IMPACT OF THE CARES ACT STIMULUS PAYMENTS ON CONSUMPTION

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ABSTRACT: Consumer response to transitory income shocks is of academic interest in many disciplines. During the 2020 COVID-19 epidemic, the Federal government in the US passed the CARES Act that among other measures provides direct payments to households. In this article we utilize a large database on debit cards to analyze changes in consumer expenditures following the stimulus payments. We observe Zip code level daily transactions (approx. $200 million in daily spending) before and immediately following the disbursements of stimulus payments. Empirical analysis exploits geographical variation in timing of Federal deposits to identify marginal propensity to consume (MPC) for stimulus payments. Our results estimate the aggregate MPC of 0.43 ($0.43 of every $1 stimulus is spent within four days), split between cash transactions (unobserved in the previous literature) and purchases (concentrated in necessities). MPC is found to be higher in large urban metropolitan areas with higher rents. Our results highlight a potential shortcoming in fiscal policies that ignore cross-sectional variation in cost-of-living. Implications of findings are discussed.

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1. INTRODUCTION

Social distancing via stay-at-home orders has been one of the primary policy tools utilized globally to flatten the COVID-19 curve. Although the full extent of humanitarian costs associated with the ensuing COVID-19 pandemic are difficult to quantify, the economic fallout has been immediate and unprecedented. Supply disruptions and loss of production in many sectors have led to significant reduction in employment. For example, the first two months following the stay-at-home orders in the US has the largest increase level of unemployment recorded by the Bureau of Labor Statistics (Coibion et al. (2020)). The consequent loss of income and health insurance could result in defaults on mortgages, delinquencies on rent payments.

The pandemic crisis is challenging governments worldwide to implement monetary and fiscal policies to mitigate disruptions in the credit markets and restore economic activity. In the US, on the March 25, 2020, the US Congress passed the CARES act (116th Congress, 2020). This has a number of provisions to provide $2.2 trillion in assistance to businesses and individuals. Section B of this act approves Recovery Rebates (henceforth called stimulus payment) for individuals that provides "(1) $1,200 ($2,400 in the case of eligible individuals filing a joint return), plus (2) an amount equal to the product of $500 multiplied by the number of qualifying children". These stimulus payments are provided to US Citizen or Resident Alien with income income under $150,000 (joint), or $112,500 (head of household), or $75,000 [1]. As of June 3rd, 2020 the IRS has distributed $267 billion dollars to individual households (irs.gov, 2020).

Besides providing direct relief, a fiscal stimulus via transfer payments to low-income households is expected to have 'multiplier' effects by boosting demand for goods and services and thereby stimulating subsequent production (see Jappelli and Pistaferri (2010) for a survey). However, the magnitude of this multiplier effect hinges critically on household's marginal propensity to consume (MPC), i.e. the fraction of the extra dollar of aid that a household spends on consumption versus using it for debt payment or saving (as predicted by the permanent income hypothesis). Evidence from the 2001 economic growth and tax relief reconciliation act and the 2008 economic stimulus act following the 2001 and 2008 financial crises shows mixed consumer response to rebates (Shapiro and Slemrod (2003), Johnson et al. (2006), Shapiro and Slemrod (2009), Parker et al. (2013))[2]. For example, survey conducted by Shapiro and Slemrod (2009) found that a large proportion of stimulus was saved or used to pay off debt, with only 20 percent of the respondents

[1]With reduced amounts to individuals and households above these thresholds.

[2]President Council of Economic Advisors (2003) provides a more detailed review of the findings so far and their relevance to policy

indicating direct spending. Parker et al. (2013) on the other hand use data from the Consumer Expenditure Survey and report a much larger marginal propensity to consume between 0.6 and 0.9 for the 2008 economic stimulus.

In this article we provide early estimates on changes in spending following the disbursement of stimulus payments due to COVID-19. We utilize a large debit card database that provides daily number of transactions and spending at Zip code level. These transactions are drawn from over thousand financial institutions and payment companies and aggregated over approximately 12 million debit cards. Total daily spending across all Zip codes in our data is approximately \$200 million. The customer base for the debit cards in our data is cards is relatively young and skewed towards low- to mid-income customers. For each Zip code, we observe aggregate expenditures as well as transactions broken down by different sectors (e.g Grocery, Fast Food). A key advantage of these data are that we observe all card transactions including cash withdrawals and wire transfers. Note that unlike the 2008 financial crises, certain goods and services are not available to consumers due to the imposed lockdown. Our empirical analysis examines changes in overall expenditures as well as changes by different industry sectors.

Besides expenditures, another crucial piece of information in the data relates to Federal deposits from CARES stimulus package. In our data we observe daily number and amount of deposits from Federal government for each Zip code. According to the IRS, payments were sent starting April 9 to accounts where direct deposits information was available. For households without direct deposit information, paper checks were scheduled to be mailed towards end of April. As of June 3rd, 159 million payments have been paid (75% by direct deposit) representing \$259 billion, or an average \$1,628 per payment. (irs.gov, 2020). Our Federal deposit data corresponds well with IRS information and we observe first payments starting April 10. Total stimulus across all Zip codes in the data is approximately \$137 million. There is however significant variation in timing and amount of deposits across Zip codes. These differences in timing of stimulus represent differences in IRS deposit schedule or due to bank processing (Baker et al., 2020). Our empirical analysis exploits this variation in deposits for identification of consumer response to stimulus transfers. Finally, several studies on 2001 tax cut and stimulus from 2008 financial crisis show heterogeneous response based on income and households credit constraints (Agarwal et al. (2007), Carroll (2012), Broda and Parker (2014), Misra and Surico (2014)). To understand heterogeneity we collected wealth, income, and other demographics using data from IRS (wealth and direct deposits), Zillow (for property prices) and ACS (2013-18) to examine heterogeneity in response to stimulus payment.

Our results show that the stimulus resulted in an immediate increase in spending, with a large proportion of stimulus spent within a few days of receiving the payment. We estimate the overall MPC as 0.43 or that for every \$ of stimulus, spending increased by \$0.43.

We find that consumers increase spending is in the form of purchases, cash withdrawals and money orders. Observing these cash withdrawals is a unique feature of our data and our results show that these forms of spending account for half the immediate impact of stimulus. We find the largest increase in spending for necessities (grocery stores, particularly Walmart, 7-eleven, Safeway and Target), and essential utilities. We explore heterogeneity in response (both with data sub samples and using a flexible deep learning model) and find substantial variation across Zip codes. We find MPC being higher in Zip codes located in populous urban cities with higher rents, indicating higher MPCs in geographic areas with a higher cost-of-living. Consistent with the extant empirical literature we find higher MPCs in areas with lower income and more poverty.

Zip code variation in MPC estimates reported in this paper point to a potential flaw in stimulus policies that don't consider differences in geographic cost of living. Under the CARES act passed by the Congress (as in 2001 and 2008), all qualifying households received equal payments despite large differences in living costs for metropolitan cities vs. rural towns[3]. These differences are exacerbated in the current crises since many of the hardest hit areas by Covid-19 (e.g. New York City Tri-State Area and California) also have higher living costs. In addition, inflationary pressures on many necessities such as groceries are already emerging[4] and calls for living-cost adjusted payments have been made by lawmakers and in popular press(e.g. "Here's An Idea: Don't Give Americans Second Stimulus Checks Of Equal Face Value", Forbes, May 14, 2020). From a macroeconomic perspective, inflation-adjusted targeted payments to liquidity constraint households is also likely to have larger impact on fiscal multiplier and economic recovery.

This paper adds to a rapidly growing and diverse literature related to COVID-19. Topics range from analyzing political partisanship in social distancing compliance Allcott et al. (2020), to theoretical simulations quantifying the multiplier effect of the stimulus package. Our work is most closely related to a current working paper by Baker et al. (2020). These authors use data from a personal financial app and estimate a MPC of magnitude (0.25 to 0.35) for the CARES stimulus. An advantage of data used in their analysis is that transactions are observed at individual level. However, the sample used from SaverLife app (a non-profit helping working families to develop savings habits) is relatively small (approx. 5K accounts, $2.5 million in stimulus deposits) and likely to have imperfect selection. Data used in our paper is broader in scope even though it represents a sub-population of relatively young and low-income. In particular, data are aggregated over 12 million debit cards with over $200 million in daily spending, & capture about

[3]See for example cost of living indices produced by Economic Policy institute and Bureau of Economic Analysis.

[4]CPI index for food-at-home (which comprises large budget in low income families) has risen sharply even with large drops in energy prices (BLS: https://www.bls.gov/news.release/cpi.nr0.htm)

$140 million of stimulus deposits. Additionally, data spans across the US (over 20,000 Zip codes) which allows us to (a) control for state level closures and economic drivers and (b) examine heterogeneity in MPC across areas with different living costs. On the flip side, our measures of wealth or other demographics are based on location (Zip code) rather than direct measures of household income or credit constraints. Finally, Baker et al. (2020) focus on spending in certain categories[5], in our paper we report all spending including cash withdrawals and money transfers. Our estimate of MPC for purchases is 0.31 which is similar to the estimates reported in Baker et al. (2020). However, we also find a large and significant increase in cash transaction and money orders.

Rest of the paper is organized as follows. In the next section we describe the data and empirical context. Section 3 provides our empirical approach, identification strategy and aggregate results. This section also presents a deep learning algorithm to explore heterogeneity in MPC estimates. Section 4 concludes with a discussion on implication of our findings and directions for future work.

2. Data

Primary data for our analysis comes from data aggregation firm Facteus which provides daily number of transactions and total spending at Zip code level (see appendix for a detailed description). These transaction data are collected from over 12 million bank cards form a large set of financial institutions and payment companies. Facteus uses proprietary methodology to provide granular transaction histories across various sectors (e.g Grocery) and brands (e.g Kroger) while ensuring consumer privacy. A large proportion of the debit cards in the sample are distributed by retailer stores or brands (e.g Walmart Visa or MC) as well primarily online Challenger banks. According to the information provided by Facteus, approximately 80 percent of the customer base in 2019 comprised of Gen X and Millennial's, with some spillovers to Boomers and Gen Z. In addition, clientele for these cards is skewed towards low- to mid-income customers, who are also the primary recipients of the CARES stimulus package.

Our data spans four months (January 1, 2020 to April 17, 2020) and we observe daily transactions from approximately 22,000 Zip codes across the US. However, there are large cross-sectional and inter-temporal differences in the number of cards, transactions, and spending. In the empirical analysis, we create a balanced panel where we observe daily transactions with no missing dates (a total of 21,570 Zip codes). As noted above, data includes consumer expenditures broken down by merchant category codes (MCCs)—a standard classification system used in the financial services industry—which allows us

[5]On page 9 they report categories as "Food, Household goods and personal care, Durables like auto-related spending, furniture, and electronics, Non-durables and services, and Payments including check spending, loans, mortgages, and rent."

to analyze the impact of stimulus by the type of goods or services. Finally, an important piece of data relates to direct Federal deposits (e.g. tax returns). In the current context, data provides information on number and amount of Federal deposits from CARES stimulus package. Our empirical strategy exploits variation in timing and amount of Federal deposits to analyze changes in consumer expenditures.

We supplement the information on consumer expenditure with data from several other sources. We use data from IRS to get information on Income distribution within Zip codes. In addition, IRS provides information on proportion of households that filed taxes online. This serves as a robustness check to deposit information observed in our primary data since stimulus payments were sent to households that file taxes online. We use data from Zillow (for property prices), US Census and ACS (2013-18, for demographics, income, population and rent). These data allow use to examine heterogeneity in response to stimulus based on consumer wealth.

Figure 1 consider the coverage of our data before the covid-19 pandemic. The charts on the right shows that the total amount of spend per day (top row) and the spend per transaction (bottom row) in the month of January. The average daily spend is about $200 million, with about $35 per transaction. Both charts also show large day of week effects. The chart in the top right shows the Zip codes covered in the data and shows representation from population across the United States. One issue with the data is that we do not have a clean measure on the number of active cardholders for a given Zip code. To approximate this we consider a measure of the mean number of daily transactions in January 2020[6], before fears of the Covid 19 pandemic emerged in the United States (For example, Google Trends on Coronavirus or COVID starts to trend up in end of Feb, peaking in mid-March. Similarly, Google mobility data does not show any reduced movement till middle of March). The chart on the bottom right compares our measure of scale to Zip population from the US census. We find that our Zip code level scale measure is highly correlated (r = 0.86) to the total population. For the remainder of this paper we will consider scaled expenditure and scaled deposits to compare across Zip codes.

[Figure 1 about here.]

We focus our analysis on the time period after the CARES act was passed (March 27) to the end of our data (April 17th). The spending and federal deposit data for this period is shown in in figure 2. The top right displays the spending, where we see aggregate expenditure increase by more that 15% after the distribution of stimulus (April 10th, 2020 onward). The key variation used in our empirical identification is differences in timing of the federal deposits as this allows us to separately identify time effects from stimulus effects. As noted in Baker et al. (2020), differences in timing of stimulus could be due to

[6]In the appendix we show our main results are robust to using different normalization periods.

(a) timing of IRS deposits, (b) households receiving a check instead of the direct deposit, or (c) delays due to banks processing. [7] The chart on the top right of figure 2 shows the distribution of federal deposits across Zip codes, which includes all deposits to bank accounts from the federal government [8]. In all we see $137 million dollars deposited in bank accounts nationwide (clustered on April 10, 13 and 15) and at the end of our data we see consumers in 66% of Zip codes having received some level of deposits. These deposits were made in about 82K accounts with the average deposit $1,678 (consistent with irs.gov (2020) distribution of the CARES act stimulus payments).

We consider the variation in stimulus across Zip codes in the bottom row of figure 2. To see if the variation we capture is consistent with IRS's electronic deposit data, figure on the bottom left shows the average scaled deposit by quantiles of electronically filed taxes by Zip (from 2017). We find that Zip codes in the top quantile of electronic deposits do see higher levels of (scaled) federal deposits in our data. The overall correlation between percent online filed taxes and our scale measure is positive but low ($r = 0.11$, [95% CI: $0.09, 0.12$]), suggesting that variation in time of receipt could be driven by a number of factors including bank processing delays. In the table in the bottom right we consider the demographic differences between Zip codes: (66%) in which consumers any stimulus and the Zip codes (34%) that had no stimulus deposits till April 17th. We notice that Zip codes that received stimulus tend to have larger populations and located in more urban areas. We also find that Zip codes without stimulus have higher income, rent (proxy for home values) and lower unemployment, which is consistent with stimulus being targeted to lower incomes.

[Figure 2 about here.]

3. Empirical Model and Results

Identification in our empirical model is based on the variation of distribution of tax stimulus across Zip codes. Before presenting a formal model we consider simple first difference across Zip codes. In figure 3, we show the geographical variation in stimulus payments. We observe large geographic variation in stimulus distribution: April 10 (top) deposits are made primarily in the North East and Midwest, April 13 deposits occur in all other regions (besides April 10 recipients), and April 15 deposits are made nationally.

To see how this variation corresponds to spending behavior, we compare first differences between geographic areas that received the stimulus on April 10 to areas that received the stimulus later. The charts on the right panel show the first difference in scaled

[7] In Baker et al. (2020) sample of 5,746 users, only 28% received stimulus payments before April 21st.

[8] Note that few deposits seen before April 10 are deposits from the 2019 Tax refunds. However 97% of our deposits occurred after April 10th when the stimulus from the CARES act were distributed

spend (line) and scaled stimulus payments (bar), averaged across all Zip codes in respective geographic areas. The top chart compares Illinois (April 10) to neighbouring Iowa, the middle chart compares Pennsylvania (April 10) to Colorado and the bottom chart New York city (April 10) to Seattle. In all three charts we notice that before stimulus payments, the difference is statistically zero and constant across days (before April 10). Importantly, on (and immediately after) April 10, the difference in spending is large and positive in geographic areas receiving stimulus payments on April 10. Further after April 13, when stimulus payments are made to the comparison geographic areas, the trend is reversed. This suggests that the stimulus payments have an immediate impact on consumption.

Focus of the next section will be on estimating the magnitude of causal impact of stimulus on spending. We explore product and geographical differences in subsequent sections.

[Figure 3 about here.]

3.1. *Marginal Propensity to Consume (MPC)*

For the main empirical analysis we will consider the variation in amount and the timing of when different consumers receive the stimulus. To establish a causal impact of the stimulus, we need to control for potential confounding factors. While our data consider a spending in a short time frame (March 27 to April 17), during this period there was significant geographic variation in unemployment benefits and the intensity of the economic shutdowns. In the US, unemployment benefits vary by state (see https://www.usa.gov/unemployment for details), and the nature of economic lock downs imposed were based on state policies. To control for these factors, our empirical model considers State-Day Fixed effects. Our causal estimate is identified by considering variation in stimulus timing across Zip codes within a state.

Our model[9] will estimate the (scaled) spending in zip code on day t ($s_{z,t}$) as:

$$s_{z,t} = \alpha_z + \alpha_{s(z),t} + \sum_{j=-1}^{5} \delta_j r_{z,t-j} + \varepsilon_{z,t} \tag{1}$$

here α_z represents the Zip code fixed effects and $\alpha_{s(z),t}$ is a state-day fixed effect that impacts all Zip codes within the same state as z (note our scaling measure is important to estimate correct day-state fixed effects). r_{t-j} represents the (scaled) stimulus at on day $t-j$. Our parameters of interest are δ_j which captures the impact of a stimulus on spend spending j days after receipt. To estimate the aggregate Marginal Propensity to Consume (MPC), we consider the aggregate estimated increase in spending due to stimulus across

[9]In the appendix we show that this model does correctly recover individual MPC estimates and does not suffer from an aggregation bias.

all Zip codes divided by the total size of the stimulus[10]. The standard errors are clustered by Zip code.

Panel A of figure 4 displays the point estimates of our model. The numbers in this chart can be interpreted as the Marginal Propensity to Consume (MPC) or proportion of the stimulus that is spent. Here we estimate that there is no saving before the stimulus (δ_{-1}). This is consistent with randomization in the distribution of stimulus - if consumers could plan, we should see a reduction in spend before the stimulus. We find an immediate increase in spending on the day of stimulus receipt that lasts for 4 days after the receiving stimulus payment. Overall our estimated MPC is 0.43, or $722 of a $1,678 stimulus (average stimulus) is spent within the first four days of receipt.

[Figure 4 about here.]

Our results are consistent with findings reported by (Ganong and Noel (2019)) who utilize micro de-identified bank account data to examine sensitivity of consumer spending to both increases and declines in income arising from unemployment spells. One of the striking findings from Ganong and Noel (2019) is for households in New Jersey that receive last employment checks and unemployment benefits at the same time. Authors find that the extra money from unemployment check is spent immediately, even though households know their income is likely to fall sharply in the following month. Our results show similar pattern in that a large proportion of stimulus is spent within a few days of receiving the payment. Recent work by Baker et al. (2020) in the context of CARES act estimate a MPC of 0.25 to 0.35. We believe some of the difference between their results and our MPC estimate is driven by the categories used in the analysis. Next section explores spending patterns by broad product classes as well as individual brands.

3.2. *Where are the the stimulus payments spent?*

In this section we consider the change in different types of spending after the stimulus. An advantage of our data is that we observe all forms of transactions including cash withdrawals from ATM machines, money orders wire transfers, and product purchases (all other products such as grocery, utility etc.). We first consider independent models for three broad types of expenditures and re-estimate equation 1 (common approach used in literature Johnson et al. (2006), Parker et al. (2013), Misra and Surico (2014) and Baker et al. (2020)).

Panel B of Figure 4 shows the results from our regression models. We observe an increase in spending in all three types but with different spending patterns. We estimate that stimulus payments result in an increase both cash withdrawals and purchases. The

[10]While the model parameters, δ_j are homogeneous across Zip codes, our overall MPC measure accounts for differences in stimulus distribution across Zip codes.

estimate for cash withdrawals is unique in our data as prior studies have focused only on an increase in purchase spending. The increase in cash payment and wire transfers could be a form of debt repayment among our consumers. We note that our estimated MPC on purchases (i.e excluding financial transactions) is similar to estimates reported in Baker et al. (2020) (0.25-0.35).

As noted above, our data includes spending by Merchant Category Code (MCC) as well as major brands. To explore where stimulus money is spent, we consider separate models (estimate equation 1) for each MCC/outlet. We find the largest increase in spend in financial intuitions and retail outlets (including Walmart, 7-eleven, Food Lion, Kroger and Target). These are consistent with recent survey evidence where respondents indicate a higher propensity to use the stimulus checks for monthly bills or day-to-day essentials such as food or supplies [11] We should note that during the periods of analysis, certain spending mediums (e.g. dine in restaurants, travel) were not available to consumers due to pandemic lock-down.

[Figure 5 about here.]

3.3. *Who spends the stimulus?*

This section explores heterogeneity in response to stimulus checks based on geography and demographic characteristics of Zip codes. We consider two different approaches to understand heterogeneity in consumption. First, we estimate separate models for Zip code groups based on different measures of population size, density, and wealth. Similar to the approach above, we re-estimate model 1 for various sub-samples of data based on median splits on income, home values and population (as in Johnson et al. (2006), Parker et al. (2013), Baker et al. (2020)). Second, we examine heterogeneous treatment effects by estimating a flexible machine learning model and describe differences across zip codes using a variety of demographic characteristics (similar to approach in Misra and Surico (2014)).

3.3.1. *Stimulus spending by income, home values and population.* We consider several measures of Zip code income and housing information. For income, we collect Zip code 2018 mean adjusted gross income from the IRS and median household income from the 2018 American Community Survey from the US census. For housing, we collect Zip code 2020 mean home values from Zillow research and median household rent from the 2018 American Community Survey. We note these measures represent geographic variation in cost of living variations, and not necessarily variation in wealth of consumers in our sample.

[11]Bankrate survey, March 30-31, 2020 https://www.bankrate.com/surveys/coronavirus-and-stimulus-checks/

Finally, we use information on Census population and population density measures to capture spending difference between Zip codes.

Results from estimating model 1 by considering a median split based on income, housing, and population measure are show in figure 6. We find differing patterns for our income and housing measures. For income we find decreasing MPC by income (top row), which is consistent with lower-income consumers being more likely to spend stimulus. For home values (middle row), we find the larger MPCs are in areas with the highest rental prices (and no difference in Zillow home values). In our data sample most consumers are likely to rent, measures of rent likely describe cost of living differences across different areas. Our results are consistent with MPCs being is higher in areas with higher costs of living. In the bottom row, we estimate that MPCs are estimated to be higher in areas with greater population or population density. Based on the 2018 Consumer expenditure survey [12], average annual household expenses are about 50% higher in densely more populated urban areas. These correlated across Zip codes in the next section we will jointly estimate the effect of different demographic variables.

[Figure 6 about here.]

3.3.2. *Heterogeneity of stimulus spending.* To formally examine differences in response to stimulus payments, this section develops a flexible statistical model capturing heterogeneity across Zip codes. In particular, we develop a deep learning model (feed forward neural network) to predict heterogeneous impact of the stimulus payouts across Zip codes (see Schmidhuber (2015) for an overview). In the econometric literature, Farrell et al. (2018) describe such a model as a non-parametric estimator with the basis function estimated flexibly from the data[13].

The architecture of our model will consider two main features. First, since we have over 20,000 Zip codes, we use a data reduction method from natural language processing to map Zip codes on a smaller dimension space. This dimensional reduction is similar to the common Word2vec in NLP (Mikolov et al., 2013) or product2vec as used in Marketing (Chen et al., 2020). Second, we allow for multi-level inputs where stimulus payments (we use the same representation as our main model, $r_{z,t-j}$, $j \in [-1, 5]$) and fixed effects (Zip and State-day) enter the neural network in different layers (See Du et al. (2019) for an application in Marketing). The other aspects of our model are standard in the literature: we use a four layers of the network (as suggested in Shaham et al. (2018)), with ReLu activation (Nair and Hinton, 2010) between layers. For regularization, we use dropout

[12]see `https://www.bls.gov/cex/2018/combined/population.pdf` for complete data

[13]Note these models are characterized by a very high number of parameters, the our final model has 78,323 parameters

and l2 (ridge) regularization. Our final layer considers a linear model to predict spending. We tune all the features of our model, and consider 25 fold cross-validations [14]

To assess the impact of stimulus we limit our analysis to the Zip codes where we observe a stimulus. For each Zip code (z), we define $\hat{S}_z(R = R_z)$ and $\hat{S}_z(R = 0)$ as the predicted spend (aggregated over days) for the Zip code with observed stimulus ($R = R_z$) and with no stimulus ($R = 0$) respectively. MPC for Zip code z (MPC_z) is defined as $\frac{S_z(\hat{R=R_z}) - S_z(\hat{R}=0)}{R_z}$ (as in the matrix completion methods described in Athey et al. (2018)). The overall MPC of stimulus payments is defined as $\frac{\sum_z \hat{S}_z(R=R_z) - \hat{S}_z(R=0)}{\sum_z R_z}$.

Our results are shown in figure 7. The chart on the top right shows the distribution of estimated MPC across Zip codes, and suggest a large amount of heterogeneity in the 'treatment effects'. The implied overall MPC is 0.50, consistent with the results from the homogeneous model 4. The chart on the top right shows that geographic distribution of the estimated MPC, in this chart darker colors represent higher MPC. MPCs are higher in large metropolitan cities across the US (e.g. Atlanta, Chicago, Dallas, Denver, Houston, Los Angeles, New York, Miami, Philadelphia, Seattle, San Francisco). This result is consistent with the bottom row of figure 6, where we estimated higher MPC in more populated Zip codes.

Finally we consider a second stage regression where we regress the estimated MPC_z on the demographics of the Zip code. The results from a standardized regression (estimates impact of 1 s.d. variation on MPC) are show on the right hand panel of figure 7.

We focus on three main results. First, MPCs are higher in more urban and populated areas (population, population density). Second, MPC are higher in Zip codes with higher rental prices[15]. Given that our sample is primarily drawn from mid- to low-income consumer group[16], we interpret both higher population and rents as areas with higher cost-of-living. As noted earlier, average annual household expenses are about 50% higher in densely more populated areas.

Third, MPCs decrease in measures of income, specifically our estimates are negative for median income and positive for poverty. During the shutdown many service jobs were negatively impacted, consistent with our income measure we find that MPCs are higher in areas with higher unemployment (2018) and more service jobs. After controlling for cost-of-living, we interpret these income measures as measures of liquidity constrained

[14]The out of sample R^2 of our model is 0.78, compared to 0.53 in-sample R^2 from the linear model (with Zip code and state-day fixed effects).

[15]Our measure of Zillow home price and rent are highly correlation, our results are consistent if we consider Zillow home prices instead of rent

[16]for higher income consumers, spending with high illiquid assets (house value) would suggest behavior of 'wealthy hand-to-mouth' consumer as in the model proposed by Kaplan and Violante (2014).

consumers. Therefore our results suggest consumers in Zip codes with higher credit constraints have higher MPCs. This result is consistent with economic theory (Kaplan and Violante (2014), Kaplan et al. (2018)) and empirical findings in the literature on tax rebates (e.g. Shapiro and Slemrod (2003, 2009), Parker et al. (2013), Broda and Parker (2014), Baker et al. (2020)).

[Figure 7 about here.]

4. Discussion

Understanding consumer response to transitory income shocks is of interest in many academic disciplines. In experimental psychology, inducing resource scarcity vs. abundance in otherwise equivalent participants has been shown to impact self-control and evoke short-term orientation at the expense of long-term planning Mani et al. (2013). Likewise, evaluating the impact of cross-sectional or temporal changes in consumer income/wealth on product choices Dubé et al. (2018) or response to marketing mix (e.g. small price differences Khan et al. (2016) has long been of interest in the marketing literature. In economics, a growing literature examines the impact of negative (e.g. due to unemployment) or positive (e.g stimulus) income changes on spending behavior. Empirical evidence on household responses to financial shocks has challenged fundamental theories such as the Permanent Income Hypothesis and led to a rich and diverse set of alternative models describing behavior and decision-making Kaplan and Violante (2014), Ganong and Noel (2019)).

Consumer response to income shocks also have important policy implications. For example, impact ('multiplier effect') of stimulus payments such as as those analyzed in this paper, critically depend on money circulating back through the economy. To this end, we present early estimates on consumer propensity to spend the stimulus receipts in the context of COVID-19 pandemic. Our results suggest that between 43% (homogeneous model) and 50% (heterogeneous model) of the stimulus was spent over a short window of few days. Our estimates suggest that in our sample, the stimulus ($137 million) was responsible for between $59 million and $69 million increase in spending. This represents a 2.6% to 3% increase in aggregate spending between April 10 and April 17 due to the stimulus.

Our results show that a large proportion of the money is allocated to financial transactions (particularly cash withdrawal) and non-durable necessities like grocery and utilities. We observe systematic differences based on geographical locations, with MPC being significantly larger in metropolitan Zip codes with high living expenses. Our findings question the rationale of CARES act that provides equal payments to all qualifying households without considering cost of living differences across the country. A cost-of-living adjusted payment policy is also likely to have larger multiplier effect and be more effective in stimulating economic recovery. Household expenditures are 50% higher in densely populated areas, and therefore stimulus payment are more effective in increasing spending.

There are many caveats to our analysis and directions for future research. First, our conclusions come with important caution that results are based on debit card purchases from relatively young, and middle- to low-income households, not a representative sample of US population. Many of the findings reported may be specific to this economically vulnerable sub-population, e.g., Hacioglu Hoke et al. (2020) show that UK lower income household had a negative saving rate during this time. In addition, data are aggregated to Zip code level and usual caveats apply. Individual credit card transactions, such as those utilized in Ganong and Noel (2019), as well as release of nationally representative Consumer Expenditure Surveys capturing the episode (as used by Parker et al. (2013) study 2008 Financial crises) would certainly improve our longer term understanding of consumption changes induced by COVID-19 lock down and the impact of stimulus payments. Finally, updates of scanner data from IRI and Nielsen would allow examination of hoarding behavior leading up to lockdown and consumption response to stimulus payments at micro household level.

REFERENCES

116TH CONGRESS (2020): "H.R.748 - CARES Act," https://www.congress.gov/bill/116th-congress/house-bill/748/text.

AGARWAL, S., C. LIU, AND N. S. SOULELES (2007): "The reaction of consumer spending and debt to tax rebates—evidence from consumer credit data," *Journal of political Economy*, 115, 986–1019.

ALLCOTT, H., L. BOXELL, J. CONWAY, M. GENTZKOW, M. THALER, AND D. Y. YANG (2020): "Polarization and public health: Partisan differences in social distancing during the Coronavirus pandemic," *NBER Working Paper*.

ATHEY, S., M. BAYATI, N. DOUDCHENKO, G. IMBENS, AND K. KHOSRAVI (2018): "Matrix completion methods for causal panel data models," Tech. rep., National Bureau of Economic Research.

BAKER, S. R., R. A. FARROKHNIA, S. MEYER, M. PAGEL, AND C. YANNELIS (2020): "Income, Liquidity, and the Consumption Response to the 2020 Economic Stimulus Payments," Tech. rep., National Bureau of Economic Research.

BRODA, C. AND J. A. PARKER (2014): "The economic stimulus payments of 2008 and the aggregate demand for consumption," *Journal of Monetary Economics*, 68, S20–S36.

CARROLL, C. D. (2012): "Implications of wealth heterogeneity for macroeconomics," Tech. rep., Working Paper.

CHEN, F., X. LIU, D. PROSERPIO, AND I. TRONCOSO (2020): "Product2Vec: Understanding Product-Level Competition Using Representation Learning," *Available at SSRN*.

COIBION, O., Y. GORODNICHENKO, AND M. WEBER (2020): "Labor markets during the covid-19 crisis: A preliminary view," Tech. rep., National Bureau of Economic Research.

DU, R., Y. ZHONG, H. NAIR, B. CUI, AND R. SHOU (2019): "Causally Driven Incremental Multi Touch Attribution Using a Recurrent Neural Network," *arXiv preprint arXiv:1902.00215*.

DUBÉ, J.-P., G. J. HITSCH, AND P. E. ROSSI (2018): "Income and wealth effects on private-label demand: evidence from the great recession," *Marketing Science*, 37, 22–53.

FARRELL, M. H., T. LIANG, AND S. MISRA (2018): "Deep neural networks for estimation and inference: Application to causal effects and other semiparametric estimands," *arXiv preprint arXiv:1809.09953*.

GANONG, P. AND P. NOEL (2019): "Consumer spending during unemployment: Positive and normative implications," *American economic review*, 109, 2383–2424.

HACIOGLU HOKE, S., D. R. KÄNZIG, AND P. SURICO (2020): "Consumption in the Time of Covid-19: Evidence from UK Transaction Data," .

IRS.GOV (2020): "159 million Economic Impact Payments processed," https://www.irs.gov/newsroom/159-million-economic-impact-payments-processed-low-income-people-and-othe

[Online; accessed 15-June-2020].

JAPPELLI, T. AND L. PISTAFERRI (2010): "The consumption response to income changes," *Annu. Rev. Econ.*, 2, 479–506.

JOHNSON, D. S., J. A. PARKER, AND N. S. SOULELES (2006): "Household Expenditure and the Income Tax Rebates of 2001," *American Economic Review*, 96, 1589–1610.

KAPLAN, G., B. MOLL, AND G. L. VIOLANTE (2018): "Monetary policy according to HANK," *American Economic Review*, 108, 697–743.

KAPLAN, G. AND G. L. VIOLANTE (2014): "A model of the consumption response to fiscal stimulus payments," *Econometrica*, 82, 1199–1239.

KHAN, R., K. MISRA, AND V. SINGH (2016): "Will a fat tax work?" *Marketing science*, 35, 10–26.

MANI, A., S. MULLAINATHAN, E. SHAFIR, AND J. ZHAO (2013): "Poverty impedes cognitive function," *science*, 341, 976–980.

MIKOLOV, T., K. CHEN, G. CORRADO, AND J. DEAN (2013): "Efficient estimation of word representations in vector space," *arXiv preprint arXiv:1301.3781*.

MISRA, K. AND P. SURICO (2014): "Consumption, income changes, and heterogeneity: Evidence from two fiscal stimulus programs," *American Economic Journal: Macroeconomics*, 6, 84–106.

NAIR, V. AND G. E. HINTON (2010): "Rectified linear units improve restricted boltzmann machines," in *Proceedings of the 27th international conference on machine learning (ICML-10)*, 807–814.

PARKER, J. A., N. S. SOULELES, D. S. JOHNSON, AND R. MCCLELLAND (2013): "Consumer spending and the economic stimulus payments of 2008," *American Economic Review*, 103, 2530–53.

PRESIDENT COUNCIL OF ECONOMIC ADVISORS (2003): "The Economic Impact of the American Recovery and Reinvestment Act of 2009 First Quarterly Report," https://obamawhitehouse.archives.gov/administration/eop/cea/Economic-Impact.

SCHMIDHUBER, J. (2015): "Deep learning in neural networks: An overview," *Neural networks*, 61, 85–117.

SHAHAM, U., A. CLONINGER, AND R. R. COIFMAN (2018): "Provable approximation properties for deep neural networks," *Applied and Computational Harmonic Analysis*, 44, 537–557.

SHAPIRO, M. D. AND J. SLEMROD (2003): "Consumer response to tax rebates," *American Economic Review*, 93, 381–396.

——— (2009): "Did the 2008 tax rebates stimulate spending?" *American Economic Review*, 99, 374–79.

Figures

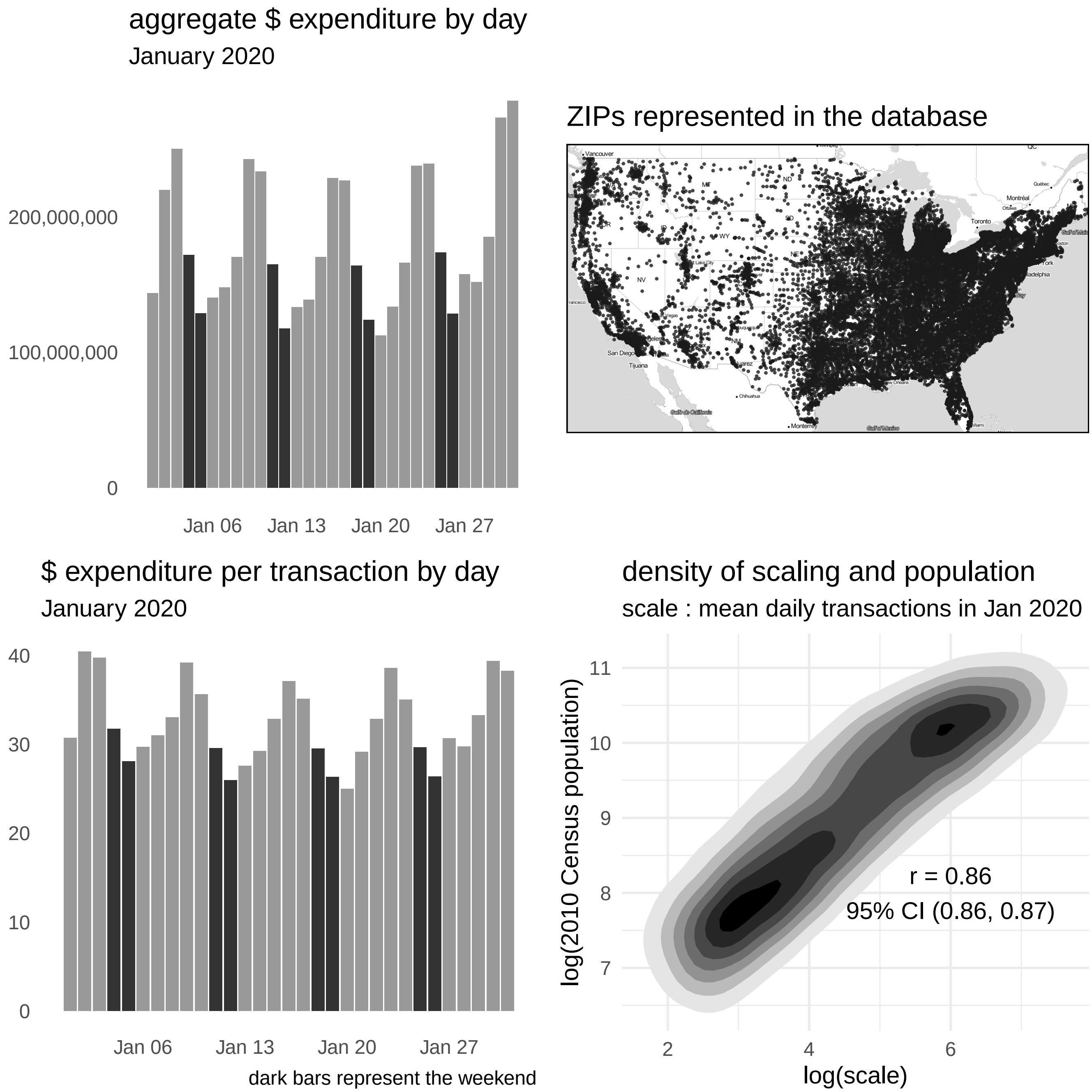
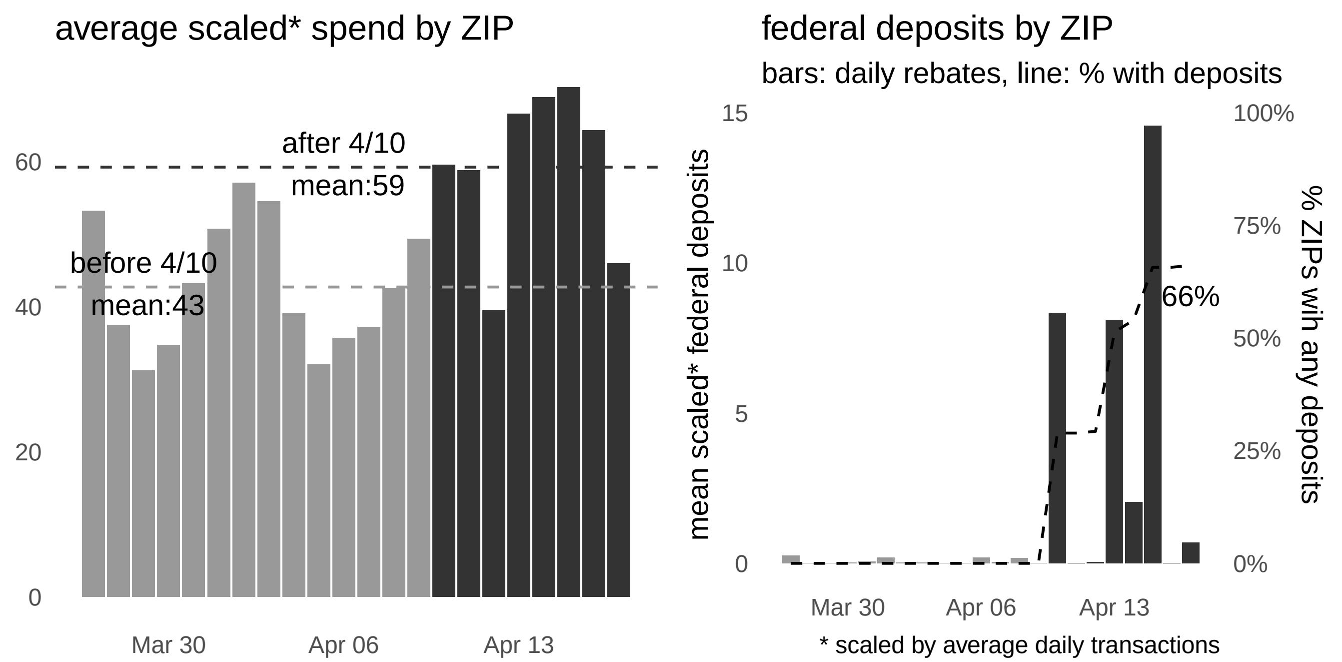
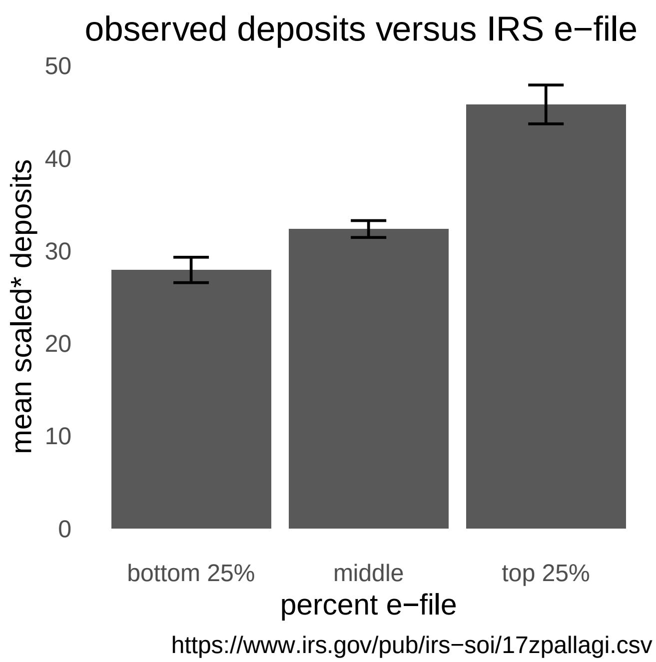


FIGURE 1. Coverage of the spending data: Top (bottom) right chart shows the total spend per day ($ spend per transaction) across all Zip codes in January 2020. The top right chart show the coverage of Zip codes in the data sample. In our data we scale the Zip codes code level sales with the number to transactions in January. The chart on the bottom right shows the scaling for each Zip codes is highly correlated of the Zip codes population.





demographic differences

	No	Stimulus	Some	Stimulus
	Mean	S.D	Mean	S.D
med income ($K)	68	31	57	21
med rent	987	479	925	330
population (K)	62	81	180	160
pop density	1126	5061	2101	6088
unemployed	8	5	10	5
urban	35	42	62	40

FIGURE 2. data for spending and stimulus: Top row shows the average scaled spend per day across all Zip codes and shows that aggregate spending increased after April 10th. The top right shows the distribution of stimulus. The dotted line shows the % of Zip codes with stimulus. At the end of our data individuals in 66% of Zip codes received some stimulus payments. The bottom row considers differences between Zip codes that received stimulus in our sample before April 17th. The chart on left compares the stimulus with quantities of IRS e-filings across Zip codes and the table on right shows demographic differences between Zip codes that received any stimulus versus Zip codes that did not receive stimulus in our sample before April 17th.

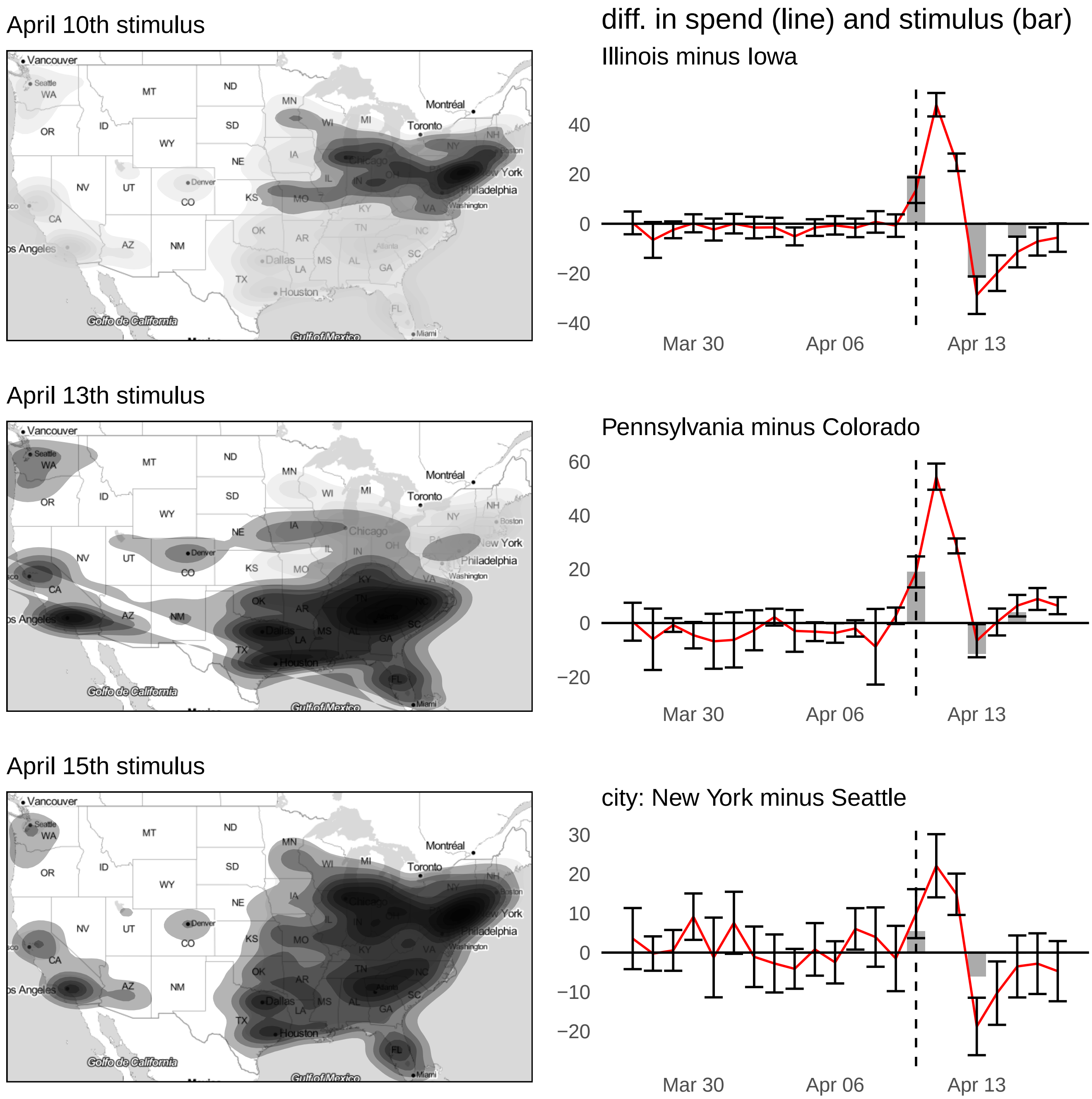


FIGURE 3. distribution of stimulus: the charts on the left show the stimulus in the 3 days of distribution. Charts on the right compare scaled spend and stimulus average by Zip across states or cities.

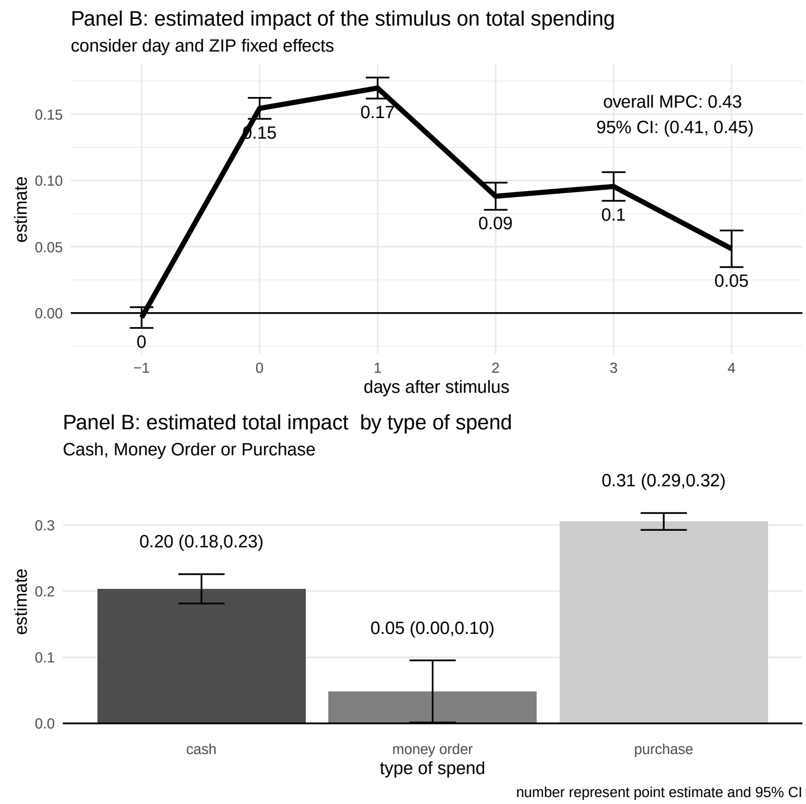


FIGURE 4. main results: Panel A shows the estimates from a statistical model controlling for Zip and state-day fixed effects. This shows an increase in the day of the stimulus and this extend to 4 days after receipt. Panel B show that overall impact of stimulus payments across type of spend - either cash, money order or purchase (all other).

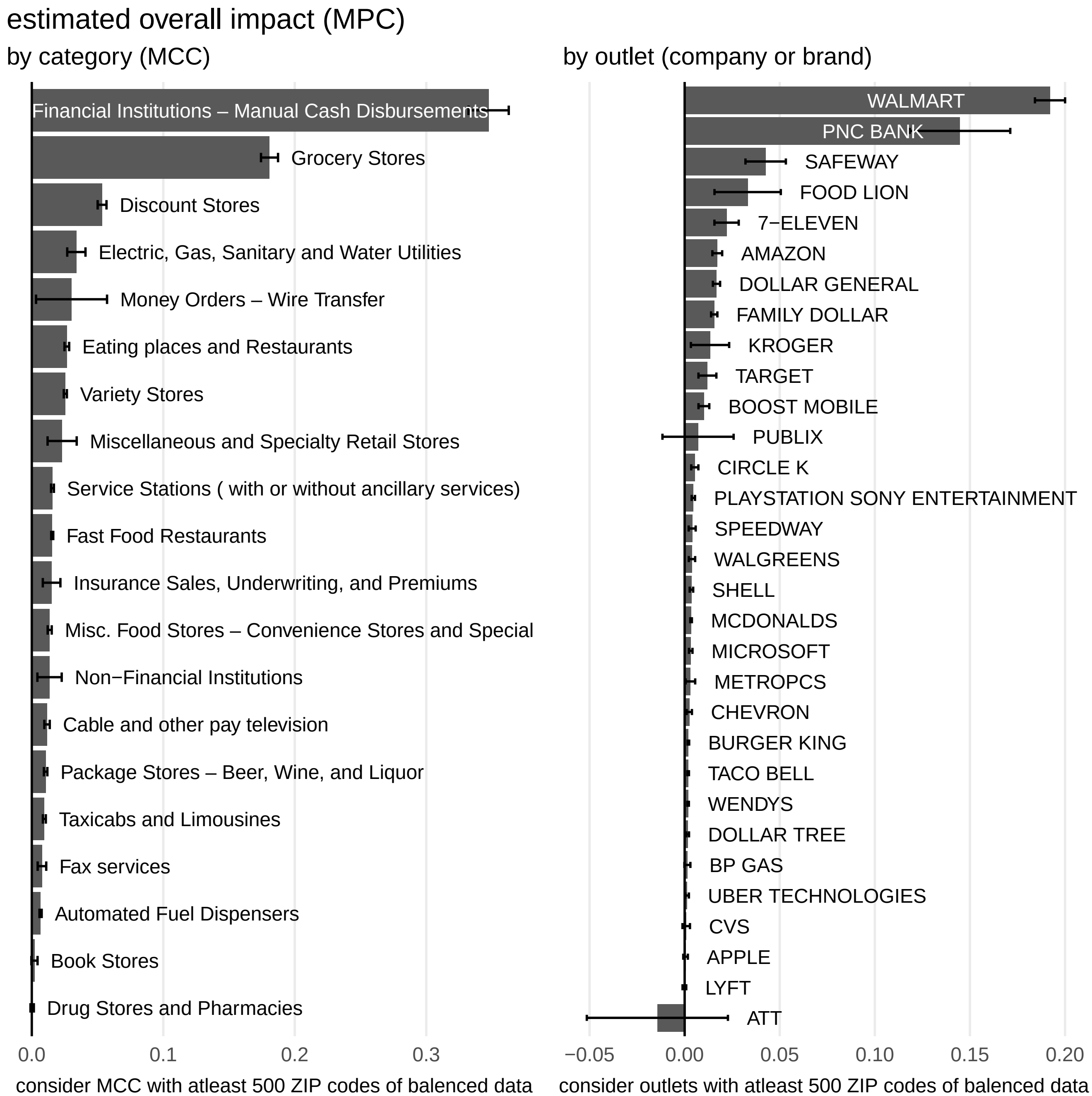


FIGURE 5. MPC by category: estimated impact of the stimulus for each Merchant Category Code (MCC) [left] or merchants [right]

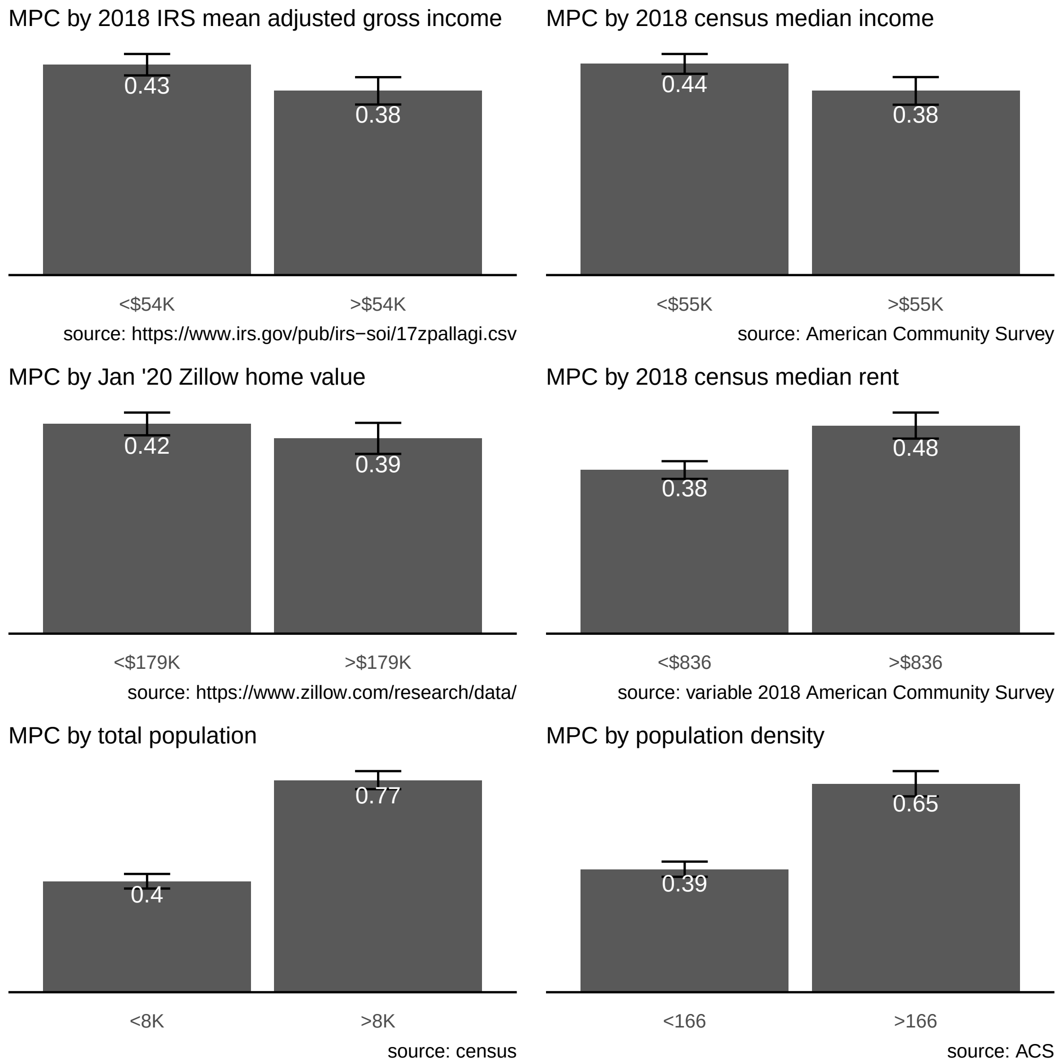


FIGURE 6. MPC by median split of Zip code income, home value and population: Model estimated separately for each subsample for each chart. The top row considers income: left consider IRS adjusted gross income and right consider median income from the Census. The middle row consider home values (spend) left consider average Zillow home value and right consider median rent based on the Census. The bottom row consider population either as total population or density of population (population per square mile) from the Census.

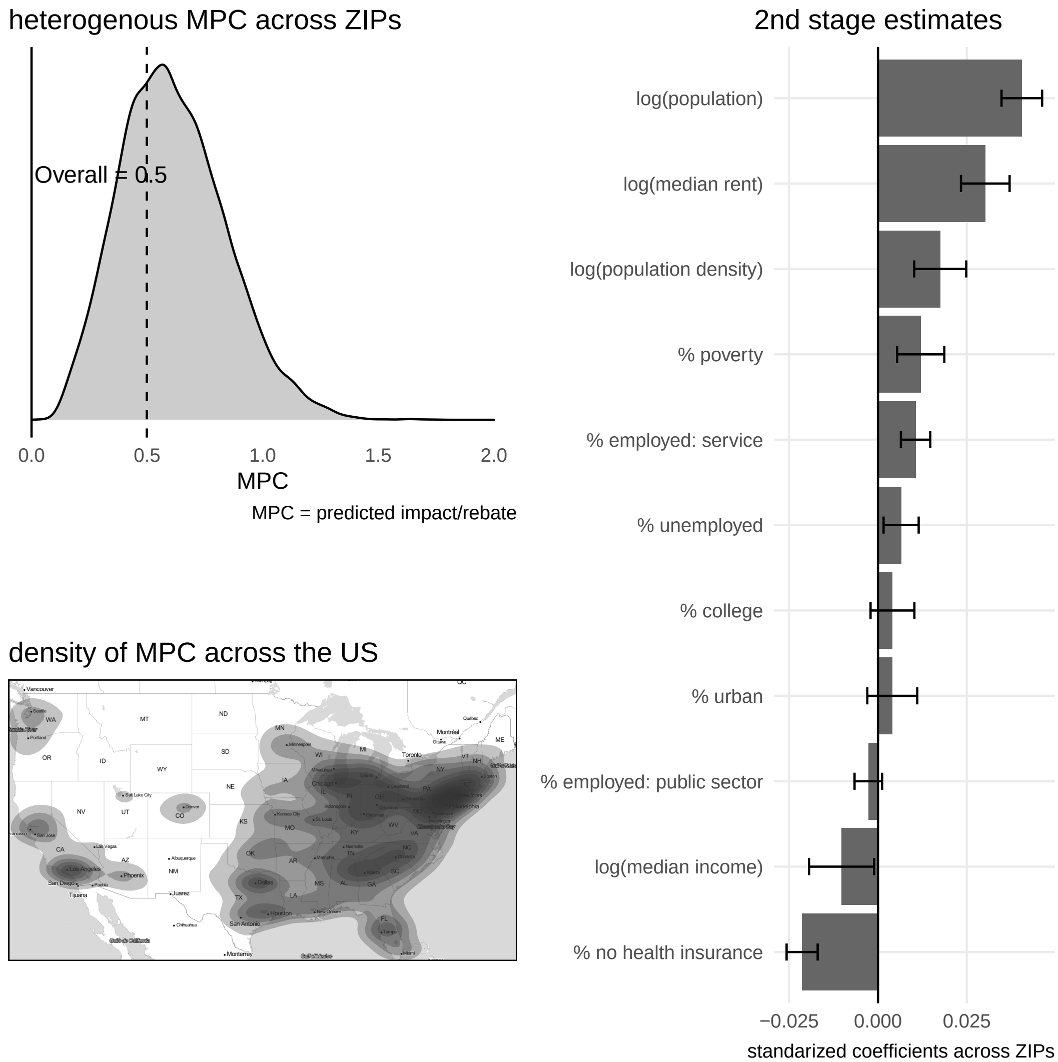


FIGURE 7. Heterogeneous inferred MPC: Charts represent the estimated treatment effects using the Deep Learning model. The chart on the top left consider the distribution of the estimated MPC by Zip code. MPC is calculated for each Zip code (and overall) as predicted spend due to stimulus divided by total stimulus. The horizontal line represents the inferred overall MPC. The chart on the bottom left considers the geographic distribution of MPCs, darker colors represent higher MPCs. The chart on the right displays the coefficients of a second stage regression to understand the drivers of the heterogeneity across Zip codes