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# Impact of COVID-19 on Disaggregate Consumption and Online Retail Sales: Evidence from the USA

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**Abstract**

This study applies the difference-in-difference technique to analyze the consumption pattern during COVID-19 against pre-COVID-19 years. We analyze the online retail sales before and after COVID-19 using time series and linear regression models. Time series intervention analysis results suggest that COVID-19 has caused a statistically significant change in the mean level of online retail sales share in e-commerce. Using a difference-in-difference approach, we find a 4% decrease in aggregate consumption from March to December 2020 compared to the benchmark period although statistically insignificant. Further, using a fixed effects model with time dummies, we find a nearly 8% significant decrease in March–April and a 2% decrease in May–June, which is not significant maybe because the lockdown restrictions were lifted during that time. We infer that the aggregate consumption decreased during the strictest months of lockdown and COVID-19 had a heterogeneous impact across categories of consumption.

**Keywords:** COVID-19, Consumption, E-commerce, Difference-in-Difference, Intervention Analysis

## 1 Introduction

The COVID-19 pandemic has had unprecedented economic consequences around the globe. It has disrupted the consumption pattern and made the world economy sluggish through lockdowns to shutdowns of businesses. On September 15, 2020 there were more than 6.5 million confirmed cases and 195,000 deaths in the United States [2]. The pandemic has disrupted the food supply chain, economic uncertainty occurred due to lockdown, social distancing, travel restrictions, quarantine, among others, which resulted in uneven household spending. Similarly, dramatic changes have been observed in consumer spending across different sectors since the pandemic in January 2020. Baker et al. [1] find an overall increase in household spending by approximately 50% from 26 February to 11 March 2020 and an almost double decrease in overall spending during the lockdown as it was increased at the time of the outbreak of COVID. The U.S. retail sales increased 17.7% from April to May, the largest monthly jump on record, recouping 63% of March and April's losses. Growth in retail sales continued through the summer: by August, retail sales were 2.6% above their August 2019 level [20]. The government provided an almost 6 trillion dollar relief package and the Federal Reserve Bank decreased its overnight benchmark interest rate to zero to lift the economy. Since the outbreak of COVID in December 2019, several studies have explored the impact of COVID on diverse types of consumption in different countries using transaction and survey-level data including offline, online, and foot traffic taken from banks, online forums, and other institutions by employing Ordinary Least Square (OLS) and fixed effect models to assess the COVID impact on consumption [1, 22, 15, 7]. Other studies from China and France [5, 3] used the DID approach to see the causal impact of COVID on consumption for different regions within the countries without studying the sensitivity of consumption against COVID for various categories including necessary goods, luxurious goods, durable and non-durable. In [14] the authors examined the impact of COVID for various categories in Iran using the difference-in-difference methodology taking the months as treatment and control groups regions. Months as treatment means that we considered the treatment group of months when there was COVID, which include months of the year 2020 and control group of months when there was not COVID, which consider the months of the year 2018 and 2019 to compare the consumption pattern with and without COVID. However, they also used transaction-level data.

In this article, we use a contrasting approach to those used in earlier studies. More specifically, we aim to analyze the causal impact of COVID-19 on household

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spending across different categories of consumption using national-level, comprehensive, real personal consumption expenditure data from the US. To estimate the COVID impact on consumption across different subsections like energy goods, food, services, and durable and non-durable goods in the United States from January to December 2020, we use the difference-in-difference (DID) methodology and further explore the impact of COVID for each category of consumption using a fixed effect model. The identification for DID of causal months relies on the assumption that in the absence of COVID-19, the counterfactual trend of consumption in the treatment period, i.e., year 2020, would have been parallel to the trend of consumption in the control period, i.e., years 2018 and 2019. We first analyzed the aggregate consumption results using DID and found an almost 4% negative impact of COVID on consumption in the treatment period as compared to the control period; however, the results were statistically insignificant. We further explored the impact of COVID for each category of consumption, which shows that COVID has negatively impacted durable and non-durable goods, services, and energy categories during the peak months of COVID (March and April). During the same months, COVID had positive effect on food consumption. We found positive COVID impact on consumption after the month of April for all categories after the relaxation of lockdown restriction and the issuance of stimulus checks, but there was a consistent negative impact on energy goods for the entire year of 2020. Our findings provide real-time COVID-19 consequences for each category of consumption throughout the pandemic period. Our results indicate that the pandemic did change the consumption pattern, the consumption recovered as it is sensitive to temporary change in income.

## 2 Literature Review

Hosseini and Valizadeh [14] study the effect of the COVID-19 pandemic on the style of consumption in Iran. The paper uses monthly data from November 22, 2018, to June 21, 2020, obtained from Shaparak, a clearinghouse of all online transactions, which is a unique aspect of the study. The study uses the DID methodology to identify the effects of the COVID-19 pandemic on consumption. Results show that due to the COVID-19 outbreak, the choice of consumers changed from offline to online shopping. The results obtained from the DID estimation show a 41% decrease in the annual growth of transactions during the time of the severe lockdown (March and April 2020) in Iran. Overall, there was a 5.25% contraction in spending in the year 2020. Results show the effect of the pandemic was different across different provinces and sectors. Further, tourist destinations and semi-durable goods like clothing experienced the most adverse effects, while non-durable goods were affected the least. We found the paper to be helpful for our project as we decided to use the DID technique and extend our paper across categories. However, we also ran a separate OLS with fixed effects in our paper which would be a contribution from our part, whereas the OLS is a method to estimate the parameters of the regression model for the best representation of the data by minimizing the sum of squared error.

Bounie et al. [3], Study the impact of COVID-19 on consumers' mobility consumption patterns change from in-person to online in France. The study uses data sets from 2019 to 2020 consisting of nearly 5 billion payment card data from nearly 70 million cards issued by all French Banks. Results show that the total value and the total volume of card spending decreased by 50% and 59% respectively during the containment period (after March 17, 2020). Similarly, offline and online transactions show a fall of 60% and 30% by March 18, 2020 respectively. This shows that the impact of the COVID-19 crisis on consumption expenditure decreased by promoting online shopping thereby raising the economy's resiliency.

Chen et al. [5] uses daily-level data on offline consumption covering 214 cities in China. Overall results confirm that the COVID-19 pandemic severely affect the average daily consumption in China. Results show that the daily offline consumption in each city drop by 21.63 million after the lockdown. Also, a 42% fall in offline consumption is observed. Moreover, every consumption category adversely affect, where dining and entertainment drop the most and necessities the least. The study findings show a loss of 1% of China's 2019 GDP through offline consumption in the eight-week period. We use a similar DID estimation technique and extended it to categories. However, we apply the DID model and use OLS with fixed effects.

Kubota et al. [16] study the responses of household consumption to a Special Cash Payment (SCP) program in Japan during the pandemic. The OLS results show a sudden jump in household spending on the week of SCP payments, which then declined gradually, week by week. The results also show significant heterogeneity in household consumption with respect to family size, liquidity, financial assets, and COVID-19 income shocks. The paper estimates a sizable marginal propensity to consume (MPC) and significant heterogeneity in financial status and recommends using other measures of heterogeneity in MPC's to obtain better estimates in the pandemic environment. We liked the empirical methodology of OLS with fixed effects used in the paper and used a similar methodology of OLS with fixed effects, though varied in the approach of the outcome variable, and extended it across consumption categories, which is the contribution of our paper.

In the Kubota et al. paper, we found the heterogeneity test by family size, COVID-19 income shocks, liquidity constraints, and demand deposit balances. However, the paper could have also considered the age factor for the heterogeneity test to see how consumption responds to different age groups due to the SCP program.

Martin et al. [17] measures the socio-economic impact of the COVID-19 pandemic on household consumption and poverty. They use census tract data and build a micro-economic model divided into crisis and recovery periods to measure the effectiveness of social benefits. They utilize the San Francisco Bay Area as a case study and evaluate the effect of lockdown and the Unemployment Insurance (UI) benefits along with the CARES Act. Results show that in the absence of social protection, the pandemic might have an adverse effect to the system. In a simulation of a three-month lockdown, the poverty rate would rise by 8.8% in the Bay Area, while household consumption would fall significantly. Similarly, with the government benefits provided in the form of the state's UI and the Federal CARES Act, the poverty rate would rise only by 1.9%, while consumption would be almost at the same level. Further, a nearly perfect execution of the CARES Act would decrease the poverty rate by 0.6%. All in all, the paper presents a micro-economic model for estimation, which we found to be a good model to capture the effect of COVID on household consumption. However, the model would have bene more complete if the the paper had considered disaggregate consumption across categories like essential and non-essential, durable and non-durable, etc. We will not use the same model but incorporate consumption across categories in our paper.

Sheth [18] studies the effect of COVID-19 on consumer behavior. The paper is based on behavioral points rather than the econometric model to see the changes in consumer habits before and after the pandemic. The paper finds that not all old habits would return, as consumers have developed creative and convenient ways to change their lifestyles, such as switching from movie theatres to Netflix and Disney, sharing drives with Uber rather than taking a taxi, preferring online shopping to in-store ones, etc. Although this research differs from our paper in terms of estimation and outcomes, it helps us observe the effect of the pandemic on consumption from a different perspective.

Baker et al. [1] finds significant changes in the consumption pattern during the peak month of COVID-19 based on the shelter-in-place order across the United States: individual spending rapidly increases by 40% in the first half of March and declines by 25–30% in the second half of March. They further estimate that older people reduce their expenditure substantially during the peak time of COVID-19, though there is not significant differences in spending based on political orientation. They use the primary data of the Gallup survey for this analysis. This study uses the DID method to analyze the impact of COVID-19 on individual spending and follow the shelter-in-place order's policy for selection of the months and days of COVID-19. During the peak time of COVID-19 stay at home orders were issued for a few months in specific places where the number of cases was high and people were restricted to their homes which is also called the shelter-in-place order. They select 3 weeks from 26 February till 30 March and estimate the impact on aggregate and individual spending. However, COVID-19 has a potential longer-term effect, which is not fully addressed through relying on one-month data, as the pandemic started in December 2019 and peaked in the months from January to May 2020.

Coiboin et al. [6] estimate that overall consumer spending drop by $1000 per month between the months of January and April and employment decreases by 5% due to the lockdown. Further, their outlook estimates indicate that the employment levels may not improve for up to three to five years. The paper studies the heterogeneous impact of lockdown across the counties in the US. They use two stages of regression on the first stage: they first estimate the lockdown variable dependent on confirmed COVID cases and then use it as an independent variable to see its impact on consumer spending. However, the impact of COVID is not limited to the lockdown days but it has been changing since the pandemic started. In addition, they also use some online survey data, which is not as reliable as our data taken from the authentic source of the Bureau of Economic Analysis (BEA).

Yang et al. [21] focus on the short- and long-term effects of stimulus checks on consumer spending and foot traffic. Results of the paper suggest that stimulus checks increase short-term consumer spending but have a negligible impact on foot traffic. They use card transaction data for spending and mobile device location tracking data for foot traffic. The authors use an interrupted time series model to capture the effect of interruption in the overall spending, and they conclude that government lockdown policies do not significantly impact spending and have only a temporary effect. However, the interrupted time series model might not capture the effect of all the specific events, e.g., government policies, the business community, and consumer behavior, because there were some categories such as food consumption where there is an increase, while non-durable consumption decrease. Further, they consider the 15th of April date for stimulus checks; however, these were not distributed until June and their effect on spending might be medium and longer term. In contrast, we are considering the various categories of consumption and estimating the impact of COVID on each category and at the aggregate level as well.

Yue et al. [22] take a different time frame household survey level data from February 12 to March 11 and from March 12 to March 22 from China. The authors use OLS and ordered probit models to show that COVID-19 infections and deaths decreased overall income by 0.73 and 0.14 respectively. The Ordered probit is a generalization of the widely used probit analysis to the case of more than two outcomes of an ordinal dependent variable (a dependent variable for which the potential values have a natural ordering, as in poor, fair, good, excellent). They use two proxy variables, i.e., COVID-infected people and COVID deaths, to capture the effect of COVID on household income. They restrict the sample to the COVID-infected people. However, their sample size miss the people who were not infected with COVID but still lost their jobs and income; consumption was affected due to restrictions and reduced economic activities, which might cause the sample selection bias. Therefore, we are considering overall consumption collected through BEA data analysis and dividing it into categories.

Kim and Lee [15] analyze the effectiveness of the 2016 South Korea program on household spending, which provided redeemable vouchers to small household businesses like COVID-19 stimulus checks. Due to this program, 30% of households increased their food and overall household spending. First, the authors analyze the impact of stimulus checks on household consumption and savings since 2000. Second, they analyze the causal effect of the 2016 voucher program on economic outcomes using a difference-in-difference method. They extend the methods to the COVID-19 case considering survey data by the Korea Institute of Public Finance (KIPF) between June 26 and July 1, 2020. They capture the time and district fixed effects using time- and cross-section-specific dummies. They divide households into 6 income groups based on monthly income and analyze the impact of the stimulus checks on household expenditures. The study concludes that the high-income group spending was not affected by stimulus checks, whereas the low-income group increased its spending significantly.

Cotton et al. [7] estimates the negative impact of COVID-19 on consumer spending in the US using weekly data and applies the fixed effect method. They use the consumer spending data taken from Affinity Data Solutions that is captured based on Zip-codes Tabulation Area (ZCTA). They match the data with American Community Survey (ACS) based on the zip codes. Further, they collect COVID-related data from the Centers for Disease Control and Prevention (CDC). They decompose the effect of spending using the fields' decomposition approach creating interaction term of time dummies across various economic factors (income, education, occupation), demographic factors (age, political affiliation, ruralness, gender, ethnicity) and COVID factors (number of cases, vaccination rate, lockdown, etc.). Results show that Hispanic and college-educated populations faced relatively larger declines in spending. They find that political affiliation and COVID factors have a strong influence on spending. However, they use weekly data and compare the results relative to a week (Jan 27 to Feb 2) when COVID was already in progress. Thus, it might not be the true counterfactual for the reference period. In contrast, we consider the monthly data and compare it with a time when there was no COVID.

# 3 Conceptual Framework

Personal Consumption Expenditures (PCE) are a key factor to observe the economic consequences of COVID on consumer spending, as they account for two-thirds of the final domestic spending. Consumer preferences changed during the pandemic period and affected the demand for consumption expenditure in various sectors, hard and swift. Indivuduals' concerns about safety measures and the input supply chain disruption also increased the cost of production and decreased the supply of goods and services at the same time. COVID-19 affected consumption expenditures adversely when an emergency order was issued in January 2020. This led to the temporary shutdown of businesses, industries, and notably, restaurants. The loss of jobs and salary cut for employees pushed hard on the wallets of consumers. Overall, there was a change in consumption patterns due to the pandemic and people were inclined to save more. Due to the considerable risk of job loss and uncertainty in earnings, people switched their preferences toward the well-being of their families. This drove an increase in savings rate by almost double at the end of December 2020 relative to December 2019. Similarly, people were also expecting fewer earnings in the future and changing their consumption patterns accordingly.

However, the sensitivity of the change in demand for goods and services was heterogeneous across categories. People preferred healthy food and beverages, possibly to increase their immunity, which led to an increase in food consumption by 23% from February to March 2020. Further, consumption of food increased when people started spending more time at home and working remotely, which thereby increased grocery spending. Similarly, the consumption of services and energy goods sectors were negatively affected by the pandemic because the demand for recreation, accommodation, transportation services were highly sensitive to COVID, which decreased the demand for these services by 15% during the lockdown months (March–April); this is shown in Figure 1. The demand for gasoline decreased by 27% because people avoided communal transportation and preferred staying at home. The consumption of durable and non-durable goods declined during the months of lockdown and demand was reversed after two months due to the increased demand for durable goods such as home appliances and wellness equipment. Similarly, the demand for non-durable goods, services, and foods sharply increased after April as people started gathering, traveling, and spending their savings on leisure and recreation activities that they missed in the previous months.

The pattern of consumption expenditures by various groups is presented in the graph that are depicted in Figures 1–3. Figure 2 and Figure 3 show parallel trends in the consumption of services, durable goods, energy goods and excluding food and energy. They show a sharp fall in their demand in March and April, which then starts to recover gradually when the restrictions eased and the first and second rounds of stimulus checks followed. Similarly, the demand for non-durable goods show a drop in April while the demand for food rose during these months.

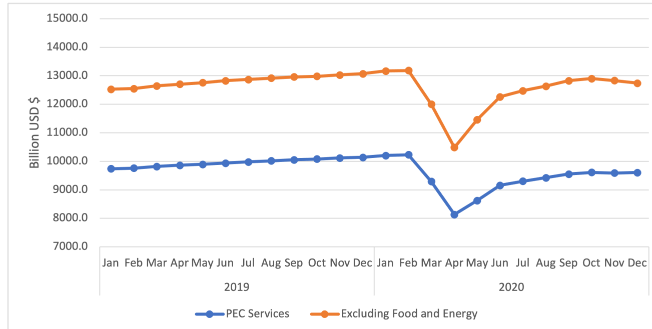


Figure 1: PCE on services and excluding food and energy.

## 4 Data

Data for personal consumption expenditure in various categories were taken from the federal reserve economic, which is collected by the Bureau of Economic Analysis (BEA). We used the monthly data from 2018 to 2020 for all the sub-categories to analyze the impact of COVID-19 on various consumption groups in different months. The overall personal consumption expenditure is classified by different categories including durable and non-durable goods. These consist of tangible commodities that can be stored or inventoried, but they also include certain intangible products, such as software. The Bureau of Economic Analysis defines the durable and non-durable goods as: "Durable goods are goods that have an average useful life of at least 3 years. Non-durable goods are goods that have an average useful life of fewer than 3 years. Services are commodities that cannot be stored or inventoried and that are usually consumed at the place and time of purchase" (Bureau of Economic Analysis). Further, we took the data of the unemployment rate obtained from the Federal Reserve Bank's economic data (FRED), originally collected from the US Bureau of Labor Statistics. The following are the categories of consumption:

- Durable goods: motor vehicles and parts, furnishings and durable household equipment, recreational goods and vehicles, and other durable goods.
- Non-durable goods: food and beverages purchased for off-premises consumption, clothing and footwear, gasoline and other energy goods, and other non-durable goods.
- Services: housing and utilities, health care, transportation services, recreation services, food services

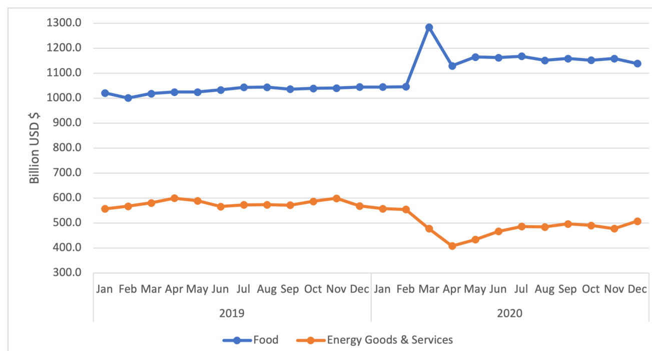


Figure 2: PCE on food and energy goods and services.

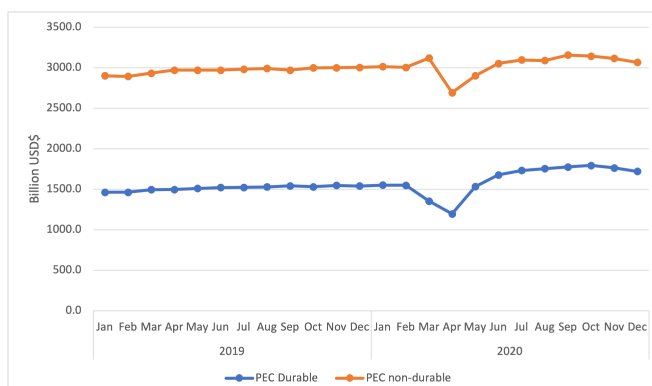


Figure 3: PCE on durable and non-durable goods.

and accommodations, financial services and insurance, and other services.

- Food includes value of commodity produced and consumed at farms, alcoholic beverages and non-alcoholic food and beverages measured by commodity flow method of Economic census.

# 5 Empirical Strategy

We first used a Difference-in-Differences (DID) technique to measure the causal impact of COVID-19 on aggregate consumption. In March 2020 all states in the US declared an emergency due to COVID-19. Therefore, we fixed this date as the beginning of the post period. Similarly, in the month of December, the second round of stimulus checks were sent, which we took as the end of our post period. The first COVID case in the US was seen in January 2020. Thus, the year 2020 is taken as our treatment variable. Table 1 shows our treatment and control period and pre-post months. We followed the assumption of DID that in the absence of COVID-19, the counterfactual trend of consumption in the treatment period would move parallel to the trend of consumption of the control period. We used the following equation:

$$\ln(\mathrm{PCE})_{i,t} = \beta_0 + \beta_1[\mathrm{Treat}_{i,t}] + \beta_2[\mathrm{Post}_{i,t}] + \beta_3[\mathrm{dd}_{i,t}] + \epsilon_{i,t} \quad (1)$$

where $\mathrm{PCE}_{i,t}$ is the personal consumption expenditures for period $i$ at time $t$, $\mathrm{Treat}_{i,t}$ is the dummy variable that takes value 0 for the months Jan–Feb and value 1 for the months March to December, $\mathrm{Post}_{i,t}$ is 1 for the 2020 period and 0 for the 2018, 2019 period, and $\mathrm{dd}_{i,t}$ is the interaction term of the post and treatment variable. Furthermore in equation 1, $\ln(\mathrm{PCE})_{i,t}$ is the outcome of interest that shows the log of personal consumption expenditure (PCE) in different categories $i$ like energy goods, food, services, market-based PCE, and durable and non-durable goods at time $t$. The $\beta_0$ represents the log personal consumption expenditure with zero effect of pre and post treatment. We take $t = 1$ for the period between March to December of 2018, 2019, and 2020 and zero otherwise. The interaction term of Treat and Post variable shows the months after the emergency order was declared in the US in year 2020, i.e., the pandemic period. Lastly, $\epsilon_{i,t}$ is the error term that captures the unobserved effect of the model.

We further extend model 1 by adding the fixed effect as given in the following:

$$\ln(\mathrm{PCE})_{i,t} = \beta_0 + \beta_1[\text{Jan–Feb}]t + \beta_2[\text{Mar–Apr}]t + \beta_3[\text{May–June}]t + \beta_4[\text{July–Sept}]t + \beta_5[\text{Oct–Dec}]t + \epsilon_{i,t} \quad (2)$$

Table 1: Set up of difference-in-difference strategy.

| | **Pre-Period** (Jan–Feb) $t = 0$ | **Post-Period** (Mar–Dec) $t = 1$ |
|---|---|---|
| **Control Year** (2018, 2019) | No COVID-19 | No COVID-19 |
| **Treatment Year** (2020) | No COVID-19 | COVID-19 |

Table 4 depicts a comparison of OLS and the fixed effect model. It captures all those unobservable characteristics affecting consumption that are kept fixed over time. Including categories with fixed effect eliminates the risk of a bias due to omitted factors that vary across categories but not over time. All $\beta$ denotes the impact on consumption expenditures in different periods of the year 2020 relative to the reference group, i.e., January 2018 to December 2019, the period before the pandemic. The different span of months in the above model coincides with the different federal and local influences on consumption during the pandemic. In January–February, the model measures the impact of the pandemic on consumption when people started hoarding goods and shortage rumors and uncertainty happened. In March and April, the "stay at home order" was issued, and many businesses and economic and social activities were adversely affected. In the months of May–June, the restrictions started easing, and in June, the first round of stimulus checks started, which increased the purchasing power of the consumer relative to the earlier months. Likewise, the second round of stimulus checks started in early December. For the comprehensive analysis of consumption patterns, we measured the consumption association at different months based on the severity of COVID and restrictions.

# 6 Results and Discussion

Table 2 presents the results of DID estimation, it shows the positive and statistically significant treat and post coefficients at 5% and 1% respectively. The treat variable implies a 3.91% increase in aggregate consumption in the months of January and February in the year 2020 as compared to 2018 and 2019. Similarly, the post variable shows a 2.48% increase in consumption from March to December in 2018 and 2019 as compared to January and February in 2018 and 2019. DID, which is the interaction term of treat and post, is negative. Results show a 4% drop in consumption in the pandemic period from March to December in the year 2020 as compared to the control years in 2018 and 2019, when there was no COVID. However, the drop is insignificant, which may be

Table 2: Difference-in-difference estimates.

| | Coef. | Std. Err. | z | P > $\|z\|$ | [95% Conf.] | Interval |
|---|---|---|---|---|---|---|
| treat | 0.0391* | 0.0171 | 2.28 | 0.023 | 0.0055 | 0.0727 |
| post | 0.0248** | 0.0027 | 9.35 | 0.000 | 0.0196 | 0.0300 |
| dd | −0.040 | 0.0498 | −0.80 | 0.421 | −0.1376 | 0.0575 |
| _cons | 7.58*** | 0.5328 | 14.24 | 0.000 | 6.5397 | 8.6281 |
| Model Fit and Variance Decomposition | | | | | | |
| $\sigma_u$ | $\sigma_e$ | $\rho$ | Wald $\chi^2$ | prob $\chi^2$ | Number of Obs | Groups |
| 1.1894 | 0.0707 | 0.9965 | 189 | 0.0000 | 180 | 5 |

$^*p \leq 0.1$, $^{**}p \leq 0.05$, $^{***}p \leq 0.01$

due to the varied effects on the categories of consumption during the pandemic that could not be shown separately in the above results. Thus, we also extended our results based on consumption categories using different methodologies to capture the true effects of COVID on different consumption categories.

In model fit, $\sigma_u$ is standard deviation of the random effects (also known as the individual-specific effects or unobserved heterogeneity). In the context of a panel data model, this often represents unobservable factors that are constant for each individual but may vary across individuals. A higher value mean the greater variability across individual. $\sigma_e$ shows the less variability in the error term. There is a strong correlation between the unobserved individual-specific effects and the error term, suggesting that there may be unobserved factors influencing both the dependent variable and the individual-specific effects. The chi-square value also suggests that there is an autocorrelation in the model.

## 6.1 Summary statistics

Table 3 shows the results of summary statistics of personal consumption expenditure of each category of consumption for the treatment and control time-period. The categories given in the table are labelled as 1 for the durable goods with mean 1491.22 billion US dollars, 2 for the energy goods with mean 586 billion US dollars, 3 with mean 12569.96 billion US dollars for the services, 4 for food with mean 1015.63 billion US dollars, and 5 for non-durable goods with mean 2925.09 billion US dollars. The overall results show that consumption had significant variation among all the categories. On the average, consumption slightly increased after the COVID emergency was issued (year 2020). We see that the average consumption is higher in the treatment period for durable goods, non-durable goods and food as compared to control period (2018–2019). Consumption of services and energy goods and services decreased in the treatment group as compared to control group. Table 4 shows the results of

Table 3: Summary statistics of consumption across categories.

| | **Treat** | | **Total** |
|---|---|---|---|
| | **0** | **1** | |
| **Group 1** | 1491.23 | 1616.42 | 1532.96 |
| Std. Err. | 32.50 | 187.49 | 123.79 |
| N | 24 | 12 | 36 |
| **Group 2** | 586.09 | 486.90 | 553.03 |
| Std. Err. | 16.70 | 42.29 | 54.72 |
| N | 24 | 12 | 36 |
| **Group 3** | 12569.40 | 12414.00 | 12517.60 |
| Std. Err. | 308.53 | 782.48 | 510.40 |
| N | 24 | 12 | 36 |
| **Group 4** | 1015.63 | 1146.66 | 1059.31 |
| Std. Err. | 18.75 | 61.20 | 73.02 |
| N | 24 | 12 | 36 |
| **Group 5** | 2925.10 | 3037.43 | 2962.54 |
| Std. Err. | 53.46 | 129.73 | 100.26 |
| N | 24 | 12 | 36 |
| **Total** | 3717.49 | 3740.28 | 3725.09 |
| Std. Err. | 4516.45 | 4468.27 | 4487.96 |
| N | 120 | 60 | 180 |

OLS and fixed effect models. Model 1 is an OLS using the control variable in which the beta coefficients show the change with respect to the reference group. Here, we see that all variables are positive and statistically insignificant. The first row implies an increase in aggregate consumption in January and February of year 2020 by 1.44% relative to the reference period (2018–2019), which is statistically insignificant. Although the periodic variables are insignificant in the model, the signs of magnitude follow our convention except for the months from March to June. We see that the coefficient of the unemployment rate is negative, which follows the basic convention but is statistically insignificant so we dropped this variable in the next model. Similarly, in Model 2,

Table 4: Results of OLS and fixed effect models.

| | Model 1 | Model 2 |
|---|---|---|
| Variables | OLS | OLS with FE |
| (Jan–Feb)2020 | 0.0144 | 0.0184 |
| | (0.3582) | (0.022) |
| (Mar–Apr)2020 | 0.0037 | −0.0787*** |
| | (0.5109) | (0.022) |
| (May–June)2020 | 0.0996 | −0.0192 |
| | (0.6362) | (0.022) |
| (July–Sept)2020 | 0.1088 | 0.0367** |
| | (0.4366) | (0.0183) |
| (Oct–Dec)2020 | 0.0818 | 0.0392** |
| | (0.3525) | (0.0183) |
| Unemployment Rate | −0.0143 | |
| | (0.0633) | |
| Constant | 7.6586*** | 7.6046*** |
| | (0.2591) | (0.0061) |
| Observations | 180 | 180 |
| R-squared | 0.0008 | 0.1279 |
| Number of type | 5 | 5 |

Standard errors in parentheses

* $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

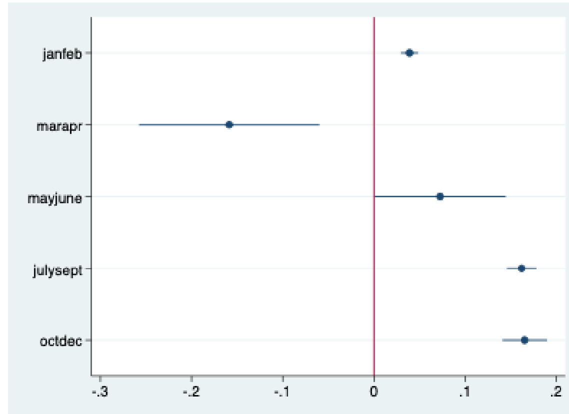


Figure 4: Coefficient plot for durable goods.

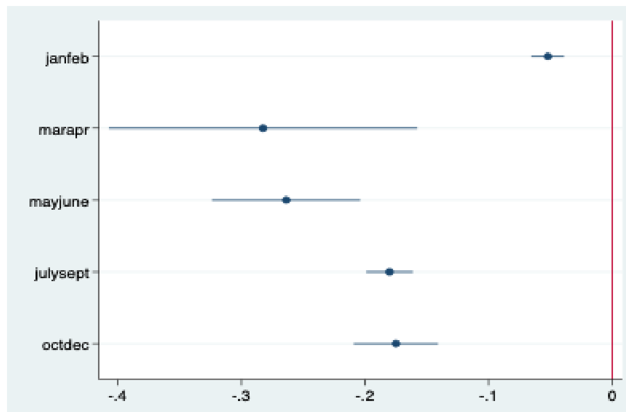


Figure 5: Coefficient plot for energy goods.

we used a fixed effects model, where we found a 7.87% significant decrease in aggregate consumption in March and April 2020 relative to the reference period. This significant decrease was because of the stay-at-home order and the emergency order, which led many businesses to close temporarily. However, there is a significant increase in aggregate consumption by nearly 4% from July to December 2020 due to the response of the first and second rounds of stimulus checks on consumption. Additionally, positive results in January and February and negative results in May and June follow our basic convention though being statistically insignificant. We extended our study to various categories of consumption using a coefficient plot to capture the response of COVID to various categories. Using this diagnostic test, we determined which categories were affected the most and the least.

## 6.2 Coefficient plot

To better understand the heterogeneous effect of COVID across categories, we applied the fixed effect model to see the COVID affect on each categories across various months. We made the coefficient plots for each category presented in Figure 4, which shows the coefficient values across each month represents with dots on line. It also shows an approximately 4% increase in the consumption of durable goods in January and February of the year 2020 relative to the reference period. Thereafter, due to the severity of COVID, people started to postpone purchasing durable goods like motor vehicles, kitchen items, and furniture, which led to a decrease in their demand by 15%. Then, following the decision to provide fiscal stimulus, consumers restricted their travel and stopped eating at restaurants, and started buying durable goods. Thus, we see the shift in demand for durable goods every month from nearly 9% in May and June to nearly 16% from October to December.

Figure 5 shows the coefficient plot of energy goods and services estimated with fixed effect model. It shows a decrease in the consumption of energy goods and services throughout the 2020 period. In January and February, it dropped by nearly 5% relative to the reference period. Thereafter, when the emergency order and stay at home order was issued in March and April, it dropped drastically by nearly 27% where people demanded less energy goods like petroleum products due to the temporary shutdown of business. Specifically, as crude oil demand halted due to the COVID-19 pandemic, oil prices plummeted, making gasoline in the US its cheapest in nearly 20 years.

In April 2020, the gasoline demand in the United States was half of what it was in April 2019. Following the months of May and June, pandemic restrictions began to ease, and we see a gradual increase in the consumption of energy goods though being negative all through the year.

Figure 6 presents the coefficient plot that shows the services dropped sharply by almost 11% in March and April when people were forced to stay at home due to the pandemic. Businesses like housing, financial services, food, and recreation services were shut down temporarily resulting in lower consumption. Also, businesses were facing hard times during COVID due to supply chain disruption, a decline in demand, shortages in supplies and inputs, and government-mandated closures. However, the decision of the federal government to help keep employees on payroll relieved some stress on the businesses. Following the months of May and June, it started to improve gradually due to the support from federal and state governments to these businesses and the response to stimulus checks.

Food is a necessary item for people, but the coefficient values represented with dots on line in Figure 7 shows a reverse trend during the pandemic period. Wholesale and retail food stores were open throughout the pandemic period. Early in the COVID-19 pandemic, retail food sales rose sharply and peaked during March 16–22, 2020, with 57% higher food-at-home sales compared with the same week in 2019. In March and April, people spent most of their time at home and stopped traveling and eating outside due to government-mandated regulations to fight COVID. This led to an increase in the demand for food by nearly 18% in March and April compared to previous months. Thereafter, it was around 12% throughout the year. All in all, the demand for food was positive in 2020.

The coefficient plot of Figure 8 of non-durable goods shows that the demand for non-durable goods was less sensitive during the pandemic period. In March and April coefficient value shown with dot on the line represent nearly 1% drop in consumption due to restrictive containment measures involving social distancing, remote working, and the closure of commercial activities. However, the demand for petroleum products, drugs, and other goods improved beginning in May, leading to a significant increase in consumption of non-durable goods throughout the year.

## 7 Modeling Consumer Behavior

This study used intervention analysis to model consumer behavior. We used the e-commerce retail sales data before and after COVID-19, which includes the sales of goods and services where the buyer places an order, or the price and terms of the sale are negotiated over the internet,

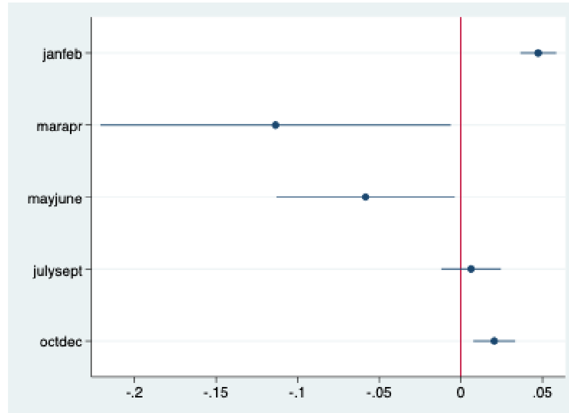


Figure 6: Coefficient plot for services.

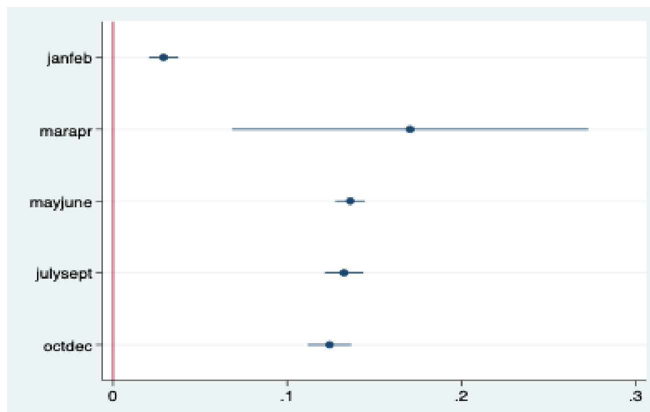


Figure 7: Coefficient plot for food.

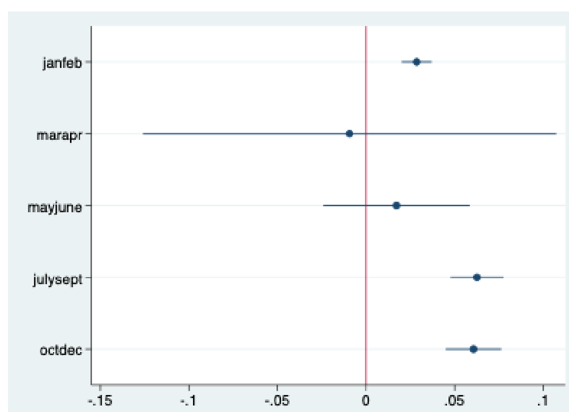


Figure 8: Coefficient plot for non-durable goods.

or mobile device, extranet, Electronic Data Interchange (EDI) network, electronic mail, or another comparable online system (Federal Reserve Bank). The US leads the global e-commerce market, followed by Japan and China. COVID-19 affected the trend and structure of US e-commerce retail sales producing cumulative excess retail e-sales of 227.820 billion US dollars and cumulative additional e-share of 10.61% [19].

Accurate sales forecasting is of paramount importance in retailing, as retail businesses rely on sales predictions for various operational decisions. There are many different methods for conducting intervention analysis; our study follows two approaches to assess the online retail sales before and after the COVID-19.

## 7.1 Time series approach

For time series analysis of the retail sales, we used a common method, which is an autoregressive integrated moving average (ARIMA) model. In the ARIMA model, intervention can be incorporated as an additional regressor in the model, or as a structural break that changes the parameters of the model. The impact of the intervention can be quantified by estimating the change in the coefficients of the model or by comparing the forecasted values with the actual values after the intervention. The general equation of the ARIMA model is given as follows:

$$Y_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \quad (3)$$

In equation 3, $Y_t$ is the dependent variable, $y_{t-p}$ is the $p$ number of lags of the dependent variable—called the auto-regressive (AR) term—and $e_{t-q}$ is the $q$ number of lags of error term or external shocks—called the moving-average (MA) terms. We used the R package auto.arima to find the best fitted model. To remove the autocorrelation, we used the lag of stationarized series, i.e., we applied the random-walk-with-growth model with retail series ($y$). The predicted equation of the model can be written as

$$\hat{Y}(t) - Y_{t-1} = \mu \quad (4)$$

where $\hat{Y}$ is the estimated values and $Y_{t-1}$ is the lag of the actual e-commerce retail sale series and $\mu$ is the constant term that represents the mean change in the e-ecommernce retail sales ($Y$). Since it includes (only) a nonseasonal difference and a constant term, it is classified as an "ARIMA $(0, 1, 0)$ model with constant."

## 7.2 Results of the ARIMA model.

Results presented in Table 5 show the ARIMA $(0, 1, 0)$ model, which is selected automatically using auto.arima R package. It is an integrated ordered I(1) model random walk with drift, which has comparatively lower values of AIC and BIC.

Table 5: ARIMA $(0, 1, 0)$ estimation results.

| | | | |
|---|---|---|---|
| Coefficients | | | |
| | drift | (std. error) | |
| | 0.1611 | (0.0126) | |
| Goodness of Fit | | | |
| $\sigma^2$ | | Log-likelihood | |
| 0.005873 | | 41.9 | |
| Training Set Error Measures | | | |
| ME | RMSE | MAE | MASE |
| 0.000109 | 0.07454 | 0.063777 | 0.99153 |

Table 6: Ljung-Box test of ARIMA $(0, 1, 0)$.

| Q-stat | D.F | P-Value | No. of Lags |
|---|---|---|---|
| 8.3908 | 07 | 0.2994 | 07 |

Table 6 shows the Ljung-Box test, which has the null hypothesis that residuals are normally distributed, and we cannot reject the null hypothesis as the $p$-value is greater than the alpha level of significance. It implies that when residuals normally distributed means series does not have autoccorelation problem.

For a better selection of the ARIMA model, we further explore the pattern of the residuals and use the autocorrelation function. The residuals graph shows some persistence and seems not fully white noise; however, there is not any statistically significant spike in the ACF graph, and the histogram also shows a bell-shaped pattern, which means that residuals are normally distributed and ARIMA $(0, 1, 0)$ is the best model to forecast the and predict the pattern of e-commerce retail sales.

Figure 10 shows that e-commerce sales would have followed the pattern highlighted in blue shades if COVID had not occurred. The shaded blue values are the forecasted values based on the quarterly data from 2010 to 2019. Based on this data, we forecasted the values for the years 2020 and 2021.

Figure 11 shows the comparison of the actual and forecasted values of e-commerce retail sales in the US. If COVID-19 had not intervened, the pattern would have been different. Now we can see that the e-commerce sales share increased from 10% in 2019 to more than 16% during the second quarter of 2020, which later reduced to 14.2%. It shows that consumer behavior changed after COVID-19 as people adopt online shopping and ordering using the internet and mobile phone apps rather than purchasing in person.

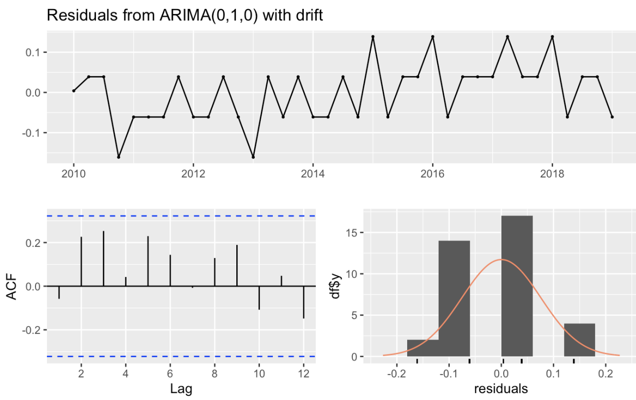


Figure 9: Residuals and auto-correlation function.

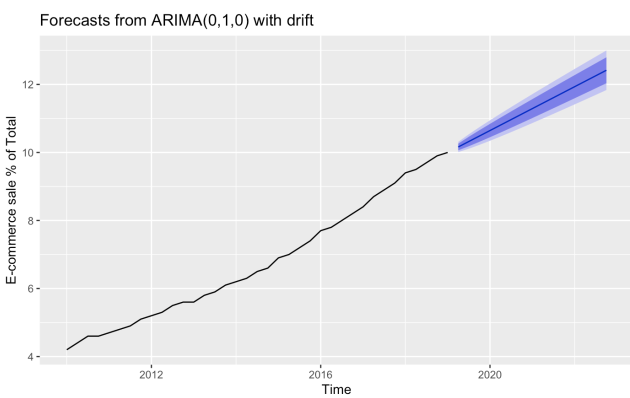


Figure 10: Forecasting based on ARIMA model.

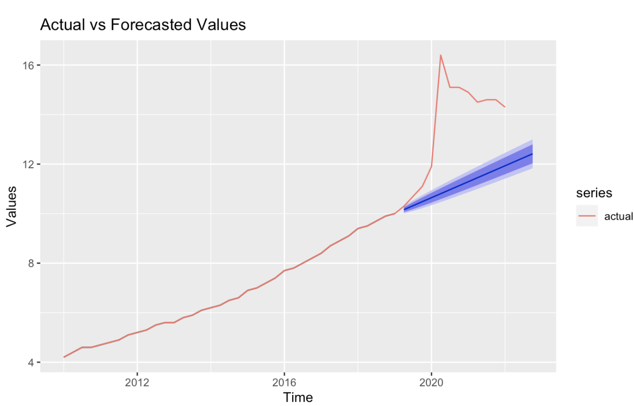


Figure 11: Actual vs. forecasted online sales.

Table 7: Posterior inference (causal impact).

| **Stats** | **Average** | **Cumulative** |
|---|---|---|
| Actual | 15 | 175 |
| Prediction (s.d) | 7.1 (0.66) | 85.2 (7.89) |
| 95% C.I | [5.8, 8.4] | [69.5, 100.5] |
| Absolute Effect (s.d) | 7.5 (0.66) | 90.0 (7.89) |
| 95% C.I | [6.2, 8.8] | [74.7, 105.7] |
| Relative Effect (s.d) | 108% (20%) | 108% (20%) |
| 95% C.I | [74%, 152%] | [74%, 152%] |
| Posterior tail-area Prob. | | 0.00101 |
| Posterior Prob. of Causal Impact | | 99.8995% |

In conclusion, the retail sales industry was greatly affected by the COVID-19 pandemic, leading to a decline in sales but an increase in e-commerce. This shift towards online shopping is expected to continue even after the pandemic, as it has become more efficient and convenient for consumers, and businesses see the potential for growth through digital retail channels. This change in consumer behavior may be long-lasting due to the possibility of future pandemic waves and the costs involved in learning new methods. Entrepreneurs are also motivated to invest in e-commerce to take advantage of the benefits it offers. In addition, we analyzed the intervention in retail sales using causal impact posterior inference method. It is a statistical method used to estimate the causal effect of a particular event or intervention on a time series data. Brodersen et al. [4] estimated the causal impact of advertising on the automobile sales using the posterior inference method. This method takes into account the both observed data and uncertainty associated with the casual impact.

During the post-intervention period, the response variable had an average value of approx. 14.60. By contrast, in the absence of an intervention, we would have expected an average response of 7.10. The 95% interval of this counterfactual prediction is $[5.79, 8.38]$. Subtracting this prediction from the observed response yields an estimate of the causal effect that the intervention had on the response variable. This effect is 7.50 with a 95% interval of $[6.22, 8.81]$. For a discussion of the significance of this effect, see below.

Summing up the individual data points during the post-intervention period (which can only sometimes be meaningfully interpreted), the response variable had an overall value of 175.20. By contrast, had the intervention not taken place, we would have expected a sum of 85.19. The 95% interval of this prediction is $[69.49, 100.53]$.

The above results are given in terms of absolute numbers. In relative terms, the response variable showed an

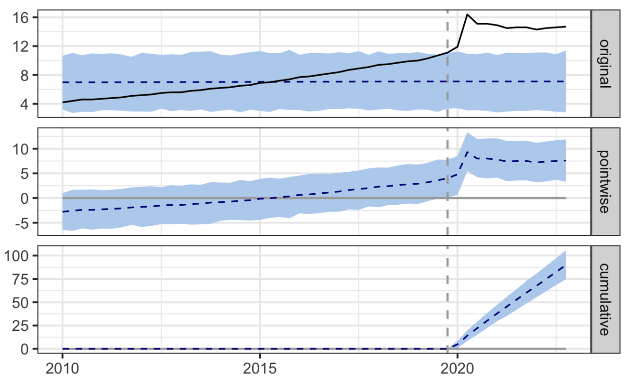


Figure 12: Intervention analysis causal impact.

increase of +108%. The 95% interval of this percentage is [+74%, +152%].

This means that the positive effect observed during the intervention period is statistically significant and unlikely to be due to random fluctuations. It should be noted, however, that the question of whether this increase also bears substantive significance can only be answered by comparing the absolute effect (7.50) to the original goal of the underlying intervention.

The probability of obtaining this effect by chance is very small (Bayesian one-sided tail-area probability $p = 0.001$). This means the causal effect can be considered statistically significant.

Figure 12 shows the original series, point-wise effect and the cumulative effect of COVID-19 on the online sales. It depicts that there is almost 7.5% change in the point-wise change in the online sales and if we look at the cumulative effect it shows that COVID-19 had 99% effect on the online sales.

### 7.3 Transformed linear regression model

Intervention analysis describes the change in the mean and variance level of a series due to an intervention occurring at a certain time without effecting the level and direction of the drift [12]. We transformed the ARIMA $(0, 1, 0)$ model to a linear regression model to test the intervention hypothesis. The linear regression model estimates the mean level change before and after the COVID-19.

The general formulation for estimating and testing the intervention effect on the mean level can be approached by linear statistical models. Suppose that $X_t$ follows a first order autoregressive process. For $n_1$ time points prior to intervention, let the structure of $X_t$ be

$$X_t - \mu = \phi_1(X_{t-1} - \mu) + a_t$$

where $\mu$ is the mean of the series, $a_t$ are identically and independently distributed random variables with 0 mean and $\sigma^2$ variance, and $-1 < \phi_1 < 1$ for stationary assured. Assume that the unobservable $x_0$ is associated with an error 0. Hence, we have $X_0 = \mu$, and it makes $X_1 = \mu + a_1$ and $Y_1 = X_1 = \mu + a_1$. Similarly, $Y_2 = \mu + \phi_1(X_1 - \mu) + a_2$. Following these equations, it is suggested that general expression for the transformation from AR(1) model in which dependence among $X_t$ is imbedded to a linear model is

$$Y_t = X_t - \phi_1 X_{t-1} = (1 - \phi_1)\mu + a_t \tag{5}$$

By a linear model, we mean an equation 5 that involves random variables, mathematical variables, and parameters and in the random variables. In particular the model $Y = X\beta + e$ is such that $Y$ is a random observed vector, $e$ is a random vector, $X$ is an $n \times p$ matrix of known fixed quantities, and $\beta$ is a $p \times 1$ vector of unknown parameters. The assumption here is that $e$ is distributed $N(0, \sigma^2 I)$, where $\sigma^2$ is unknown [13].

Consider the introduction of an intervention at $t = n_1 + 1$ and assume that the mean of the series shifts by a magnitude of $\delta$, thus giving us

$$X_t - (\mu + \delta) = \phi_1[X_{t-1} - (\mu + \delta)] + a_t$$

When $X_{n+1}$ is transformed via equation (4), we obtain

$$Y_{n_1+1} = (1 - \phi_1)\mu + \delta + e_{n_1+1} \tag{6}$$

The subsequent $Y$'s will have the following form:

$$Y_t = (1 - \phi_1)\mu + (1 - \phi_1)\delta + e_t, \quad n_1 + 1 < t < N \tag{7}$$

The equations 6 and 7 can be expressed in the form of a linear model as

$$\left[\begin{array}{c} Y_1 \\ Y_2 \\ Y_3 \\ \vdots \\ Y_{n_1} \\ \hline Y_{n_1+1} \\ Y_{n_1+2} \\ Y_{n_1+3} \\ \vdots \\ Y_N \end{array}\right] = \left[\begin{array}{cc} 1 & 0 \\ 1-\phi_1 & 0 \\ 1-\phi_1 & 0 \\ \vdots & \vdots \\ 1-\phi_1 & 0 \\ \hline 1-\phi_1 & 1 \\ 1-\phi_1 & 1-\phi_1 \\ 1-\phi_1 & 1-\phi_1 \\ \vdots & \vdots \\ 1-\phi_1 & 1-\phi_1 \end{array}\right] \begin{bmatrix} \mu \\ \delta \end{bmatrix} + \left[\begin{array}{c} e_1 \\ e_2 \\ e_3 \\ \vdots \\ e_{n_1} \\ \hline e_{n_1+1} \\ e_{n_1+2} \\ e_{n_1+3} \\ \vdots \\ e_n \end{array}\right]$$

We can write down this equation in the form

$$Y = A\beta + a$$

For a fixed value of $\phi_1$, the least-square estimates are given by

$$\begin{bmatrix} \hat{\mu} \\ \hat{\delta} \end{bmatrix} = (A^{`}A)^{-}1A^{`}Y'$$

Let $Z^*_{tk}$ $(t = 1, \ldots, n,\ k = 1, \ldots, m)$ denote the weight of the intervention effect in the transformed variable, $Y$. Also let $Z^*_{1k} = Z_{1k}$. Then we have

$$Z^*_{tk} = Z_{tk} - \sum_{j=1}^{t-1} \Phi_j Z^*_{t-j}, k$$

Thus, $Y_t$ will have the expression

$$Y_t = Z^*_{t1}\mu + Z^*_{t2}\delta_1 + \cdots + a_t$$

which is recognizable as the linear model

$$Y = Z^*\beta + \epsilon.$$

That is, we have

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_N \end{bmatrix} = \begin{bmatrix} Z^*_{11} & Z^*_{12} & \cdots \\ Z^*_{21} & Z^*_{22} & \cdots \\ \vdots & \vdots & \ddots \\ Z^*_{N1} & Z^*_{N2} & \cdots \end{bmatrix} \begin{bmatrix} \mu \\ \delta_1 \\ \delta_2 \\ \vdots \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_N \end{bmatrix}$$

This transformation technique can be applied to any ARIMA process. For example, consider ARIMA $(0, 1, 0)$ scheme with an intervention at $t = n_1 + 1$. for the first $n_1$ time periods we observe $X_t$, and at the $n_1 + 1$ set time point, an intervention event occurs. It sustains its effect on $X_t$ until time point $N$. The pre- and post-intervention representations are

$$X_t = \mu + (1 - \phi_1)\mu + a_t, \qquad (t \leq n_{11})$$

and

$$X_t = \mu + \delta + a_t, \qquad (t > n_{11})$$

which agree with the design matrix for the $Y$ transformation from the ARIMA $(0, 1, 0)$ process. The following matrix form shows the appropriate transformation for the intervention effect analysis of some ARIMA $(0, 1, 0)$ model when $k = 1$.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \\ \vdots \\ Y_{n_1} \\ \hline Y_{n_1+1} \\ Y_{n_1+2} \\ \vdots \\ Y_N \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1-\phi_1 & 0 \\ 1-\phi_1 & 0 \\ \vdots & \vdots \\ 1-\phi_1 & 0 \\ \hline 1-\phi_1 & 1 \\ 1-\phi_1 & 1 \\ \vdots & \vdots \\ 1-\phi_1 & 1 \end{bmatrix} \begin{bmatrix} \mu \\ \delta \end{bmatrix} + \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_{n_1} \\ \hline a_{n_1+1} \\ a_{n_1+2} \\ \vdots \\ a_n \end{bmatrix}$$

Where the dependent variable $Y_t = Y_t - Y_{t-1}$ difference series at order $d = 1$. Results of the estimated model are given in Table 5.

Table 8: Linear regression model results.

| | Estimate | Std. Error | t value | Pr(>$\|t\|$) |
|---|---|---|---|---|
| (Intercept) | 0.1637 | 0.0223 | 7.33 | 0.0000 |
| $\mu$ | 0.0393 | 0.0922 | 0.43 | 0.6724 |
| $\delta$ | 0.2206 | 0.0910 | 2.42 | 0.0205 |

The results shown in Table 8 are estimated using a linear regression model, which is a transformed model based on the ARIMA $(0, 1, 0)$. It shows that $\mu$ is the parameter before the intervention (COVID-19) and $\delta$ is effect on the online sales after the intervention. It also shows that the COVID-19 impact was statistically significant on the online sales as the intervention parameter $\delta$ has statistically significant impact on the sales. It shows that due to COVID-19 online sales increased by 22%. These results are aligned with our previous results and graphical representation.

# 8 Conclusions

This study estimated the impact of COVID-19 on personal consumption expenditure across categories using the difference-in-difference and fixed effect methods, as well as time series and linear regression models. We have found that the DID coefficient negatively affected consumption in the treatment period as compared to the control period, but the effect is statistically insignificant. This is because consumption varies across different categories and due to changing policies during the pandemic period. Therefore, we moved forward to see the fixed effect method using a categorical variable of the treatment months compared to the control months. We found a significant decline in consumption of nearly 8% during March and April (2020) because of the strict lockdown in these months. Similarly, we found a 2% drop in consumption in May and June, though this was statistically insignificant because of the first stimulus check issued in the month of June. Hence, a significant increase in consumption was shown in the months afterward. When we analyzed the consumption across each category, we found a significant increase in food consumption during March, April, May, and June. However, it was negative for all other categories during these months. Thereafter, the consumption pattern changed to positive for all the categories except energy goods and services after the month of July until December. In addition, we also found significant change in the retail online sales after COVID-19. However the online retail sales series shows a similar trend when forecasted with the ARIMA model using the online retail sales data before COVID-19. We further found the significant causal impact of COVID-19 on the online retail sales, and our linear regression model showed that the intervention was statistically significant, which is an evidence of the change in the mean level after COVID-19 at 5% significance level. This implies that the consumption pattern inclined to e-commerce after COVID-19 and we can reap the benefits by easing and advancing the e-commerce sector.

# References


[1] Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., and Yannelis, C. (2020). How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. *The Review of Asset Pricing Studies*, 10(4):834–862.

[2] Bauer, L., Broady, K., Edelberg, W., and O'Donnell, J. (2020). Ten facts about COVID-19 and the US economy. Brookings Institution, 17.

[3] Bounie, D., Camara, Y., and Galbraith, J. W. (2020). Consumers' mobility, expenditure and online-offline substitution response to COVID-19: Evidence from French transaction data. Available at SSRN 3588373.

[4] Brodersen, K. H., Gallusser, F., Koehler, J., Remy, N., and Scott, S. L. (2015). Quantifying the Effects of Advertising on Sales in Time Series: The Case of the Automobile Industry. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, 178(3):749–781.

[5] Chen, H., Qian, W., and Wen, Q. (2021). The impact of the COVID-19 pandemic on consumption: Learning from high-frequency transaction data. *AEA Papers and Proceedings*, 111:307–311.

[6] Coibion, O., Gorodnichenko, Y., and Weber, M. (2020). The cost of the COVID-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending. NBER Working Paper No. w27141. National Bureau of Economic Research.

[7] Cotton, C., Garga, V., and Rohan, J. (2021). Consumption Spending during the COVID-19 Pandemic. Federal Reserve Bank of Boston Research Paper Series Current Policy Perspectives Paper, (93430).

[8] Cox, N., Ganong, P., Noel, P., Vavra, J., Wong, A., Farrell, D., and Deadman, E. (2020). Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending, and savings data. *Brookings Papers on Economic Activity*, 2020(2):35–82.

[9] Davis, G. (2021). The many ways COVID-19 affects households: consumption, time, and health outcomes. *Review of Economics of the Household*, 19(2):281–289.

[10] Dunn, A., Hood, K., Batch, A., and Driessen, A. (2021, May). Measuring Consumer Spending Using Card Transaction Data: Lessons from the COVID-19 Pandemic. *AEA Papers and Proceedings*, 111:321–325.

[11] Garner, T. I., Safir, A., and Schild, J. (2020). Changes in consumer behaviors and financial well-being during the coronavirus pandemic: results from the US Household Pulse Survey. *Monthly Labor Review*, 143(1).

[12] Glass, G. V., Willson, V. L., and Gottman, J. M. (1975). Design and analysis of time-series experiments. Boulder: University of Colorado Press.

[13] Graybill, F. A. (1976). Theory and application of the linear model (No. 04; QA279, G7.)

[14] Hoseini, M. and Valizadeh, A. (2021). The effect of COVID-19 lockdown and the subsequent reopening on consumption in Iran. *Review of Economics of the Household*, 19(2):373–397.

[15] Kim, M. J. and Lee, S. (2021). Can stimulus checks boost an economy under COVID-19? Evidence from South Korea. *International Economic Journal*, 35(1):1–12.

[16] Kubota, S., Onishi, K., and Toyama, Y. (2021). Consumption responses to COVID-19 payments: Evidence from a natural experiment and bank account data. *Journal of Economic Behavior & Organization*, 188:1–17.

[17] Martin, A., Markhvida, M., Hallegatte, S., and Walsh, B. (2020). Socio-economic impacts of COVID-19 on household consumption and poverty. *Economics of Disasters and Climate Change*, 4(3): 453–479.

[18] Sheth, J. (2020). Impact of Covid-19 on consumer behavior: Will the old habits return or die? *Journal of Business Research*, 117:280–283.

[19] Tudor, C. (2022). Integrated Framework to Assess the Extent of the Pandemic Impact on the Size and Structure of the E-Commerce Retail Sales Sector and Forecast Retail Trade E-Commerce. *Electronics*, 11(19):3194.

[20] U.S. Census Bureau. (2020a). Quarterly E-commerce Report 2020a Retrieved from https://www.census.gov/retail/ecommerce.html

[21] Yang, Z., Choe, Y., and Martell, M. (2021). COVID-19 economic policy effects on consumer spending and foot traffic in the US. *Journal of Safety Science and Resilience*, 2(4):230–237.

[22] Yue, P., Korkmaz, A. G., Yin, Z., and Zhou, H. (2021). Household-owned businesses' vulnerability to the COVID-19 pandemic. *Emerging Markets Finance and Trade*, 57(6):1662–1674.