order to focus on a sample of individuals who primarily use their Chase account to manage their finances. Specifically, we filter on those who have a nonbusiness account, had at least five checking account transactions and at least three card transactions in every month between January 2018 and March 2020, and had at least $12,000 in labor income in both 2018 and 2019.[8] This leaves us with a sample of just over five million individuals.

We measure labor income using information on payroll direct deposits. We further measure industry of employment based on the payer associated with direct deposits in February 2020. However, there is an important caveat that we can match the payer associated with payroll income to an identified payer for only 24 percent of households, and most of these payers tend to be large employers. Finally, it is important to note that while we observe labor income through February 2020, we are still working to process and interpret data on labor income and government transfers during the pandemic. As a result, data on income change during the pandemic are not available for our current analysis. For this reason, we report various results based on prepandemic income, but do not yet have results on how spending has responded to individual income changes.

Given that our sample is drawn from account holders at a single financial institution, we use income data from the Current Population Survey (CPS) to measure how representative they are of the US population. Table 1 reports quartiles of the labor income distribution for our sample. Figure A.12 in the online appendix plots the average labor income by quartile for the Chase sample compared to average labor income for the CPS population (adjusted

8. We have explored different thresholds on transactions, and results are similar.

for income and payroll taxes since the Chase measure is posttax). This figure suggests that our sample is broadly representative, although it somewhat overstates income at the lowest end of the distribution and slightly understates income at the highest end of the distribution. The overstatement at the lowest end of the distribution is due to two factors. First, reliable measurement requires us to impose a minimum threshold of $12,000 in labor income.[9] In the CPS, 7.7 percent of households have labor income below this cutoff. They would be excluded from our analysis.[10] Second, every household in our data set has a bank account. Therefore, we do not include unbanked households, who are disproportionately low-income. The FDIC reports that 6.5 percent of US households did not have a bank account in 2017.[11] A final caveat for our analysis is that we report *average* outcomes in terms of spending and liquid balances by income quartile. However, there may be heterogeneity *within* quartiles. For example, not all households were eligible for EIPs and some unemployed households faced long delays in receiving UI payments. For all these reasons, our findings that average spending and average balances are relatively higher for low-income households should not be interpreted to mean that *all* low-income households are doing relatively well during the pandemic. There is compelling evidence that this is not the case (Bitler, Hoynes, and Schanzenbach 2020).

Our data are unique in their size, sample coverage, and in their individual-level view of income, spending, and balances. Other data sources used to research the consumer response to COVID-19 tend to be aggregated over region, store, or time (Earnest, Womply, or Affinity), which limits the analysis of household balance sheet dynamics. By observing covariates at the individual level, like geography and industry of employment, we can also directly control for confounding factors that might be correlated with income and changes in spending. For example, our data can be used to look at how spending varies with income within narrow geographic areas like zip codes, and thus help control for the fact that high-income locations differ from low-income locations along a number of dimensions. Our data

9. We require at least $12,000 in labor income since it is difficult to distinguish truly low-income households from mismeasured higher income households without reliably captured direct deposits.

10. After conditioning on households with labor income above $12,000 in the CPS, mean and median income in the bottom quartile of our sample is very similar to mean and median income in the bottom quartile of the CPS.

11. See 2017 FDIC National Survey of Unbanked and Underbanked Households, Executive Summary.

also allow us to look at how spending changes by income groups within industry of employment.

Our sample, which captures households across the income distribution, complements the work done using Facteus data (Karger and Rajan 2020; Alexander and Karger 2020) and proprietary Fintech data (Baker and others 2020) which are primarily focused on low-income households. Finally, the size of the Chase customer base allows for additional precision when calculating statistics of interest as well as for substantially more disaggregated data cuts, relative to data sets with smaller sample sizes. Our data are closest in structure to that in Andersen and others (2020), which uses similar bank account data from a Scandinavian bank. The most important distinction is that our data cover US households, and thus a dramatically different institutional environment with different social safety nets and government responses to the pandemic.

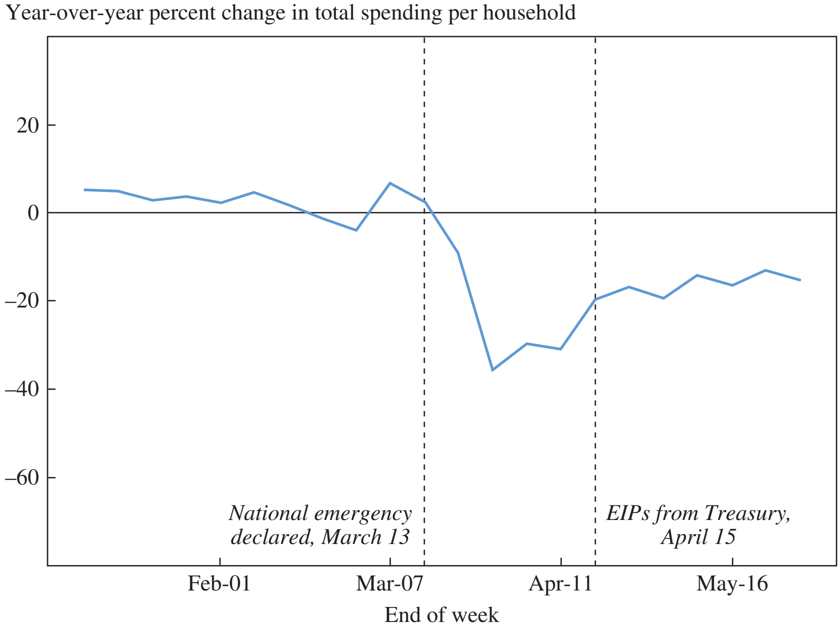
II. Household Spending

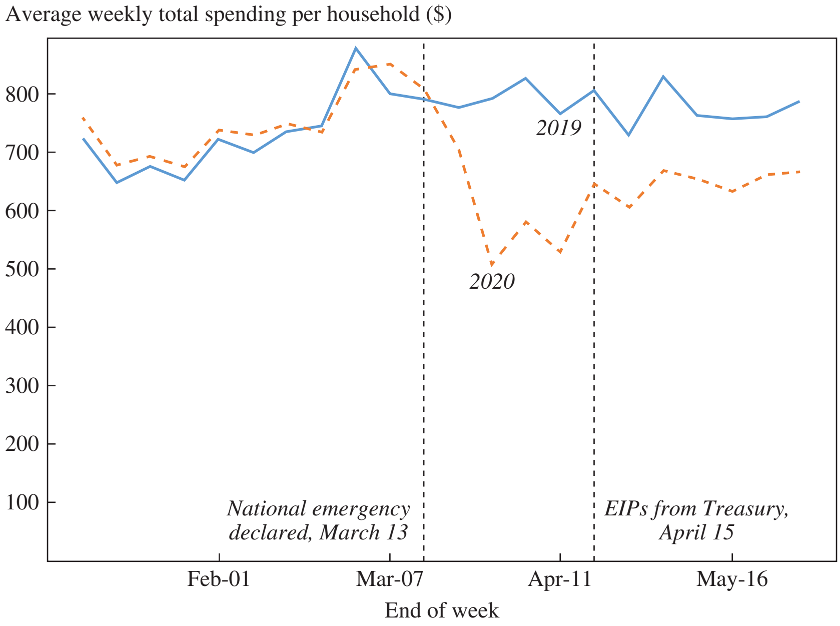
II.A. Overall Change in Spending

We begin by measuring the change in total spending. Online appendix A.1 provides changes in spending for each of the components of total spending (credit card, debit card, and cash), as well as paper checks. The top panel of figure 2 plots the 2020 to 2019 year-over-year percentage change in weekly spending. The bottom panel shows the average dollar amount of spending in 2020 and 2019. Changes in spending follow a distinctive pattern: spending is stable through the beginning of March, then declines precipitously by over 35 percent relative to 2019 from the second through fourth week of March. The size of the spending drop is largely consistent with other estimates from similar data sources during the same time frame.[12] These declines are somewhat larger than the aggregate spending declines in figure 1, but this is not particularly surprising. Personal consumption expenditures include substantial spending on components like housing services, which likely had little to no decline. Spending showed signs of recovery in May, but remains roughly 15 percent below pre-pandemic levels as at the end of May.

12. See for example, Baker and others (2020); Opportunity Insights Economic Tracker, https://tracktherecovery.org/, accessed June 15, 2020; and Facteus, Insights on Changing Consumer Behavior FIRST Report, https://www.facteus.com/reports/first-report, accessed June 15, 2020.

Figure 2. Average Spending Changes





Source: JPMorgan Chase Institute.

The timing of the initial spending drop mirrors the spread of the virus and staggered national implementation of government social distancing orders. A national emergency was declared on March 13, 2020. Over the following three weeks, the number of states with stay-at-home orders increased from zero to forty-five. The prevalence of COVID-19 also increased dramatically over the course of March.

At the same time, the drop in spending also closely tracks the pattern of initial job losses. Unemployment insurance (UI) claims began spiking in the third week of March, with more than 20 million UI claims filed by April 11. Conversely, spending begins to recover in the weeks after April 15 when a majority of EIPs arrive and as many of the unemployed workers who file claims in March and early April begin to receive benefits (Chetty and others 2020). This raises a question of how much of the drop in spending is due to the pandemic itself, the social distancing policies, or income losses.

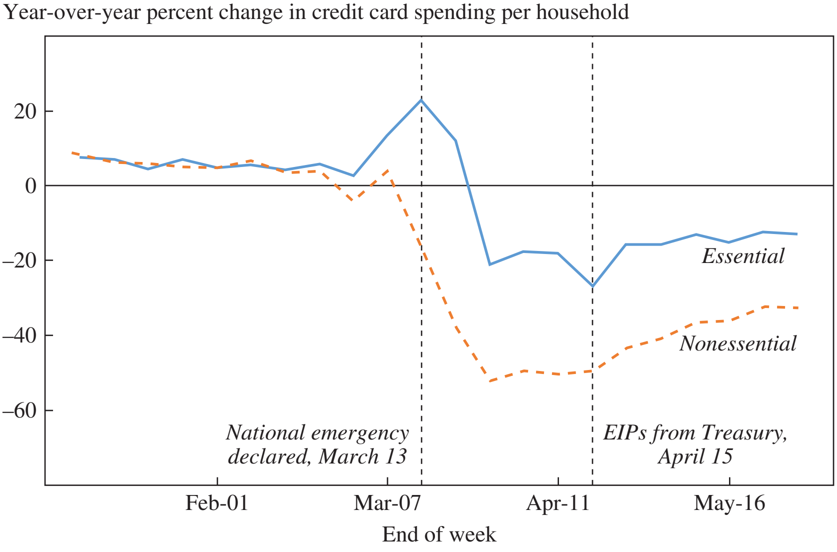
It is useful to calibrate the size of the spending drop relative to what we have observed among those who lose a job involuntarily during normal times. Ganong and Noel (2019) measure the spending drop around job loss among UI recipients, and observe an initial spending drop of roughly 6 percent. In other words, the spending drop in March 2020 is roughly six times larger than the average household spending drop in the first month of unemployment for UI recipients in normal times. This puts into perspective how dramatic the spending drop is and suggests that the pandemic and policies aimed at preventing its spread are contributing substantially to the drop in spending.

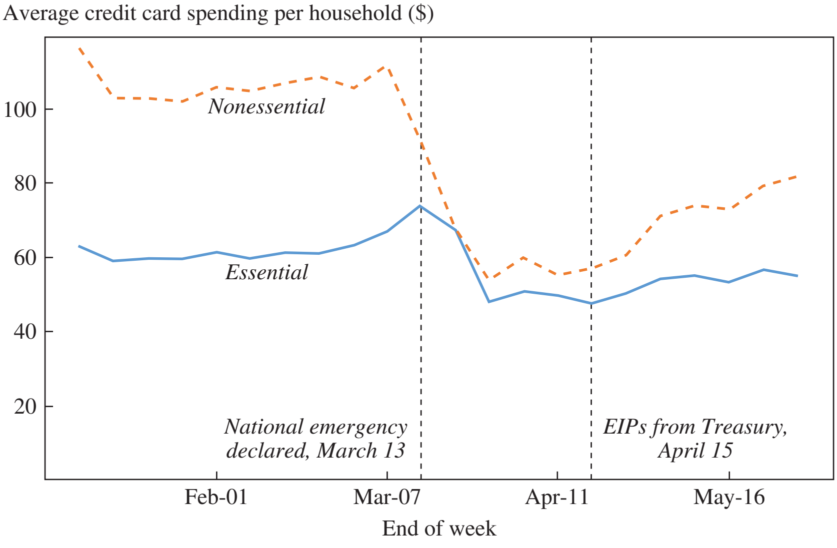
II.B. Change in Household Spending by Categories

While figure 2 shows a sharp drop in aggregate spending over March and April, there is reason to think that specific spending categories would be differentially impacted. Many nonessential businesses, like bars and salons, were closed by state and local governments. Similarly, stay-at-home orders limited the ability of individuals to travel. Beyond the mechanical effect of social distancing regulations, individuals may also have independently curtailed spending in certain categories to avoid risk of infection or as a response to income loss.

While we do not have information on debit card or cash spending by categories, we do have detailed category splits for credit card spending. We begin by disaggregating total credit card spending into essential and nonessential categories, as commonly defined in state stay-at-home orders. Figure 3 shows a dramatic difference in the path of essential and

Figure 3. Credit Card Spending on Essential and Nonessential Categories





Source: JPMorgan Chase Institute.

Note: State social distancing orders that restricted nonessential goods and services used to categorize spending. Essential category includes fuel, transit, cash, drug stores, discount stores, auto repair, groceries, telecom, utilities, insurance, and health care. Nonessential category includes department stores, other retail, restaurants, entertainment, retail durables, home improvement, professional and personal services, and miscellaneous. Although flights, hotels, and rental cars are sometimes categorized as essential and not technically closed, they are included in the nonessential category because they are affected by stay-at-home restrictions on nonessential travel.

Table 2. Credit Card Spending Changes for Essential and Nonessential Categories

	Essential		*Nonessential*	
	Share of spending (%)	*Year-over-year change (%)*	*Share of spending (%)*	*Year-over-year change (%)*
April 2019	35		65	
April 2020	46	−18	54	−49
Contribution to aggregate drop in spending	16		84	

Source: JPMorgan Chase Institute.

Note: Percent contribution to aggregate drop in spending is calculated as (% drop in category A) × (baseline share of category A) / (% drop in aggregate).

nonessential spending. Essential spending spiked in early March as households stockpiled goods like groceries. It then fell substantially before eventually stabilizing at a year-over-year decline of around 15 percent.[13] In contrast, spending on nonessential categories fell sharply throughout March, bottoming at a decline of just over 50 percent, and then began to slowly recover through late April and May.

Given the fact that households were ordered to stay at home except to make essential trips in most states, one might ask why households were still spending roughly $50 a week on nonessential categories in April. First, there was variation in both the degree of closures and in what was deemed nonessential across locations. Second, our spending categories do not map perfectly to each specific nonessential category. Third, households may be able to switch some nonessential services from in-person to remote, for example, from movie theater entertainment to online streaming or from in-restaurant dining to take-out.

We also quantify how much each category contributed to the aggregate drop in credit card spending. Table 2 shows what share of aggregate spending went toward essential and nonessential categories before and during the pandemic. Multiplying the prepandemic shares by their relative percentage drops, we find that nonessential spending accounted for 84 percent of the aggregate decline, and essential spending accounted for 16 percent.

13. The downward spike in year-over-year essential spending in the week ending April 18, 2020 likely arises because of the timing of Easter, which occurred during this week in 2020 but during the previous week in 2019. Many grocery stores are closed on Easter, which may explain a dip during this week in 2020 relative to the same week in 2019, which did not include the Easter closures.

To further illustrate the divergence in spending patterns across categories, we split essential and nonessential spending into more disaggregated categories in figure 4. Total essential spending spiked by roughly 20 percent in early March before dropping by 20 percent by the end of March. However, there is a wide range of spending responses among goods and services deemed essential. In the first few weeks of March there was a temporary surge in spending on groceries, discount stores, and pharmacies. Spending at grocery stores, which contributes the largest share of total essential spending, remained elevated through the end of our sample, aside from a brief decline in the week including Easter, when many grocery stores are closed. In contrast, spending fell in several other essential categories like hospital, other health care, transit and ground transportation, and fuel. Total dollar declines in these categories exceed the dollar increases in grocery spending, so that overall essential spending declines. Focusing on nonessential spending, declines are strongest in restaurants, hotel accommodations, and clothing and department stores. Overall, these results largely mirror those computed in other aggregate data sets and provide reassurance that our data are consistent with external evidence.

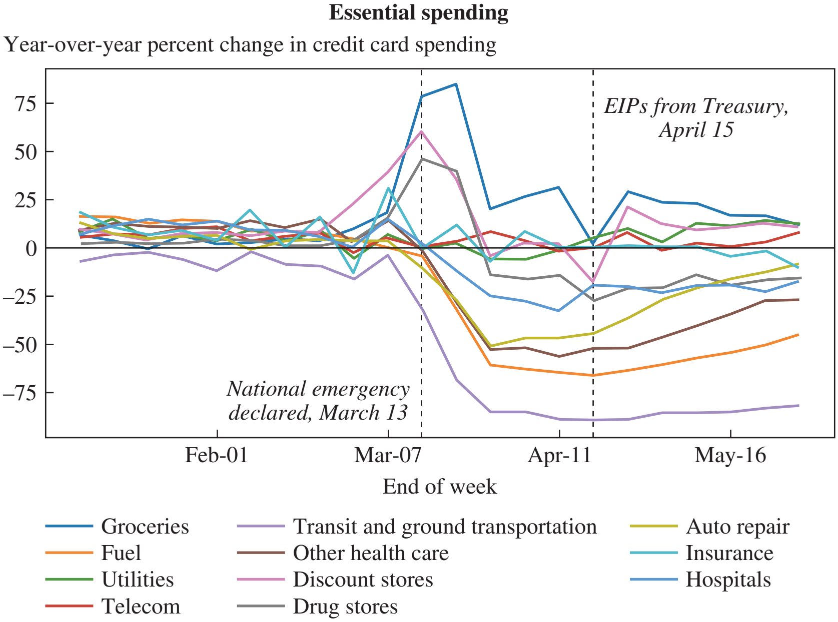
II.C. Heterogeneity in Spending Changes by Income

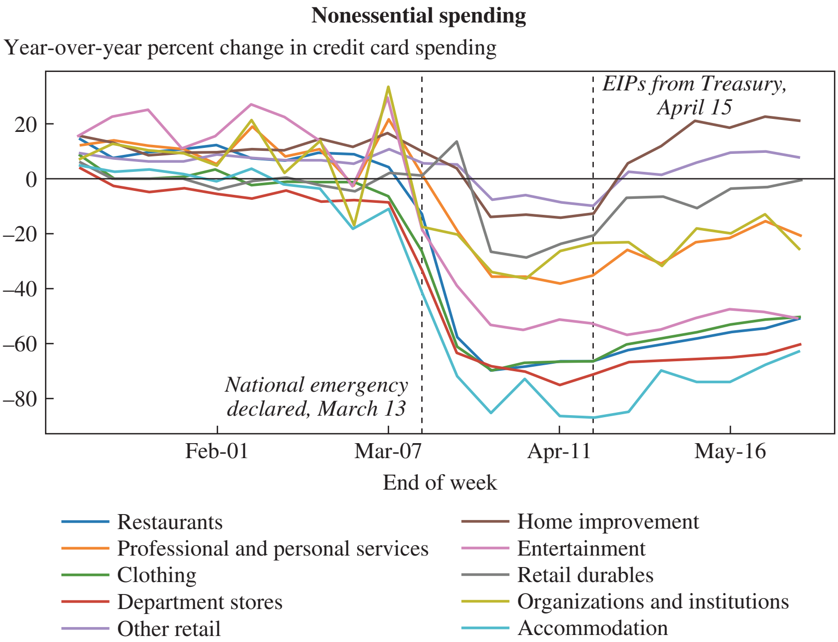
SPENDING CHANGES OVER THE INCOME DISTRIBUTION We next explore whether spending reductions (both in aggregate and by category) vary with pre-pandemic income. We stratify our sample into income quartiles based on total labor inflows in 2019.[14] For context, those in the bottom quartile make less than $28,000 in take-home labor income per year, while those in the top quartile earn more than $63,000. As discussed in section I, our bottom quartile misses unbanked households and the 8 percent of US households with labor income below $12,000, since we cannot reliably measure their income.

Figure 5 plots the year-over-year change in spending for each quartile, both in percentage and dollar terms. The top income quartile reduces spending by about 39 percent, or $400, by the fourth week of March, while the bottom quartile reduces spending by 32 percent, or $100. The difference in the spending drop between income quartiles is starker in dollar terms than percentages, since high-income households have a higher baseline level of spending. However, divergence in spending over the income distribution starting in the second half of April is more striking. By the end

14. In future work, we plan to explore also the relationship to income changes during the pandemic.

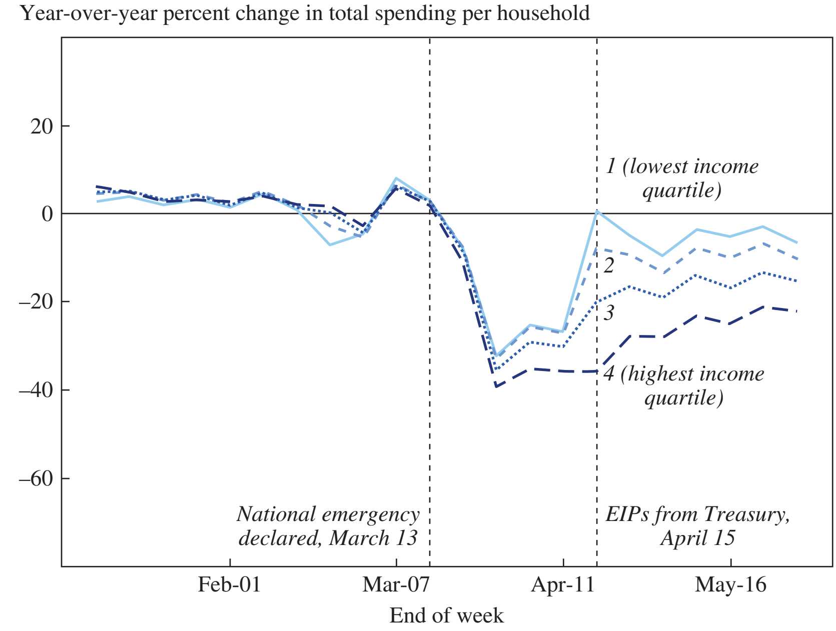
Figure 4. Credit Card Spending Growth across Spending Categories

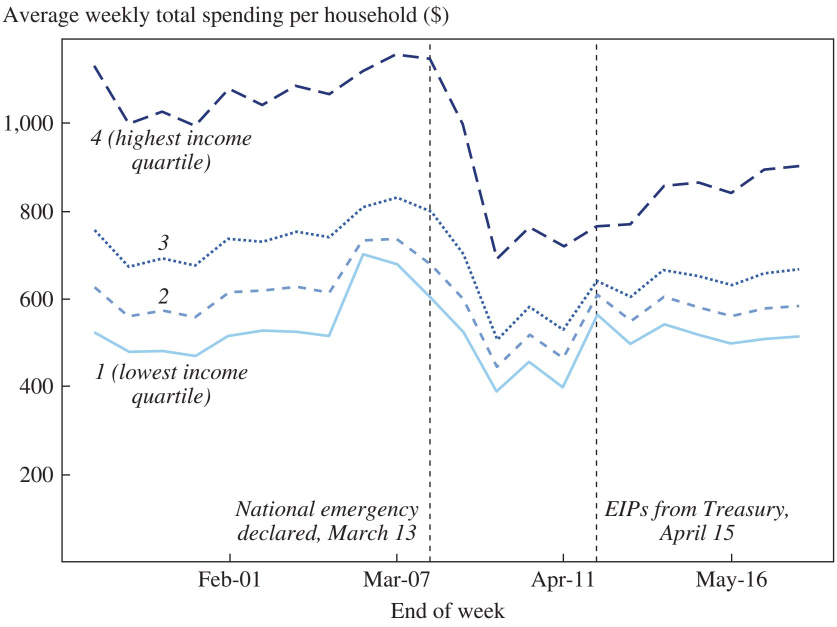




Source: JPMorgan Chase Institute.

Figure 5. Spending by Income Quartiles





Source: JPMorgan Chase Institute.

of April, the decline in spending partially recovers, with the recovery most pronounced for the lowest income quartiles. The recovery in spending for the lowest income quartiles occurs in the same week when many stimulus payments are made in mid-April. The timing of the divergence in spending by income suggests that stimulus payments may have played an important role in restoring the ability of low-income households to maintain spending during the pandemic.

Online appendix A.2 provides the spending changes over the income distribution by form of payment (debit, credit, cash, and check). We observe similar patterns of spending changes across all forms of payments.

Table A.1 in the online appendix reports the cumulative change in spending by income quartile in 2020 relative to 2019 for the eleven pandemic weeks in our data set between March 15 and May 30. The highest income quartile contributes disproportionately to the change in spending, accounting for 37 percent of initial spending and 50 percent of the spending decline. As a result, the share of spending for the highest income quartile declined.

While the results so far show that households with higher income cut spending by more and have slower recoveries in spending than low-income households, it is important to note that income is correlated with many other factors which might also affect spending responses, so these are not necessarily causal relationships. One particular concern in the context of the pandemic is that income is correlated with physical location, and locations vary in the strength of the pandemic. In particular, high-income individuals tend to live in cities, which have greater disease burden and more restrictive shutdowns. This means that the relationship between income and spending dynamics could reflect features of where high-income households live, rather than effects of income itself.[15]

To differentiate the role of income from the role of physical location, we look at the relationship between income and spending over the pandemic within narrow geographic areas. In particular, we compute the following regression:

$$\frac{c_{2020,z,q} - c_{2019,z,q}}{\bar{c}_{2019,q}} = Quartile_q + ZIP_z + \varepsilon_{z,q},$$

15. Note that measuring spending at the geography level rather than household level introduces additional concerns on this front: high-income households are more likely to leave cities than low-income households in response to the pandemic, which might induce spurious declines in spending in locations with many high-income households prior to the pandemic.

where $c_{t,z,q}$ is average spending per customer with t as the year (for the time period April 15–May 28), z is zip code, and q is the income quartile. We take two steps to minimize the influence of outliers. First, note that the denominator is $\overline{c}_{2019,q}$ which uses everyone in the income quartile. This prevents having one very large or very small ratio from skewing our results. Second, $c_{t,z,q}$ is Winsorized at the 1st and 99th percentile. We focus primarily on specifications with geography z equal to five-digit zip codes but also explore more aggregated three-digit zip codes to again limit the influence of measurement error.

Comparing odd columns in table 3 without geographic fixed effects to even columns with fixed effects shows that relationships between income and spending over the pandemic within zip codes are very similar to unconditional relationships. That is, high-income households cut spending more during the pandemic relative to low-income households living in the same zip code.[16] The similarity of results with and without fixed effects shows that these relationships are not driven by any observed or unobserved differences across locations where high- and low-income households live.

Finally, we further decompose the decline in credit card spending by income quartiles into essential and nonessential categories.[17] Figures 6 and 7 show that the spending declines for essential categories are indistinguishable across income groups, while nonessential credit card spending diverges more across income groups.

Although all households cut spending dramatically, the fact that high-income households cut spending by somewhat more may be surprising. Recent research suggests that lower-income households work in jobs that are harder to perform at home, require higher physical proximity, and therefore may be more impacted by distancing restrictions (Mongey, Pilossoph, and Weinberg 2020). Perhaps as a result, recent evidence from administrative ADP data shows that job losses were four times larger for workers in the bottom income quintile than those in the top income quintile, with a staggering 35 percent employment decline for the lowest-income workers (Cajner and others 2020). In response to greater income losses, we might have expected lower-income workers to have cut their spending by more. In fact, we find the reverse: higher-income households cut their spending by slightly more and their spending recovers more slowly.

16. Note that our information on address is as of early 2020.

17. Unfortunately, as mentioned above, we do not have the spending split by categories for the other forms of payment (debit, cash, and check).

Table 3. Income-Spend Relationships within Geography

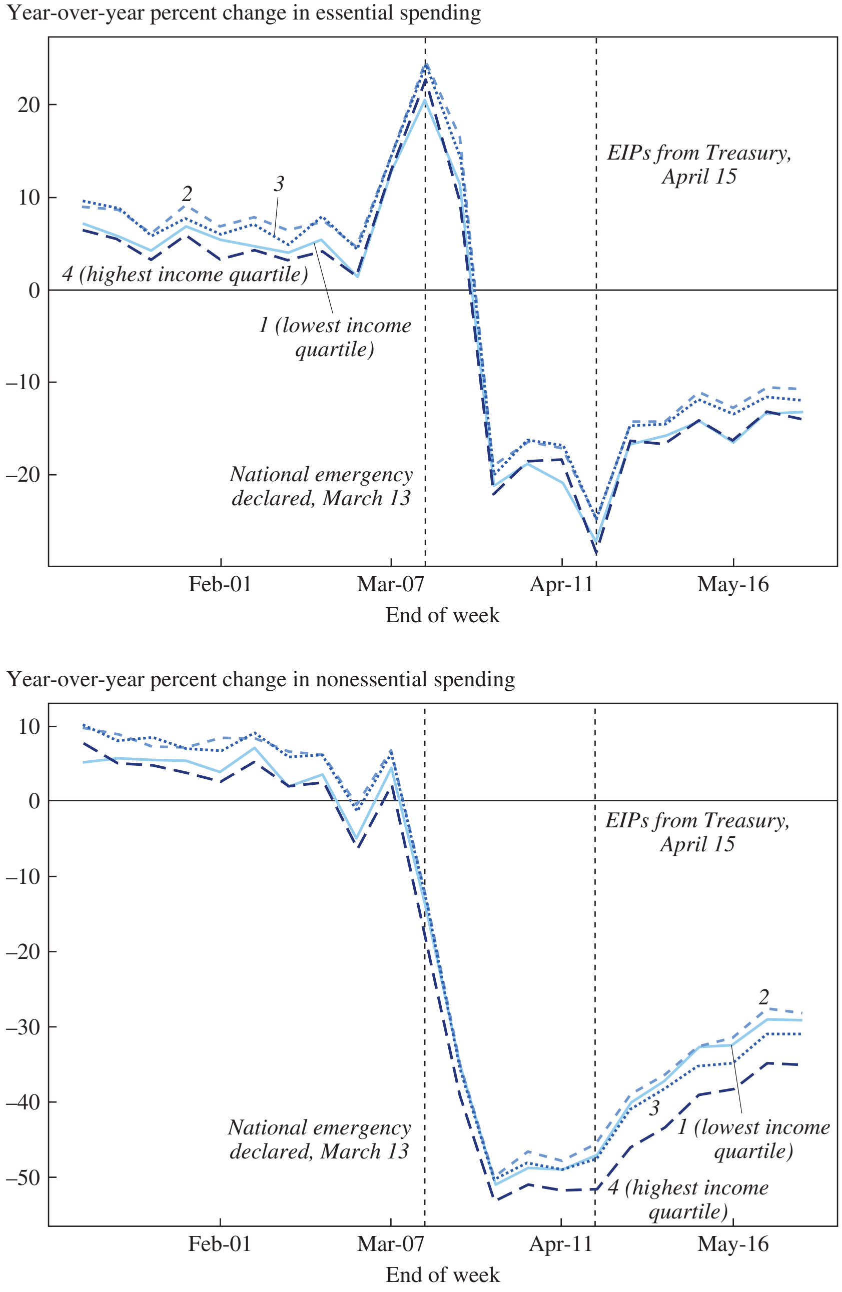
	Dependent variable: spending growth							
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Income Q2	–0.032*	–0.028*	–0.048*	–0.039*	–0.035*	–0.034*	–0.032*	–0.033*
	(0.004)	(0.004)	(0.002)	(0.001)	(0.003)	(0.002)	(0.009)	(0.008)
Income Q3	–0.080*	–0.079*	–0.118*	–0.092*	–0.094*	0.085*	–0.082*	–0.081*
	(0.004)	(0.004)	(0.002)	(0.001)	(0.003)	(0.002)	(0.009)	(0.008)
Income Q4	–0.154*	–0.142*	–0.217*	–0.161*	–0.179*	–0.159*	–0.149*	–0.147*
	(0.004)	(0.004)	(0.002)	(0.001)	(0.003)	(0.002)	(0.009)	(0.008)
Constant	–0.043*		–0.047*		–0.049*		–0.061*	
	(0.003)		(0.001)		(0.002)		(0.006)	
Inclusion of geography fixed effects	NO	YES	NO	YES	NO	YES	NO	YES
Number of observations	70,189	70,189	70,189	70,189	25,432	25,432	3,608	3,608
Adjusted R^2	0.024	0.235	0.238	0.557	0.137	0.506	0.082	0.272

Source: JPMorgan Chase Institute.

Note: Year-over-year spending growth regression for the period April 15–May 28, 2020, for individual geography times income quartiles on income quartile dummies with and without geography fixed effects. Columns 1 and 2 define geography as five-digit zip codes and equal weight. Columns 3 and 4 use five-digit zip codes and are weighted by number of customers in each zip code times income quartile. Columns 5 and 6 use equal weights and five-digit zip codes but are restricted to zip code times income quartiles with at least twenty customers. Columns 7 and 8 use equal weights and define geographies as three-digit zip codes.

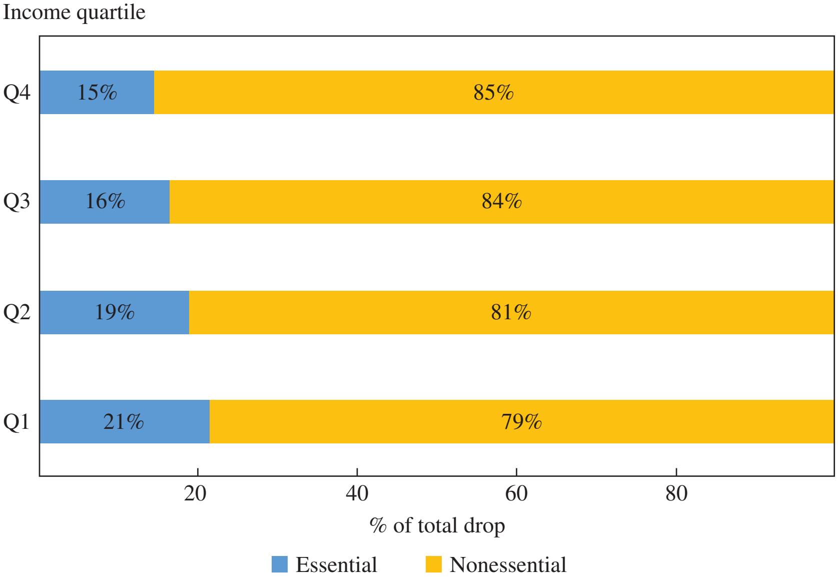
Significance: * $p < 0.01$.

Figure 6. Share of Credit Card Spending Decline Accounted for by Essential and Nonessential Credit Card Spending by Income Quartiles



Source: JPMorgan Chase Institute.

Figure 7. Reduction in Essential versus Nonessential Spending by Income Quartiles



Source: JPMorgan Chase Institute.

Differences between high- and low-income households in the composition of spending may be one reason why spending falls by more for high-income households. Nonessential categories represent a larger share of spending for high-income households—67 percent of spending in April 2019 for households in the top income quartile—compared to 59 percent for those in the bottom income quartile. In addition, higher-income households have slightly larger drops in their essential spending. Together, these facts imply that reductions in nonessential spending account for a somewhat larger share of total spending declines for high- versus low-income households (85 percent compared to 79 percent, figure 7). Since these nonessential categories are most affected by the pandemic shutdowns, overall spending of higher-income households may be more affected by supply-side restrictions. In other words, the effective price of consumption rises more for higher-income households relative to lower-income households. Thus, the composition of spending of higher-income households likely contributed to the larger decline in their spending. As discussed above, the widening of these initial spending declines during the recovery phase may reflect an important role for economic stimulus and transfer programs. The stimulus checks that began to arrive in April amount to a larger share of total income for a low-income household than for a high-income household. Ganong, Noel, and Vavra (2020) also show that the $600 expansion in UI benefits enacted through Federal Pandemic Unemployment Compensation (FPUC) boosted wage replacement rates to well over 100 percent for many low-income unemployed workers, providing a substantial income boost once they began receiving benefits.

Finally, higher-income households may be more exposed to negative wealth effects. Higher-income households hold more financial assets, and therefore are exposed to declines in asset prices during the initial stages of the pandemic. However, wealth effects are unlikely to be a key driver of the heterogeneous spending responses by income, given previous estimates on the strength of wealth effects together with the fact that the stock market had recovered most of its pandemic-related losses by the end of May.

CHANGE IN SPENDING BY INDUSTRY OF EMPLOYMENT We next examine whether workers in sectors most affected by employment disruptions adjust spending in ways that differ from workers in less affected sectors.

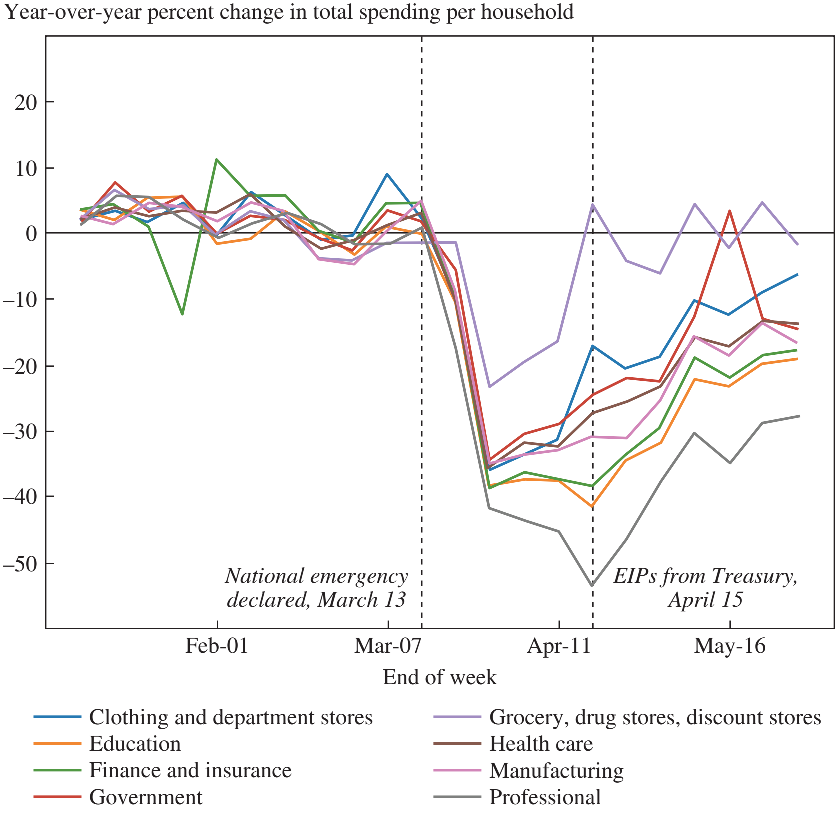
Figure 8 plots spending changes by industry of employment, for each industry where we have significant sample size. We aggregate to industries at the two-digit NAICS code. The one exception is retail, which we break out into grocery stores, drug stores, and discount stores—generally considered essential businesses and kept open under social distancing policies—and clothing and department stores, which were generally deemed nonessential businesses and where layoffs have been greater (Cajner and others 2020).

Overall, it is hard to discern systemic patterns between spending declines and the distribution of employment losses by industries. It is true that essential workers like those in grocery stores exhibit smaller spending declines. At the same time, professionals exhibit the largest spending declines, even though many jobs in this category can more easily be performed remotely.

While industry of employment is closely related to job losses, it is important to note that it is also highly correlated with income levels and that this may be explaining some of these differences.[18] For example, grocery store workers are typically low-income, while professional workers are typically high-income. In this sense, patterns when splitting by industry of employment in many ways mirror those when splitting by income: the

18. See online appendix table A.6.

Figure 8. Spending Changes Split by Industry of Employment



Source: JPMorgan Chase Institute.

largest drops in spending and slowest recoveries occur in higher-income industries of employment.

To provide a further sense of the separate role of income and industry, in figure A.11 in the online appendix, we compute spending by industry of employment separately for workers in the highest and lowest quartile of prepandemic income. Comparing variation across industries within income quartile in figure A.11 to variation across industries without conditioning on income in figure 8 shows that controlling for income substantially reduces the role of industry of employment. Similarly, comparing the same colored line between panels (a) and (b) in figure A.11 versus comparing different lines in figure 8 also shows that income generally has a greater correlation with spending dynamics than does industry of employment.

One potential interpretation is that the income channel accounts for only a small share of spending changes through the end of May. This may not be surprising given the magnitude of the spending decline. As mentioned previously, we document that average household spending fell over 35 percent, while the typical unemployed worker receiving UI only cuts spending around 6 percent in normal times (Ganong and Noel 2019).

However, there are several reasons for caution in concluding that income losses play a small role in spending effects. First, industry of employment may not fully proxy for job loss in our sample. To the extent that we can ascertain industry of employment primarily for employees of large firms, we may not be capturing the income losses for employees of small businesses.

Second, current conditions of the pandemic make comparing the magnitude of the spending response in April 2020 to that of UI recipients during normal times highly uncertain. On the one hand, the economic situation is highly uncertain, and labor markets weakened at an unprecedented pace. This might cause the unemployed to cut spending by more than during normal unemployment spells. On the other hand, as a result of the CARES Act, UI benefits are much more generous in level and duration, and available to many more workers. Furthermore, sizable stimulus checks were also sent out in April. These income supports might buffer against labor-income-related spending declines if this stimulus continues. The more rapid recovery of spending for low-income households suggests this channel is at work. The rest of the paper looks at the behavior of household savings to provide additional evidence on these channels.

III. Household Liquid Balances

Given the unprecedented reduction in spending across income and industries documented above, we next explore whether there were changes in the distribution of household liquid balances. Figure 1 shows that aggregate private savings increased substantially over the pandemic, reflecting the combination of large declines in spending and large increases in government transfers from stimulus programs. However, there are reasons to think that the pandemic could have heterogeneous impacts on household savings and substantial resulting effects on the distribution of wealth: households experiencing job loss may draw down on savings (or further draw on sources of borrowing), while those with job security may be essentially forced to save more, as consumption of many nonessential goods and services is more restricted. In addition, stimulus payments and other income support programs represent a larger share of prepandemic income for low-income households than for high-income households.

To explore these effects, we calculate how the distribution of end-of-week balances in household checking accounts evolved during the pandemic. Specifically, we explore how various unconditional moments of checking account balances evolved as well as how balances changed across the income distribution and by industry of employment. While checking account balances are only a subset of total savings and wealth, they represent some of the most liquid and easily accessible cash on hand available for households to smooth consumption and self-insure. A large literature has shown that liquid assets of this form play a crucial role in consumption. Furthermore, checking account balances have the practical advantage of being precisely and easily measured since checking accounts are one of our primary data sources.

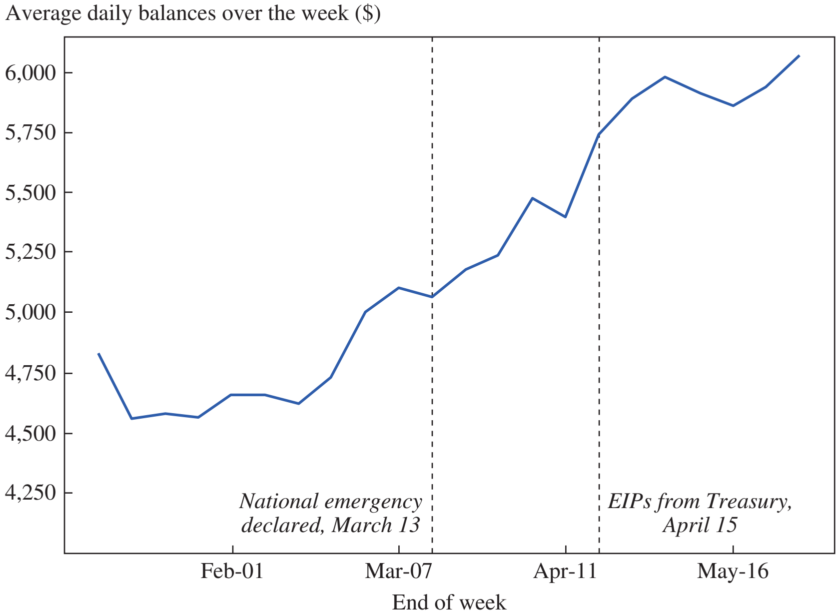
We begin by plotting the average level of liquid balances, and the percentage year-over-year change from January through the end of May 2020. Figure 9 shows that by the last week of May, average balances increased by 33 percent year-over-year, or about $1,500 relative to earlier in the year. This increase is consistent with the large increase in the personal savings rate shown in figure 1 and with the growth in the stock of commercial bank deposits shown in online appendix figure A.13.[19] Much of the year-over-year growth in checking balances occurred during and after the week when most EIP stimulus checks were deposited, which suggests that the increase was driven by these income inflows, in addition to the reduced spending we documented in the previous section.[20]

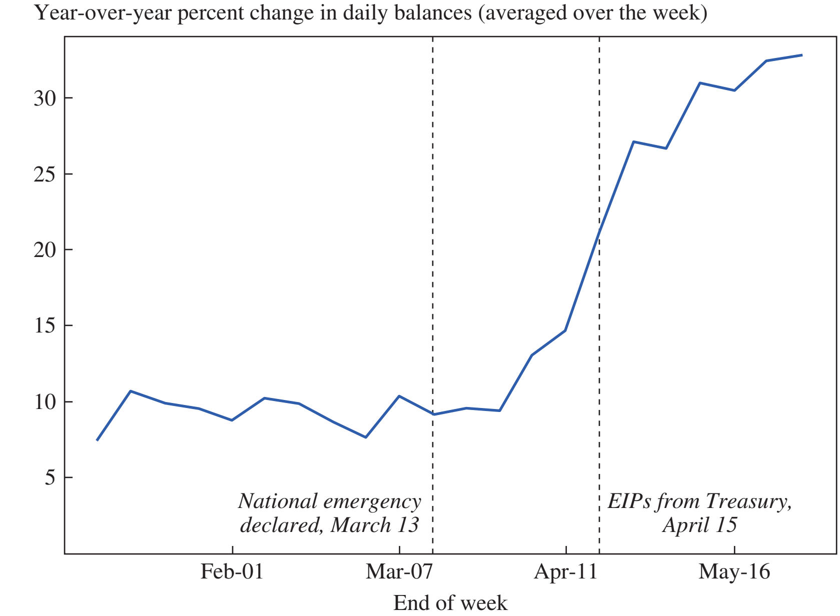
Figure 10 plots additional moments of the distribution of liquid balances over time. The top panel shows that increases in liquid balances are pervasive, with increases observed at various percentiles of the distribution. The dollar increase in balances is greater for households with larger initial prepandemic balances. However, it is important to note that scale effects would be expected to drive that type of pattern: for example, if all balances double, the accounts with the largest initial balances will have the largest absolute increases. The bottom panel shows that the lower end of the distribution is growing more than the top end of the distribution. Interestingly,

19. Note that figure 9 should not be compared directly to the personal savings rate in figure 1, since aggregate personal savings is a flow variable while checking account balances are a stock variable.

20. We further decompose this trend into checking account inflows and outflows in the online appendix.

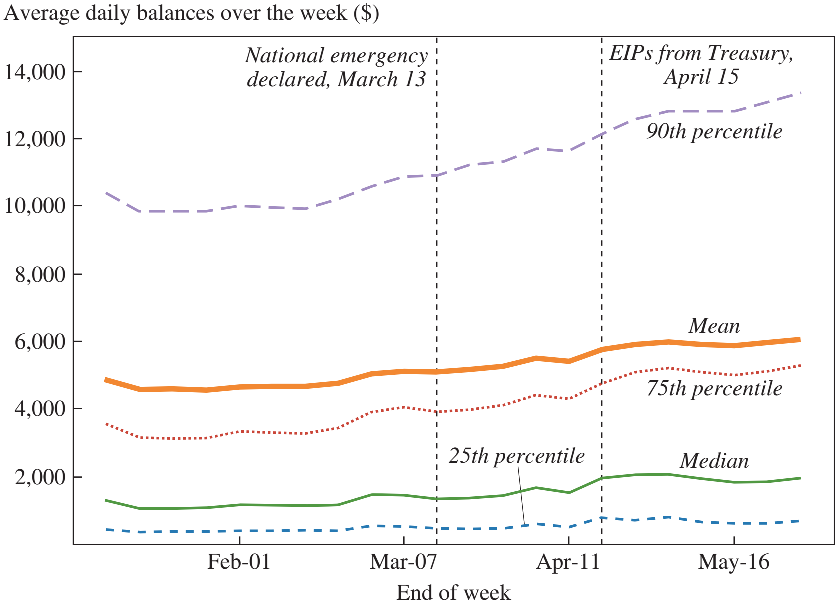
Figure 9. Level and Year-on-Year Change in Average Checking Account Balances

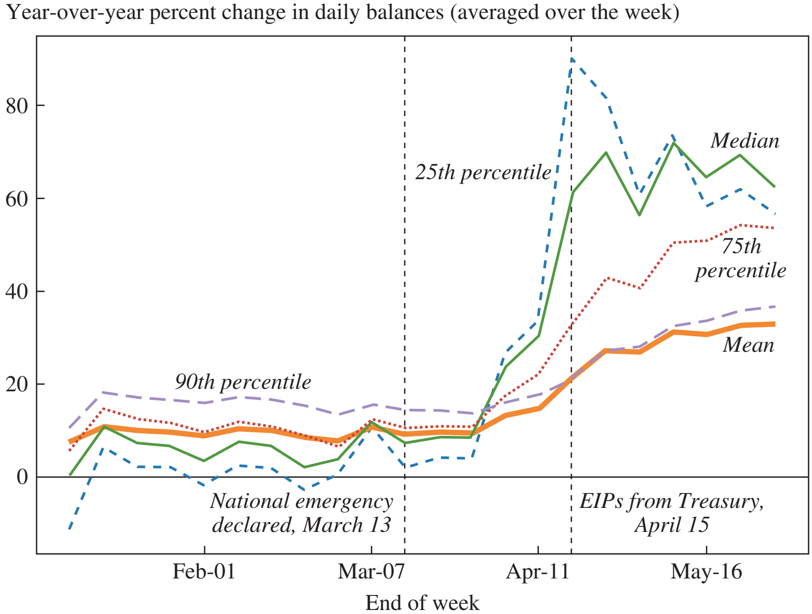




Source: JPMorgan Chase Institute.

Figure 10. Change in Distribution of Checking Account Balances





Source: JPMorgan Chase Institute.

the year-over-year growth for lower percentiles shoots up around the time of stimulus payments and then trends down. This suggests that households with low initial liquidity received a large increase in liquidity from stimulus payments, but they may be fairly rapidly using up this additional cash.

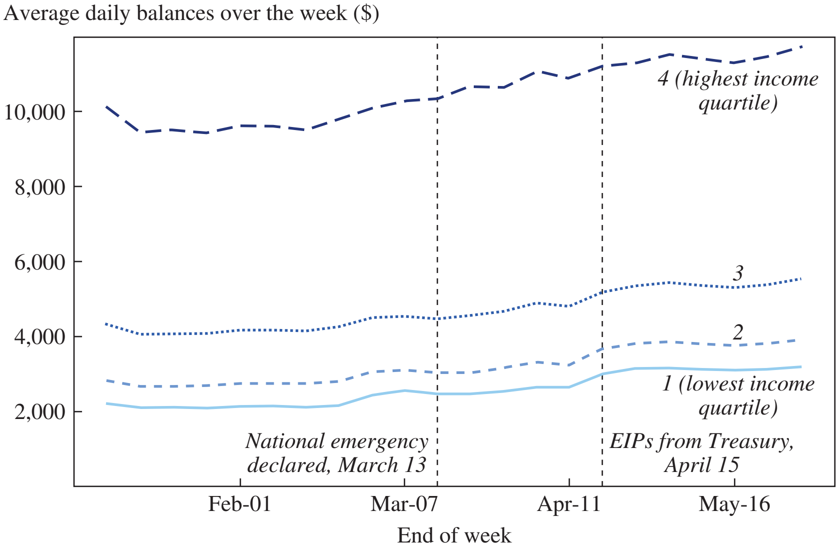
While the results in Figure 10 show that increases in liquid balances are pervasive, it is interesting to explore the relationship with pre-pandemic income. In particular, it is useful to know whether the increase in aggregate liquid balances was primarily driven by gains at the top of the income distribution (e.g., by individuals who cut spending most dramatically while generally maintaining labor income), or by gains at the bottom of the income distribution (e.g., individuals who cut spending somewhat less and faced larger declines in labor market income, but also had larger government transfers). Figure 11 plots checking account balances (in levels and growth rates) by income quartiles. Similar to the unconditional distribution of balances, we see pervasive increases in balances with increases observed for all groups. Also similar to the unconditional distribution, there are clear scale effects: the highest income quartile posted the largest dollar gains of around $2,000. The lowest income quartile increased balances by more than $1,000, which was the largest increase in year-on-year percentage terms.

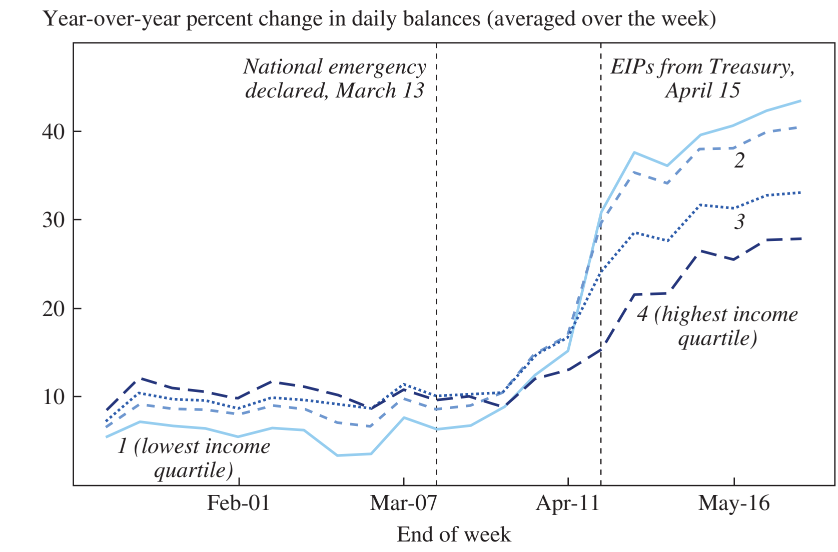
Given these scale effects, what should we conclude about the relative role of high- versus low-income households in driving the increase in liquid wealth? One way to answer this question is to compare each group's contribution to the aggregate increase, relative to that group's initial share of savings. If all groups' savings grow by the same amount, then each group's contribution to the aggregate increase is equal to its initial share and the wealth distribution is unchanged. If low-income households have higher savings growth, then they will contribute more to the aggregate increase than their initial share and wealth inequality will decline.

To explore this more formally, table 4 reports the initial balances in February 2020, the increase in balances from February to May, and the final balances in May for each income quartile. Unsurprisingly, higher income quartiles contribute more to the level and change in total liquid balances, since these households have much more liquid wealth. For example, 51.5 percent (12.02/23.35) of total liquid balances come from the top income quartile.

It is also true that the top income quartiles drive the majority of the increase in liquid balances over the pandemic (36 percent), but

Figure 11. Change in Average Checking Account Balances by Income Quartile





Source: JPMorgan Chase Institute.

Note: This figure plots both average dollar balances and year-on-year percentage change in checking account balances by income quartile. Balance increases are larger in dollar terms for high-income households (who have higher prepandemic balances), and in percent terms for low-income households (who have lower prepandemic balances).

Table 4. Decomposition of Total Liquid Balances Changes by Income Quartile

	Initial balances ($ billion)	*Share of initial balances (%)*	*Increase in balances ($ billion)*	*Share of increase in balances (%)*	*Final balances ($ billion)*	*Share of final balances (%)*
Quartile 1	2.67	11.4	1.28	19.0	3.95	13.1
Quartile 2	3.44	14.7	1.39	20.7	4.83	16.1
Quartile 3	5.22	22.3	1.60	23.8	6.82	22.7
Quartile 4	12.02	51.5	2.45	36.4	14.47	48.1
Total	23.35	100.0	6.72	100.0	30.07	100.0
Top decile	7.19	30.8	1.305	19.4	8.49	28.2
Top 1 percent	1.84	7.9	0.294	4.4	2.13	7.1

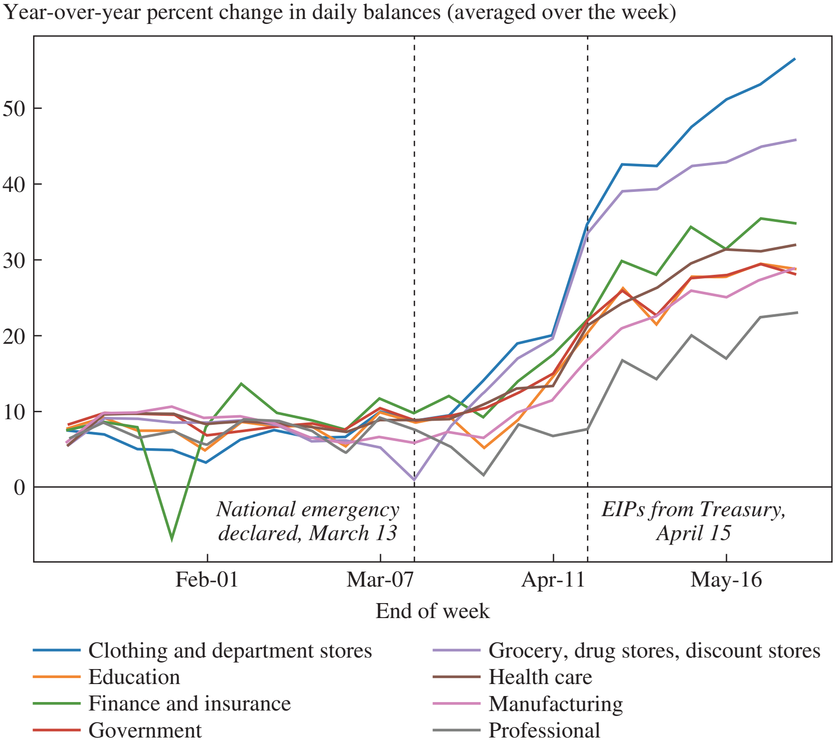
Source: JPMorgan Chase Institute.
Note: Initial balances are computed in February 2020 and final balances are calculated in May 2020.

importantly, this increase is less than proportional to the initial share of liquid wealth held by the top quartile. Table 4 shows that lower-income quartiles are actually driving more of the aggregate increase in balances than would be expected from their initial balance shares, so liquid wealth inequality decreases between February and May. This provides a concrete sense in which the poor are disproportionately increasing savings relative to the rich during this pandemic. While this shift in the wealth distribution toward low-income households may not seem huge, it implies a more than three percentage point decline in the share of liquid wealth held by the richest quartile occurring over a matter of weeks. One important caveat is that we only measure checking account balances. If higher-income households transferred more assets out of the checking account, it is possible that we understate the increase in their total assets.[21]

This increase in savings for the poor very likely reflects the fact that stimulus checks and expanded UI benefits provide a disproportionate increase in income for these households. This also means that this shift may reverse in the near future if stimulus is reduced. For example, the expanded federal supplement to UI which has led to replacement rates above 100 percent for many families, is set to expire at the end of July 2020. The magnitude of the additional spending drop induced by initial disease avoidance and social distancing restrictions may also dominate the consumption response caused solely by income loss. This could lead to an

21. On the other hand, if delayed tax payments contributed to the growth in cash balances among high-income families, liquid asset growth could be short-lived.

Figure 12. Growth of Balances by Industry of Employment



Source: JPMorgan Chase Institute.

increase in savings, even for those experiencing job loss, but it might not continue as social distancing is relaxed.

Finally, figure 12 shows liquid balance growth by industry of employment. While increases are again pervasive, we find that grocery store and department store workers have the largest growth in checking account balances. This is directly in line with checking account growth by income, since these are also the lowest income industries in our split.

IV. Conclusion

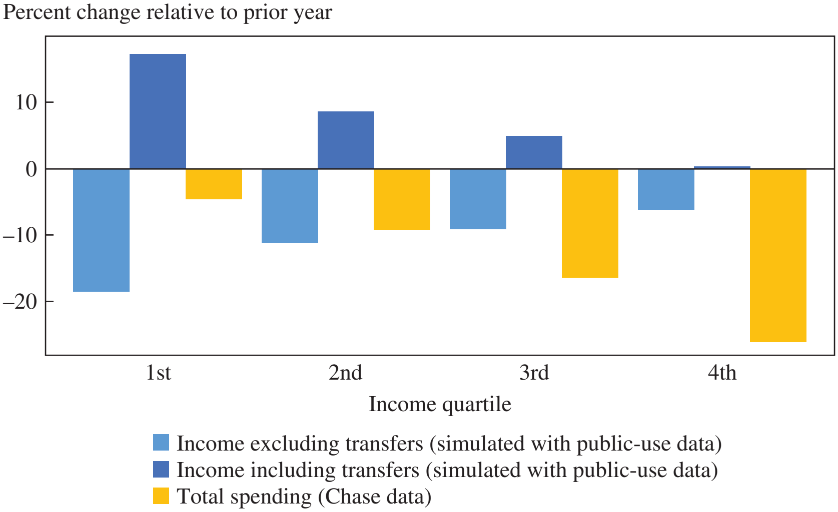
We find that all individuals across the income distribution cut spending at the start of the pandemic. These declines are massive relative to typical spending responses to unemployment. While high-income households cut spending more than low-income households, these differences are small relative to the huge common declines in spending. However, beginning in mid-April, substantial differences by income emerge: while spending begins to recover for all groups, it does so much more rapidly for the lowest income quartile. Similar patterns emerge when cutting by industry of employment, with workers in all industries initially cutting spending dramatically and then workers in low-wage industries seeing spending recover more quickly.

One limitation of this paper is that Chase micro data on income during the pandemic period are still being processed at the time of writing and are not yet available for analysis. We therefore turn to public-use data to explore how the income distribution has changed in recent months. Specifically, we simulate how income has likely changed in the first few months of the pandemic using statutory provisions of the CARES Act, information from the CPS, and the unemployment insurance calculator in Ganong, Noel, and Vavra (2020). Although *labor income* fell the most for lower-income households, we estimate that *total income,* including transfers, actually increased the most for those at the bottom of the income distribution for two reasons. First, the EIPs were a flat payment and therefore constituted a larger share of income for low-income households. Second, because the temporary $600 supplement to UI benefits under the CARES Act is the same for all unemployed workers, it drives up the replacement rate and resulting income disproportionately for low-income workers. In fact, UI benefits now replace more than 100 percent of lost earnings for low-income households (Ganong, Noel, and Vavra 2020). The details of this simulation are described in the online appendix.

Figure 13 juxtaposes simulation-based estimates of the change in income alongside the change in spending from figure 2. There is a suggestive correlation between the pattern of income changes and the relative pattern of spending changes. Spending falls the least for the group receiving the most income support, and decreases the most for the group with the least income support. In future work, when Chase micro data on income during the pandemic become available, we plan to explore the joint dynamics of income and spending at the household level to better understand these patterns.

Two other pieces of evidence in our paper suggest that government income support could be driving spending during this period. First, the timing of the more rapid rebound in spending for low-income households coincides closely with the timing of EIP stimulus and expanded UI benefits, suggesting an important role for government support in stabilizing spending during the pandemic, especially for low-income workers.

Figure 13. Estimated Changes in Income and Spending by Income Quartiles



Source: JPMorgan Chase Institute.

Note: The change in income compares March, April, and May 2020 to average quarterly income in the prior year. The change in income reflects the decline in labor income, the EIPs, and unemployment benefits. The change in spending compares April 15–May 30 to spending in the same period in the prior year. Our estimate focuses on this narrower time horizon after the most immediate impacts of the lockdown—which depressed spending across the income distribution—had subsided.

Second, while increases in liquid balances are widespread during the pandemic and driven in large part by general declines in spending, we see that households at the bottom end of the income distribution—who see the largest stimulus relative to prepandemic income—have the largest growth in liquid savings during this period. As a result, liquid wealth inequality falls between February and May.

Taken together, our results suggest that labor market disruptions were unlikely to be a primary factor driving spending declines in these initial months of the recession. Many of the effects of labor market disruptions on spending were likely offset by sizable fiscal stimulus and insurance programs. Instead, direct effects of the pandemic were likely the primary factor driving overall declines in spending. Our analysis does not claim to disentangle the effect of pandemic-related channels—that is, regulatory shutdowns versus disease prevalence and fear of infection—on the spending decline. It instead focuses on the impact of income changes brought about by job loss and government transfers.

There are some important cautionary implications for future policy. First, it is important to note that even though aggregate spending has recovered substantially from its nadir, it remains well below normal. Spending on May 31st, when our sample currently ends, remains very low in absolute terms, even when compared to spending declines in other severe episodes like the Great Recession. Spending has partially recovered, but still remains severely depressed relative to prepandemic levels. Policy makers should thus not be too quick to conclude that the economy has rapidly recovered to normal. Even more importantly, our results suggest that an important share of this spending recovery has in fact been driven by aggressive fiscal stimulus and insurance payments. While we see a large spike in savings for low-income households immediately after the EIP, these increases may erode as the EIP gets used and if UI benefits get scaled back. This suggests that new support may be needed to maintain spending for low-income, vulnerable households in the near future. Phasing out broad stimulus too quickly could potentially transform a supply-side recession driven by direct effects of the pandemic into a broader and more persistent recession caused by declines in income and aggregate demand.

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