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Consumption Spending during the COVID-19 Pandemic

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We use a novel empirical approach to decompose the impact of different economic, demographic, and COVID-19-related factors (such as lockdowns, case counts, and vaccination rates) on consumption spending on a week-by-week basis during the pandemic. This allows us to study how demographic and economic groups were differentially affected by the pandemic while crucially controlling for other factors. Our results imply that Hispanic and college-educated populations showed particularly large and persistent declines in relative spending. We also compute the relative importance of factors in driving consumption spending differences. We find that spending differences were persistently driven by political affiliation, age, education, and COVID factors. At a more disaggregated level of spending, political affiliation and COVID factors had a much stronger and more persistent impact on spending that was social-distancing sensitive (SDS), such as travel and restaurant dining, than on non-SDS spending.

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1 Introduction

The COVID-19 pandemic dramatically affected everyday life beginning in March 2020. It had enormous economic and public health effects as countries recorded unprecedented rates of unemployment, sharp contractions in output, and massive death counts. Recent studies highlight the concentration of these negative effects among certain disadvantaged groups as well as unequal recoveries among these groups. For example, Alon et al. (2020) emphasize the larger decrease in labor force participation rates among women compared with men during the pandemic; Abedi et al. (2020) show that counties with higher poverty rates suffered worse health outcomes from the virus; Couch, Fairlie, and Xu (2020) document a disproportionately higher rise in unemployment among Hispanic Americans compared with Caucasian Americans.

An important aspect of the economic effect of COVID-19 is on consumption spending. Blundell and Preston (1998) and Krueger and Perri (2006) show that the distribution of consumption expenditures is a key measure of household well-being. This motivates our two key questions. One, how did a range of demographic, economic, and COVID-related factors affect consumption spending? Two, which of these factors were most important in explaining consumption differences between geographic areas during the pandemic? During the pandemic, the situation constantly and swiftly changed, and any comprehensive answer to these questions needs to take this dynamic nature of the pandemic into account.

In this paper, we use high-frequency credit/debit card spending data to determine how different factors affected consumption spending during the pandemic and quantify the importance of these factors in explaining consumption differences between areas on a week-by-week basis. We are particularly interested in analyzing the impact of demographic, economic, and COVID-19–related factors on consumption spending. Our demographic factors include age, political affiliation, ruralness, race, ethnicity, and gender. Our economic factors include education, income, and occupation. Our COVID factors include COVID-19 case counts, restrictions such as lockdowns/containment measures, and vaccination rates. Crucially, we assess the impact of each of these factors while holding other factors constant. This allows us to get closer to a causal interpretation.

Our analysis employs a novel empirical approach to high-frequency spending data. First, we conduct regressions of Zip Code Tabulation Area (ZCTA)–level consumption spending on a range of different factors.[1] We allow for a differential week-by-week impact of each factor on ZCTA-level consumption spending. This is necessary to identify the effects of demographic and economic variables that are fixed across weeks. For example, we capture how having a higher share of college-educated individuals affects ZCTA-level spending differentially in each week of the pandemic. Second, we use a Fields' decomposition to assess which factors are most important in explaining differences in consumption spending between ZCTAs. We conduct this analysis for each week of the pandemic and are therefore able to assess how the importance of each factor in explaining consumption differences changed through every week of the pandemic.

We have four main findings. First, there were disparities in consumption spending during the pandemic along several demographic and economic dimensions. These disparities were starker at the start of the pandemic than later on. Total spending by ZCTAs with a higher share of

[1] ZCTAs are geographical measures developed by the Census Bureau that approximately correspond to Zip codes.

Republican voters relative to Democratic voters rose at the start of the pandemic (controlling for other factors), while relative spending by ZCTAs with a higher share of older people fell at the start of the pandemic. There were also differences along racial and ethnic lines. Spending by ZCTAs with a higher share of Blacks relative to Caucasians dropped at the start of the pandemic before recovering. Spending by ZCTAs with a higher share of Asian Americans and Hispanics relative to Caucasians and non-Hispanics, respectively, fell at the start of the pandemic, but still had not fully recovered as of May 2021. ZCTAs with higher-income, higher-educated people spent less on consumption than ZCTAs with lower-income, less-educated people during the pandemic, and the relative spending of the higher-educated group still had not recovered as of May 2021. Therefore, overall we find evidence that the pandemic differentially negatively affected some groups more than others, but the situation seemed to improve over time.

Second, demographic, economic, and COVID-19–related factors were all important in explaining consumption differences at various points during the pandemic, albeit to varying degrees in different weeks. Political affiliation was a particularly important factor in driving consumption differences during the pandemic. Race and ethnicity played a key role in driving consumption dynamics in the early part of the pandemic but played a much smaller role as the pandemic proceeded. Median income and education were particularly important in explaining differences in consumption later on in the pandemic and once vaccinations began. COVID case counts played an important role in explaining consumption patterns earlier in the pandemic, and restrictions particularly explained consumption differences in weeks with stricter lockdowns. COVID vaccinations were an important factor in explaining consumption differences in early 2021.

Third, there was heterogeneity in the response of different types of spending to our factors. We decompose total spending into social-distancing-sensitive (SDS) spending and non-SDS spending using credit card spending categories. By SDS spending, we mean spending on categories such as restaurant dining and travel that were very sensitive to social distancing. Unsurprisingly, we see that there were much larger and more persistent declines in SDS spending compared with non-SDS spending. While political-affiliation-based and median-income-based differences appear to have recovered in aggregate spending, they persisted for SDS spending even as of May 2021. Most factors more strongly explain cross-ZCTA differences in SDS than non-SDS spending, which makes sense since there is more variation in SDS spending to explain. We observe that political affiliation and COVID–related factors appear to have affected SDS spending particularly strongly relative to non-SDS spending. ZCTAs with a higher share of Republican voters showed higher SDS spending but smaller differences in non-SDS spending relative to predominantly Democratic ZCTAs during the pandemic. Similarly, COVID factors substantially reduced SDS spending but had only limited effects on non-SDS spending.

Fourth, state-level containment policies such as mobility restrictions had a large effect on consumption spending at the start of the pandemic but a small effect later on. This speaks to a key policy question during the pandemic, which was whether localities should impose mobility restrictions to reduce the transmission of COVID-19. A potential major cost of such policies was that they could have further depressed economic outcomes. Therefore, it is important to understand the degree to which restrictions caused lower output. Our approach allows us to decompose the impact of restrictions on consumption spending on a week-by-week basis during the pandemic while controlling for other factors. This finding implies that state-level restrictions did not have large costs in terms of reduced consumption except at the start of the pandemic.[2]

Related Literature

Our paper contributes to two main literatures. First, we contribute to the literature studying the dynamics of consumption spending during the COVID-19 pandemic. Baker et al. (2020) show that there was heterogeneity in spending across demographics such as age and family structure. They conclude that these factors explain a larger degree of the heterogeneity in the ratio of spending to income at the start of the pandemic. In contrast, Chetty et al. (2020) and Cox et al. (2020) consider a longer time frame and find that while spending decreased across all households, high-income households made bigger cuts in spending, and it took a longer time for their spending to recover to its pre-pandemic level. Baker et al. (2020), Chetty et al. (2020), and Alexander and Karger (2020) also analyze different categories of spending and find that the increase in spending at the onset of the pandemic was due to an increase in household and grocery spending, and once the virus began to spread more broadly, spending decreased among "nonessential" goods and services (such as restaurants, retail, and travel). The novel contribution of our paper is that we control for a large set of demographic, economic, and COVID factors at the same time and allow these factors to have a differential effect over time. This allows us to estimate an approximately causal impact as well as the relative importance of each factor in explaining aggregate and disaggregated consumption spending differences during the pandemic on a week-by-week basis.

Second, we contribute to the debate on whether the decrease in consumption spending during the pandemic was due to the virus itself or the policies (such as lockdowns) that were put in place to counteract the virus. Coibion, Gorodnichenko, and Weber (2020) find that lockdown measures account for a majority of the decrease in spending that occurred during the pandemic. However, Goolsbee and Syverson (2020) argue that while stay-at-home orders played a significant role in shifting spending from "nonessential" to "essential" goods and services, they do not account for decreases in aggregate economic activity—this was due to fear of the pandemic itself. Chetty et al. (2020) come to a similar conclusion, finding that the reopening of states had only a small impact on returning spending to pre-pandemic levels. Chen, Wenlan, and Qiang (2021) find that in a sample of Chinese cities during the initial lockdown period, day-to-day changes in COVID-19 case counts negatively impacted spending, even after the authors control for lockdown measures. Our decomposition allows us to assess the impact of lockdowns while controlling for other factors that explain spending. Our results imply that state-level lockdowns had a large effect on consumption at the start of the pandemic but only a small effect as the pandemic continued.

The rest of the paper proceeds as follows. Section 2 discusses the data used in the analysis. Section 3 discusses our empirical approach. Section 4 discusses the impact of demographic, economic, and COVID factors on consumption spending through various phases of the pandemic. Section 5 quantifies the relative contribution of these factors in explaining consumption differences across ZCTAs during the various phases. Section 6 concludes.

[2]Our consumption data are limited to card spending, and our restrictions data do not allow us to speak to the relative importance of sub-state-level restrictions.

2 Data

In analyzing the effect of demographic and economic factors on consumption spending during the pandemic, we use information from two main sources: high-frequency card spending data from Affinity Data Solutions (Affinity) and survey results from the American Community Survey (ACS). We supplement these sources with three sources of COVID-19–related information: data on vaccines from the Centers for Disease Control and Prevention (CDC), case counts from the *New York Times* (NYT), and a measure of restrictions from IHS Markit/Macroeconomic Advisers.

Affinity Affinity has relationships with many banks and financial institutions for marketing purposes, and as part of this arrangement Affinity has access to detailed information on credit/debit card transactions from these institutions. The Affinity data measure activity on a sample of 40 million active cards, capturing 6 to 9 percent of all card transactions in the United States.[3] These data are aggregated and available at various levels of geographic and spending-category disaggregations. In particular, we have weekly data on spending at the Zip-code level by merchant classification code (MCC)—the worldwide classification system used by Visa and other credit card providers that assigns a transaction category to each merchant. The sample is fairly representative if slightly weighted toward the relatively affluent.[4] However, our approach looks at the consumption differences across groups rather than in the aggregate, so the only impact of imperfect representation is a lower significance of results for groups with smaller quantities of data, and low significance does not appear to be a problem for our analysis.

Since we observe only high-frequency card spending, we miss cash transactions and other transactions not involving cards, such as payments for health procedures that go directly through the insurance company, mortgage/rent payments, cash payments to contractors, or auto purchases through loans. One could think of the data set as providing information on spending on retail (except autos), some service expenditures, and some durable expenditures, such as refrigerators and recreation equipment.

ACS While the Affinity data provide weekly Zip-code-level card spending, there is no demographic or economic information in this data set. For this reason, we combine the data with demographic and economic information from the 2014–2018 ACS 5-year sample. The lowest level of geography that is easily compatible with the Affinity data and for which demographic and economic information is available in the ACS is a Zip Code Tabulation Area (ZCTA).[5] Thus,

[3]According to our back-of-the-envelope calculations based on the work of Kumar and O'Brien (2019), this represents 3.06 to 4.59 percent of total transactions in the United States.

[4]In terms of geography, the sample is fairly representative, with the Middle Atlantic states being slightly under-represented. Comparing the share of spending by region in the Affinity data with the share in the 2017 Economic Census data shows that the Middle Atlantic states account for 14.58 percent of spending in the Census and 8.29 percent in Affinity. Other states seem to be represented approximately correctly. In terms of age, conditional on knowing ages and adjusting for the number of unique cards for a given age group in a spending category at a point in time, roughly 17 percent of the sample is 18 to 34 years old, 40 percent is 35 to 54, and 42 percent is 55 or older. In terms of income, 5 percent of the sample annually earns \$0 to \$35,000, 50 percent earns \$35,000 to \$85,000, and 45 percent earns more than \$85,000. Thus, the sample comprises a relatively affluent banked population. We thank Daniel Cooper for providing these details on the sample representativeness of Affinity.

[5]"Zip code" is a trademark of the U.S. Postal Service, whereas a ZCTA is the U.S. Census Bureau's measure of

we convert the Zip-code-level spending data from Affinity to the ZCTA level using a crosswalk provided by the U.S. Census Bureau.

We obtain the ZCTA-level demographic and economic data on age, gender, race, ethnicity, median income, and educational attainment from the ACS sample. For employment, the most precise measure of occupation available at the ZCTA level is SOC major groups.[6] The major groups are defined by a two-digit code and sort an occupation into one of 22 categories. These categories include occupations such as "personal care and service," "legal," and "protective services." We supplement this information with the percentage of the ZCTA population living in rural/urban regions from the 2010 U.S. Census and with county-level results from the 2016 presidential election from the MIT Election Lab.

COVID-19 data We obtain the ZCTA-level COVID-19 information from a variety of sources. We obtain the percentage of the ZCTA's county population (over age 18) that is fully vaccinated from the CDC (using state-level data when county-level data are not available), the weekly average COVID-19 case count (per 100,000) of the ZCTA's county from the NYT github, and the containment index of the ZCTA's state from IHS Markit/Macroeconomic Advisers.

3 Empirical Approach

Our empirical strategy in decomposing the role of different factors exploits the variation in the pre-pandemic demographic and economic composition of ZCTAs to estimate the effect of each factor on consumption spending during each week of the pandemic. We capture the time-varying impact of time-invariant variables by allowing for the impact of these variables to vary on a week-by-week basis. For consistency, we also allow for the impact of the COVID factors (which are not time invariant) to vary across weeks.

In simple terms, our empirical approach is to examine how the consumption spending of a ZCTA with a higher share of a given factor compares with a similar ZCTA with a lower share of that factor during each week of the pandemic. Equation (1) summarizes our empirical approach. Observations are compared by ZCTA, which is represented by z, and by week, which is represented by t.[7] The dependent variable is the five-week moving average of the log of spending by consumers residing in a ZCTA z in week t. We use the five-week moving average to reduce the noise in our high-frequency data. We take the log of spending to look at the percentage change in spending across ZCTAs so that spending differences in larger ZCTAs do not dwarf spending differences in smaller ZCTAs. We also include ZCTA fixed effects (α_z) and weekly time fixed effects (γ_t) in all our regressions. To avoid multicollinearity, we omit the week of Jan. 27 through Feb. 2, 2020,

a Zip code. The main difference between them is that while Zip codes can correspond to standalone buildings and often change over time, ZCTAs are slightly less disaggregated and tend to be stable over time. There are 42,000 Zip codes versus 32,000 ZCTAs in the United States.

[6] The ACS classifies occupations using 2018 Census Occupation Codes (OCC), which are derived from the Office of Management and Budget's Standard Occupation Classification (SOC) codes. SOC codes classify occupations on four different levels, with "major group" being the broadest and "detailed occupation" being the narrowest.

[7] To prevent the results from being driven by large changes in the number of credit/debit cards within a ZCTA (due to, for example, consumers moving), we exclude ZCTAs for which the absolute log difference between the average number of cards used in January 2020 and the average number used in January 2021 is greater than 0.5.

which then becomes the baseline week relative to which all the coefficients are indexed.

$$
\begin{aligned}
log\_spending_{z,t} = \alpha_z + \sum_{t=1}^{T-1} \gamma_t \times week\_dummy_t + \sum_{j=1}^{J-1} \sum_{t=1}^{T-1} \beta_{j,t} \times fixedfactor_z^j \times week\_dummy_t \\
+ \sum_{j=1}^{J-1} \sum_{t=t_j^0}^{T} \chi_{j,t} \times covidfactor_{z,t}^j \times week\_dummy_t + u_{z,t}
\end{aligned} \tag{1}
$$

$fixedfactor_z$ refers to the ZCTA-level demographic and economic controls that are time invariant. The demographic controls include the share of the ZCTA population over age 65 and the share aged 18 to 29; the share of the ZCTA that identifies as male; the shares of the ZCTA that identify as Black, Asian American, multiple races, and other non-Caucasian races; the share of the ZCTA that identifies as Hispanic; the share of the ZCTA that is in a rural area; and the share of the ZCTA's county that voted for the Republican Party in the 2016 presidential election and the share that voted for a third party. The economic controls include the median income of the ZCTA, the share of the ZCTA population with a college degree, and the share of the ZCTA employed in the different two-digit SOC groups. We include these fixed factors interacted with the week dummies to capture consumption spending of various demographic and economic groups differing from each other during each week of the pandemic. For example, this approach would capture older people choosing to stay at home more and spending less relative to younger people in response to the health risks posed by the pandemic, and it would capture the varying degrees to which they did so during the pandemic.

For all demographic and economic factors that we consider (except median income), we need to exclude a dummy variable baseline category to avoid multicollinearity. The coefficients are relative to this baseline category. For example, we include controls for the shares of the population that is aged under 30 and over 65, but we have to exclude a control for the share of the population that is 30 to 64 years old. Therefore, the coefficient for the spending of the over-65 population reflects the impact of having more over-65s and a corresponding fall in the share of the population that is 30 to 64. This is true for all demographic and economic factors (except median income). The baseline categories are age group, "share of the ZCTA population aged 30 to 64 years"; gender group, "share of the ZCTA that identifies as female"; race group, "share of the ZCTA that identifies as Caucasian"; rural group, "share of the ZCTA that is in an urban area"; political group, "share of the ZCTA's county that voted for the Democratic Party in the 2016 presidential election"; education group, "share of the ZCTA without a college degree"; and occupation group, "protective services," which include occupations such as correctional officers, firefighters, and police.[8] We normalize each fixed factor by its standard deviation before interacting it with the week dummies. Therefore, the $\beta_{j,t}$ coefficient on $(fixedfactor_z^j \times week\_dummy_t)$ represents the percentage increase in the consumption of a ZCTA with a one standard deviation (s.d.) higher share of fixed factor j and a corresponding lower share of the omitted group of the fixed factor in week t relative to the baseline week (Jan. 27 through Feb. 2, 2020).

[8] The reason we use "protective services" as our omitted category is because it has a fairly average education and income level compared with other occupations.

We also control for ZCTA-relevant COVID factors, $covidfactor_{z,t}$, interacted with the week dummies. These factors include the share of the ZCTA's county that is fully vaccinated, the weekly COVID-19 case count (per 100,000) for the ZCTA's county (or the ZCTA's state when the county-level data are unavailable), and the COVID-19–related restrictions captured by the containment index of the ZCTA's state.[9] Unlike the fixed factors, these COVID factors vary over time. However, we also interact them with week dummies to capture the fact that they may affect spending differently during each week of the pandemic and to maintain a consistent approach. For example, COVID-19 case counts may have had a larger negative impact on spending at the start of the pandemic when there was less of an understanding of the virus transmission and greater fear of hospitals reaching capacity. Since $covidfactor_{z,t}$ is not absorbed by the ZCTA fixed effect, we do not need to omit a baseline week dummy-COVID factor interaction unlike for the fixed factors. As we did for the fixed factors, we normalize the vaccination share and case count measures by their standard deviation (by week) across ZCTAs before interacting it with the week dummies. We normalize by week because this allows for the dispersion of these variables to have a differential impact. This is helpful, for example, because at the start of the pandemic a small rise in case counts in an area was likely to have had a differential (presumably larger) impact on consumption compared with later in the pandemic. We do not normalize the restrictions by week since we want to compare the common effect of restrictions throughout the pandemic. Therefore, the $\chi_{j,t}$ coefficient on $(covidfactor^{j}_{z,t} \times week\_dummy_t)$ represents the percentage increase in the consumption of a ZCTA with a one s.d. (one p.p.) higher share of COVID cases/vaccines (restrictions) in week t relative to the baseline week (Jan. 27 through Feb. 2, 2020).

In addition to analyzing overall spending dynamics, we also estimate the impact of the various factors on two separate disaggregated categories of spending: social-distancing-sensitive (SDS) and non-social-distancing-sensitive (non-SDS). This is estimated by replacing aggregate spending in equation (1) with disaggregated spending. SDS spending comprises "nonessential" goods and services that required close proximity between people and was likely most impacted by lockdown measures. This includes spending on leisure, transportation, food-out, and beauty/massage. Non-SDS spending includes spending on grocery store items, utilities, retail, and all other spending. These two categories provide a framework for categorizing all the available consumption spending data.

Affinity allows us to perform this disaggregation by providing a merchant classification code (MCC) associated with each transaction. For each spending category, we select a basket of MCCs that are representative of spending in the category. We then classify these spending categories into SDS or non-SDS spending. To see which MCCs are sorted into which spending categories, please see Appendix C.[10]

[9] We could instead include county or state fixed effects in the regression, but those are highly correlated with our demographic and economic controls, so the impact of these demographic and economic controls could be misattributed to county or state fixed effects.

[10] We thank Daniel Cooper for his help with organizing these spending categories.

4 Results

In this section, we discuss the results of the analysis of the impact of demographic, economic, and COVID factors on spending on a week-by-week basis. We analyze both aggregate spending and disaggregated spending. The results of the total, SDS, and non-SDS spending regressions are presented in columns 1, 2, and 3, respectively, of Figures 1, 2, and 3. We consider demographic, economic, and then COVID factors in the following three subsections.

4.1 Impact of Demographic Factors

The impact of demographic factors on consumption spending during each week of the pandemic is shown in Figure 1.[11] Each column of this figure plots the coefficients estimated from a different regression as described in Section 3. Each row plots the coefficients corresponding to different factors. The y-axis shows the impact of a one standard deviation (s.d.) increase in the factor on spending (total spending in column 1, SDS spending in column 2, non-SDS spending in column 3), while the x-axis shows the date/week. The impact coefficients are re-scaled so that the baseline week (Jan. 27 through Feb 2., 2020) is at 100. It is worth noting that the impact of a factor on total spending does not equal the sum of the impact on SDS and non-SDS spending since we are conducting regressions with log dependent variables, which will emphasize different ZCTAs in each case.

Political Affiliation. Panel (a) shows the impact on consumption spending of a one standard deviation higher share of Republican voters relative to Democratic voters in each week relative to the baseline week. ZCTAs with a higher share of Republican voters spent relatively more earlier in the pandemic, but from July 2020 onward, their aggregate spending was statistically indistinguishable from ZCTAs with a higher share of Democratic voters. The aggregate spending masks heterogeneity in trends between SDS and non-SDS spending. ZCTAs with higher Republican voter shares had relatively higher SDS spending at the onset of the pandemic, and it remained elevated even as of May 2021. On the other hand, they had relatively lower non-SDS spending at the onset of the pandemic, but by May 2021 it had more or less converged with the non-SDS spending of ZCTAs with higher Democratic voter shares. This result is consistent with that of Barrios and Hochberg (2020), who find that Republican counties were less likely to follow social-distancing measures.

Race. Panel (b) shows the impact on consumption spending of a one standard deviation higher Asian American–population share relative to the Caucasian population in each week relative to the baseline week, while panel (c) shows the corresponding relative spending impact of a one standard deviation higher Black-population share. ZCTAs with a higher share of Asian Americans relative to Caucasians spent relatively less during the pandemic. Their aggregate spending trend mirrors their non-SDS spending trend. Their SDS spending was relatively lower until October 2020 but had converged to the level of the SDS spending by ZCTAs with a higher share of Caucasians by

[11] The graphs for gender, rural, multiple/other non-Caucasian race, and third-party political affiliation are relegated to Appendix Figure 5.

May 2021. ZCTAs with a higher share of Blacks relative to Caucasians spent less initially in the pandemic, but their spending began recovering in summer 2020. This is true for both SDS and non-SDS categories. This suggests that there will still some differences in spending across racial groups later in the pandemic, albeit less so than at the onset of the pandemic.

Ethnicity. Panel (d) shows the impact on consumption spending of a one standard deviation higher Hispanic-population share relative to the non-Hispanic population in each week relative to the baseline week. ZCTAs with a higher share of Hispanics relative to Caucasians spent relatively less during the pandemic. The difference was very pronounced early in the pandemic, especially for SDS spending.[12]

Age. Panel (e) shows the impact on consumption spending of a one standard deviation higher older-population share relative to the middle-aged population in each week relative to the baseline week. We see that relative to ZCTAs with a higher share of middle-aged people, ZCTAs with a higher share of older people spent less during the pandemic. We might have expected this difference to recover as vaccination rates increased and the risks of catching the virus, which tends to have worse health outcomes for older people, diminished. A deeper look into disaggregated spending reveals that while SDS spending does seem to have risen relatively for older ZCTAs in line with this explanation, non-SDS spending actually had fallen relatively as of May 2021. This could be because large stimulus payments prompted credit-constrained households to spend more on non-SDS items and older people are less likely to be credit constrained.

Panel (f) shows the corresponding relative impact on consumption spending of a one standard deviation higher younger-population share relative to the middle-aged. Younger ZCTAs had much higher SDS spending relative to middle-aged ZCTAs during the pandemic, which is in line with their perceived lower cautiousness given their lower risk of significant negative health outcomes from COVID-19. They had similar or slightly less non-SDS relative spending, and overall the impact on total spending was therefore similar to what it was for the middle-aged.

Overall, we find that there were significant differences in spending across demographic groups at the start of the pandemic, but these differences diminished as the pandemic continued. The populations that continued to show relatively lower total spending are Asian Americans, Hispanics, and older people. The relative spending of the Black population recovered to pre-pandemic levels, and the spending gap between the Hispanic and non-Hispanic population decreased. Therefore, racial and ethnic inequities were still issues later in the pandemic, but less so than they were at the onset. We also find that aggregated spending sometimes masks the trends in disaggregated spending. This is particularly true for political affiliation, where Republicans spent statistically similarly to Democrats in the aggregate, but this was driven by opposing trends in SDS and non-SDS spending—Republicans spent persistently more on SDS consumption and persistently less on non-SDS consumption.

[12] The impact of Hispanics may potentially be capturing the impact of urbanness as Hispanics tend to live in urban areas and our control of the ZCTA's urbanness is not perfect.

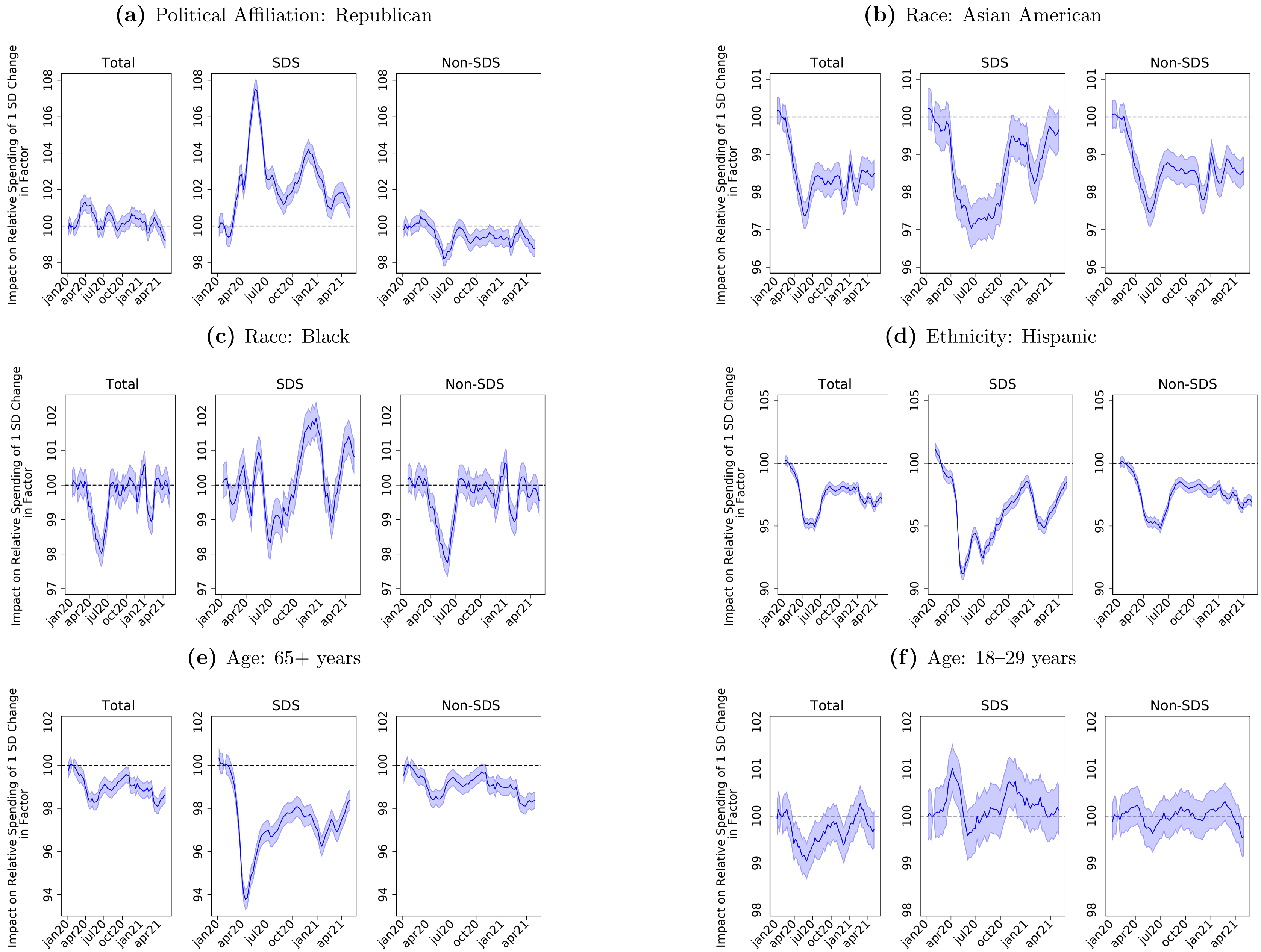


Figure 1. Demographic Factors: Aggregate versus SDS versus Non-SDS Spending.

Sources: Affinity Data Solutions; MIT Election Lab; American Community Survey.

4.2 Impact of Economic Factors

Next, we discuss the impact of economic factors on consumption spending during each week of the pandemic. This is shown in Figure 2. The columns of this figure plot the estimated coefficients from the same three regressions that produced the impact estimates of the demographic factors—column 1 for total spending, column 2 for SDS spending, and column 3 for non-SDS spending. As in Figure 1, each column corresponds to a level of spending, and each row corresponds to an economic factor. The y-axis shows the impact of a one standard deviation increase in the "row" factor on the relative "column" spending, while the x-axis shows the date/week. The impact coefficients are re-scaled so that the baseline week is at 100.

Education. Panel (a) shows the impact on consumption spending of a one standard deviation higher college-educated-population share relative to the non-college-educated population in each week relative to the baseline week. ZCTAs with a higher share of college-educated people relative to the non-college-educated spent relatively less during the pandemic. The effect was substantial relative to other factors. In terms of aggregate spending, the impact was very persistent and comparable to the start of the pandemic. However, most of the spending differences were due to SDS spending—non-SDS spending differences between ZCTAs converged to their pre-pandemic level pretty quickly after the pandemic began.

Income. Panel (b) shows the impact on consumption spending of a one standard deviation higher median income in each week relative to the baseline week. ZCTAs with a higher median income had relatively lower aggregate spending at the onset of the pandemic, but it had mostly recovered by July 2020. There was then a seasonal spike around Christmas time followed by another dip in relative spending. The bulk of the decline in relative spending as well as its persistence was due to SDS rather than non-SDS spending. The relative decline in SDS spending was also very persistent but had recovered somewhat by January 2021. Interestingly, the lowest points in relative SDS spending of the higher-income groups coincided with the weeks that the federal government made the three economic impact stimulus payments: April 2020, January 2021, and March 2021. One potential explanation is that the relative spending decline represents the spending increase of the lower-income groups (with greater marginal propensity to consume out of stimulus checks) rather than a spending decrease of the higher-income groups in absolute terms. [13]

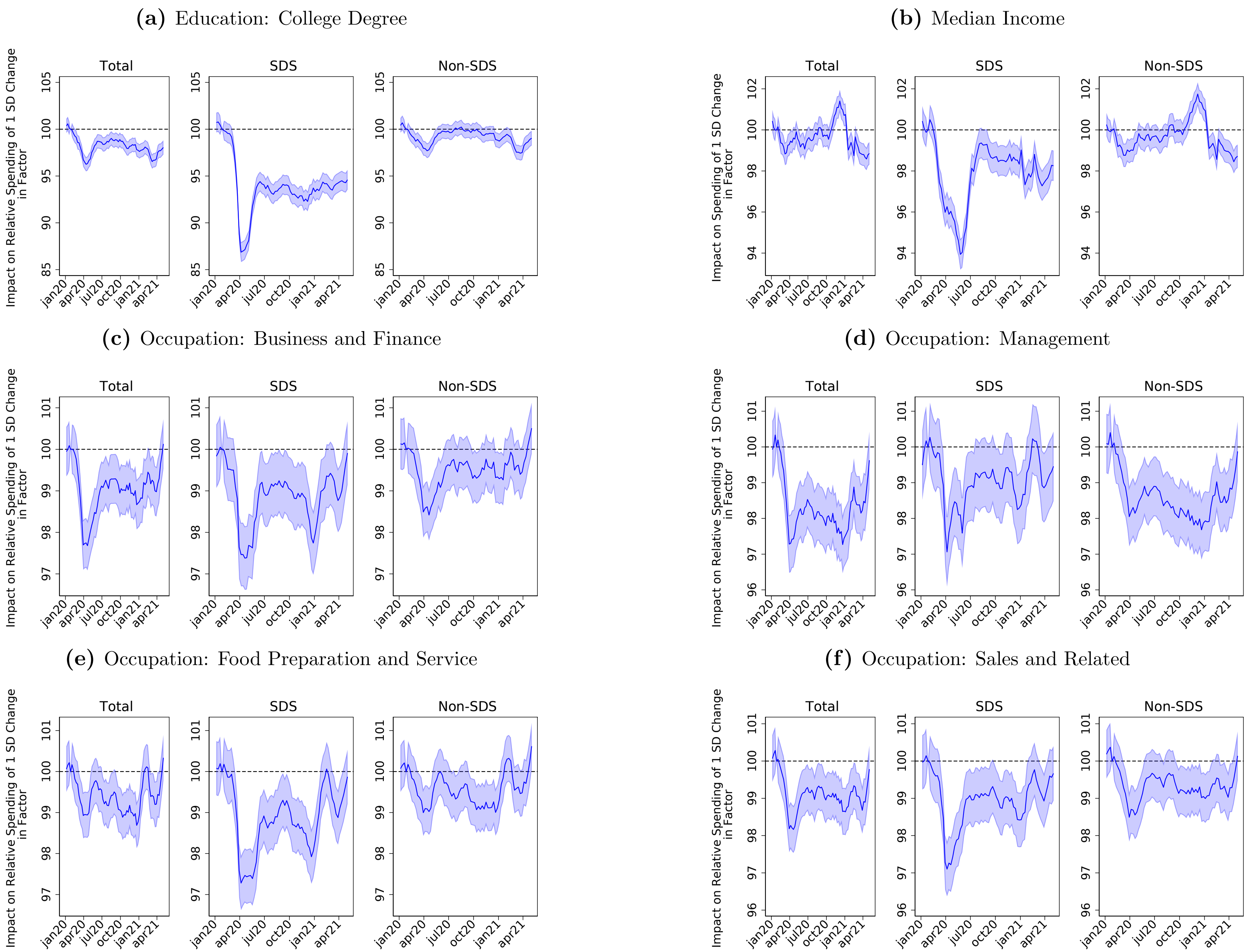
Occupation. Panels (c) through (f) show the impact on consumption spending of a one standard deviation higher share of a stated occupation relative to "protective services" in each week relative to the baseline week.[14] We see that at the start of the pandemic, ZCTAs with higher shares of occupations with higher human capital requirements, such as business and finance or manage-

[13] While Hispanics tend to be a lower income group, their relative spending fell at the start of the pandemic. These findings are consistent both because we control for income when estimating the impact of ethnicity on spending, and because Hispanics were less likely to receive stimulus checks as documented by the popular press (see https://www.usatoday.com/story/news/politics/2020/07/20/coronavirus-blacks-latinos-poor-less-likely-get-1-200-checks/5471086002/).

[14] There are 21 different plots corresponding to the different two-digit SOC occupations. For space considerations, we present four here. The corresponding plots for the remaining occupations are relegated to Appendix Figure 6.

ment occupations, had relatively larger declines in spending compared with ZCTAs with higher shares of occupations with lower human capital requirements, such as food preparation and services or sales and related occupations. Later in the pandemic, the relative spending differences were muted, and the occupations converged to some degree in terms of both SDS and non-SDS spending.

Overall, we find that the main economic factor that caused lower relative spending during the pandemic was college education. College-educated groups continued to spend relatively less even as the pandemic began to recede. This was especially true for SDS spending. This suggests that going forward from May 2021, the higher-educated groups would be expected to drive the recovery in spending, and most of this would be in the SDS categories of spending.



(a) Education: College Degree

(b) Median Income

(c) Occupation: Business and Finance

(d) Occupation: Management

(e) Occupation: Food Preparation and Service

(f) Occupation: Sales and Related

Figure 2. Economic Factors: Aggregate versus SDS versus Non-SDS Spending.

Sources: Affinity Data Solutions; American Community Survey.

4.3 Impact of COVID Factors

Finally, we discuss the impact of COVID-19–related factors on consumption spending during each week of the pandemic. This is shown in Figure 3. As in the preceding two subsections, the y-axis shows the impact of a one unit increase in the "row" factor on the "column" spending, while the x-axis shows the date/week. The impact coefficients are re-scaled so that the baseline week is at 100.

COVID case count. Panel (a) shows the impact on consumption spending of a one standard deviation higher COVID case count (for the ZCTA's county) in each week. ZCTAs in counties with higher case counts had only slightly lower consumption spending earlier in the pandemic, when case counts were very inaccurate. However, case counts had a larger negative impact on spending in July 2020 and late 2020 as the number of cases spiked and case counts became more accurate. The impact was driven mostly by SDS spending, perhaps unsurprisingly, as non-SDS consumption was not as likely to risk virus spread.

Vaccination rate. Panel (b) shows the impact on consumption spending of a one standard deviation higher vaccination rate (of the 18-plus population and for the ZCTA's county, with vaccination meaning a fully completed regiment of vaccines) in each week. The estimated impact was at 100 (implying no relative difference from the baseline week) until December 2020, when the vaccines began to be administered. Starting in 2021, ZCTAs with a higher share of fully vaccinated population had higher spending, both in SDS and non-SDS categories. The effect on SDS categories was more gradual and more persistent, presumably because it took some time for people to get used to returning to pre-pandemic activities, such as travel and indoor recreation. As the vaccination rollout continued and most adults who wanted a vaccine were able to get one, its effect on spending became insignificant.

Containment index. Panel (c) shows the impact on consumption spending of a 1 percentage point higher containment index (for the ZCTA's state) in each week.[15] ZCTAs with a higher containment index, which implies stricter lockdown measures, had much lower spending at the start of the pandemic. Later in the pandemic, the effect diminished, though there were still some effects on SDS spending around July 2020 and then again around January 2021 as lockdown measures were reinforced in some states.

Overall, we find that COVID factors had a large and significant impact on spending driven by SDS consumption. We should expect to see a further recovery in SDS spending as the pandemic recedes further and case counts fall, lockdowns are removed, and more people become fully vaccinated.

[15] To see results for the normalized containment index, comparable to other normalized COVID variables, see Appendix figure 7.

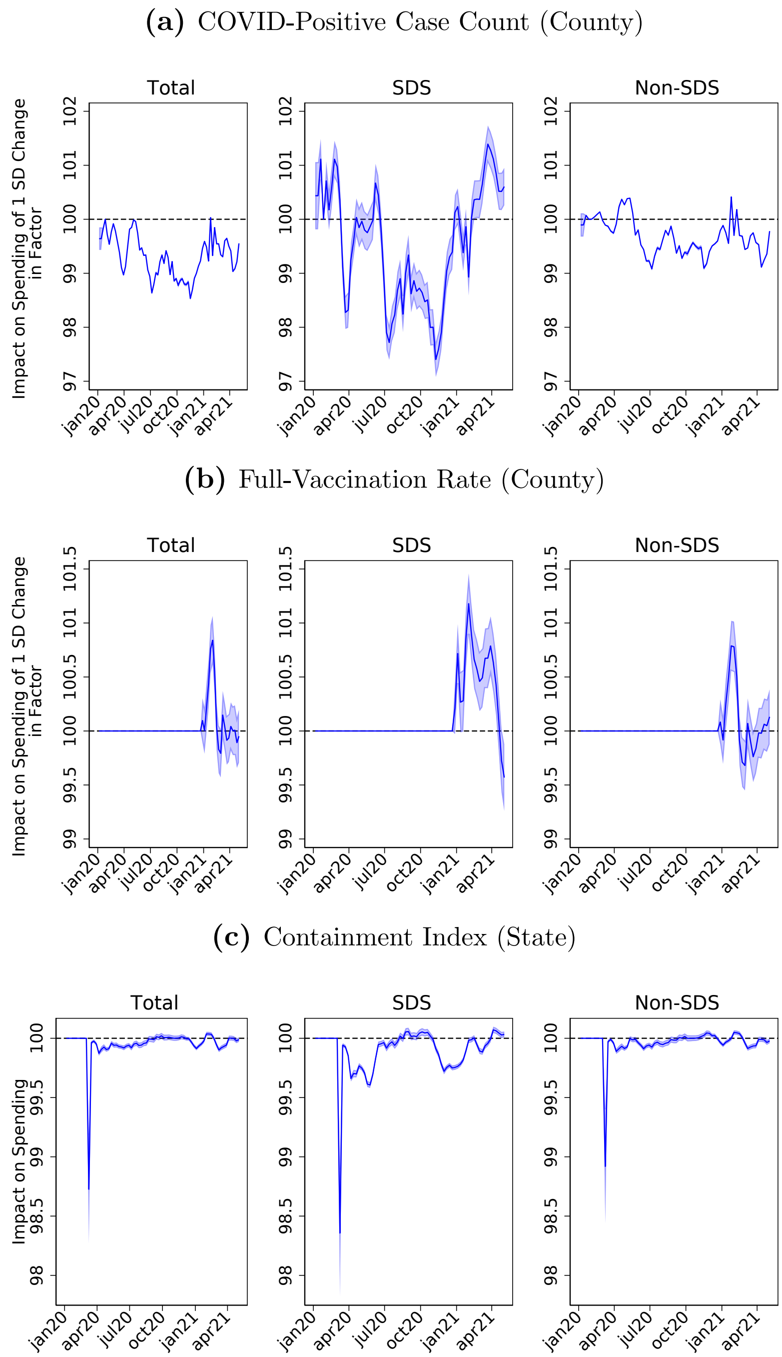


Figure 3. COVID Factors: Aggregate versus SDS versus Non-SDS Spending.

Sources: Affinity Data Solutions; *New York Times*; Centers for Disease Control; IHS Markit/Macroeconomic Advisors.

5 Relative Importance of Factors in Explaining Consumption Spending Differences

In this section we investigate the relative importance of each factor in driving spending differences between ZCTAs through each week of the pandemic. To do this, we follow a modified approach to the decomposition by Fields (2003), who studies the factors that drive income inequality in the United States.

5.1 Fields' Decomposition Application

The basic idea behind a Fields' decomposition is that if we believe two factors explain consumption, then we can decompose how much of the R^2 is explained by each of the two factors. To see this mathematically, we can consider a regression of y_i on $x_{1,i}, x_{2,i}$, which is shown in equation (2). Equation (3) holds by the definition of covariance. We can then separate this out into equation (4). Dividing by the variance of y_i allows us to get the Fields' decomposition in equation (5).

$$y_i = \hat{\alpha} + \hat{\beta}_1 x_{1,i} + \hat{\beta}_2 x_{2,i} + \hat{u}_i \tag{2}$$

$$Var(y_i) = Cov(\hat{\alpha} + \hat{\beta}_1 x_{1,i} + \hat{\beta}_2 x_{2,i} + \hat{u}_i, y_i) \tag{3}$$

$$Var(y_i) = \hat{\beta}_1 Cov(x_{1,i}, y_i) + \hat{\beta}_2 Cov(x_{2,i}, y_i) + Cov(\hat{u}_i, y_i) \tag{4}$$

$$1 = \underbrace{\hat{\beta}_1 \frac{Cov(x_{1,i}, y_i)}{Var(y_i)}}_{R^2 \text{ due to } x_{1,i}} + \underbrace{\hat{\beta}_2 \frac{Cov(x_{2,i}, y_i)}{Var(y_i)}}_{R^2 \text{ due to } x_{2,i}} + \underbrace{\frac{Cov(\hat{u}_i, y_i)}{Var(y_i)}}_{\text{Unexplained Sum of Squares}} \tag{5}$$

We want to find how important different factors are in explaining consumption through each week of the pandemic, so we conduct these regressions on a weekly basis. We demean the variables to remove the fixed effects, which would otherwise be the dominant driver of spending between ZCTAs of different sizes. To find the Fields' decomposition for a given week t, we therefore run the regression in equation (6). We again use the five-week moving average for spending.

$$\begin{aligned} &log\_spending_{z,t} - \overline{log\_spending_{z,t}} \\ &\quad = \sum_{j=1}^{J-1} \beta_{j,t} \times (fixedfactor_z^j \times week\_dummy_t - \overline{fixedfactor_z^j \times week\_dummy_t}) \\ &+ \sum_{j=1}^{J-1} \chi_{j,t} \times (covidfactor_{z,t}^j \times week\_dummy_t - \overline{covidfactor_{z,t}^j \times week\_dummy_t}) + u_{z,t} \end{aligned} \tag{6}$$

The Fields' decomposition for total spending is plotted in figure 4a. The x-axis shows the date, while the y-axis shows the share of R^2 due to each factor. The variables are ordered with the demographic variables at the top of the graph followed by the economic factors in the middle and then the COVID factors at the bottom of the graph. Gender is the first factor at the top of the graph, and vaccinations are the last factor shown at the bottom of the graph. We plot the share of R^2 explained by each factor.[16]

As can be seen in equation (5), a factor's contribution in the Fields' decomposition is determined by the interaction of the factor's regression coefficient and the covariance of log spending and the factor. Therefore, even if a factor has a strong positive coefficient and therefore raises spending a lot, if its covariance with spending is weak, its contribution in the Fields' decomposition will be small.[17] This is why some of the factors that seem to drive large consumption changes in

[16] The mean R^2 we are able to explain in each week is 0.052, with the maximum at 0.197 toward the beginning of our sample period and the minimum at 0.009 toward the end of our sample period.

[17] This may seem counterintuitive, but it can occur when $\hat{\beta}_1 > 0$ but variable $x_{1,i}$ is strongly positively correlated

Section 4 may not be as important sometimes in the Fields' decomposition. For similar reasons, it is even possible for a factor to make a negative contribution toward explaining consumption differences. As can be seen in equation (5), this happens if a variable is positively correlated with spending ($cov(x_{1,i}, y_i) > 0$) but the coefficient for the variable is negative ($\hat{\beta}_1 < 0$). These negative explanatory factors are the reason for the small movements below zero in some weeks, which is why the positive factors sometimes sum to more than 100 percent. The Fields' decomposition for SDS spending and non-SDS spending is plotted in figure 4b and figure 4c, respectively.

5.2 Fields' Decomposition Results

Looking first at demographic variables, we observe that the share of Republican voters was an important factor in driving consumption differences across ZCTAs during the pandemic. This was particularly true in the later lockdown periods around January 2021. This fits with the common observation that there were significant differences in the degree to which Democratic and Republican voters engaged in social distancing, and also with the notion that these differences seemed to grow as the pandemic continued (Clinton et al., 2020). Living in an urban area was also an important factor at certain points during the pandemic, again particularly in the later lockdown periods. Age played a moderate role in explaining consumption differences during the pandemic. This is perhaps surprising, since older people were more at risk of the virus. However, we control for some of this risk using our case count measure, and older people are also likely to live in rural areas and vote Republican, which may reduce the ability of age to explain consumption differences. Gender seems to have had very little explanatory power, perhaps unsurprisingly given the similar gender composition of most ZCTAs.

Race and ethnicity each played a key role in driving consumption differences across ZCTAs in the early part of the pandemic. We see that in May and June 2020, race and ethnicity variables explained about 50 percent of consumption differences. However, as the pandemic continued, these differences diminished. This corresponds with our finding that the degree of consumption differences across ZCTAs with different racial and ethnic compositions fell as the pandemic continued.

Economic factors played an important role in explaining consumption differences during the pandemic. Median income and education were particularly important in explaining changes in consumption later in the pandemic and once vaccinations began. The occupations that people work consistently was an important factor during the pandemic, but this factor did not vary in its importance over time.

Unsurprisingly, each factor associated with COVID-19 played an important role in explaining consumption differences. The number of COVID-positive cases played an important role as case counts spiked in July 2020 and then again in late 2020. During this period, there were notable differences in COVID-19 case counts across different areas of the United States. Interestingly, case counts had a very small impact at the start of the pandemic, but presumably this is because with low testing at that time, it was very difficult to get an accurate picture of the number of

with another variable for which the coefficient is strongly negative. One example of this is that young people might be expected to spend more during the pandemic, which would mean a large coefficient. However, young people are often located in urban areas where spending is lower, so the covariance between young people and spending may be weak.

cases. State-level lockdowns played a more consistent role during the pandemic, with increases in importance around high-case-count periods at the start of the pandemic, in July 2020, and in early 2021. Vaccinations seemed to have had a significant impact at the start of the vaccination rollout. However, as the rollout continued, the impact of vaccinations diminished.

We also analyze the relative importance of these factors in explaining SDS and non-SDS spending differences in figure 4b and figure 4c, respectively. Political affiliation and COVID factors seem to have been more important in driving SDS spending differences than non-SDS spending differences across ZCTAs. This makes sense given that differences in the degree to which Republicans and Democrats social-distanced primarily affected SDS spending. And the number or degree of cases/restrictions/vaccines was likely to have driven how comfortable people felt spending on SDS categories more than on non-SDS categories. On the flip side, race/ethnicity and economic variables seem to have played a larger role in driving non-SDS spending. Comparing the factor decomposition of pandemic-period spending with pre-pandemic (Jan. 1 through Feb. 2, 2020) spending, we see that this may partly just reflect that non-SDS spending was less affected by the pandemic and continued to be driven by more standard factors.

6 Conclusion

We have used a novel empirical approach to study which factors caused differences in high-frequency consumption spending and how the importance of these factors in explaining consumption differences varied during the pandemic. First, we interacted demographic, economic and COVID-factors with weekly dummy variables to study the differential impact of these factors over time. Second, we used Fields' decompositions to study the importance of each of these factors in driving consumption differences between ZCTAs. We find that demographic, economic, and COVID factors were all important in explaining consumption spending differences, albeit to varying degrees during the pandemic. Within each group, having large Hispanic populations, high numbers of college-educated people, and high COVID case counts were especially likely to reduce consumption.

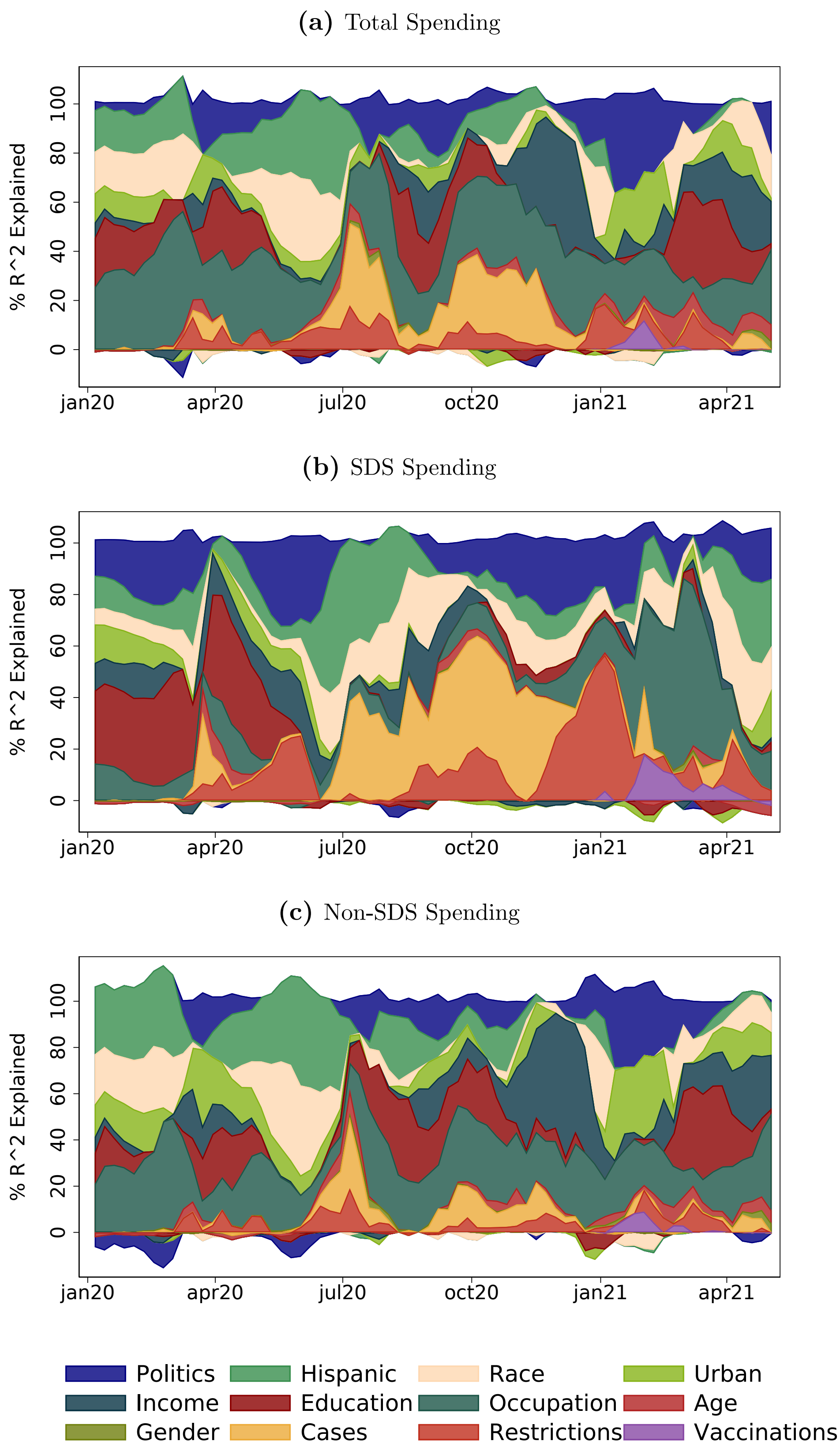


Figure 4. Fields' Decompositions.

Sources: Affinity Data Solutions; American Community Survey; MIT Election Lab; U.S. Census; *New York Times*; Centers for Disease Control; IHS Markit/Macroeconomic Advisors.

References

Abedi, Vida, Oluwaseyi Olulana, Venkatesh Avula, Durgesh Chaudhary, Ayesha Khan, Shima Shahjouei, Jiang Li, and Ramin Zand. 2020. "Racial, Economic, and Health Inequality and COVID-19 Infection in the United States." *Journal of Racial and Ethnic Health Disparities* 732–742. doi: https://doi.org/10.1007/s40615-020-00833-4.
URL https://link.springer.com/article/10.1007/s40615-020-00833-4#citeas.

Alexander, Diane, and Ezra Karger. 2020. "Do stay-at-home orders cause people to stay at home? Effects of stay-at-home orders on consumer behavior." Working Paper 2020-12. Federal Reserve Bank of Chicago. doi: 10.21033/wp-2020-12.
URL https://www.chicagofed.org/publications/working-papers/2020/2020-12.

Alon, Titan, Matthias Doepke, Jane Olmstead-Rumsey, and Michèle Tertilt. 2020. "The Impact of COVID-19 on Gender Equality." Working Paper 26947. National Bureau of Economic Research. doi: 10.3386/w26947.
URL http://www.nber.org/papers/w26947.

Baker, Scott R, R.A. Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis. 2020. "How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic." Working Paper 26949. National Bureau of Economic Research. doi: 10.3386/w26949.
URL http://www.nber.org/papers/w26949.

Barrios, John M, and Yael Hochberg. 2020. "Risk Perception Through the Lens of Politics in the Time of the COVID-19 Pandemic." Working Paper 27008. National Bureau of Economic Research. doi: 10.3386/w27008.
URL http://www.nber.org/papers/w27008.

Blundell, Richard, and Ian Preston. 1998. "Consumption Inequality and Income Uncertainty." *Quarterly Journal of Economics* 113(2): 603–640.

Chen, Haiqiang, Qian Wenlan, and Wen Qiang. 2021. "The Impact of the COVID-19 Pandemic on Consumption: Learning from High-Frequency Transaction Data." *AEA Papers and Proceedings* 111.

Chetty, Raj, John N. Friedman, Nathan Hendren, Michael Stepner, and the Opportunity Insights Team. 2020. "The Economic Impacts of COVID-19: Evidence from a New Public Database Built from Private Sector Data." Working paper. Harvard University.

Clinton, Joshua, Jon Cohen, John S. Lapinski, and Marc Trussler. 2020. "Partisan Pandemic: How Partisanship and Public Health Concerns Affect Individuals' Social Distancing During COVID-19." Technical Report. SSRN Working Paper No. 3633934.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. 2020. "The Cost of the Covid-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending." Working Paper 27141. National Bureau of Economic Research. doi: 10.3386/w27141.
URL http://www.nber.org/papers/w27141.

Couch, Kenneth A., Robert W. Fairlie, and Huanan Xu. 2020. "Early evidence of the impacts of COVID-19 on minority unemployment." *Journal of Public Economics* 192: 104287. ISSN 0047-2727. doi: https://doi.org/10.1016/j.jpubeco.2020.104287.
URL https://www.sciencedirect.com/science/article/pii/S0047272720301511.

Cox, Natalie, Peter Ganong, Pascal Noel, Joseph Vavra, Arelen Wong, Diana Farrell, Fiona Greig, and Erica Deadman. 2020. "Initial Impacts of the Pandemic on Consumer Behavior: Evidence from Linked Income, Spending, and Savings Data." *Brookings Papers on Economic Activity*.

Fields, Gary. 2003. "Accounting for Income Inequality and Its Change: A New Method, with Application to the Distribution of Earnings in the United States, Research in Labor Economics." *Research in Labor Economics*.

Goolsbee, Austan, and Chad Syverson. 2020. "Fear, Lockdown, and Diversion: Comparing Drivers of Pandemic Economic Decline 2020." Working Paper 27432. National Bureau of Economic Research. doi: 10.3386/w27432.
URL https://www.nber.org/system/files/working_papers/w27432/w27432.pdf.

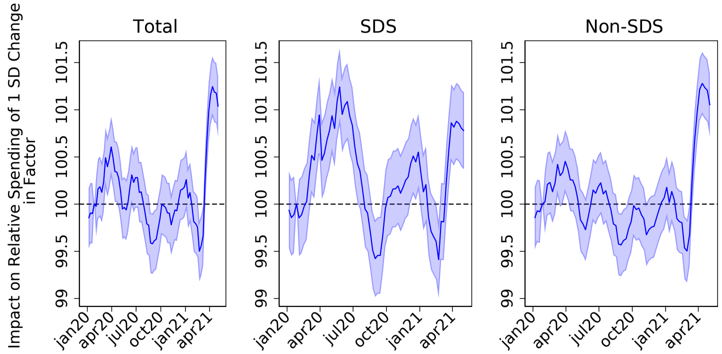
Krueger, Dirk, and Francisco Perri. 2006. "Does Income Inequality Lead to Consumption Inequality? Evidence and Theory." *Review of Economic Studies* 73: 163–193.

Kumar, Raynil, and Shaun O'Brien. 2019. "2019 Findings from the Diary of Consumer Payment Choice." Fednotes. Federal Reserve Bank of San Francisco.

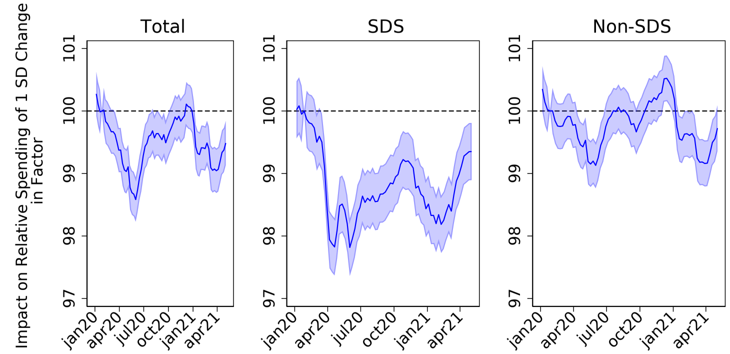
Appendices

A Additional Results

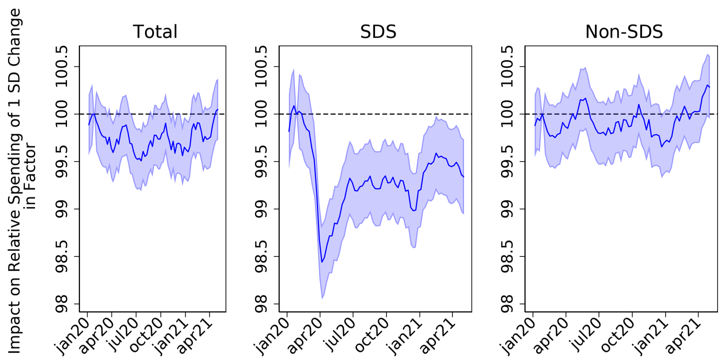
(a) Race: Multiple Races



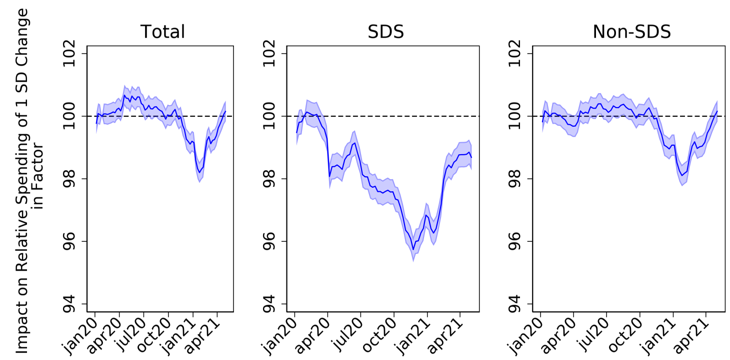
(b) Race: Pacific Islander, Native American Race, Not Elsewhere Classified



(c) Gender: Percent Male



(d) Political Affiliation: Percent Third Party



(e) Rural-Urban: Percent Urban

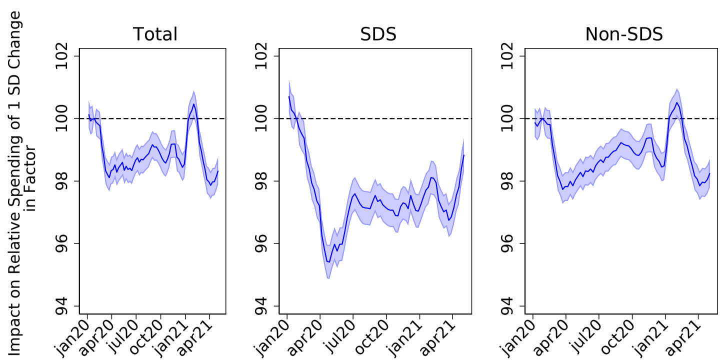
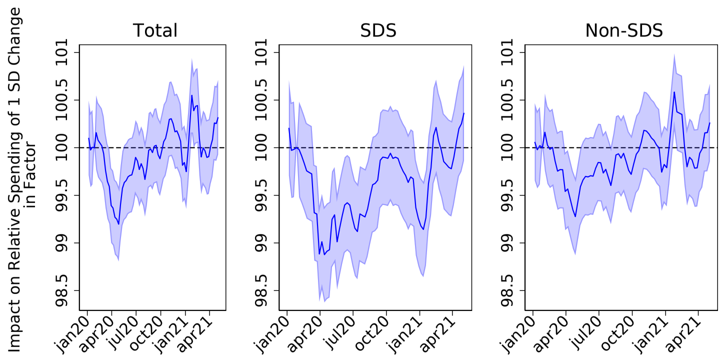


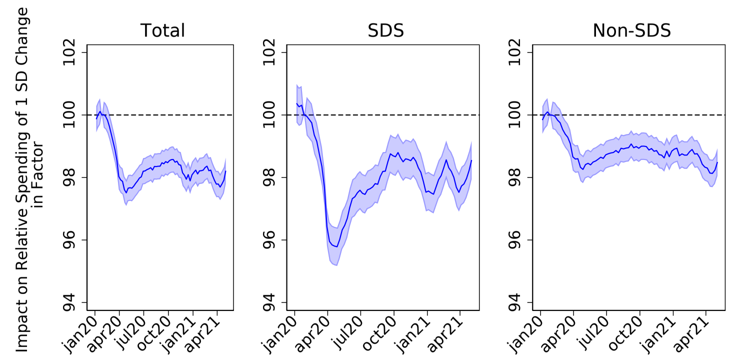
Figure 5. Additional Demographic Factors

Sources: Affinity Data Solutions; American Community Survey; U.S. Census; MIT Election Lab.

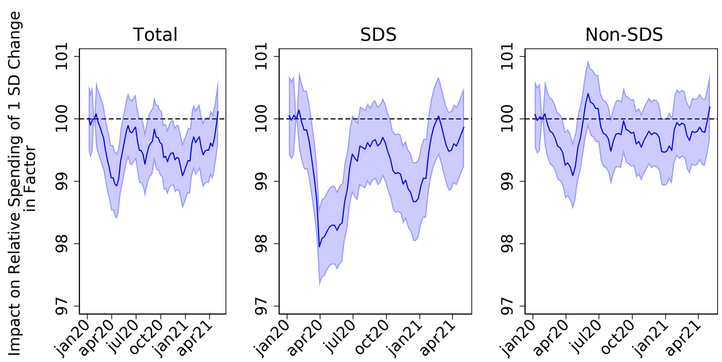
(a) Occupation: Architecture and Engineering



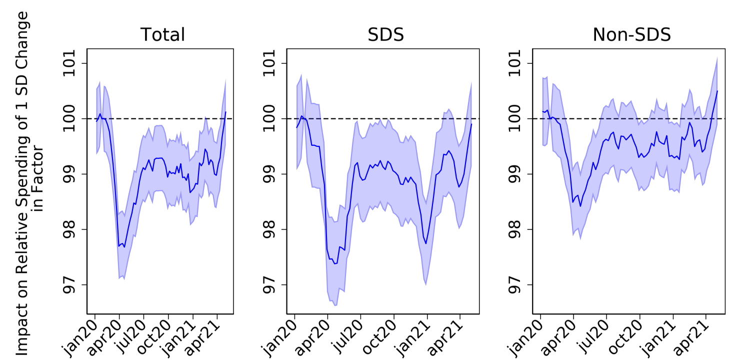
(b) Occupation: Arts, Design, Entertainment, Sports, and Media



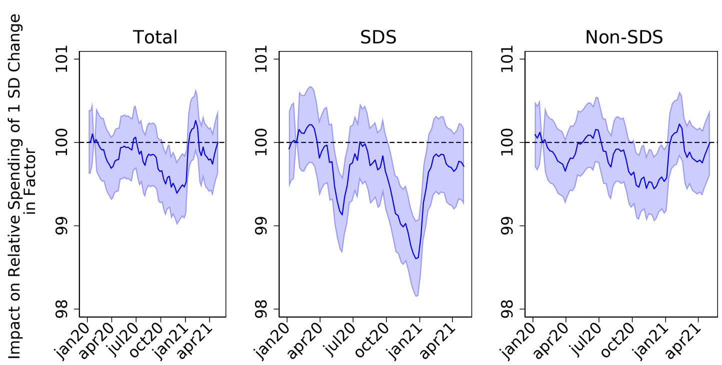
(c) Occupation: Building and Grounds Cleaning and Maintenance



(d) Occupation: Business and Finance



(e) Occupation: Community and Social Service



(f) Occupation: Computer and Mathematical

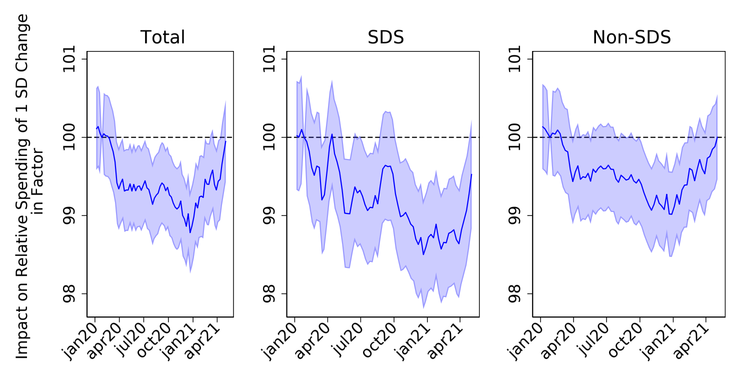
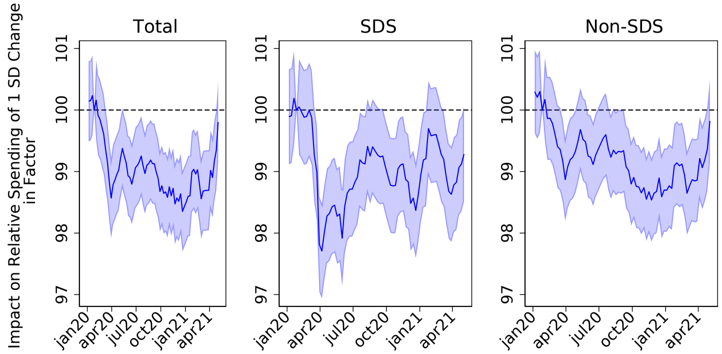


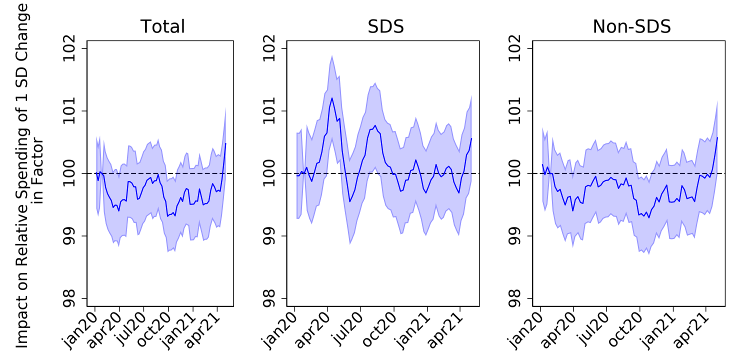
Figure 6. Additional Occupation Plots.

Sources: Affinity Data Solutions; American Community Survey.

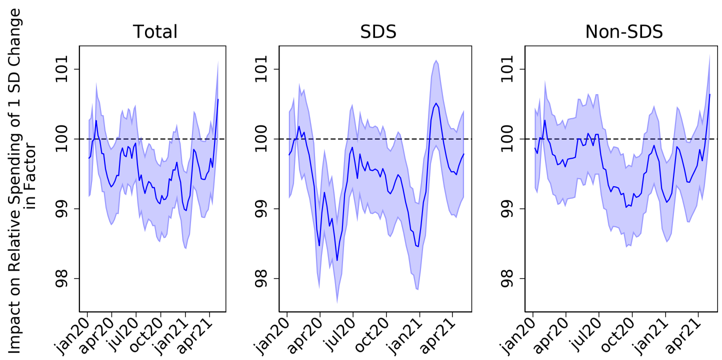
(g) Occupation: Construction and Extraction



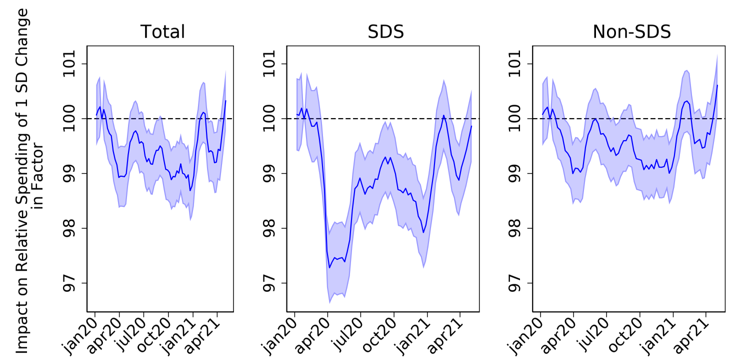
(h) Occupation: Educational Instruction and Library



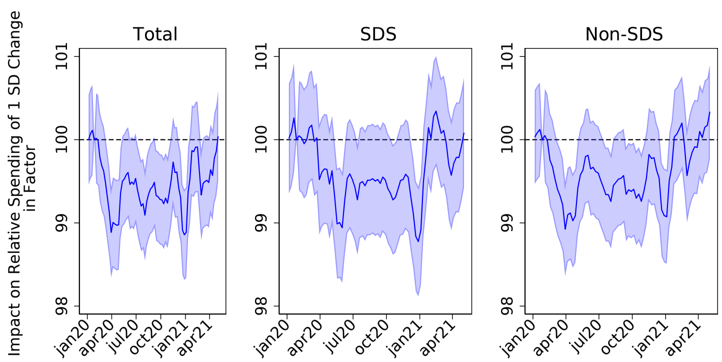
(i) Occupation: Farming, Fishing, and Forestry



(j) Occupation: Food Preparation and Service



(k) Occupation: Healthcare Practitioners and Technical



(l) Occupation: Healthcare Support

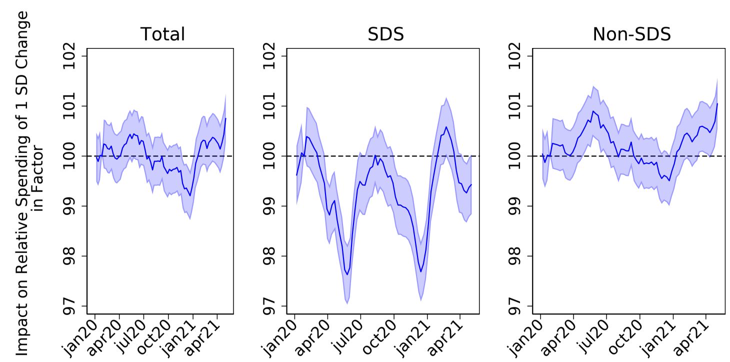
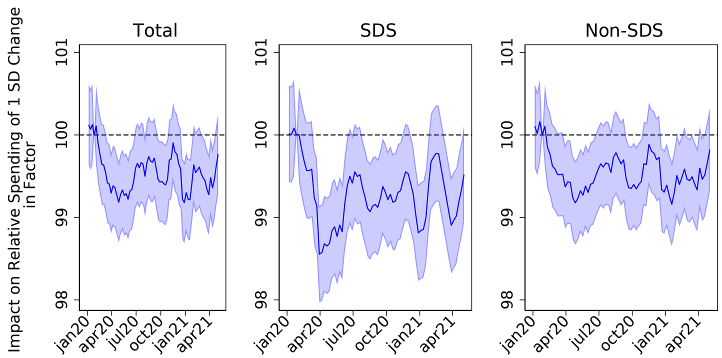


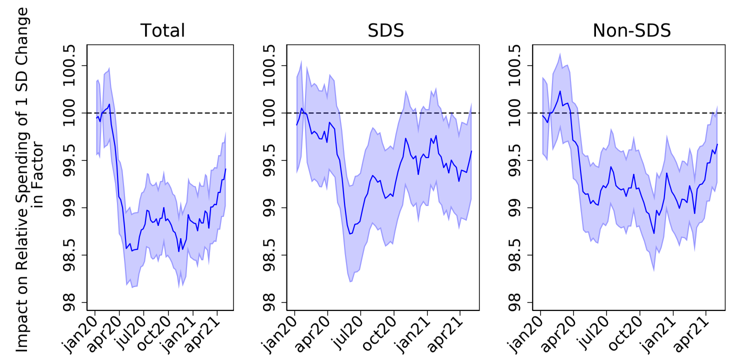
Figure 6. Additional Occupation Plots.

Sources: Affinity Data Solutions; American Community Survey.

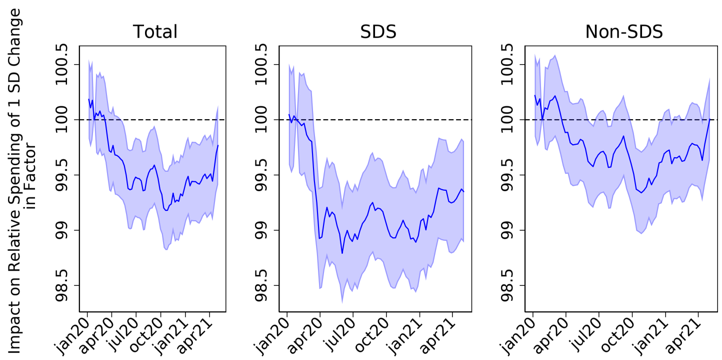
(m) Occupation: Installation, Maintenance, and Repair



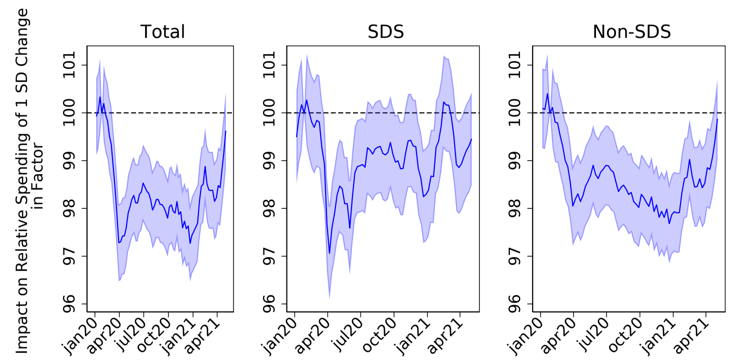
(n) Occupation: Legal



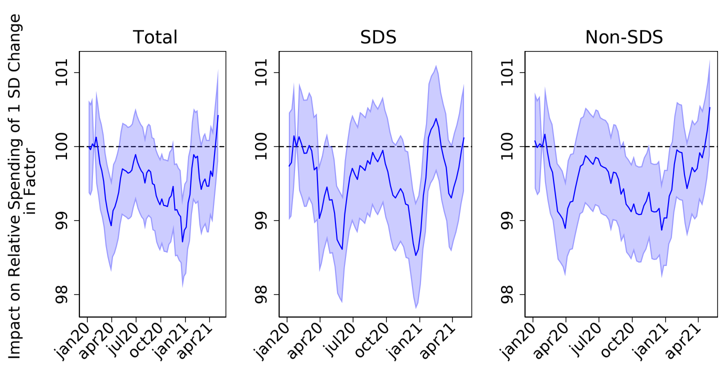
(o) Occupation: Life, Physical, and Social Science



(p) Occupation: Management



(q) Occupation: Office and Administrative Support



(r) Occupation: Personal Care and Service

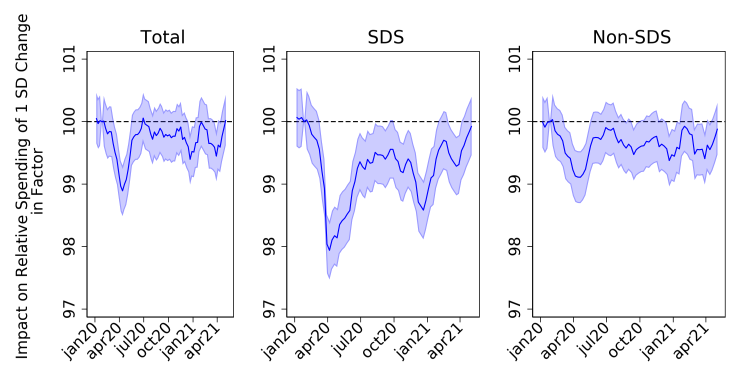
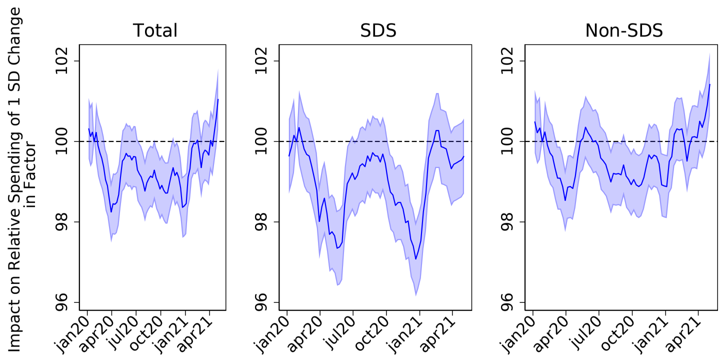


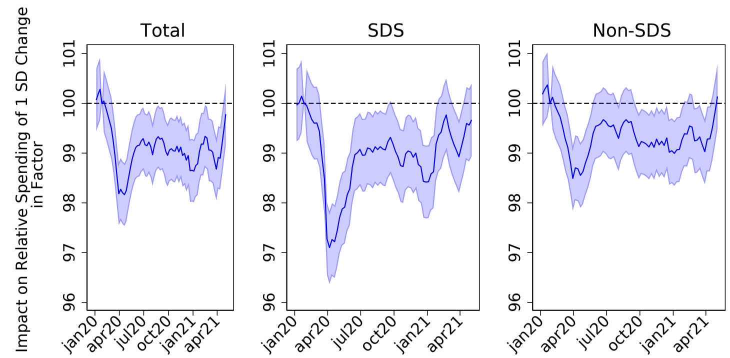
Figure 6. Additional Occupation Plots.

Sources: Affinity Data Solutions; American Community Survey.

(s) Occupation: Production



(t) Occupation: Sales and Related



(u) Occupation: Transportation and Material Moving

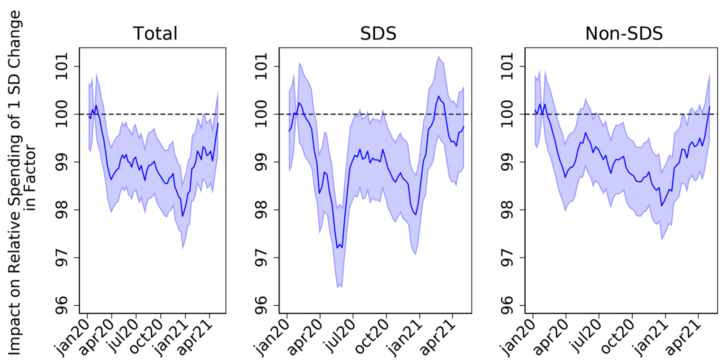
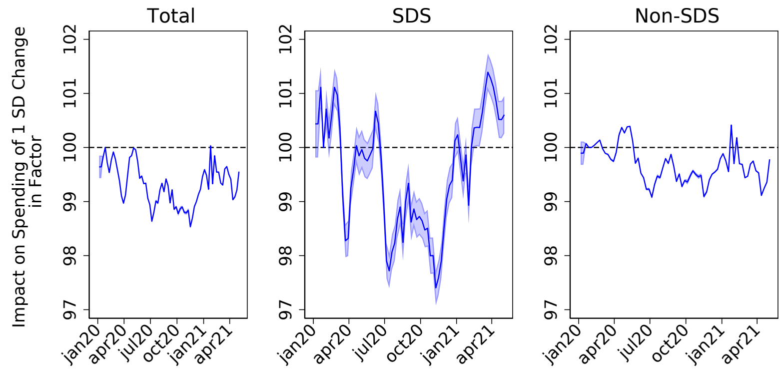


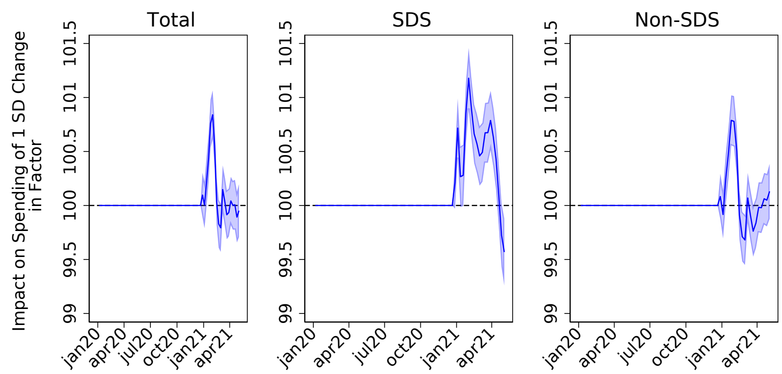
Figure 6. Additional Occupation Plots.

Sources: Affinity Data Solutions; American Community Survey.

(a) COVID-Positive Case Count (County)



(b) Full-Vaccination Rate (County)



(c) Containment Index (State)

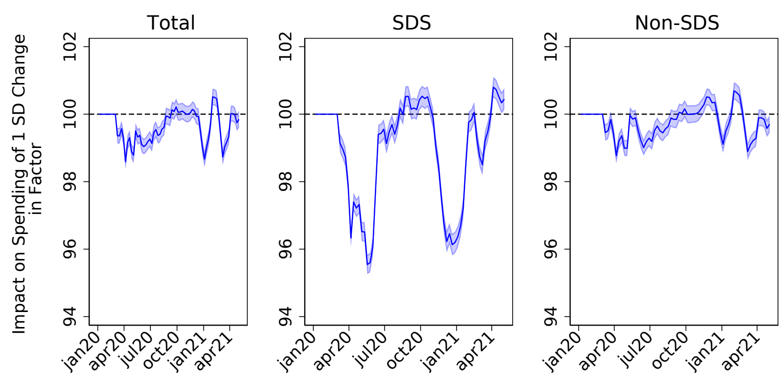


Figure 7. COVID Factors (All Normalized): Aggregate versus SDS versus Non-SDS Spending.

Sources: Affinity Data Solutions; Centers for Disease Control; New York Times; IHS Markit/Macroeconomic Advisors.

B Means and Standard Deviations for Normalized Factors

Since the demographic and economic factors are time invariant, there is one mean and one standard deviation per factor for the entire sample. These are summarized in Table 1.

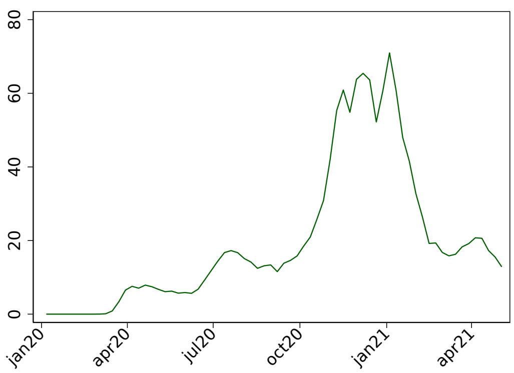
Table 1. Demographic and Economic Factors

Panel A: Demographic Factor	*Mean*	*Standard Deviation*
Age: Percent 18-29 years	14.74	6.82
Age: Percent 65+ years	17.54	7.27
Ethnicity: Percent Hispanic	11.15	16.67
Gender: Percent male	49.75	3.71
Political Affiliation: Percent Republican	52.6	16.98
Political Affiliation: Percent Third Party	5.69	3.01
Race: Percent Asian American	3.04	6.4
Race: Percent Black	8.97	16.02
Race: Percent Multiple Races	2.64	2.7
Race: Percent Pacific Islander, Native American, Race Not Elsewhere Classified	4	8.19
Rural: Percent Urban	53.83	42.86

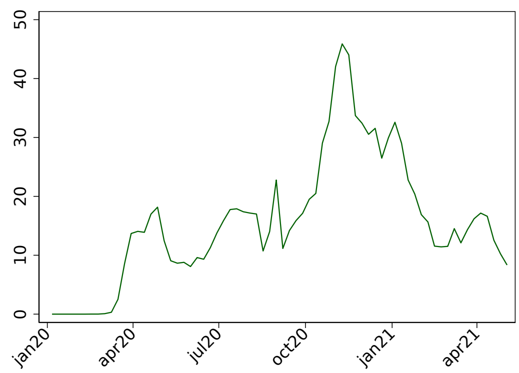
Panel B: Economic Factor	*Mean*	*Standard Deviation*
Education: Percent with College Degree	36.54	16.15
Log Median Income	10.98	0.37
Occupation: Percent Architecture and Engineering	1.6	1.5
Occupation: Percent Arts, Design, Entertainment, Sports, and Media	1.6	1.72
Occupation: Percent Building and Grounds Cleaning and Maintenance	3.98	2.89
Occupation: Percent Business and Finance	4.48	3.09
Occupation: Percent Community and Social Service	1.69	1.43
Occupation: Percent Computer and Mathematical	2.22	2.47
Occupation: Percent Construction and Extraction	5.98	4
Occupation: Percent Educational Instruction and Library	5.87	3.21
Occupation: Percent Farming, Fishing, and Forestry	1.36	3.23
Occupation: Percent Food Preparation and Service	5.36	3.12
Occupation: Percent Healthcare Practitioners and Technical	5.94	3
Occupation: Percent Healthcare Support	3.35	2.57
Occupation: Percent Installation, Maintenance, and Repair	3.74	2.55
Occupation: Percent Legal	0.88	1.39
Occupation: Percent Life, Physical, and Social Science	0.83	1.32
Occupation: Percent Management	10.16	5.11
Occupation: Percent Office and Administrative Support	11.39	3.76
Occupation: Percent Personal Care and Service	2.62	1.91
Occupation: Percent Production	6.9	5.03
Occupation: Percent Sales and Related	9.84	3.86
Occupation: Percent Transportation and Material Moving	8	4.33

Since the COVID factors are time variant, there is a mean and standard deviation per factor for each week of the sample period. These time-varying means and standard deviations are shown in Figure 8.

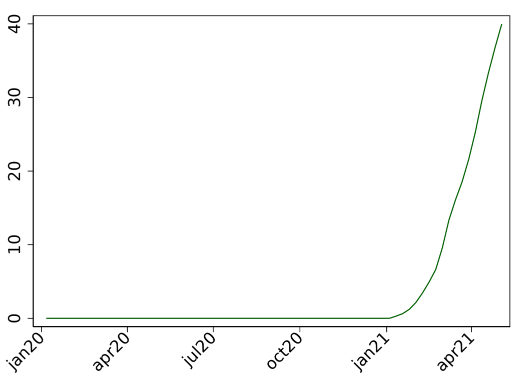
(a) Covid-Positive Case Count (County) Mean



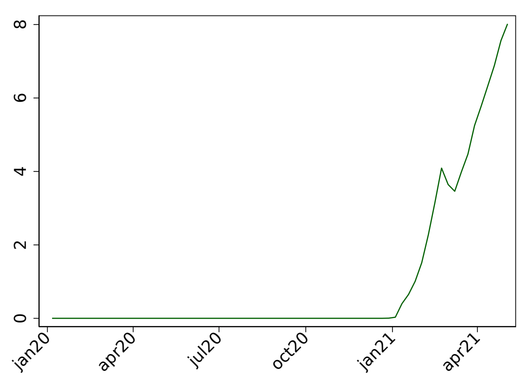
(b) Covid-Positive Case Count (County) Standard Deviation



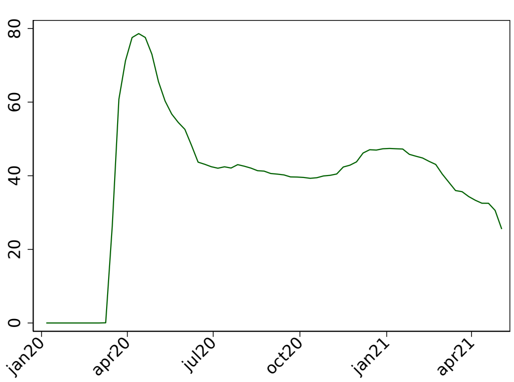
(c) Full-Vaccination Rate (County) Mean



(d) Full-Vaccination Rate (County) Standard Deviation



(e) Containment Index (State) Mean



(f) Containment Index (State) Standard Deviation

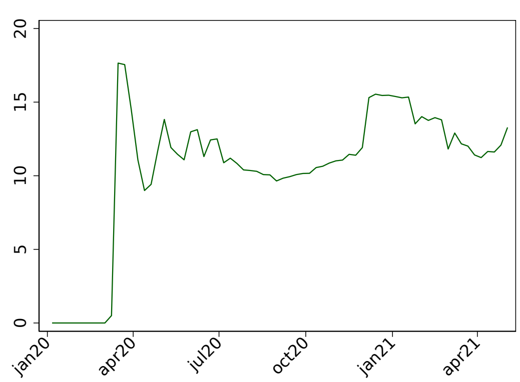


Figure 8. Means and Standard Deviations of COVID factors

Sources: Centers for Disease Control; *New York Times*; IHS Markit/Macroeconomic Advisors.

C Spending Category Definitions

For each spending category we include the following merchant classification codes (MCC):

Leisure: Airlines:

- All MCCs from 3000 through 3299, plus MCC 4511

Leisure: Car Rentals:

- All MCCs from 3351 through 3411, plus MCCs 7512 through 7513

Leisure: Hotels:

- All MCCs from 3501 through 3900, plus MCC 7011

Leisure: Recreation/Entertainment:

- 4457: Boat Leases and Boat Rentals
- 4468: Marinas, Marine Service/Supplies
- 7032: Recreational and Sporting Camps
- 7829: Motion Picture and Video Tape Production and Distributio
- 7832: Motion Picture Theaters
- 7841: Video Entertainment Rental Stores
- 7911: Dance Halls, Schools, and Studios
- 7922: Theatrical Producers (except Motion Pictures), Ticket Agencies
- 7929: Bands, Orchestras, and Miscellaneous Entertainers—not elsewhere classified
- 7932: Pool and Billiard Establishments
- 7933: Bowling Alleys
- 7941: Athletic Fields, Commercial Sports, Professional Sports Clubs, Sports Promoters
- 7991: Tourist Attractions and Exhibits
- 7992: Golf Courses, Public
- 7993: Video Amusement Game Supplies
- 7994: Video Game Arcades/Establishments
- 7995: Gambling Transactions
- 7996: Amusement Parks, Carnivals, Circuses, Fortune Tellers
- 7997: Clubs—Country Clubs, Membership (Athletic, Recreation, Sports), Private Golf Courses
- 7998: Aquariums, Dolphinariums, Zoos, and Seaquariums
- 7999: Recreation Services—not elsewhere classified
- 7800: Government Owned Lottery (U.S. Region Only)
- 7801: Internet Gambling (U.S. Region Only)
- 7801: Internet Gambling (U.S. Region Only)

Leisure: Travel:

- 7519: Motor Home and Recreational Vehicle Rental
- 7012: Timeshares
- 7033: Campgrounds and Trailer Parks
- 4411: Cruise Lines
- 4582: Airports, Airport Terminals, Flying Fields
- 4722: Travel Agencies and Tour Operators
- 4723: Package Tour Operators – Germany Only

Leisure: Entertainment Away from Home:

- 7832: Motion Picture Theaters
- 7911: Dance Halls, Studios and Schools
- 7994: Video Game Arcades/Establishments
- 7996: Amusement Parks, Circuses, Carnivals, and Fortune Tellers
- 7998: Aquariums, Seaquariums, Dolphinariums, and Zoos
- 7922: Ticket Agencies and Theatrical Producers (Except Motion Pictures)
- 7929: Bands, Orchestras, and Miscellaneous Entertainers (Not Elsewhere Classified)
- 7932: Billiard and Pool Establishments
- 7933: Bowling Alleys
- 7941: Commercial Sports, Professional Sports Clubs, Athletic Fields, and Sports Promoters
- 7991: Tourist Attractions and Exhibits
- 7992: Public Golf Courses

Transportation:

- 4111: Transportation—Suburban and Local Commuter Passenger, including Ferries
- 4112: Passenger Railways
- 4119: Ambulance Services
- 4121: Limousines and Taxicabs
- 4131: Bus Lines
- 7523: Automobile Parking Lots and Garages
- 4784: Bridge and Road Fees, Tolls
- 4789: Transportation Services—not elsewhere classified

Food-Out:

- 5811: Caterers
- 5812: Eating Places and Restaurants
- 5813: Drinking Places (Alcoholic Beverages) – Bars, Taverns, Nightclubs, Cocktail Lounges, and Discotheques

– 5814: Fast Food Restaurants

Utilities/Telecom:

– 4812: Telecommunication Equipment and Telephone Sales

– 4814: Telecommunication Services, including Local and Long Distance Calls, Credit Card Calls, Calls Through Use of MagneticStripe-Reading Telephones, and Fax Services

– 4816: Computer Network/Information Services

– 4821: Telegraph Services

– 4829: Money Transfer

– 4899: Cable, Satellite and Other Pay Television/Radio/Streaming Services

– 4900: Utilities – Electric, Gas, Water, and Sanitary

– 5983: Fuel Dealers – Fuel Oil, Wood, Coal, and Liquefied Petroleum

Beauty/Massage:

– 7297: Massage Parlors

– 7298: Health and Beauty Spas

– 7230: Beauty and Barber Shops

Grocery Stores:

– 5411: Grocery Stores and Supermarkets

Retail Stores:

– 5300: Wholesale Clubs

– 5309: Duty Free Stores

– 5310: Discount Stores

– 5311: Department Stores

– 5331: Variety Stores

– 5399: Miscellaneous General Merchandise

– 5422: Freezer and Locker Meat Provisioners

– 5441: Candy, Nut, and Confectionery Stores

– 5451: Dairy Products Stores

– 5462: Bakeries

– 5499: Miscellaneous Food Stores – Convenience Stores and Specialty Markets

– 5732: Electronics Stores

– 5733: Music Stores – Musical Instruments, Pianos, and Sheet Music

– 5734: Computer Software Stores

– 5735: Record Stores

– 5912: Drug Stores and Pharmacies

- 5921: Package Stores – Beer, Wine, and Liquor
- 5931: Used Merchandise and Secondhand Stores
- 5932: Antique Shops – Sales, Repairs, and Restoration Services
- 5933: Pawn Shops
- 5935: Wrecking and Salvage Yards
- 5937: Antique Reproductions
- 5992: Florists
- 5993: Cigar Stores and Stands
- 5994: News Dealers and Newsstands
- 5995: Pet Shops, Pet Foods and Supplies Stores
- 5997: Electric Razor Stores – Sales and Service
- 5998: Tent and Awning Shops
- 5999: Miscellaneous and Specialty Retail Shops
- 5942: Book Stores
- 5943: Stationery Stores, Office and School Supply Stores
- 5944: Jewelry Stores, Watches, Clocks, and Silverware Stores
- 5945: Hobby, Toy, and Game Shops
- 5946: Camera and Photographic Supply Stores
- 5947: Gift, Card, Novelty and Souvenir Shops
- 5948: Luggage and Leather Goods Stores
- 5949: Sewing, Needlework, Fabric and Piece Goods Stores
- 5950: Glassware/Crystal Stores
- 5970: Artist's Supply and Craft Shops
- 5971: Art Dealers and Galleries
- 5972: Stamp and Coin Stores
- 5973: Religious Goods Stores
- 5975: Hearing Aids – Sales, Service, and Supply
- 5976: Orthopedic Goods – Prosthetic Devices
- 5977: Cosmetic Stores
- 5978: Typewriter Stores – Sales, Rentals, and Service
- 7296: Clothing Rental – Costumes, Uniforms, Formal Wear
- 7622: Electronics Repair Shops
- 7623: Air Conditioning and Refrigeration Repair Shops
- 7629: Electrical and Small Appliance Repair Shop

- 7631: Watch, Clock and Jewelry Repair
- 7641: Furniture – Reupholstery, Repair, and Refinishing
- 7692: Welding Services
- 7699: Miscellaneous Repair Shops and Related Services

Clothing Retail:

- 5611: Men's and Boys' Clothing and Accessories Stores
- 5621: Women's Ready-To-Wear Stores ..
- 5631: Women's Accessory and Specialty Shops
- 5641: Children's and Infants' Wear Stores
- 5651: Family Clothing Stores
- 5655: Sports and Riding Apparel Stores
- 5661: Shoe Stores
- 5681: Furriers and Fur Shops
- 5691: Men's and Women's Clothing Stores
- 5697: Tailors, Seamstresses, Mending, and Alterations
- 5698: Wig and Toupee Stores
- 5699: Miscellaneous Apparel and Accessory Shops

Contractors:

- 1520: General Contractors – Residential and Commercial
- 1711: Heating, Plumbing, and Air Conditioning Contractors
- 1731: Electrical Contractors
- 1740: Masonry, Stonework, Tile Setting, Plastering and Insulation Contractors
- 1750: Carpentry Contractors
- 1761: Roofing, Siding, and Sheet Metal Work Contractors
- 1771: Concrete Work Contractors
- 1799: Special Trade Contractors (Not Elsewhere Classified)

Delivery Services:

- 4214: Motor Freight Carriers, Trucking—Local/Long Distance, Moving and Storage Companies, Local Delivery
- 4215: Courier Services—Air and Ground, Freight Forwarders
- 4225: Public Warehousing—Farm Products, Refrigerated Goods, Household Goods Storage

Building/Hardware Stores:

- 5200: Home Supply Warehouse Stores
- 5211: Lumber and Building Materials Stores

– 5231: Glass, Paint, and Wallpaper Stores

– 5251: Hardware Stores

– 5261: Nurseries and Lawn and Garden Supply Stores

– 5039: Construction Materials (Not Elsewhere Classified)

Motor Vehicle and Parts Dealers:

– 5511: Car and Truck Dealers (New and Used) Sales, Service, Repairs, Parts, and Leasing

– 5521: Car and Truck Dealers (Used Only) Sales, Service, Repairs, Parts, and Leasing

– 5532: Automotive Tire Stores

– 5533: Automotive Parts and Accessories Stores

– 5541: Service Stations (With or without Ancillary Services)

– 5542: Automated Fuel Dispensers

– 7531: Automotive Body Repair Shops

– 7534: Tire Retreading and Repair Shops

– 7535: Automotive Paint Shops

– 7538: Automotive Service Shops (Non-Dealer)

– 7542: Car Washes

– 7549: Towing Services

– 5013: Motor Vehicle Supplies and New Parts

– 5599: Miscellaneous Automotive, Aircraft, and Farm Equipment Dealers (Not Elsewhere Classified)

Recreation Equipment:

– 5551: Boat Dealers

– 5552: Electric Vehicle Charging

– 5561: Camper, Recreational and Utility Trailer Dealers

– 5571: Motorcycle Shops and Dealers

– 5592: Motor Homes Dealers

– 5598: Snowmobile Dealers

– 5940: Bicycle Shops – Sales and Service

– 5941: Sporting Goods Stores

– 5271: Mobile Home Dealers

– 5996: Swimming Pools – Sales and Service

Furniture/Appliances:

– 5712: Furniture, Home Furnishings, and Equipment Stores, Except Appliances

– 5713: Floor Covering Stores

– 5714: Drapery, Window Covering, and Upholstery Stores

- 5718: Fireplace, Fireplace Screens and Accessories Stores
- 5719: Miscellaneous Home Furnishing Specialty Stores
- 5722: Household Appliance Stores

Direct Marketing:

- 5960: Direct Marketing – Insurance Services
- 5962: Direct Marketing – Travel-Related Arrangement Services
- 5963: Door-To-Door Sales
- 5964: Direct Marketing – Catalog Merchant
- 5965: Direct Marketing – Combination Catalog and Retail Merchant
- 5966: Direct Marketing – Outbound Telemarketing Merchant
- 5967: Direct Marketing – Inbound Teleservices Merchant
- 5968: Direct Marketing – Continuity/Subscription Merchant
- 5969: Direct Marketing – Other Direct Marketers (Not Elsewhere Classified)

Insurance Premiums:

- 6300: Insurance Sales, Underwriting, and Premiums
- 6012: Financial Institutions – Merchandise, Services, and Debt Repayment
- 6051: Non-Financial Institutions – Foreign Currency, Non-Fiat Currency (for example: Cryptocurrency), Money Orders (Not Money Transfer), Account Funding (not Stored Value Load), Travelers Cheques, and Debt Repayment
- 6211: Security Brokers/Dealers

Personal Care Services:

- 7210: Laundry, Cleaning, and Garment Services
- 7211: Laundries – Family and Commercia
- 7216: Dry Cleaners
- 7299: Miscellaneous Personal Services (Not Elsewhere Classified)
- 7251: Shoe Repair Shops, Shoe Shine Parlors, and Hat Cleaning Shops

Household Services:

- 7276: Tax Preparation Services
- 7277: Counseling Services – Debt, Marriage, and Personal
- 7278: Buying and Shopping Services and Clubs
- 7311: Advertising Services
- 7321: Consumer Credit Reporting Agencies
- 7333: Commercial Photography, Art, and Graphics
- 7338: Quick Copy, Reproduction, and Blueprinting Services
- 7339: Stenographic and Secretarial Support
- 7342: Exterminating and Disinfecting Services

– 7349: Cleaning, Maintenance, and Janitorial Services
– 7361: Employment Agencies and Temporary Help Services
– 7372: Computer Programming, Data Processing, and Integrated Systems Design Services
– 7375: Information Retrieval Services
– 7379: Computer Maintenance, Repair and Services (Not Elsewhere Classified)
– 7392: Management, Consulting, and Public Relations Services
– 7393: Detective Agencies, Protective Services, and Security Services, including Armored Cars, and Guard Dogs
– 7394: Equipment, Tool, Furniture, and Appliance Rental and Leasing
– 7395: Photofinishing Laboratories and Photo Developing
– 7399: Business Services (Not Elsewhere Classified)
– 0780: Landscaping and Horticultural Services
– 7217: Carpet and Upholstery Cleaning
– 7261: Funeral Services and Crematories
– 742: Veterinary Services
– 0763: Agricultural Co-operatives
– 2741: Miscellaneous Publishing and Printing
– 2791: Typesetting, Plate Making and Related Services
– 2842: Specialty Cleaning, Polishing and Sanitation Preparations
– 7221: Photographic Studios

Health Care:

– 8011: Doctors and Physicians (Not Elsewhere Classified)
– 8021: Dentists and Orthodontists
– 8031: Osteopaths
– 8041: Chiropractors
– 8042: Optometrists and Ophthalmologists
– 8043: Opticians, Optical Goods, and Eyeglasses
– 8049: Podiatrists and Chiropodists
– 8050: Nursing and Personal Care Facilities
– 8062: Hospitals
– 8071: Medical and Dental Laboratories
– 8099: Medical Services and Health Practitioners (Not Elsewhere Classified)

Professional Services:

– 8911: Architectural, Engineering, and Surveying Services
– 8931: Accounting, Auditing, and Bookkeeping Services

- 8999: Professional Services (Not Elsewhere Classified)
- 8111: Legal Services and Attorneys

Education Services:

- 8211: Elementary and Secondary Schools
- 8220: Colleges, Universities, Professional Schools, and Junior Colleges
- 8241: Correspondence Schools
- 8244: Business and Secretarial Schools
- 8249: Vocational and Trade Schools
- 8299: Schools and Educational Services (Not Elsewhere Classified)
- 8351: Child Care Services

Other Services and Fees:

- 9211: Court Costs, Including Alimony and Child Support
- 9222: Fines
- 9223: Bail and Bond Payments
- 8398: Charitable Social Service Organizations
- 8641: Civic, Social, and Fraternal Associations
- 8651: Political Organizations
- 8661: Religious Organizations
- 8675: Automobile Associations
- 8699: Membership Organizations (Not Elsewhere Classified)
- 8734: Testing Laboratories (Non-Medical Testing)
- 9399: Government Services (Not Elsewhere Classified)
- 9402: Postal Services – Government Only
- 9950: Intra-Company Purchases
- 9702: Emergency Services (GCAS) (Visa use only)

Computer/Software:

- 5045: Computers and Computer Peripheral Equipment and Software

Business Supplies:

- 5021: Office and Commercial Furniture....
- 5039: Construction Materials (Not Elsewhere Classified)
- 5044: Photographic, Photocopy, Microfilm Equipment and Supplies
- 5046: Commercial Equipment (Not Elsewhere Classified)
- 5047: Medical, Dental, Ophthalmic and Hospital Equipment and Supplies
- 5051: Metal Service Centers and Offices

- 5065: Electrical Parts and Equipment
- 5072: Hardware, Equipment and Supplies
- 5074: Plumbing and Heating Equipment and Supplies
- 5085: Industrial Supplies (Not Elsewhere Classified)
- 5094: Precious Stones and Metals, Watches and Jewelry
- 5099: Durable Goods (Not Elsewhere Classified)
- 5111: Stationery, Office Supplies, Printing and Writing Paper
- 5122: Drugs, Drug Proprietaries, and Druggist Sundries
- 5131: Piece Goods, Notions, and Other Dry Good
- 5137: Men's, Women's, and Children's Uniforms and Commercial Clothing
- 5139: Commercial Footwear
- 5169: Chemicals and Allied Products (Not Elsewhere Classified)
- 5172: Petroleum and Petroleum Product
- 5192: Books, Periodicals and Newspapers
- 5193: Florists Supplies, Nursery Stock and Flowers
- 5198: Paints, Varnishes and Supplies.....
- 5199: Nondurable Goods (Not Elsewhere Classified)

Digital Goods:

- 5815: Digital Goods Media – Books, Movies, Music
- 5816: Digital Goods – Games
- 5817: Digital Goods – Applications (Excludes Games)
- 5818: Digital Goods – Large Digital Goods Merchant

Real Estate Payments:

- 6513: Real Estate Agents and Managers