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Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending, and savings data

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INITIAL IMPACTS OF THE PANDEMIC ON CONSUMER BEHAVIOR: EVIDENCE FROM LINKED INCOME, SPENDING, AND SAVINGS DATA*

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Abstract

We use U.S. 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 pre-pandemic shares. Taken together, our results suggest that spending declines 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 programs during this period likely played an important role in limiting the effects of labor market disruptions on spending.

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1 Introduction

The Covid-19 pandemic led to a large and immediate decline in U.S. aggregate spending and an increase in aggregate private savings. In this paper, we use anonymized bank account information on millions of JPMorgan 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 pre-pandemic income and industry of employment.

Figure 1: Aggregate Consumption and Savings

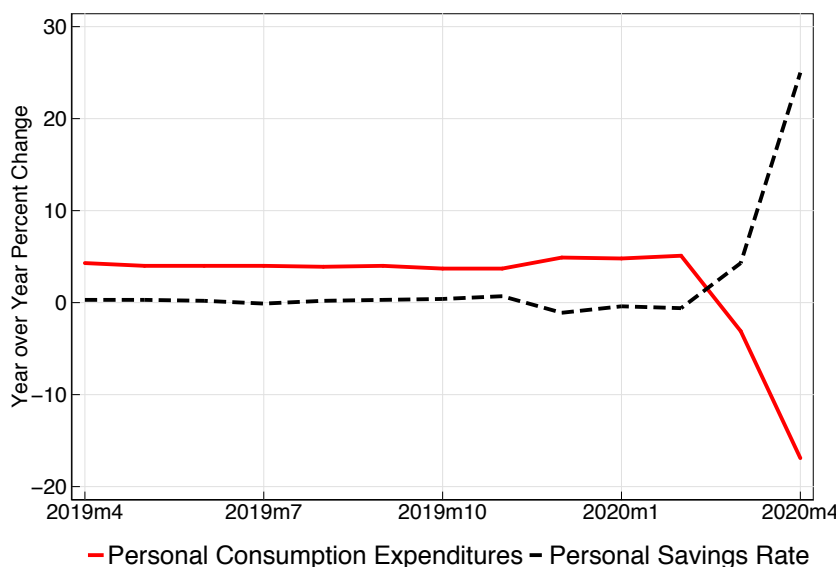


Figure shows the year-over-year growth of Personal Consumption Expenditures and the Personal Savings rate, calculated from monthly Bureau of Economic Analysis data.

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 shut-downs and reducing activities with high infection risk) versus demand factors (such as Keynesian spill-overs 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

¹See e.g. Chetty et al. (2020a).

²To 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 pre-pandemic

Focusing first on aggregate results, we find that overall card spending fell by around 40% 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 31. Declines in non-essential spending accounted for 84% of total declines in credit card spending.³ Amongst non-essential categories, declines were particularly large for restaurants, travel accommodations and personal services. Amongst essential categories, declines were most dramatic for healthcare, ground transportation and fuel. Reassuringly, these patterns are similar to those found using other aggregate sources of card spending.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 pre-pandemic income distribution. Spending by the top quartile of the income distribution falls 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.⁵

Second, we explore differences in spending by individual’s 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 recover 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 pre-pandemic income levels. We find that income appears 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 high-income workers in all industries do not.

Finally, we turn to evidence on the distribution of household savings over the pandemic to pro-

characteristics like income level, rather than by changes during the pandemic.

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

⁴See for example, Chetty et al. (2020b), EarnestResearch (2020), Baker et al. (2020), Chetty et al. (accessed on 06/15/2020), Factiveus (accessed on 06/15/2020) and Karger and Rajan (2020).

⁵High 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.

vide 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 three 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 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 programs like Economic Impact Payments (EIP) 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 savings by low-income households.

Consistent with aggregate data on savings, we find a large initial increase in savings during the pandemic in our data. By the end of May 2020, average liquid balances are 36% 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 pre-pandemic shares. That is, liquid balances at the end of May are slightly more equally distributed over the income distribution than liquid balances in February.

Taken together, our results suggest several important 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 non-essential 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 non-essential goods in normal times.

Third, various stimulus programs like EIP 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 "re-opening" 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 emphasize that our evidence for now focuses on time-series patterns for rela-

tively 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.

2 Data Description

Our analysis of spending is based on the universe of transactions made on Chase debit and credit cards through June 3, 2020. We use three main samples to separately study debit card spending, checking account balances, and credit card spending.

The sample used to track debit card spending is composed of individuals with Chase deposit accounts. 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 non-business account, made at least 3 debit transactions in every month from January 2018 to March 2020, had at least \$12,000 in labor income in both 2018 and 2019, and had at least 5 deposit account transactions in every month of 2018 and 2019.⁶ This leaves us with a sample of just over 4 million individuals.

Our checking account sample, which we use to study liquid balances, is very similar to the debit card sample – it uses the same core sample of deposit account customers, but does not impose the screen of at least 3 debit transactions in every month from January 2018 to March 2020.

For our analysis of credit card spending, we focus on a sample of 8 million families across all fifty states who have been active users (i.e. at least three transactions in every month) of their credit cards since January 2018. For a subset of our analyses we pair these credit card data with deposit account data through February 2020, which allow us to segment our population by income levels and industry of employment before the COVID-19 shock. We include all credit card users who have a Chase deposit account and meet the income and transaction screens described above. This leaves us with a sample of approximately 1 million credit card users with observed income data and an associated industry of employment.

The credit card, debit card, and checking account samples are partially, but not entirely, overlapping. Only some individuals in our debit sample also have Chase credit cards, and they tend to have slightly higher income than average (see Table 1 for the income distributions for each sample). A larger percentage of high-income individuals in the debit sample have a Chase credit card (52% vs 34% for the top vs bottom quartile). Furthermore, we see that individuals in the deposit sample, even conditional on income, have lower credit card spending than those solely in the credit card sample. This suggests that individuals tend to concentrate their spending either on their debit or credit card. Therefore, cau-

⁶Deposit account transactions refer to both account deposits and withdrawals, whereas debit transactions refer only to transactions on the debit card.

Table 1: **Income Distribution and Overlap Across Debit, Checking Account Balance, and Credit Card Samples**

	Income Quartiles			Debit/Credit Sample Overlap*	
	Debit Card Sample	Checking Account Balance Sample	Credit Card Sample	% of Debit Sample with Credit Card	Avg. Credit Card Spend (cond. on > \$0) from Debit Sample
Quartile 1	\$12,000-\$26,841	\$12,000-\$26,841	\$12,000-\$39,182	34%	\$91
Quartile 2	\$26,841-\$39,604	\$26,841-\$39,604	\$39,182-\$58,939	40%	\$103
Quartile 3	\$39,604-\$60,000	\$39,604-\$60,000	\$58,939-\$91,824	47%	\$147
Quartile 4	\$60,000 +	\$60,000 +	\$91,824+	52%	\$303
N	4074347	5015200			

*The last two columns provide the percentage and average spending of *any* individuals in the debit card sample with a Chase credit card. This is somewhat distinct from the credit card sample described in column 3, which requires that individuals have at least 3 credit card transactions in each month.

tion should be used when comparing the credit card and debit card spending plots – the "aggregate" drop is a complex weighted average of the two series that will vary by income quartile.

We also note that, for now, we focus on debit card and credit card spending and do not measure broader account outflows from e.g. cash and check withdrawals. It is possible that the use of bank cards may change differentially over the course of the recession or as a result of stimulus. For example, households may have substituted from cash to cards to avoid risk of infection, so focusing on card spending might lead us to understate total spending declines. Households who received EIP or UI payments in their bank accounts may be temporarily more likely to use bank cards than cash, and households who receive UI payments on prepaid cards may be less likely to use their Chase bank cards for spending. While we do not think these will change our broad conclusions, one should keep these caveats to our analysis in mind.

We measure income for the subset of card holders with linked checking accounts 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% of households, and most of these payers tend to be large employers. Finally, it is important to note that while we observe household 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 changes during the pandemic are not available for our current analysis. For this reason, we report various results based on pre-pandemic income, but do not yet have results on how spending has responded to individual income changes.

In our analysis below, we consistently use the income cutoffs from the checking account balance sample to define "quartiles" in all graphs. This allows us to easily compare the behavior of individuals with a similar income level across the various samples. Specifically these values are Q1: \$12,000-\$26,841, Q2: \$26,841-\$39,604, Q3: \$39,604-\$60,000, Q4: \$60,000+.⁷

⁷We require at least \$12,000 in labor income since it is difficult to distinguish truly low income households from mis-measured higher income households without reliably captured direct deposits. More generally, it is important to note that all households in our data are either Chase checking or credit card account holders, so our data does not include the lowest-income, un-banked households.

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

Our sample, which captures low, middle, and high-income families, complements the work done using Facticeus data (e.g. Karger and Rajan (2020), Alexander and Karger (2020)) and proprietary Fintech data (Baker et al. (2020)) which is 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 is closest in structure to that in Andersen et al. (2020), which uses similar bank account data from a Scandinavian bank. The most important distinction is that our data covers U.S. households, and thus a dramatically different institutional environment with different social safety nets and government responses to the pandemic.

3 Household Spending

3.1 Overall change in spending

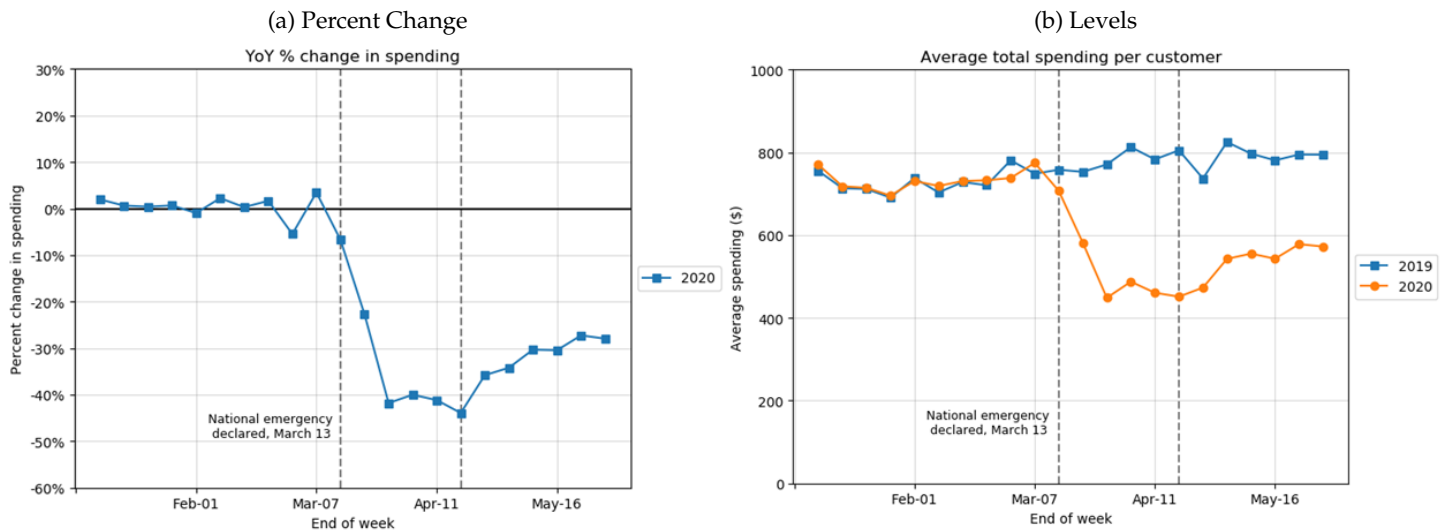
We begin by measuring the change in spending using transaction account data on credit cards. Panel (a) of Figure 2 plots the 2020 to 2019 year-over-year percentage change in weekly credit card spending. Panel (b) shows the average dollar amount of credit card spending in 2020 and 2019. Changes in spending follow a distinctive pattern: spending is stable through the beginning of March, then declines precipitously by 40 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.⁸ These declines are somewhat larger than the aggregate spending declines in Figure 1, but this is not particularly surprising. Personal consumption expenditures includes substantial spending on components like housing services, which likely had little to no decline. Credit card spending showed signs of recovery in May, but remains roughly 28 percent below pre-pandemic levels as at the end of May.

We observe similar patterns in the weekly debit card spending. Panel (a) of Figure 3 plots the year-over-year percentage change in weekly debit card spending in 2020 relative to 2019. Panel (b) plots the dollar change in weekly debit card spending in 2020 and in 2019. Spending on debit cards declined by

⁸See for example, Baker et al. (2020), Chetty et al. (accessed on 06/15/2020), and Facticeus (accessed on 06/15/2020).

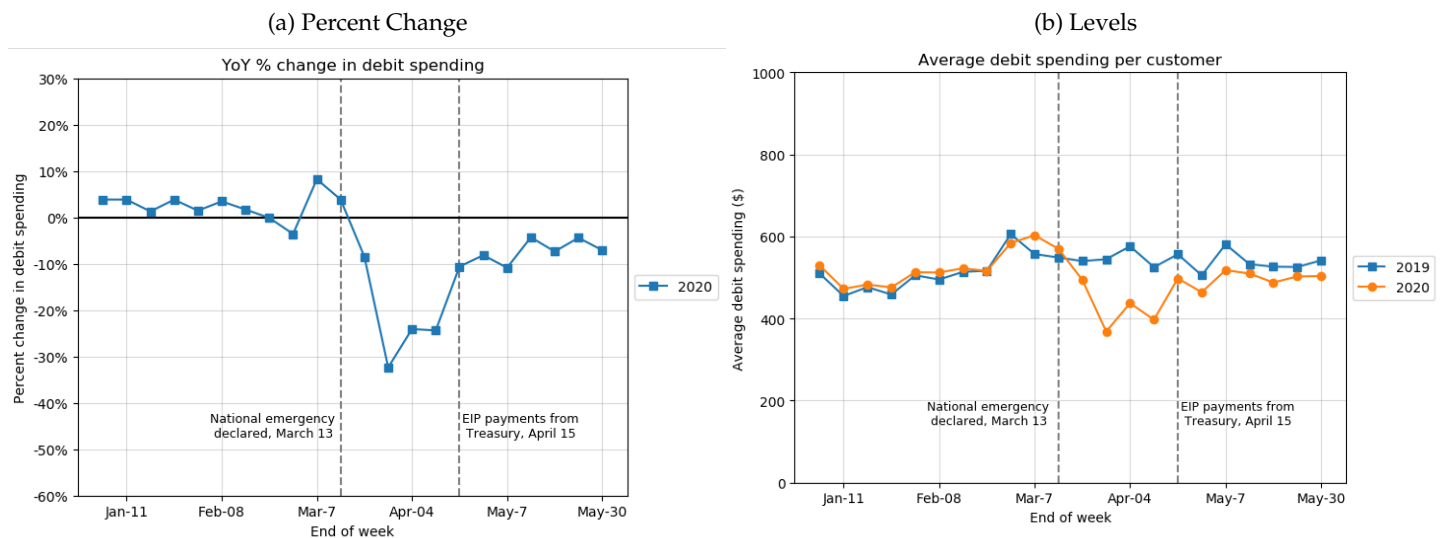
just over 30 percent relative to 2019 from the second through fourth week of March, but has recovered more strongly than credit card spending. By the end of May, debit card spend is down roughly 8% year-over-year. This is a massive recovery relative to the 30% decline in March, but is still substantially short of a full recovery in absolute terms.⁹ It will be important to continue to track spending into June and observe whether the pace of the recovery continues to pre-pandemic levels.

Figure 2: Average Spending Changes on Credit Cards



The left panel plots the year-over-year percentage change in weekly credit card spending. The right panel plots the dollar change in weekly credit card spending.

Figure 3: Average Spending Changes on Debit Cards



The left panel plots the year-over-year percentage change in weekly debit card spending. The right panel plots the dollar change in weekly debit card spending.

⁹For point of comparison, the peak decline in nominal aggregate PCE during the Great Recession was roughly 3.8%.

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 stimulus checks start to arrive and as many of the unemployed workers who file claims in March and early April begin to receive benefits. 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 credit card spending drop of roughly 5%. In other words, the spending drop in March 2020 is roughly eight times larger than the average household credit card 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.

3.2 Change in household spending by categories

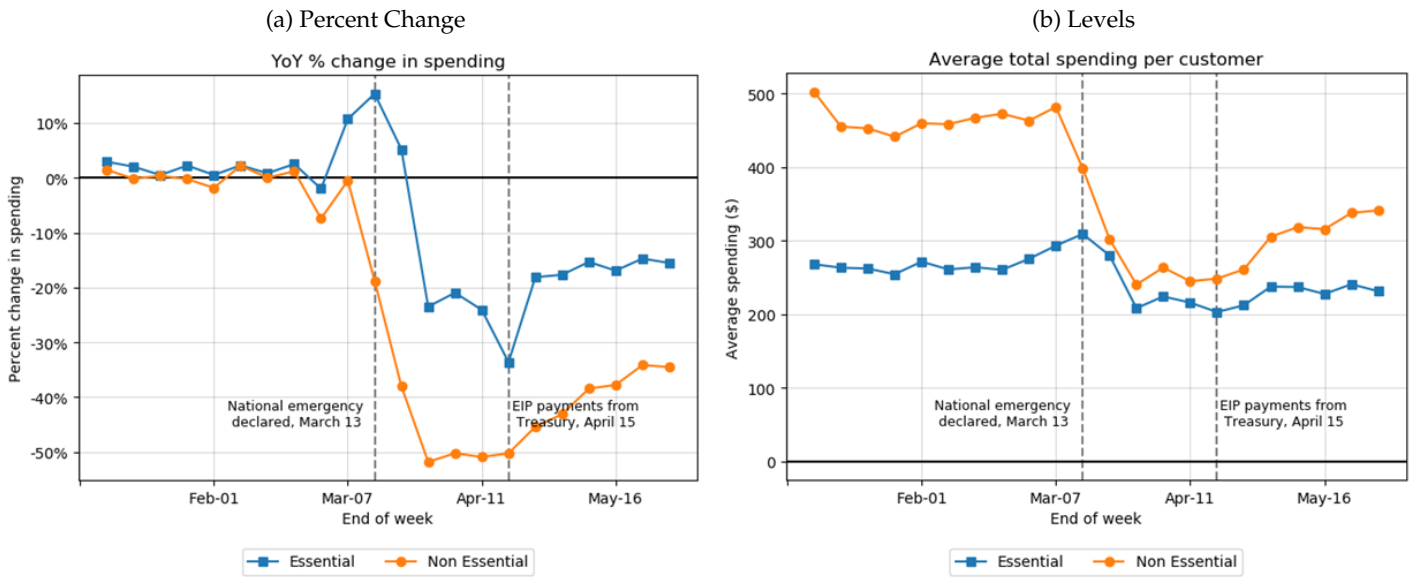
While Figures 2 and 3 show a sharp drop in aggregate spending over March and April, there is reason to think that specific spending categories would be differentially impacted. Many non-essential businesses, like bars and salons, were closed by state and local governments. Similarly, stay-at-home orders limited the ability of individuals to travel. Beyond the mechanical effect of social distancing regulations, individuals may also have independently curtailed spend in certain categories to avoid risk of infection or as a response to income loss.

While we do not have information on debit card spending by categories, we do have detailed category splits for credit card spending. We begin by disaggregating total spending into essential and non-essential categories, as commonly defined in state "stay-at-home" orders. Figure 4, panels a and b, show a dramatic difference in the path of essential and non-essential 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 20 percent.¹⁰ In contrast, spending on non-essential categories fell sharply throughout March, bottomed at a decline of just over 50 percent in early April and then began to slowly recover through 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 \$250 a week on non-essential

¹⁰The downward spike in year-over-year essential spending in the week ending April 18, 2020 arises because of the timing of Easter. Easter grocery spending spiked in that week in 2019 and would have likely spiked one week earlier in 2020 under normal conditions since Easter 2020 was one week earlier. However, in 2020 there is no comparable Easter spike in grocery spending that week because stay-at-home orders largely eliminated large family gatherings.

Figure 4: Credit Card Spending on "Essential" and "Non-Essential" Categories



We use state social distancing orders that restricted non-essential goods and services to categorize spend. "Essential" categories include fuel, transit, cash, drug stores, discount stores, auto repair, groceries, telecom, utilities, insurance, and healthcare. "Non-essential" 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, we include them in the "non-essential" group because they are affected by stay-at-home restrictions on non-essential travel.

categories in April. First, there was variation in both the degree of closures and in what was deemed non-essential across locations. Second, our spending categories do not map perfectly to each specific non-essential category. Third, households may be able to switch some non-essential 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 spend. Table 2 shows of aggregate spending went towards essential and non-essential categories before and during the pandemic. Multiplying the pre-pandemic shares by their relative percentage drops, we find that non-essential spending accounted for 84% of the aggregate decline, and essential spending accounted for 16%.

To further illustrate the divergence in spending patterns across categories, we split essential and non-essential spending into even more disaggregated categories in Figure 5. Total essential spending spiked by roughly 20% in early March before dropping by 20% by the end of March. However, there are 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. In contrast, spending fell in several other essential categories like "hospital", "other healthcare", "transit and ground transportation", and "fuel". Total dollar declines in these categories exceed the dollar

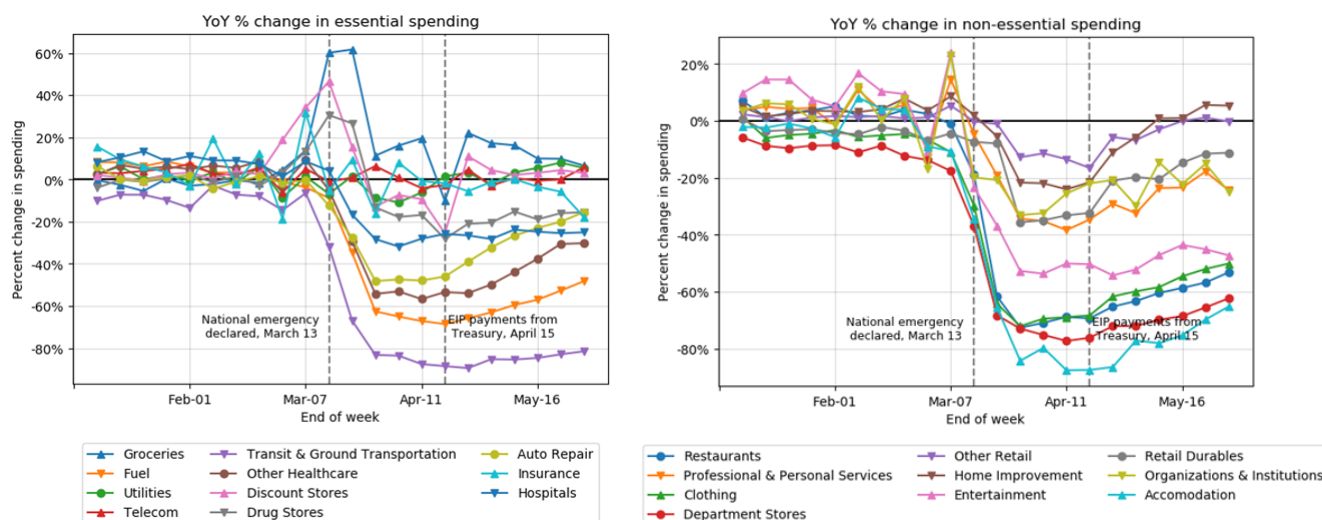
Table 2: Spending Changes for "Essential" and "Non-Essential" Categories

	Essential		Non-Essential	
	Share of spending	Year-over-year percent change	Share of spending	Year-over-year percent change
Apr-19	33%		67%	
Apr-20	45%	-20%	55%	-51%
Contribution to Aggregate Drop in Spend*	16%		84%	

* Percent contribution to aggregate drop in spend is calculate as: (% Drop in Category A)*(Baseline Share of Category A)/(% Drop in Aggregate).

increases in grocery spending, so that overall essential spending declines. Focusing on non-essential spending, declines are strongest in restaurants, travel accommodations and personal services. Overall, these results largely mirror those computed in other aggregate data sets and provide reassurance that our data is consistent with external evidence.

Figure 5: Credit card spending growth across spending categories



This figure plots the year-over-year percentage change in weekly credit card spending across categories. The surge in grocery spending was offset by large declines in spending on healthcare, transit and ground transportation, and fuel.

3.3 Heterogeneity in spending changes by income

3.3.1 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 2019.¹¹ For context, those in the bottom quartile make less than \$27,000 in take-home labor income per year, while those in the top quartile earn more than \$58,000.

Figure 6 plots the year-over-year change in credit card spending for each quartile, both in percentage and dollar terms. The top income quartile reduces spending by about 46 percent, or \$300, by the second week of April, while the bottom quartile reduces spend by 40 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.

Figure 7 shows the behavior of debit rather than credit card spending by pre-pandemic income. Patterns during the initial collapse are similar for debit and credit card spending, with spending by high-income households declining modestly more than spending by low-income household.¹² However, divergence in debit card spending over the income distribution starting in the second half of April is more striking. By the end of April, the decline in spending fully reverses to pre-pandemic spending levels for households in the lowest income quartile, while it only partially recovers for the other income quartiles. Interestingly, the recovery in debit card spending for the lowest income quartiles occurs in the same week when many stimulus payments are made in mid April. Debit cards tend to be used more frequently relative to credit cards for smaller everyday expenses and are also used more heavily by lower-income households. This observation, together with 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 on necessities during the pandemic.¹³

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.¹⁴

¹¹In future work, we plan to explore also the relationship to income changes during the pandemic as this data becomes available.

¹²As with credit card spending, 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.

¹³It is also useful to again note that substitution from cash transactions to card spending during the pandemic may lead to overstatements of the recovery in spending; in ongoing work we plan to extend our analysis to broader spending measures.

¹⁴Note that measuring spending at the geography 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.

Figure 6: Credit card spending by income quartiles

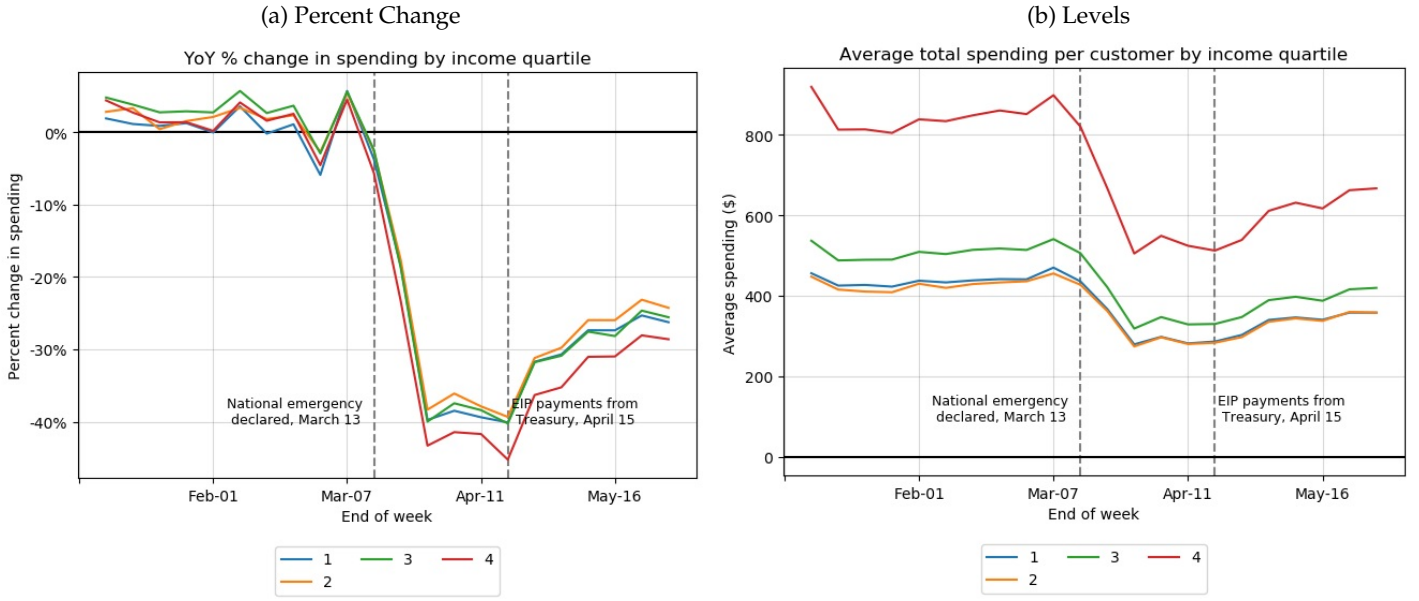
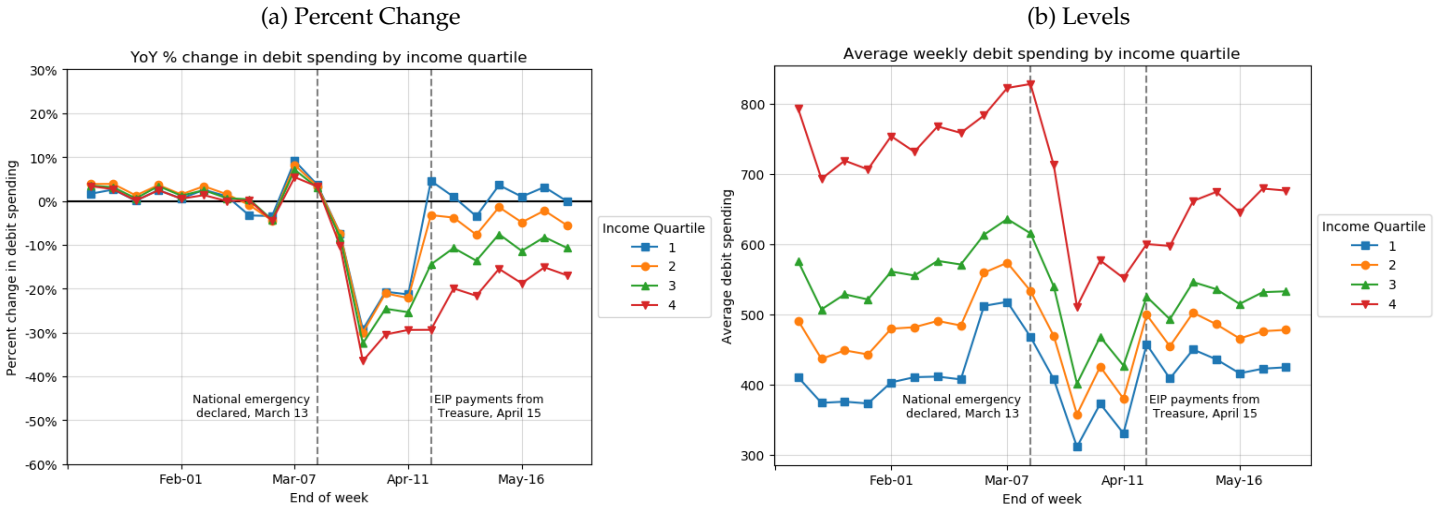


Figure 7: Debit card spending by income quartiles



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

$$\frac{c_{2020,z,q} - c_{2019,z,q}}{c_{2019,q}} = \text{Quartile}_q + \text{ZIP}_z + \varepsilon_{z,q}$$

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 $c_{2019,q}$ 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 5-digit zip codes but also explore more aggregated 3-digit zip codes to again limit the influence of measurement error.

Comparing odd columns 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. 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 household live.

Table 3: **Income-Spend Relationships within Geography**

	<i>Dependent variable:</i>							
	Debit Card Spending Growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Income Q2	−0.053*** (0.004)	−0.054*** (0.004)	−0.062*** (0.002)	−0.058*** (0.001)	−0.055*** (0.003)	−0.054*** (0.002)	−0.063*** (0.011)	−0.064*** (0.010)
Income Q3	−0.119*** (0.004)	−0.124*** (0.004)	−0.142*** (0.002)	−0.132*** (0.001)	−0.132*** (0.003)	−0.127*** (0.002)	−0.129*** (0.011)	−0.127*** (0.010)
Income Q4	−0.223*** (0.004)	−0.221*** (0.004)	−0.246*** (0.002)	−0.224*** (0.001)	−0.238*** (0.003)	−0.226*** (0.002)	−0.273*** (0.011)	−0.271*** (0.010)
Constant	0.037*** (0.003)		−0.020*** (0.001)		−0.005** (0.002)		0.070*** (0.008)	
Geography FE	NO	YES	NO	YES	NO	YES	NO	YES
Observations	65,675	65,675	65,675	65,675	24,923	24,923	3,587	3,587
Adjusted R ²	0.042	0.249	0.301	0.580	0.265	0.595	0.159	0.306

Table regresses year over year spending growth 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 5-digit zip codes and equally weight. Columns (3) and (4) use 5-digit zip codes and weight by number of customers in each zip code \times income quartile. Columns (5) and (6) use equal weights and 5-digit zip codes but restrict to zip code \times income quartiles with at least 20 customers. Columns (7) and (8) use equal weights and define geographies as 3-digit zip codes.

Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Finally, we further decompose the decline in credit card spending by income quartiles into essential and non-essential categories.¹⁵ Figures 8 and 9 show that the spending declines for essential categories are indistinguishable across income groups, while non-essential 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 house-

¹⁵Unfortunately, as mentioned above, we do not have the debit card spending split by categories.

Figure 8: Reduction in essential and non-essential credit card spending by income quartiles

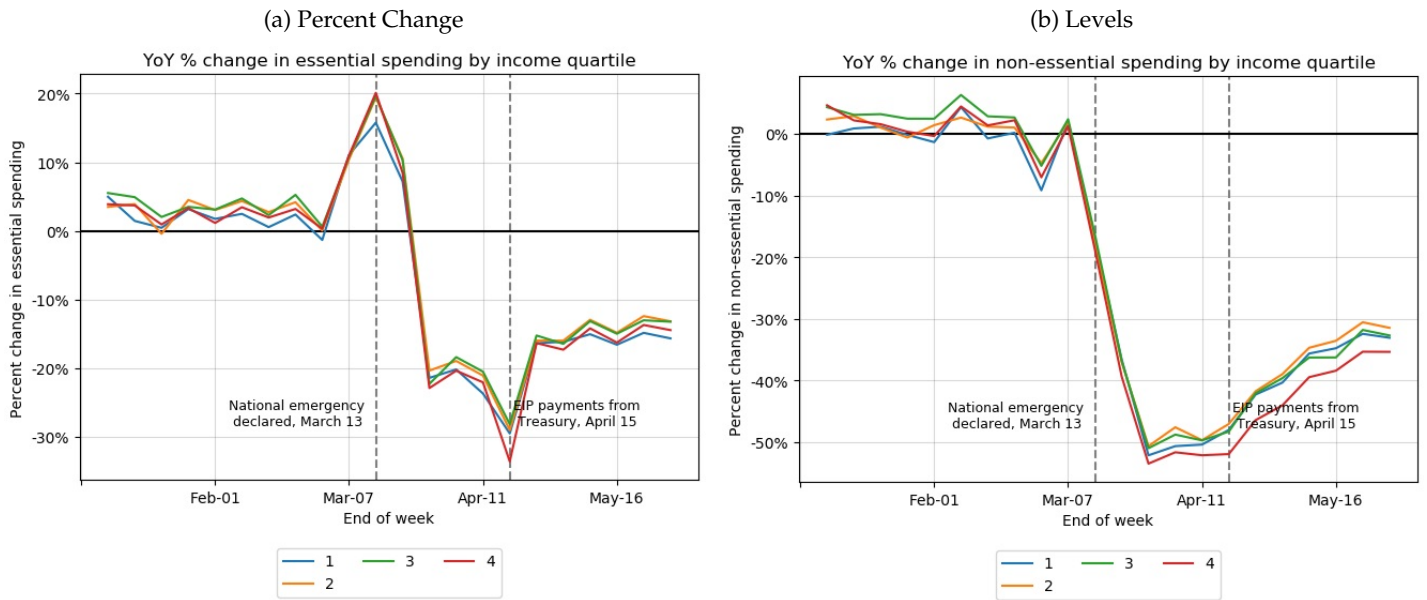
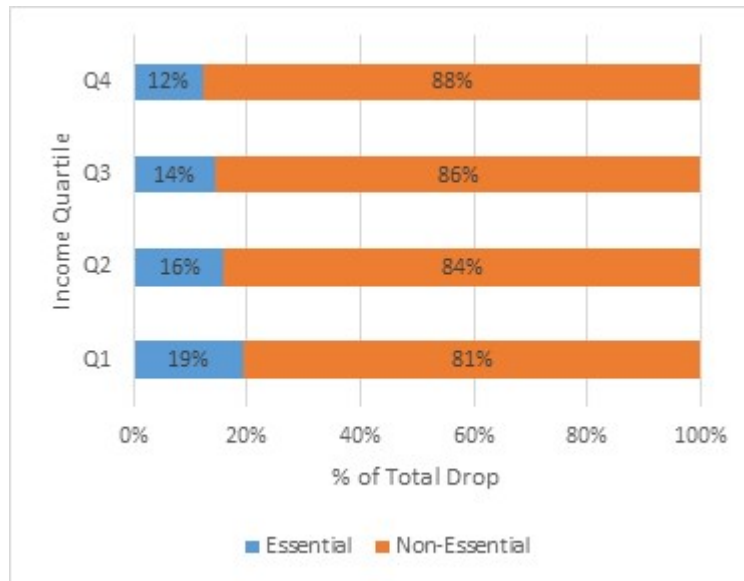


Figure 9: Reduction in essential vs. non-essential spending by income quartiles



holds 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 et al. (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.

Differences between high and low-income households in the composition of spending may also be another reason why that spending falls by more for high-income households. Non-essential categories represent a larger share of spending for high-income households – 70 percent of spending in April 2019 for households in the top income quartile compared to 61 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 non-essential spending account for a somewhat larger share of total spending declines for high- versus low-income households (88 percent compared to 81 percent, Figure 9). Since these non-essential categories are most affected by the pandemic shut-downs, 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. As a result, 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 additionally reflect an important role for economic stimulus. 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. Furthermore, Ganong, Noel, and Vavra (2020) 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 for unemployed workers 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 pandemic period. 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.

3.3.2 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. We examine a subset of our credit card sample who also have a Chase checking account and infer their industry of employment based on the payer associated with their payroll income received in February 2020. However, we observe the payer associated with their payroll income for only 24 percent of households, and most of these payers tend to be large employers.

Figures 10 plots spending changes by industry of employment, for each industry where we have significant sample size.¹⁶ 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 consid-

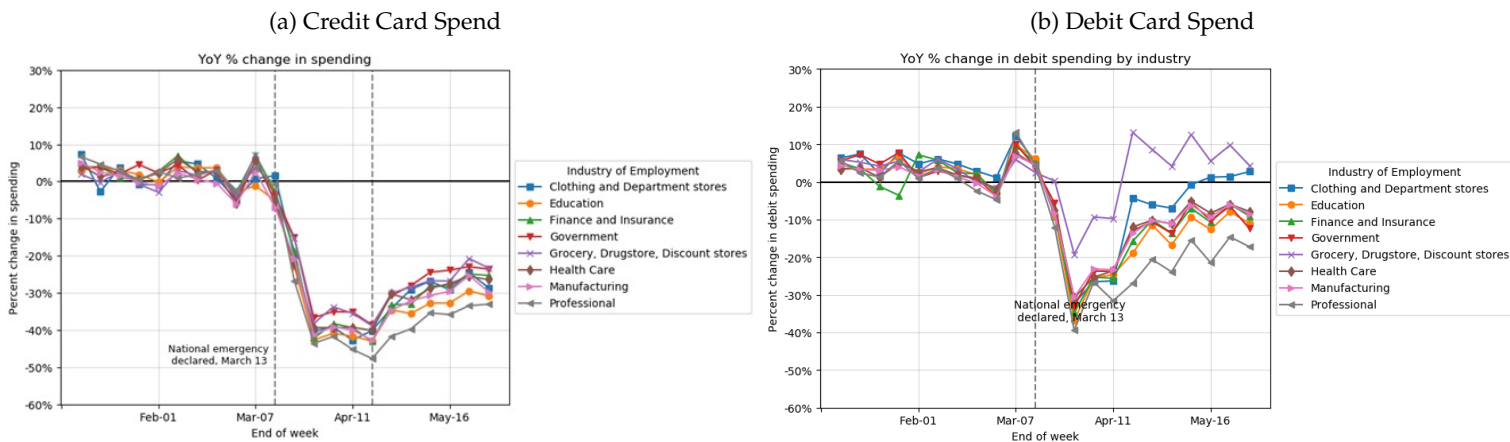
¹⁶It is useful to again note that the underlying samples for debit and credit card holders differ, so the households and covered industries in panel (a) and (b) are not identical.

ered essential businesses and kept open under social distancing policies—and clothing and department stores, which were generally deemed non-essential businesses and where layoffs have been greater (Cajner et al. (2020)).

Overall, it is hard to discern systemic patterns between spending patterns and the distribution of employment losses across industries. It is true that essential workers like those in grocery stores or the government 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.¹⁷ 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 largest drops and spending and slowest recoveries occur in higher-income industries of employment. Furthermore, these differences are more striking for debit than for credit card spending.

Figure 10: Spending Changes Split by Industry of Employment

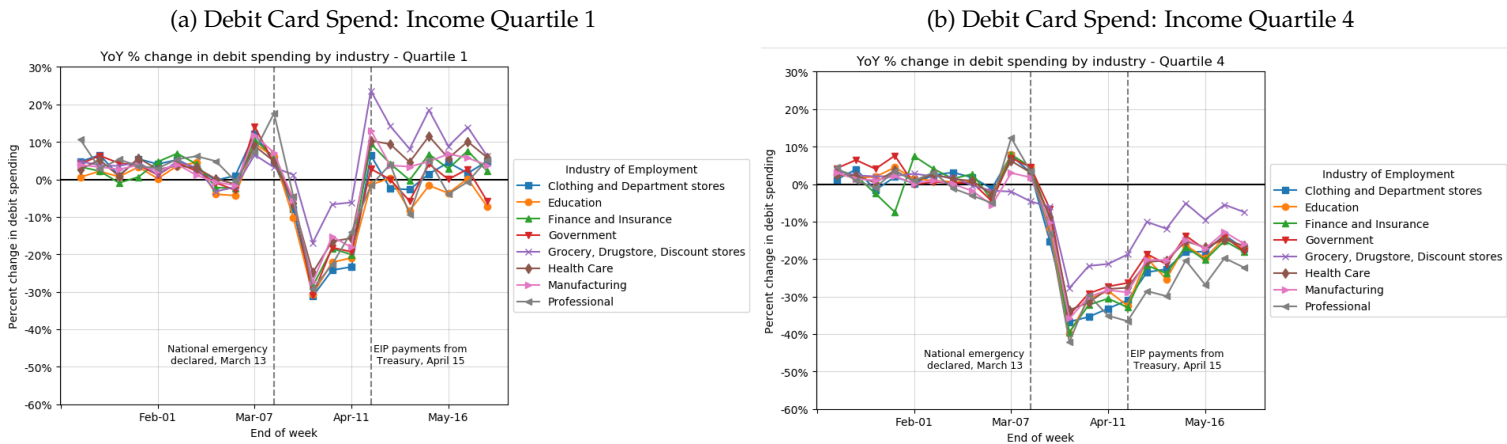


To provide a further sense of the separate role of income and industry, in Figure 11, we compute debit spending by industry of employment separately for workers in the highest and lowest quartile of pre-pandemic income. Comparing variation across industries within income quartile in Figure 11 to variation across industries without conditioning on income in Figure 10 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 11 vs. comparing different colored lines *within* panels (a) or (b) 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 de-

¹⁷See Appendix Table A.1.

Figure 11: Spending Changes Split by Industry of Employment



cline. As mentioned previously, we document that average household spending fell almost 40 percent, while the typical unemployed worker receiving UI only cuts credit card spending around 5 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 larger amounts 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, as long as this stimulus continues. The more rapid recovery of spending for low-income households may suggest exactly this channel at work, and the remainder of the paper looks at the behavior of household savings to provide additional evidence on these channels.

4 Household Liquid Balances

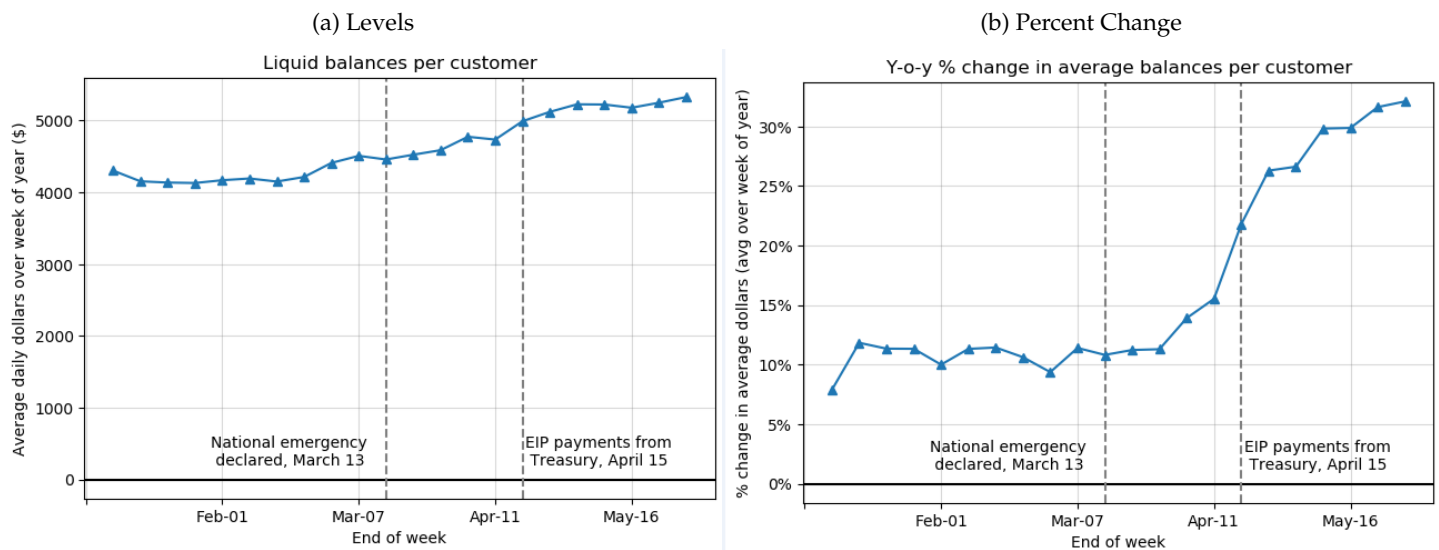
Given the unprecedented reduction in spending across income and industries documented above, we next explore whether there were changes in the distribution of household liquid balances. Figure 1 shows that aggregate private savings increased substantially over the pandemic, reflecting the combination 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 expe-

riencing 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 non-essential goods and services is banned. In addition, stimulus payments and other income support programs represent a larger share of pre-pandemic income for high- than for low-income households.

To explore these effects, we calculate how the distribution of end-of-week balances in household checking accounts has evolved throughout the pandemic. Specifically, we explore how various unconditional moments of checking account balances have evolved throughout the pandemic as well as how balances have 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, as well as the percentage year-over-year change from January through early June 2020. Figure 12 shows that by the first week of June, average balances increased by 35 percent year-over-year, or about \$1500 dollars relative to earlier in the year. This increase is in line with aggregate statistics from Bureau of Economic Analysis shown in Figure 1, which show that the national personal savings rate was almost 30 percent large in April 2020 than in April 2019. Much of the growth in checking balances seems to have occurred during and after the week when 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.¹⁸

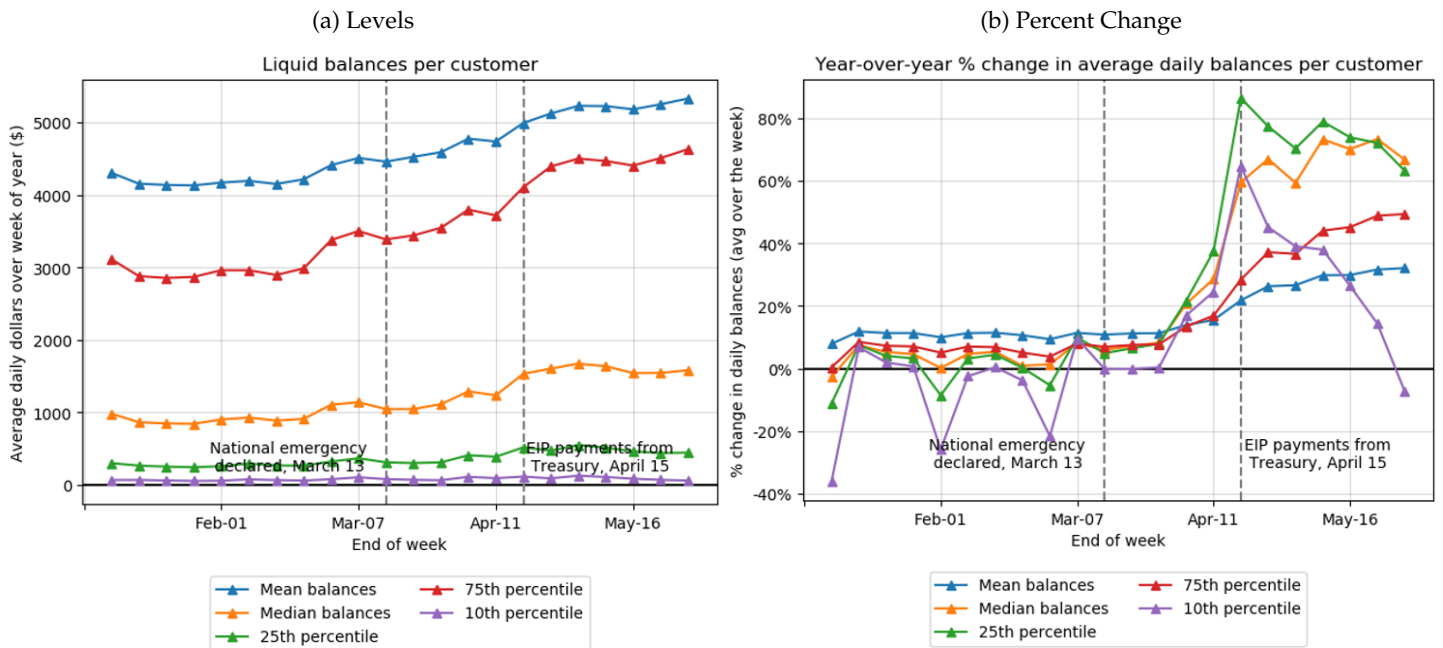
Figure 12: Level and Year-on-Year Change in Average Checking Account Balances.



¹⁸We further decompose this trend into checking account inflows and outflows in the Appendix.

Figure 13 plots additional moments of the distribution of liquid balances over time. Panel (a) shows that increases in liquid balances are quite pervasive, with increases observed at various percentiles of the distribution. The dollar increase in balances are greater for households with larger initial pre-pandemic balances. However, it is important to note that scale effects would generally 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. Panel (b) shows that the lower end of the distribution is growing somewhat more than the top end of the distribution. Interestingly, the year-over-year growth for lower percentiles shoots up around the time of stimulus payments and then trends down.¹⁹ This suggests that households with low initial liquidity received a large increase in liquidity from stimulus payments, they may be fairly rapidly using up this additional cash.

Figure 13: Change in Distribution of Checking Account Balances.

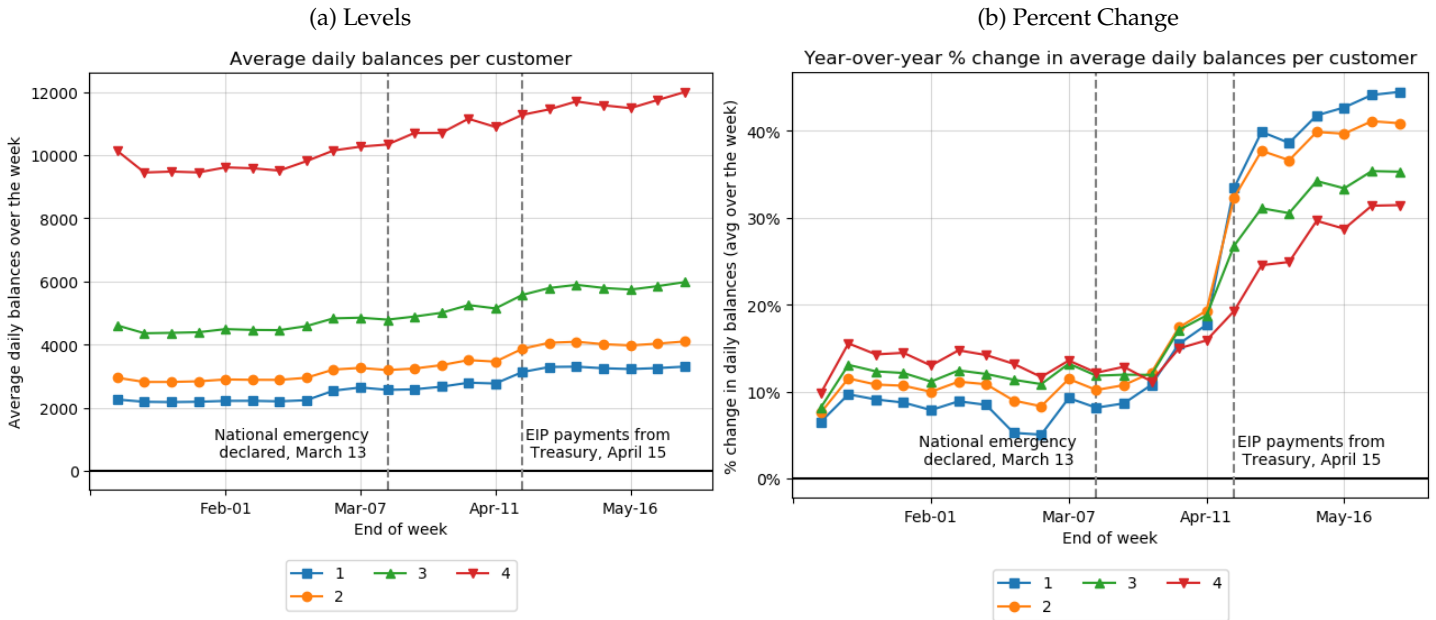


While the results in Figure 13 show that increases in liquid balances are pervasive, it is interesting to explore the relationship with pre-pandemic income. In particular, it is useful to know whether the increase in aggregate liquid balances was primarily driven by gains at the top of the income distribution (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 relative stimulus payments). Figure 14 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

¹⁹Note that the 10th percentile year-over-year growth is highly volatile, since liquid balances for this group are typically near zero.

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.

Figure 14: Change in Average Checking Account Balances by Income Quartile.



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 pre-COVID balances), and in percent terms for low-income households (who have lower pre-COVID balances).

Given these scale effects, what should we conclude about the relative role of high- vs. low-income households in driving the increase in liquid wealth? One way to answer this question is to compare each group's contribution to 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, 48.8% (12.9/26.4) 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, but importantly, this increase is less than proportional to the initial share of liquid wealth

Table 4: **Decomposition of Total Liquid Balances Changes by Income Quartile**

	Initial Balances	Share of Initial Balances	Increase in Balances	Share of Increase in Balances	Final Balances	Share of Final Balances
Quartile 1	\$3.3B	12.6%	\$0.8B	15.2%	\$4.1B	13.0%
Quartile 2	\$4.1B	15.5%	\$1.1B	19.2%	\$5.1B	16.2%
Quartile 3	\$6.1B	23.1%	\$1.4B	25.9%	\$7.5B	23.6%
Quartile 4	\$12.9B	48.8%	\$2.2B	39.7%	\$15.0B	47.2%
Total	\$26.4B	100.0%	\$5.5B	100.0%	\$30.2B	100.0%

Initial balances are computed in February 2020 and Final Balances are calculated in May 2020.

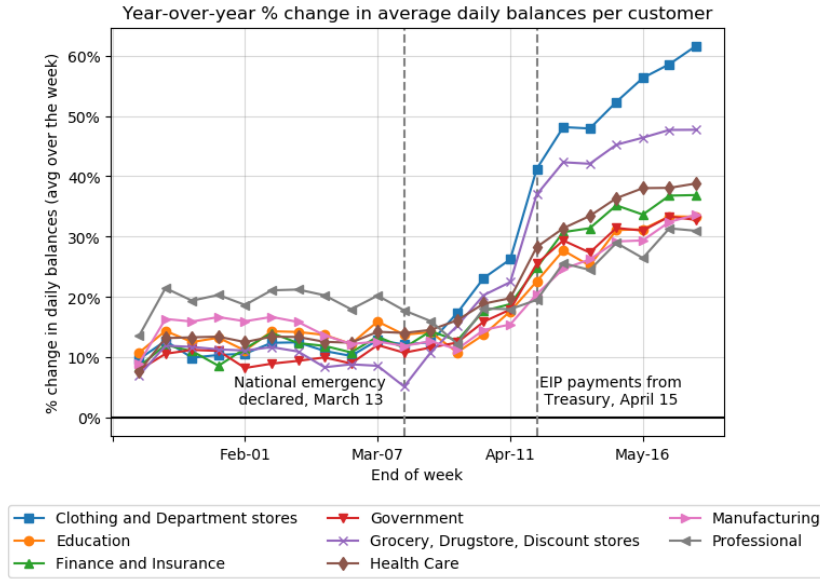
held by the top quartile. In particular, Table 4 shows that lower-income quartiles are actually driving more of the aggregate increase in balances than would be expected from their initial balance shares, so liquid wealth inequality decreases between February and May. This provides a concrete sense in which the poor are disproportionately increasing savings relative to the rich during this pandemic. While this shift in the wealth distribution towards low-income households may not seem huge, it implies an almost two percentage point decline in the share of liquid wealth held by the richest quartile occurring over a matter of weeks.

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; indeed, savings for low income households are already trending back towards normal levels in the 6 weeks after EIP payments. 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 increase in savings, even for those experiencing job loss, but it might again not continue as social distancing is relaxed.

Appendix Figure A.1 decomposes checking account balances into inflows and outflows. These results suggest that for the highest income quartile, increases in account balances are primarily driven by declines in spending, while for the lowest income quartiles, increases in account balances are primarily driven by increases in income.

Finally, Figure 15 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.

Figure 15: Growth of Balances by Industry of Employment



5 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 responses to spending responses to unemployment. While high-income households cut spending more than low-income households in the pandemic, 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 is still being processed at the time of writing and 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 using statutory provisions of the CARES Act, information from the Current Population Survey and the unemployment insurance calculator in Ganong, Noel, and Vavra (2020). We estimate that income increases are largest 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 of the supplement to UI benefits in the CARES Act, UI benefits now replace more than 100 percent lost earnings for low-income households (Ganong, Noel, and Vavra (2020)). The details of this simulation are described in the Appendix.

Figure 16 juxtaposes simulation-based estimates of the change in income alongside the change in spending from Figure 7. There is a suggestive correlation between the pattern of income changes

and the relative pattern of *debit* card spending changes. Debit card spending increases for the group receiving the most income support, and decreases for the group with the least income support. However, recall that we also found that the evidence of heterogeneity in *credit* card spending responses is much weaker. One possible interpretation of this pattern is that because EIPs and unemployment benefits were deposited into people’s bank accounts, people were more likely to spend the funds on their debit cards than their credit cards. In future work, when Chase micro data on income during the pandemic becomes available, we plan to explore the joint dynamics of income and spending at the household-level to better understand these patterns.

Figure 16: Estimated changes in income and spending by income quartiles



This figure shows the change in income and debit card spending by income quartile. The change in income compares March, April, and May 2020 relative 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 relative to spending at the same time in the prior year. Our spending estimate focuses on this narrower time horizon after the most immediate impacts of the lockdown—which depressed spending across the income distribution—had subsided.

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 debit card 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. 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 pre-pandemic 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. Instead, direct effects of the pandemic were likely the primary factor driving overall declines in spending during this period.

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 recovered some from the unprecedented declines in March, but still remains severely depressed relative to pre-pandemic 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. While we see a large spike in savings for low-income households immediately after EIP, savings levels have trended back down towards pre-pandemic levels for these households over the last six weeks. This suggests that new stimulus 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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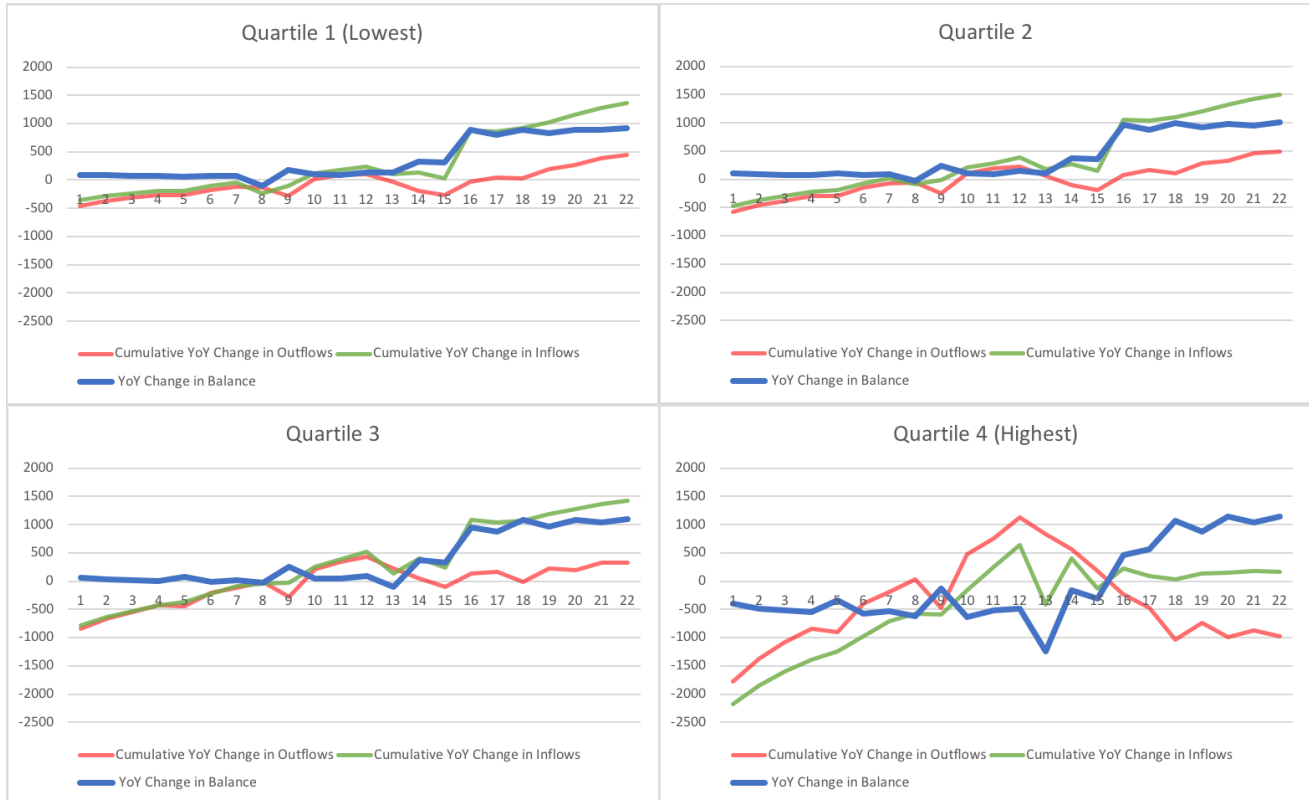
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APPENDIX

Natalie Bachas Peter Ganong Pascal Noel Joseph Vavra Arlene Wong Diana Farrell Fiona Greig

A.1 Additional Results

Figure A.1: Year-over-year change in checking account inflows and outflows, by income quartile



Each panel plots the series of the average year-over-year cumulative change in weekly inflows (green) and outflows (red) into checking accounts for individuals in a specific income quartile. Together, these two series determine the year-over-year change in checking account balances (blue). While the increase in balances for quartiles 1-3 seems mainly driven by inflows and EIP payments in week 16, it is driven primarily by a decrease in outflows for the top income quartile.

Table A.1: **Average Income by Industry of Employment**

Industry	Average Monthly Pay, Debit Sample	Average Monthly Pay, Credit Sample
Clothing/Dept Store	\$1,728	\$2,700
Grocery/Drug/Discount Store	\$1,935	\$3,358
Education	\$2,948	\$4,077
Government	\$3,264	\$4,106
Health Care	\$3,436	\$4,742
Manufacturing	\$4,630	\$6,099
Finance	\$4,638	\$7,080
Professional	\$5,033	\$5,338

This table lists the average monthly income for individuals in the debit card sample (column 2) and credit card sample (column 3) that are employed in each industry.

A.2 Simulation of distribution of income changes

We simulate the changes in income for households using the March 2019 Current Population Survey Annual Social and Economic Supplement (CPS ASEC). We require at least total labor income of \$12,000 in the prior year to be consistent with the Chase sample and average hourly earnings of at least the federal minimum wage. We simulate Economic Impact Payments (EIPs), assuming that Adjusted Gross Income (which is used to determine EIP eligibility) is equal to household income in the CPS. We randomly assign additional individuals to be unemployed so as to match the national unemployment rate in each month, including among the unemployed those who were misclassified as absent from work for other reasons. We assume that some of the unemployed receive unemployment insurance (UI). This includes both regular Unemployment Compensation (calculated as in Ganong, Noel, and Vavra (2020)) and also the \$600 weekly supplement (Federal Pandemic Unemployment Compensation). To calculate the share of unemployed receiving regular Unemployment Compensation benefits, we use the ratio of actual benefits paid out in DOL ETA Form 5159 to the implied value of benefits if every unemployed person in our simulation was receiving benefits. For example, this method implies that 51% of the unemployed are receiving regular benefits. To calculate the share of unemployed receiving Federal Pandemic Unemployment Compensation and Pandemic Unemployment Assistance, we use data on the rollout of these policies from the Hamilton Project (Nunn, Parsons, and Shambaugh 2020).