Technical Appendix

Introduction

In this report, we will be exploring the effects of lockdown and other government interventions on OmniCorp. OmniCorp is a large multi-national commercial company with stakes in the retail and hospitality sectors. Their operations are primarily in Europe, and North, Central and South America. We have been tasked with building an in house expertise on the ongoing COVID-19 virus outbreak. This report is our findings and recommendations to the company.

Analysis

Confirmed cases

In the following code chunks, we will be extracting the daily confirmed cases of COVID-19.

```
CovidData <- read.csv("tidycovid19.csv")

CovidData <- CovidData %>%
  mutate(date = as.Date(parse_date_time(CovidData$date,orders=c("y","ym","ymd"))))
```

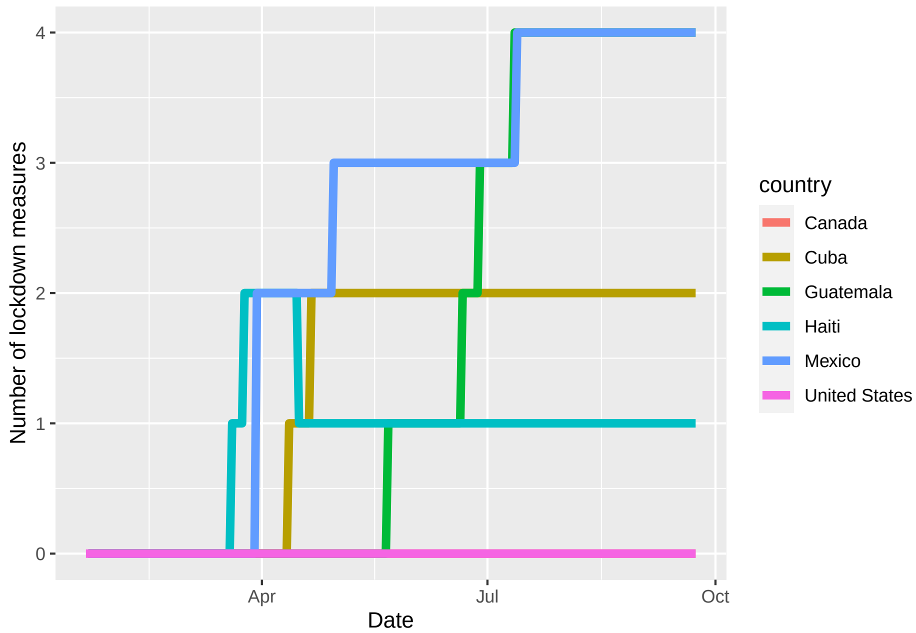
```
CaseData <- {CovidData %>%
    filter((str_detect(region, "America") | str_detect(region, "Europe"))) %>%
    select(country, date, confirmed) }

firstdiff <- function(x) {
  shifted <- c(0,x[1:(length(x)-1)])
  result = x-shifted
  which_negative = which(result<0)
  result[which_negative] = NA
  return(result)
}

CaseData <- CaseData %>%
  mutate(daily_confirmed = firstdiff(confirmed))

# Making cases relative to highest value.

UKCaseData <- CaseData %>%
  mutate(daily_confirmed = firstdiff(confirmed)) %>%
  filter(country == "United Kingdom")
UKCaseData$daily_confirmed <- scale(UKCaseData$daily_confirmed, center = FALSE)

USCaseData <- CaseData %>%
  mutate(daily_confirmed = firstdiff(confirmed)) %>%
```

```
  filter(country == "United States")
USCaseData$daily_confirmed <- scale(USCaseData$daily_confirmed, center = FALSE)

BrazilCaseData <- CaseData %>%
  mutate(daily_confirmed = firstdiff(confirmed)) %>%
  filter(country == "Brazil")
BrazilCaseData$daily_confirmed <- scale(BrazilCaseData$daily_confirmed, center = FALSE)


plot_confirmed_date <- {UKCaseData %>% ggplot(aes(x = date, y = daily_confirmed, color='Country'))} +
  geom_point(color = "blue") +
  geom_point(data = USCaseData, color = "red") +
  geom_point(data = BrazilCaseData, color = "green") +
  xlab("Date") +
  ylab("Daily Cases (% of maximum value in period)") +
  ggtitle("Daily confirmed cases is different across time for UK, US and Brazil",
          subtitle="Each point represents a single day.") +
  scale_x_date(date_breaks = "months", date_labels = "%b-%y") +
  scale_color_manual(labels = c("United Kingdom", "United States", "Brazil"),
                     values = c("red", "green", "blue")) +
  guides(color=guide_legend("Countries"))
```

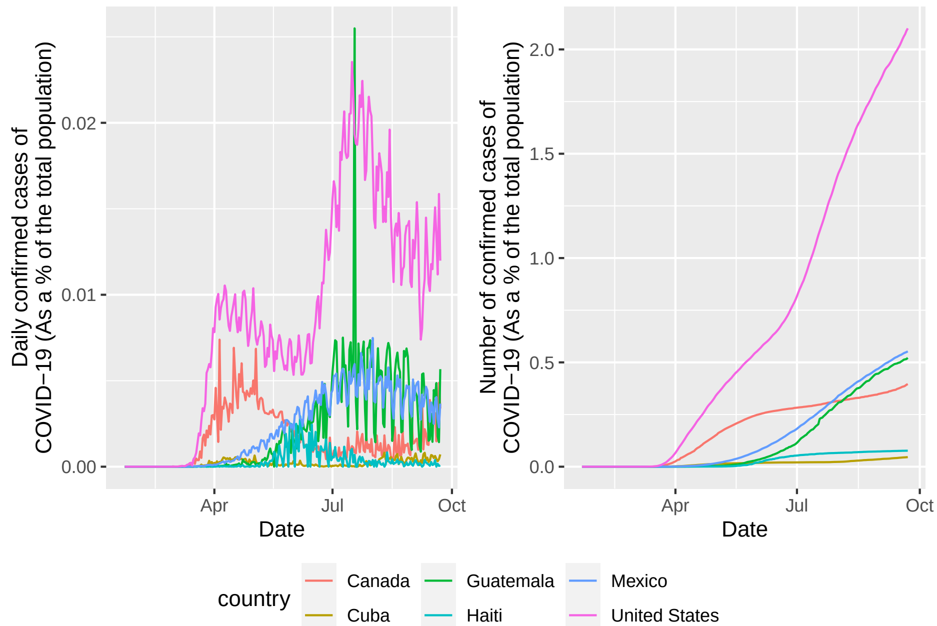
North America and Central America

```
CaseData2 <- {CovidData %>%
    filter((str_detect(region, "America") | str_detect(region, "Europe")))}

CaseData2 <- CaseData2 %>%
  mutate(daily_confirmed = firstdiff(confirmed))

AmericaData <- CaseData2 %>%
  filter(str_detect(region, "America"))

AmericaData <- AmericaData %>% mutate(daily_conf_percentagepop = (daily_confirmed/population)*100)

AmericaData <- AmericaData %>% mutate(confirmed_percentagepop = (confirmed/population)*100)
```

```
NorthCentralAmericaData <- AmericaData %>% filter(country %in% c("United States", "Mexico", "Canada", "(

TotalNorthCentralAmericaConfirmed_percen <- ggplot(NorthCentralAmericaData, aes(x = date, y = confirmed_

DailyNorthCentralAmericaConfirmed <- ggplot(NorthCentralAmericaData, aes(x = date, y = daily_conf_percen


NorthCentralAmericaLockdown <- ggplot(NorthCentralAmericaData, aes(x = date, y = lockdown, color = count
```




```
ggarrange(DailyNorthCentralAmericaConfirmed, TotalNorthCentralAmericaConfirmed_percen, ncol=2, nrow=1, c
```

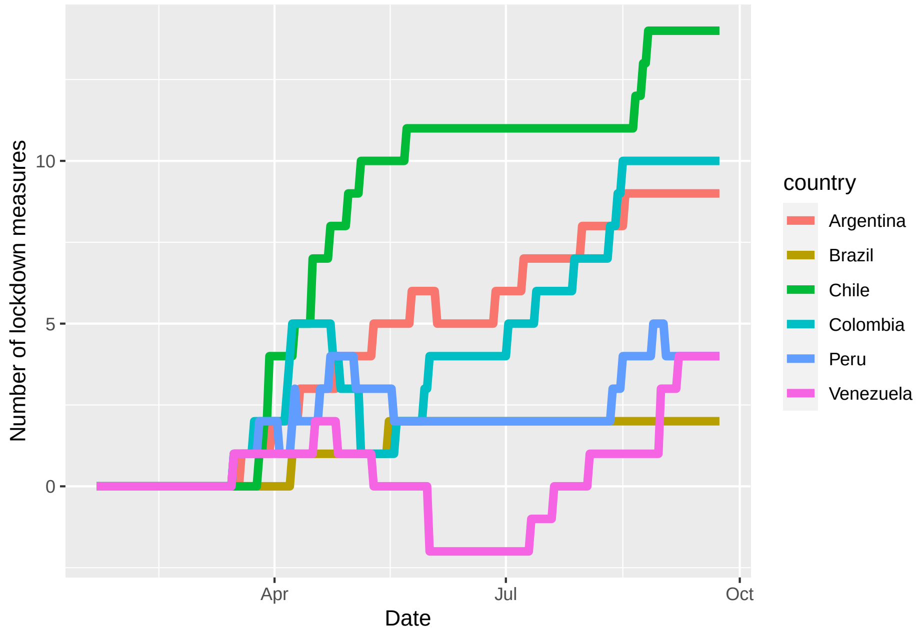


South America

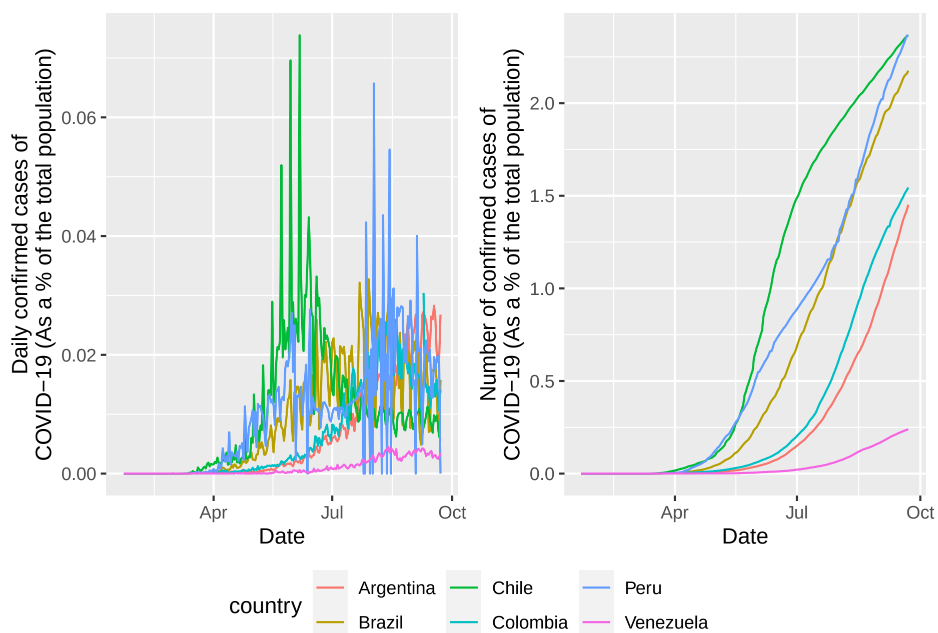
```
SouthAmericaData <- AmericaData %>% filter(country %in% c("Brazil", "Colombia", "Argentina", "Peru", "Ve

TotalSouthAmericaConfirmed_percen <- ggplot(SouthAmericaData, aes(x = date, y = confirmed_percentagepop

DailySouthAmericaConfirmed <- ggplot(SouthAmericaData, aes(x = date, y = daily_conf_percentagepop, colo
```

```
SouthAmericaLockdown <- ggplot(SouthAmericaData, aes(x = date, y = lockdown, color = country)) + geom_li
```

```
print(SouthAmericaLockdown)
```



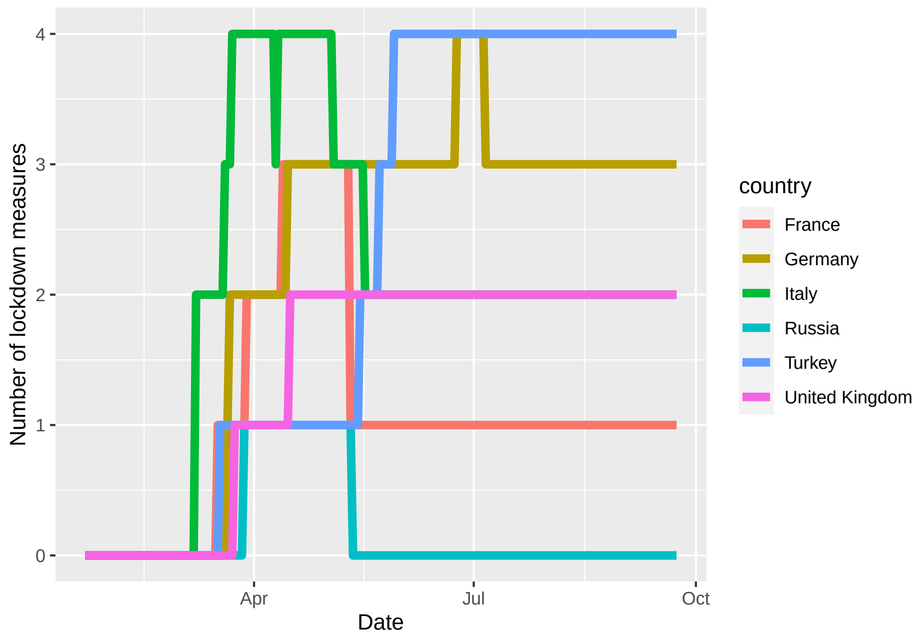

```
ggarrange(DailySouthAmericaConfirmed, TotalSouthAmericaConfirmed_percen, ncol=2, nrow=1, common.legend =
```



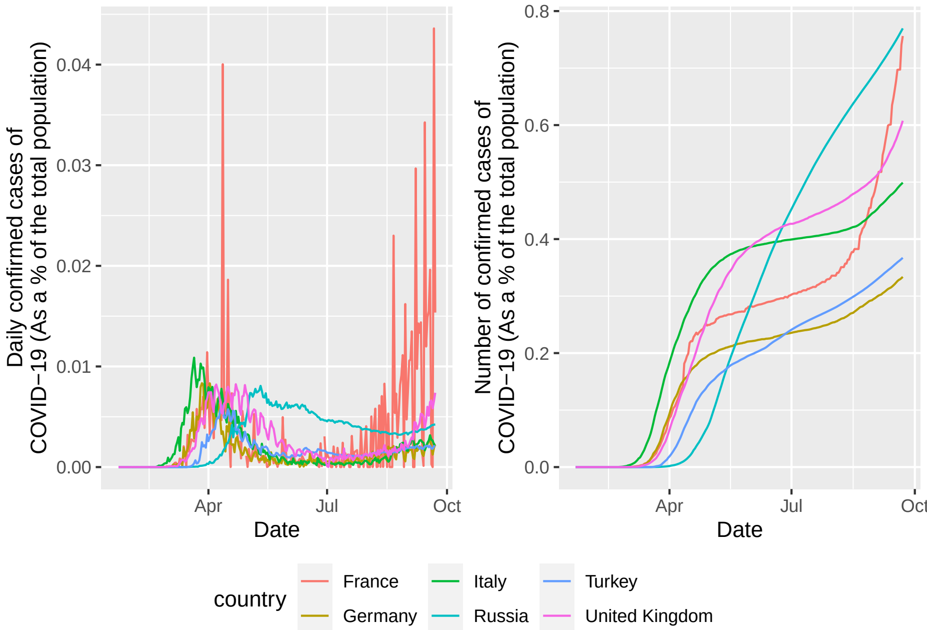
Europe

```
EuropeData <- CaseData2 %>%
  filter(str_detect(region, "Europe"))

EuropeData <- EuropeData %>% mutate(daily_conf_percentagepop = (daily_confirmed/population)*100)

EuropeData <- EuropeData %>% mutate(confirmed_percentagepop = (confirmed/population)*100)

EuropeData <- EuropeData %>% filter(country %in% c("Russia", "Turkey", "Germany", "France", "United Kin

TotalEuropeConfirmed_percen <- ggplot(EuropeData, aes(x = date, y = confirmed_percentagepop, color = co

DailyEuropeConfirmed <- ggplot(EuropeData, aes(x = date, y = daily_conf_percentagepop, color = country)


EuropeLockdown <- ggplot(EuropeData, aes(x = date, y = lockdown, color = country)) + geom_line(size = 2
```

```
print(EuropeLockdown)
```




```
ggarrange(DailyEuropeConfirmed, TotalEuropeConfirmed_percen, ncol=2, nrow=1, common.legend = TRUE, lege
```

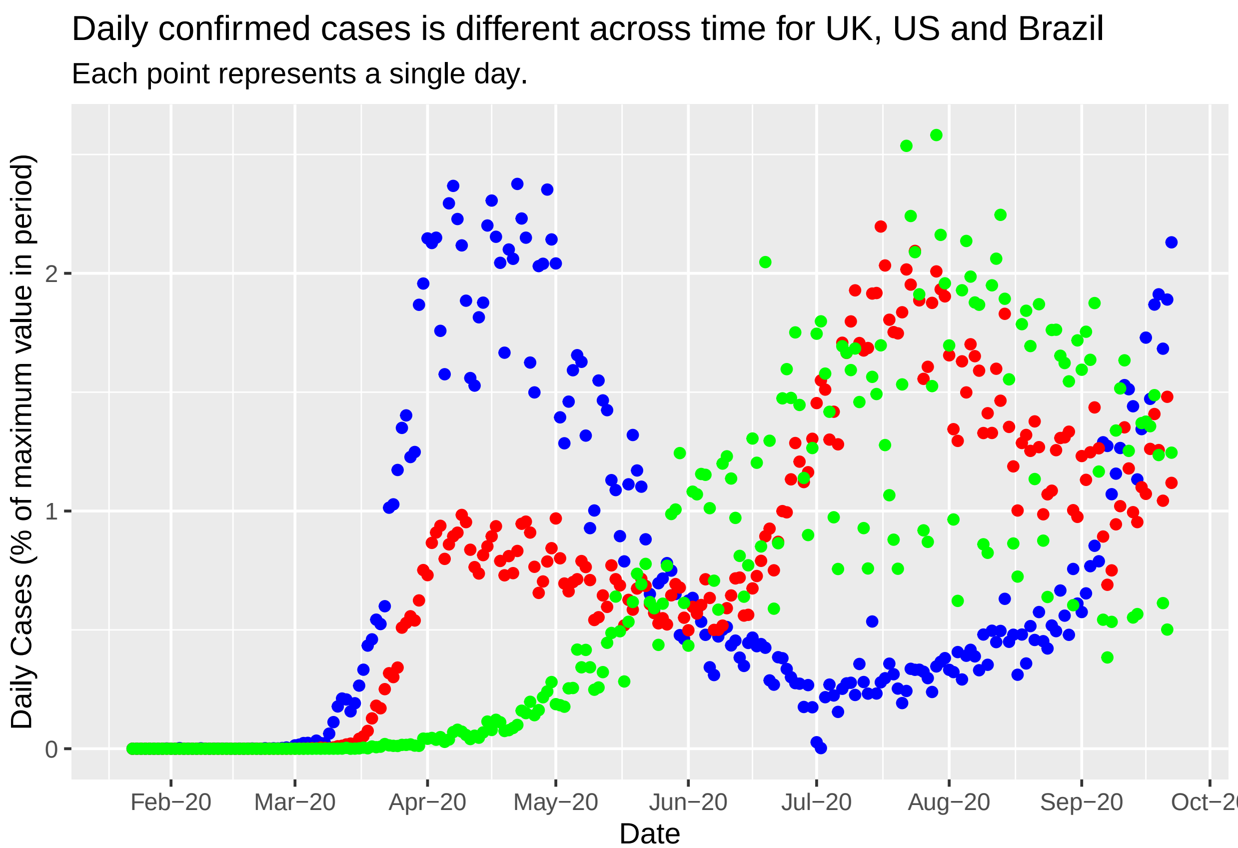


The plots above show the number of lockdown measures against the date it was implemented. The number of daily confirmed COVID-19 infections as a percentage of the total population against the date. The total number of confirmed COVID-19 infections as a percentage of the total population against the date. Despite the number of lockdown measures being a vague measure of how governments intervened, it allows us to see which governments were cautious about COVID-19 and whether they implemented any measures at all. We have sampled six countries for the regions North and Central America, South America and Europe. To generate these plots I used the lockdown variable from the tidycovid19 dataset, this variable is the number of lockdown measures reported up to date by ACAPS, net of lifted restrictions. For the number of daily confirmed cases of COVID-19 as a percentage of the total population, it was calculated by (daily_confirmed/population)*100. Similarly, the total number of confirmed COVID-19 infections as a percentage of the total population was calculated using the same method but switching out the daily_confirmed for confirmed.

The first immediate effect of lockdown is with the number of confirmed cases of the COVID-19 virus. At the start of the pandemic, the infection rate of the virus was relatively high and thus the number of confirmed cases was rising at an exponential rate. Governments around the world started imposing lockdown and restrictions in attempts to slow down the rate of infection and consequently the number of confirmed cases within populations. However, these restrictions brought with them huge changes to society in a very short period of time. These changes have both direct and indirect consequences to OmniCorp.

The main reason for lockdown is to reduce the spread of the virus. However, the types of restrictions, effectiveness of lockdown and adherence and enforcement of rules has varied significantly between countries. The effect of lockdown on confirmed cases is important for OmniCorp in order to be able to plan for potential future restrictions. The following graph shows the number of daily confirmed cases for the United Kingdom, United States and Mexico. We will use the tidycovid19 dataset, downloaded from the tidycovid19 R package on 24th September 2020. Descriptions of the different variables found in the data relating to the current epidemic and further details of the package can be found at this website (Gassen 2020).

```
print(plot_confirmed_date)
```



As we can see from the graph above, the three countries' number of confirmed cases is very different throughout the period. There are many possible explanations for this; first case time, geographical composition of land, population density, and most importantly, the types of lockdown the governments imposed. Although the distribution of confirmed cases looks very different for each country, they all seem to have a "first wave" where the number of daily cases rises to a high point then begins to fall. This would potentially indicate that lockdown and government interventions have an inverse relationship with the number of confirmed cases, that is, as restrictions are imposed, the number of cases decreases. This would make sense as many restrictions are stopping the movement and contact of people, reducing the spread of the virus. Although this

The number of confirmed cases has many effects on OmniCorp, directly and indirectly. The direct effects concern the staff, supply chain and customer base. OmniCorp Staff, as well as supply chain staff, may be affected by illness and self-isolation, meaning they cannot work. This will impact the everyday running of operations. High levels of unemployment may also mean customers do not have as much disposable income to spend in OmniCorp businesses, potentially seeing to a reduction in revenues. An indirect change is the implementation of lockdown and government interventions which in turn, may change consumer habits and behaviors. A key aspect of lockdown is restricting the movement of people. We will investigate the changes in these movement habits and how they will effect OmniCorp.

Activity in residential places and workplaces

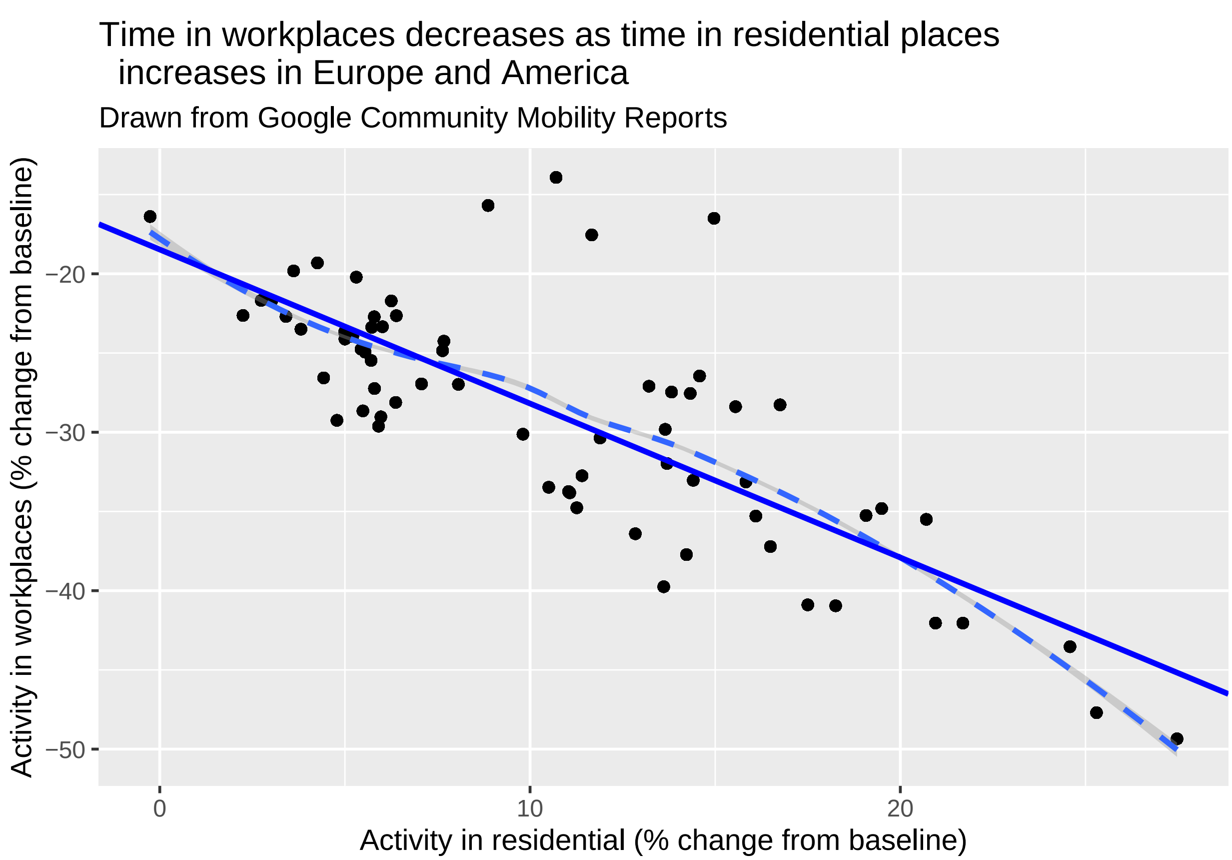
We will now look at how the frequency of people visiting residential and workplaces has changed during the pandemic for countries in Europe and North, Central and South America. In particular, we study the `gcmr_residential` and `gcmr_workplaces` variables from a community mobility report (Google, 2020). The variables are expressed as a percentage*100 change relative to the baseline period from Jan 3 to Feb 6, 2020. However, we take the data from Feb 7, as we want to look at the average percentage change in the frequency of people's visits to these places, without including the baseline in this mean. We find the mean of these variables and name them `mean_gcmr_residential` and `mean_gcmr_workplaces` respectively.

We plot the average percentage change in the frequency of visits to residential places against workplaces for countries in Europe and America from this year (Feb 7 onwards). We look particularly at the trends for Europe, North America and South America. Note that we are including the Central America Countries with North America. We fit a linear model as well as the best line of fit and see that a linear relationship between the variables fits fairly well.

```
EURUSA <- {CovidData %>%
    filter( ( str_detect(region, "America") | str_detect(region, "Europe") ) ) %>%
    select(country, date, gcmr_workplaces, gcmr_residential, region)}

europe_list=c("Albania","Andorra","Armenia","Austria","Azerbaijan","Belarus","Belgium",
              "Bosnia & Herzegovina","Bulgaria","Croatia","Cyprus","Czechia","Denmark","Estonia","Finlar
              "Georgia","Germany","Greece","Hungary","Iceland","Ireland","Italy","Kazakhstan","Kosovo",
              "Lithuania","Luxembourg","Malta","Moldova","Monaco","Montenegro","Netherlands","Macedonia
              "San Marino","Serbia","Slovakia","Slovenia","Spain","Sweden","Switzerland","Turkey",
              "Ukraine","United Kingdom","Faroe Islands","Gibraltar","Isle of Man","North Macedonia")

NA_list=c("United States","Mexico","Canada","Guatemala","Cuba","Haiti","Dominican Republic",
          "Honduras","El Salvador","Nicaragua","Costa Rica","Panama","Puerto Rico",
          "Jamaica","Trinidad and Tobago","Guadeloupe","Martinique","Bahamas","Belize","Barbarbados","St
          "St. Vincent & Grenadines","U.S. Virgin Islands","Grenada","Antigua & Barbuda","Dominica",
          "Bermuda","Cayman Islands","Greenland","St. Kitts & Nevis","Sint Maarten",
          "Turks & Caicos Islands","Saint Martin","British Virgin Islands","Barbados","Trinidad & Tobago

SA_list=c("Aruba","Brazil","Colombia","Argentina","Peru","Venezuela","Chile","Ecuador",
          "Bolivia","Paraguay","Uruguay","Guyana","Suriname","French Guiana","Falkland Islands","CuraÃ§a

EURUSA.postFeb6 <- {EURUSA %>%
    filter( (date > as.Date("2020-02-06")) ) %>%
    mutate(region=ifelse(country %in% NA_list,"North America",ifelse(country %in% SA_list,
                                                                     "South America",ifelse(country %in%
    na.omit}

EURUSA.postFeb6 = EURUSA.postFeb6[!(EURUSA.postFeb6$region=="NON"),]

mean_ <- function(...) mean(..., na.rm=T)
max_ <- function(...) max(..., na.rm=T)
EURUSA1 = {EURUSA.postFeb6 %>%
    group_by(country) %>%
    summarise(date = date,
              mean_gcmr_residential = mean_(gcmr_residential),
              mean_gcmr_workplaces = mean_(gcmr_workplaces),
              region = region)}

EUR <- {EURUSA1 %>%
    filter(region == "Europe")}

N.USA <- {EURUSA1 %>%
    filter(region == "North America")}

S.USA <- {EURUSA1 %>%
```

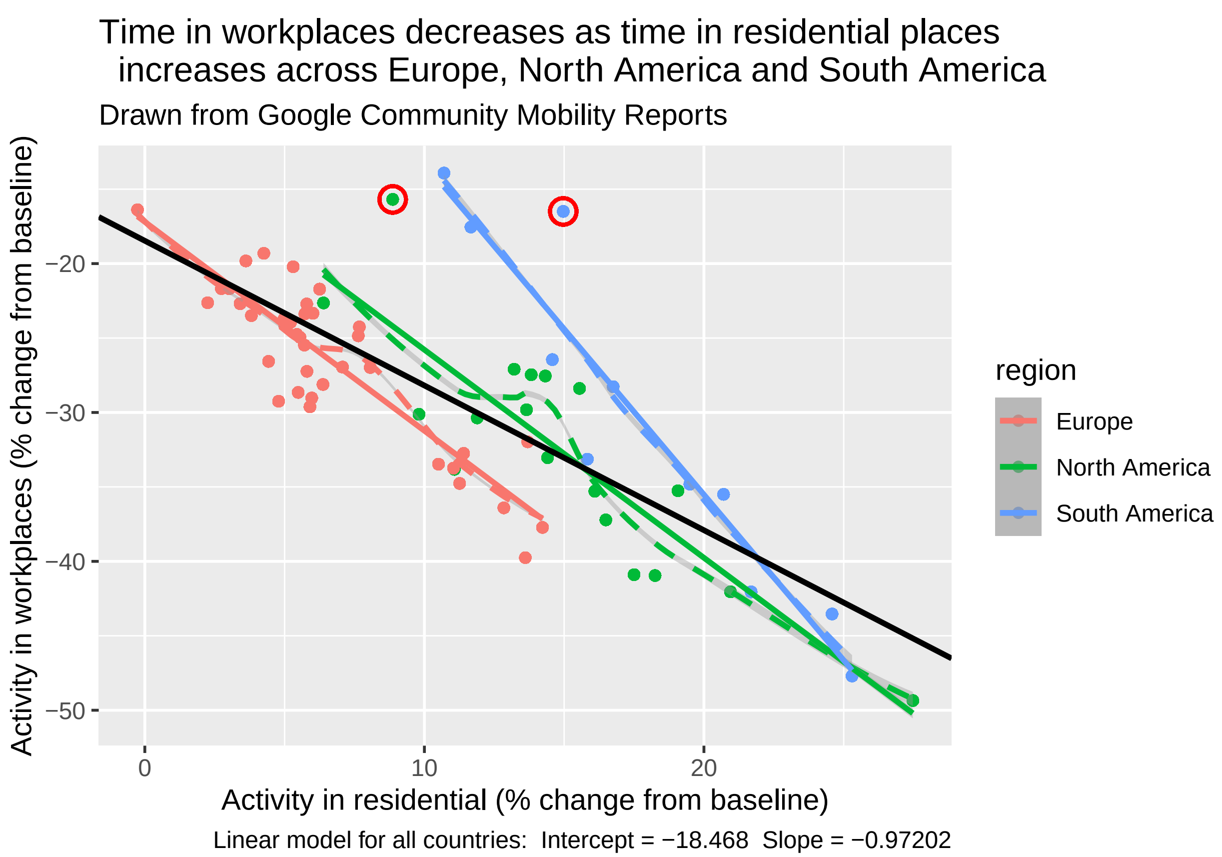
```
    filter(region == "South America")}

EUR1 <- {EUR %>%
    filter(country %in% c("France","Germany","Italy","Russia","Turkey","United Kingdom"))}

N.USA1 <- {N.USA %>%
    filter(country %in% c("Canada","Cuba","Guatemala","Haiti","Mexico","United States"))}

S.USA1 <- {S.USA %>%
    filter(country %in% c("Argentina","Brazil","Chile","Colombia","Peru","Venezuela"))}
```

```
lm.homework <- lm(mean_gcmr_workplaces ~ mean_gcmr_residential, data = EURUSA1)

EURUSA_home_work <- {EURUSA1 %>% ggplot(aes(x = mean_gcmr_residential,
                                            y = mean_gcmr_workplaces))} +
  xlab("Activity in residential (% change from baseline)") +
  ylab("Activity in workplaces (% change from baseline)") +
  ggtitle("Time in workplaces decreases as time in residential places
  increases in Europe and America",
           subtitle = "Drawn from Google Community Mobility Reports") +
  geom_point() +
  geom_smooth(method = loess, linetype = "dashed") +
  geom_abline(intercept = signif(lm.homework$coef[[1]],5),
              slope = signif(lm.homework$coef[[2]],5), color="blue", size=1)
print(EURUSA_home_work)
```



We now separate the plot into the different regions to see if the relationships of the variables differ between the regions. We also fit a linear model between `mean_gcmr_workplaces` and `mean_gcmr_residential` for all countries in Europe and America and plot this linear relationship on the graph, as well as the individual linear trends for each region.

```
EURUSA_home_work_regs <- {EURUSA1 %>% ggplot(aes(x = mean_gcmr_residential,
                                              y = mean_gcmr_workplaces,
                                              color=region))} +
  xlab("Activity in residential (% change from baseline)") +
  ylab("Activity in workplaces (% change from baseline)") +
  ggtitle("Time in workplaces decreases as time in residential places
  increases across Europe, North America and South America",
           subtitle = "Drawn from Google Community Mobility Reports") +
  geom_point() +
  geom_point(data = filter(EURUSA1, country == "Paraguay" | country == "Nicaragua"),
             pch=21, fill=NA, size = 4, colour = "red", stroke=1) +
  geom_smooth(method = loess, linetype = "dashed") +
  stat_smooth(method = "lm") +
  geom_abline(intercept = signif(lm.homework$coef[[1]],5),
              slope = signif(lm.homework$coef[[2]],5), color="black", size=1) +
  labs(caption = paste("Linear model for all countries: ",
                       "Intercept =",signif(lm.homework$coef[[1]],5),
                       " Slope =",signif(lm.homework$coef[[2]],5)))
print(EURUSA_home_work_regs)
```



We can see from this plot that the general trend is as the time spent in workplaces decreases, the time spent in residential places increases. We see that when looking at each region in isolation, a linear relationship is a fairly good model, and reflects the general trend of all countries. The linear relationship between time in residential places and time in workplaces is arguably stronger when looking at regions individually, with the strongest linear relationship in the South American countries. In fact, the linear model for South America is a very good fit.

We also note that there was a greater overall average activity in residential places in South America than in Europe. However, this could be explained by the time period. We are looking at data from Feb 7 - Sept 20, and in this time period South America is predominantly in Autumn and Winter, in which people tend to stay at home more than in Spring and Summer, so there is potential for misleading data. Given more time and data, it would be interesting to explore the structure of the economies for each of the countries as this could give more indication to why the trends appear to be different for each continent.

We look closer at the outliers in the trends for North & South America and identify that these are Nicaragua & Paraguay, respectively. A possible explanation for these countries could be due to their very low rates of infection and number of confirmed cases. This may have had an effect on the level and type of lockdown that was imposed in these countries. This could indicate to OmniCorp that these countries could transition back to normal operations quicker than other countries post lockdown.

Activity in grocery and retail

To see how the trend of staying home has affected the retail and hospitality industry, we will start investigating consumer habits and how they changed throughout the pandemic.

To have a broader view of the impact of lockdowns on retail and hospitality, we need to examine the more fundamental parts of people's consumer habits. In 1943, Psychologist Abraham Maslow introduced the Maslow Hierarchy of Needs. This model suggests that people need to fulfill basic needs before they can move on to more advanced ones such as psychological needs or self-fulfillment needs. Hence, we first start by investigating people's visits to grocery shops and pharmacies. Although this sector isn't directly connected to retail and hospitality, the principles are the same - they sell goods to consumers directly. To understand the mobility trend of people going outside and buying non-essential, retail products, we need to first understand their mobility trend of going to a grocery shop or pharmacy.

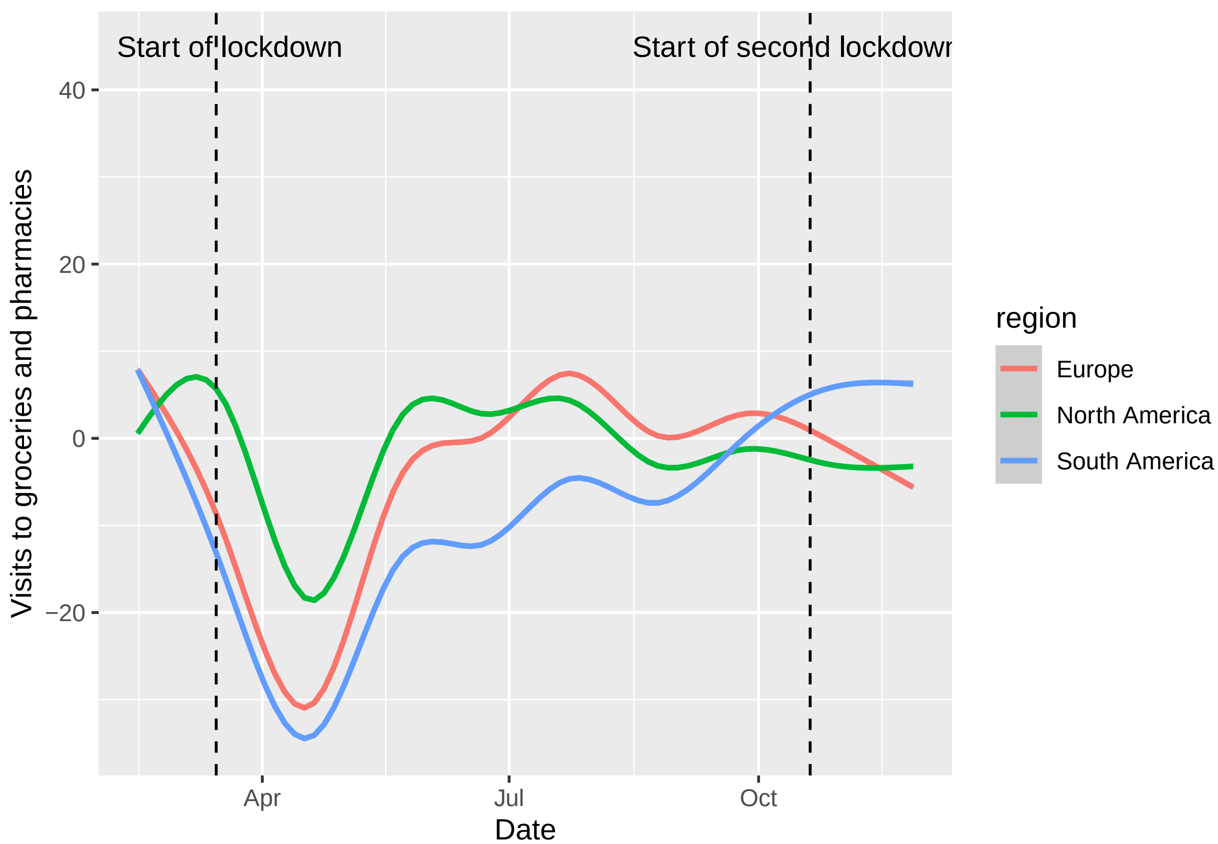
Below is a graph depicting the average percentage change in the frequency of people's visits to grocery stores and pharmacies, relative to a baseline period from Jan 3 to Feb 6, 2020 of the three regions OmniCorp is operating in.

```
glob_mob1=read.csv("https://www.gstatic.com/covid19/mobility/Global_Mobility_Report.csv")
glob_mob=glob_mob1

glob_mob=magrittr::extract(glob_mob,!names(glob_mob) %in% c("census_fips_code",
                                                            "sub_region_1","sub_region_2","metro_area",

glob_mob$date = as.Date(parse_date_time(glob_mob$date,orders=c("y","ym","ymd")))

glob_mob<- {glob_mob %>%
    filter(date > as.Date("2020-02-06"))}

glob_mob= glob_mob%>%
  mutate(country_region_code=
           ifelse(country_region %in% NA_list,"North America",ifelse(country_region %in% SA_list,
                                                                     "South America",ifelse(country_reg

colnames(glob_mob)[colnames(glob_mob) == "country_region_code"] <- "region"
colnames(glob_mob)[colnames(glob_mob) == "country_region"] <- "country"
```

```r
glob_mob=glob_mob[!(glob_mob$region=="NON"),]
```

```r
mean_ <- function(...) mean(..., na.rm=T)
max_ <- function(...) max(..., na.rm=T)
groceryData = {glob_mob %>%
    group_by(country) %>%
    summarise(mean_grocery_pharmacy = mean_(grocery_and_pharmacy_percent_change_from_baseline),
              mean_retail=mean_(retail_and_recreation_percent_change_from_baseline),
              region=region)}

groceryData=unique(groceryData)
```

```r
plot1 <- {glob_mob %>% ggplot(aes(x=date,
                                  y=grocery_and_pharmacy_percent_change_from_baseline,
                                  color=region))} +
  geom_smooth() +
  scale_colour_discrete(labels = c('Europe',"North America",'South America')) +
  xlab("Date") +
  ylab("Visits to groceries and pharmacies") +
  geom_vline(xintercept=as.numeric(as.Date("2020-03-15")),linetype=2) +
  annotate("text",x=as.Date("2020-03-20"), y=45, label = "Start of lockdown") +
  geom_vline(xintercept=as.numeric(as.Date("2020-10-20")),linetype=2) +
  annotate("text",x=as.Date("2020-10-15"), y=45, label = "Start of second lockdown")

print(plot1)
```



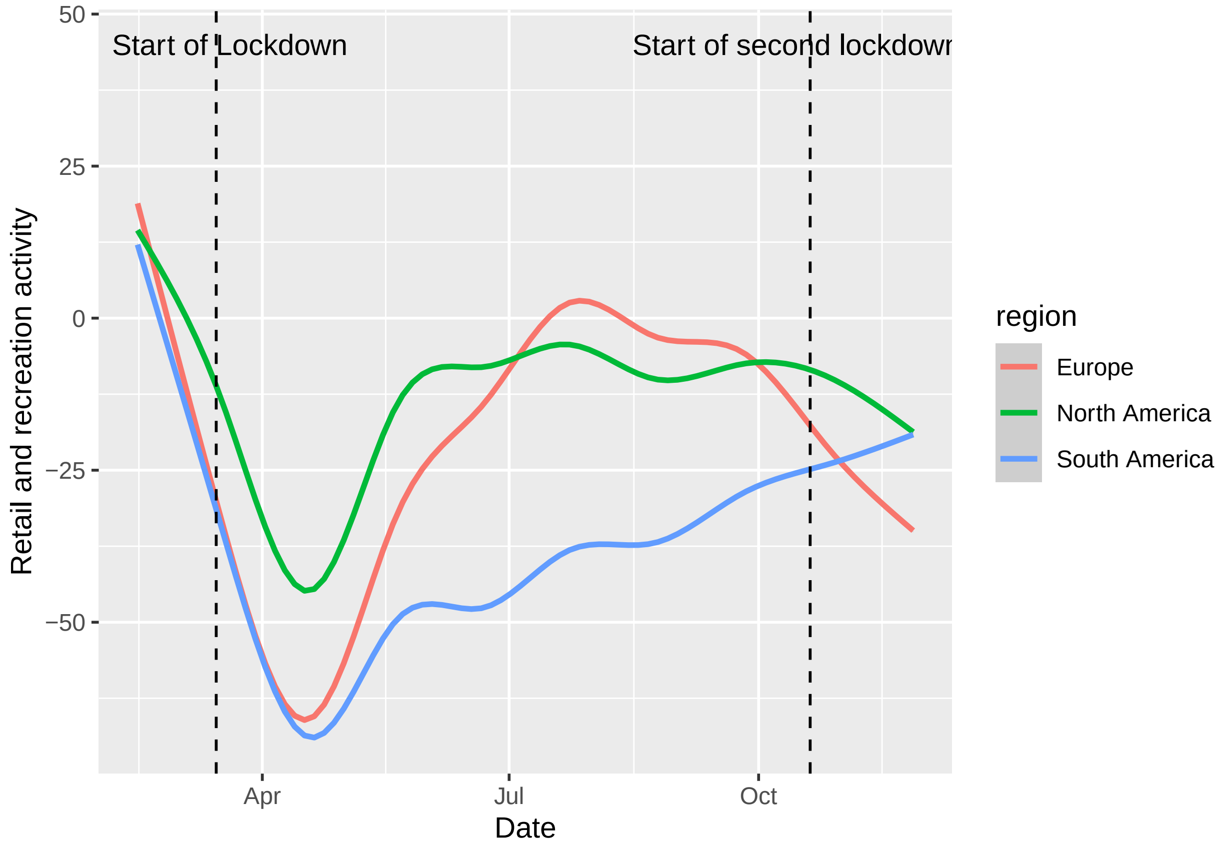
In the majority of countries throughout the regions we are looking at, lockdown restrictions were imposed during the period starting March-April. As was expected, after the enforcement of lockdown measures, visits to grocery shops and pharmacies have decreased significantly, dropping as much as 35% in North America. For Europe and South America we see a fast recovery, whilst North America had a very slow recovery.

From mid October to mid November, countries in Europe started introducing second wave of lockdowns.. This lead to a decrease in the number of confirmed cases in Europe. In South America however, we see a gradual decrease since mid July. There have been no lockdowns in these countries since the first initial lockdowns. After nearly 8 months of being in the sub 0 regions, North America recovers in October, and sees a constant increase.

To summarize, we can conclude that people during the pandemic have clearly preferred not going to grocery and pharmacy shops.

We now go on to explore retail and recreation activity during the pandemic. Below you will see the average percentage change in the frequency of people's visits to retail and recreation, relative to a baseline period from Jan 3 to Feb 6, 2020, starting from the 15th of February.

```
plot1 <- {glob_mob %>% ggplot(aes(x=date,
                                  y=retail_and_recreation_percent_change_from_baseline,color=r

print(plot1)
```



The decrease in activity to retail and recreation is much worse compared to the decrease to grocery shops and pharmacies. Europe and North America had decreased their activity as much as 65-70% in April, although there is a viable explanation to such a drop. In the majority of countries the lockdown restrictions forced non-essential stores to close and recreational activities such as Sports centers and entertainment centers were also forced to close.

Although Europe and South America have recovered significantly faster than North America after their initial drop, both regions were sub 0 level the whole period from February until November, with Europe getting half a month of increased activity compared to February. North America on the other hand did not recover as fast as the other 2 regions, but it made consistent progress throughout the whole period.

Because of the sharp decrease in people visiting retail shops, ecommerce has accelerated as a consequence.. To further emphasize, Thanksgiving Day spending rose by nearly 22% year over year to $5.1 billion, hitting a new record, according to Adobe Analytics data.

Although we cannot say that the pandemic has changed the way people purchase non-essential items permanently, a survey conducted in October, in North America and Canada has showed that 58% of people who conducted the survery are unlikely to shop online (page 11). As shown in this article, online retail purchases in the US have been growing steadily throughout the past years. We recommend OmniCorp investing in research and development in digital marketing, as consumers in the coming years will start moving more onto online spending.

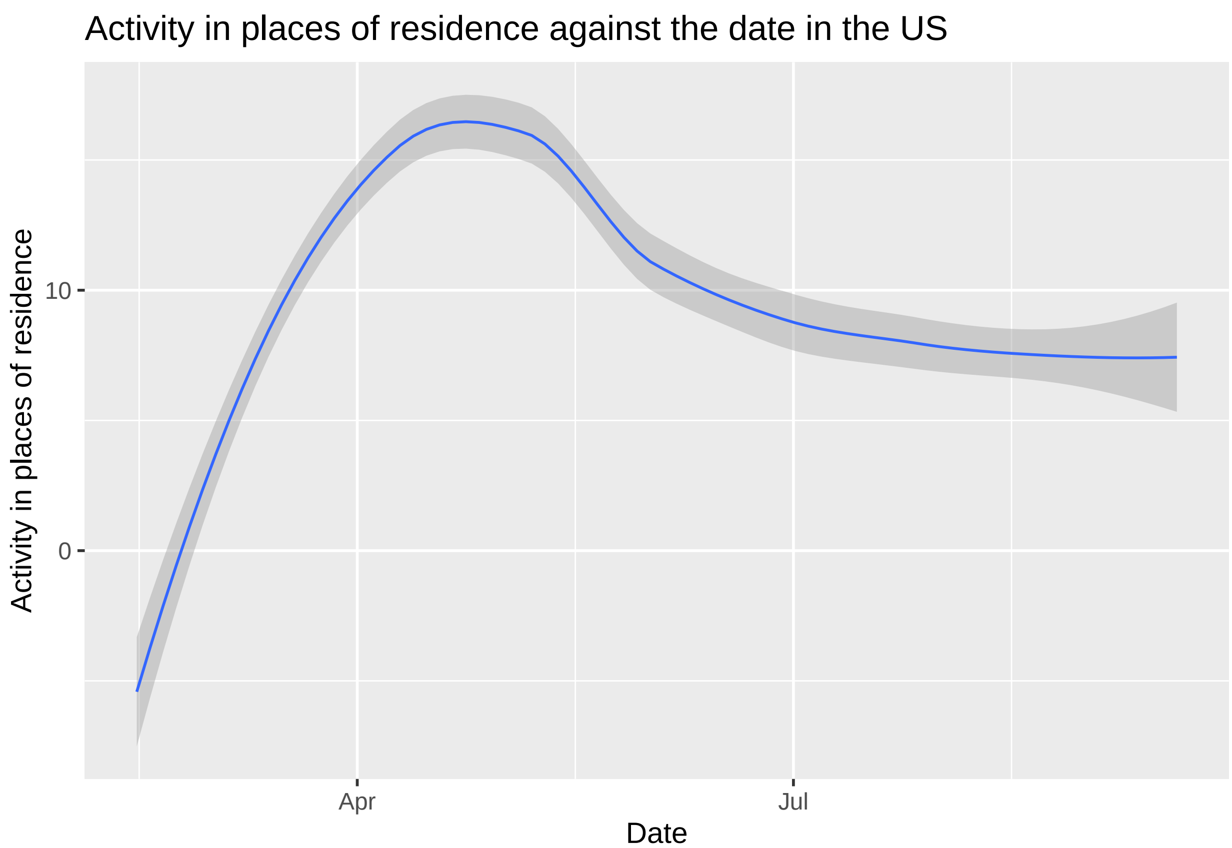
Activity in residential places and interest in 'Take out'

Using Google Trends data (Google Trends, 2020) on the search volume for various terms, we can investigate the general interest over time. Google Trends is an unbiased sample of Google search data. It's anonymised, categorized and aggregated. For the regions we are looking at - Europe, North, Central and South America - the percentage of population that uses the internet is 88%, 95%, 61% and 72% respectively. This indicates that the search patterns shown by Google Trends may be an accurate representation of the behaviors and interests of consumers in these regions.

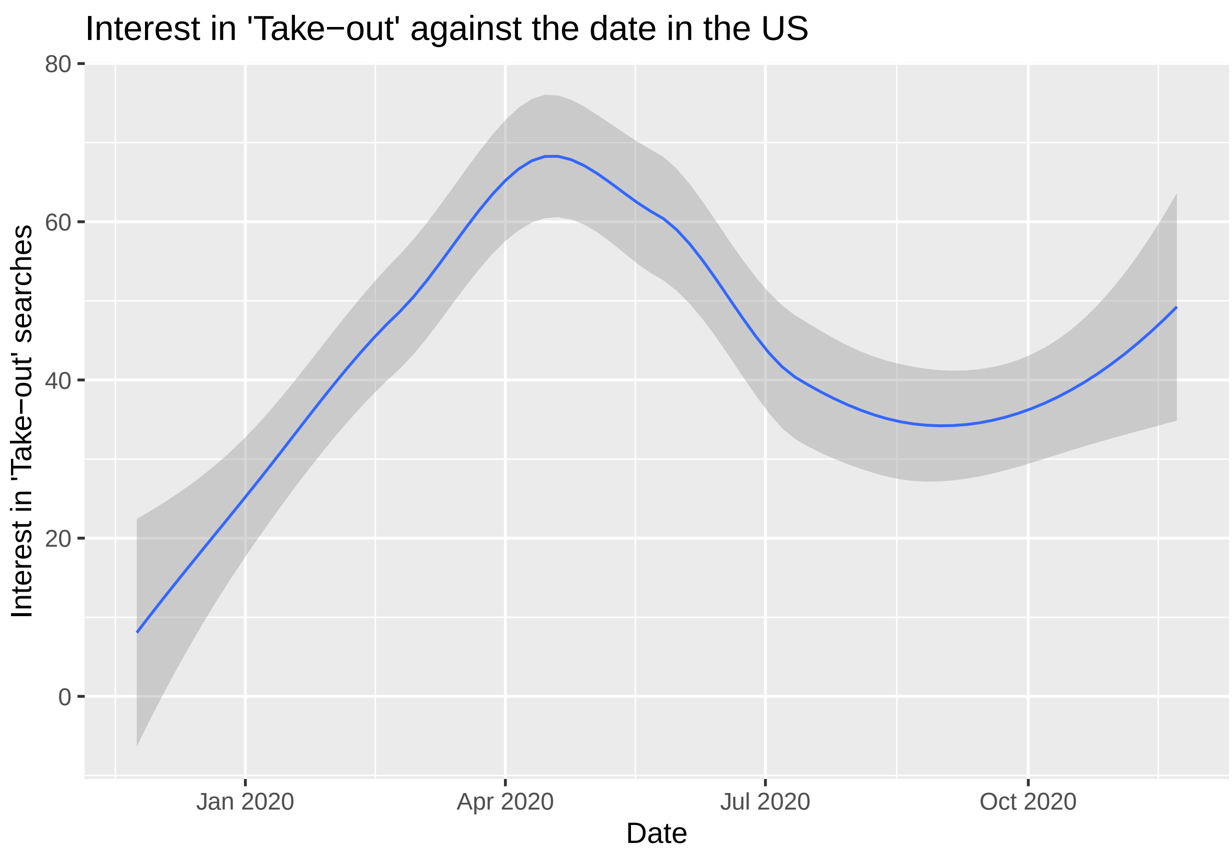
Here we are interested in investigating how the increase in the activity in places of residence affect the interest in using online delivery services. We do this by using the variable interest in 'Take out' from Google Search Trends. We will have a few plots for countries in each region to gain some idea of how these variables interact with each other. The data from Google Trends will look over the time period of 9th February 2020 to 20th September 2020.

```
EuropeAmericaDataPostFeb6 <- {CovidData %>%
    filter( ( str_detect(region, "America") | str_detect(region, "Europe") ) & (date > as.Date("2020-02-

EuropeAmericaDataPostFeb6 <- EuropeAmericaDataPostFeb6 %>%
  mutate(daily_confirmed = firstdiff(confirmed))
```

```
USResidentialData <- EuropeAmericaDataPostFeb6 %>% filter(country %in% c("United States"))

USResPlot <- ggplot(USResidentialData, aes(x = date, y = gcmr_residential)) + geom_smooth(size = 0.5) +
print(USResPlot)
```



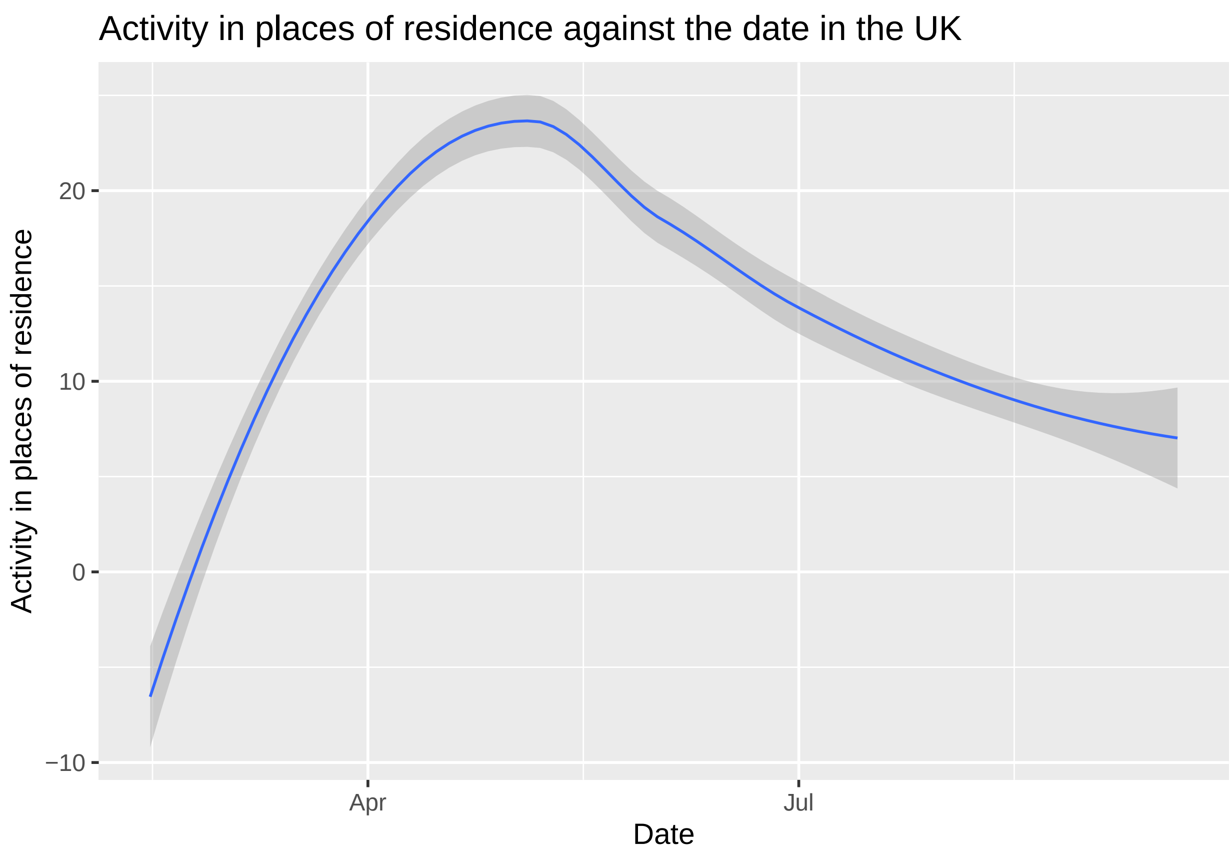

```
#Data obtained from google trends, searched terms "take-out (cuisine)" for the US in the past 12 months
USTakeoutSearch <- read.csv("USTakeoutSearchGtrends.csv")
USTakeoutSearch <- USTakeoutSearch %>% mutate(date = as.Date(parse_date_time(USTakeoutSearch$Week,c("d/

USTakeoutPlot <- ggplot(USTakeoutSearch, aes(x = date, y = Take.out...United.States.)) + geom_smooth(si

print(USTakeoutPlot)
```



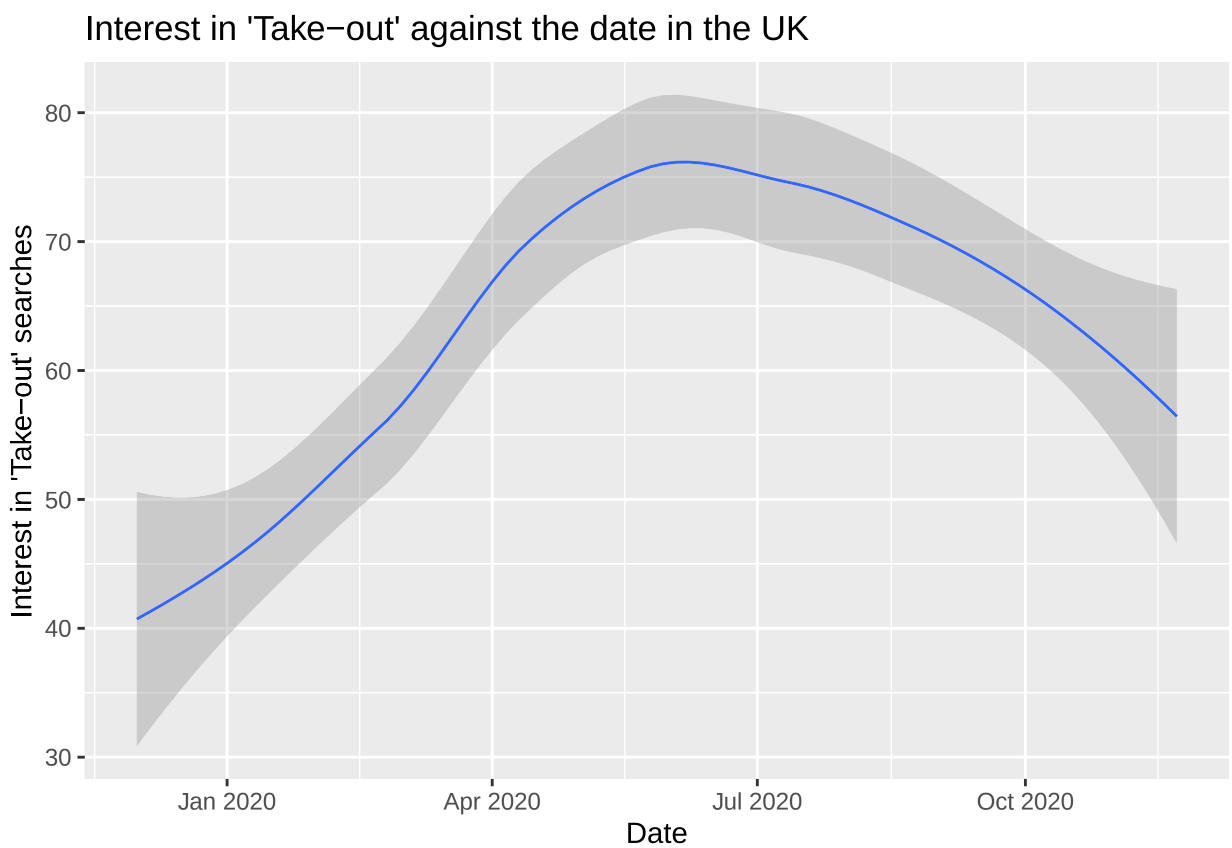

```
USTakeoutResData <- USTakeoutSearch
USTakeoutResData <- USResidentialData %>% filter(date %in% USTakeoutSearch$date) %>% select(date, gcmr_

USTakeoutResData <- USTakeoutResData %>% mutate(. = (USTakeoutSearch %>% filter(date %in% USTakeoutResDa
```

```
USTakeoutResPlot <- ggplot(USTakeoutResData, aes(x = gcmr_residential, y = Take.out...United.States.))

print(USTakeoutResPlot)
```


```r
UKResidentialData <- EuropeAmericaDataPostFeb6 %>% filter(country %in% c("United Kingdom"))

UKResPlot <- ggplot(UKResidentialData, aes(x = date, y = gcmr_residential)) + geom_smooth(size = 0.5) +
print(UKResPlot)
```

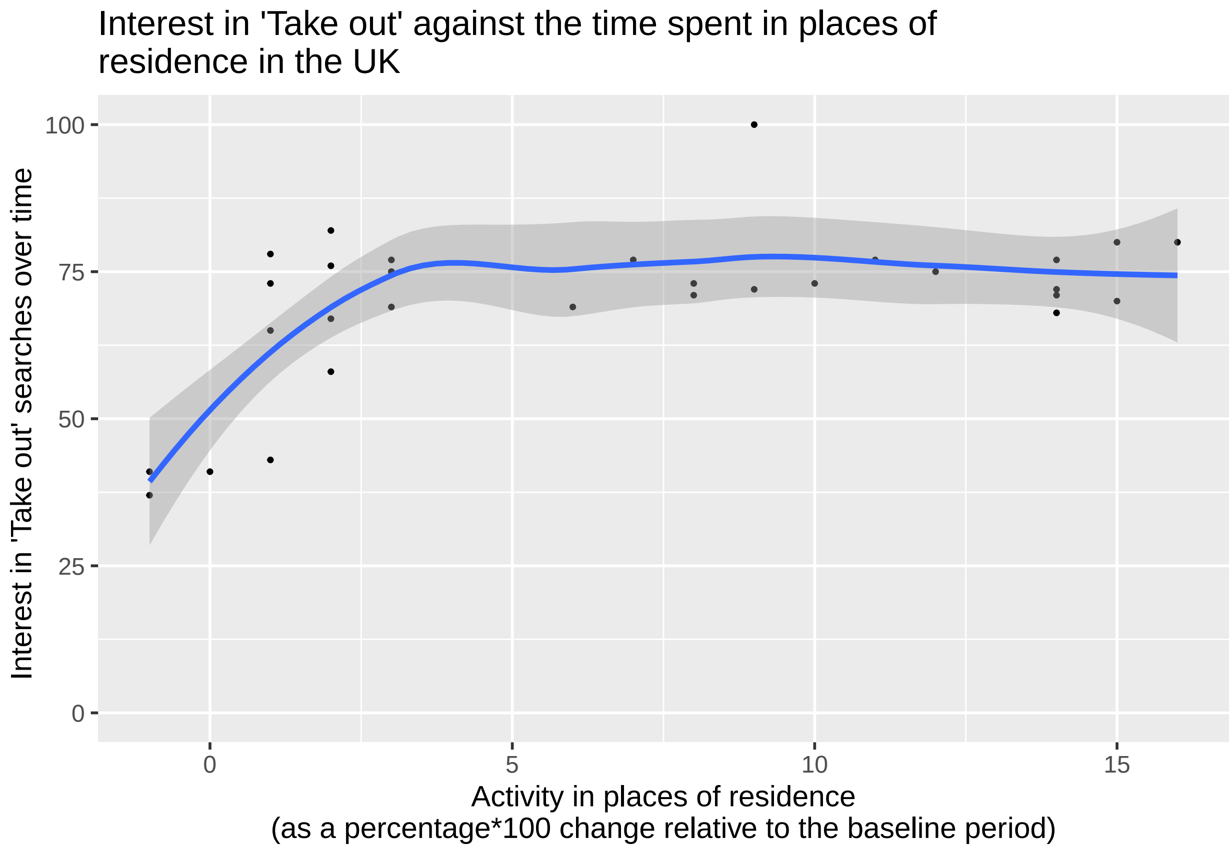



```
#Data obtained from google trends, searched terms "take-out (cuisine)" for the US in the past 12 months
UKTakeoutSearch <- read.csv("UKTakeoutSearchGtrends.csv")
UKTakeoutSearch <- UKTakeoutSearch %>% mutate(date = as.Date(parse_date_time(UKTakeoutSearch$Week,c("d/

UKTakeoutPlot <- ggplot(UKTakeoutSearch, aes(x = date, y = Take.out...United.Kingdom.)) + geom_smooth(s

print(UKTakeoutPlot)
```

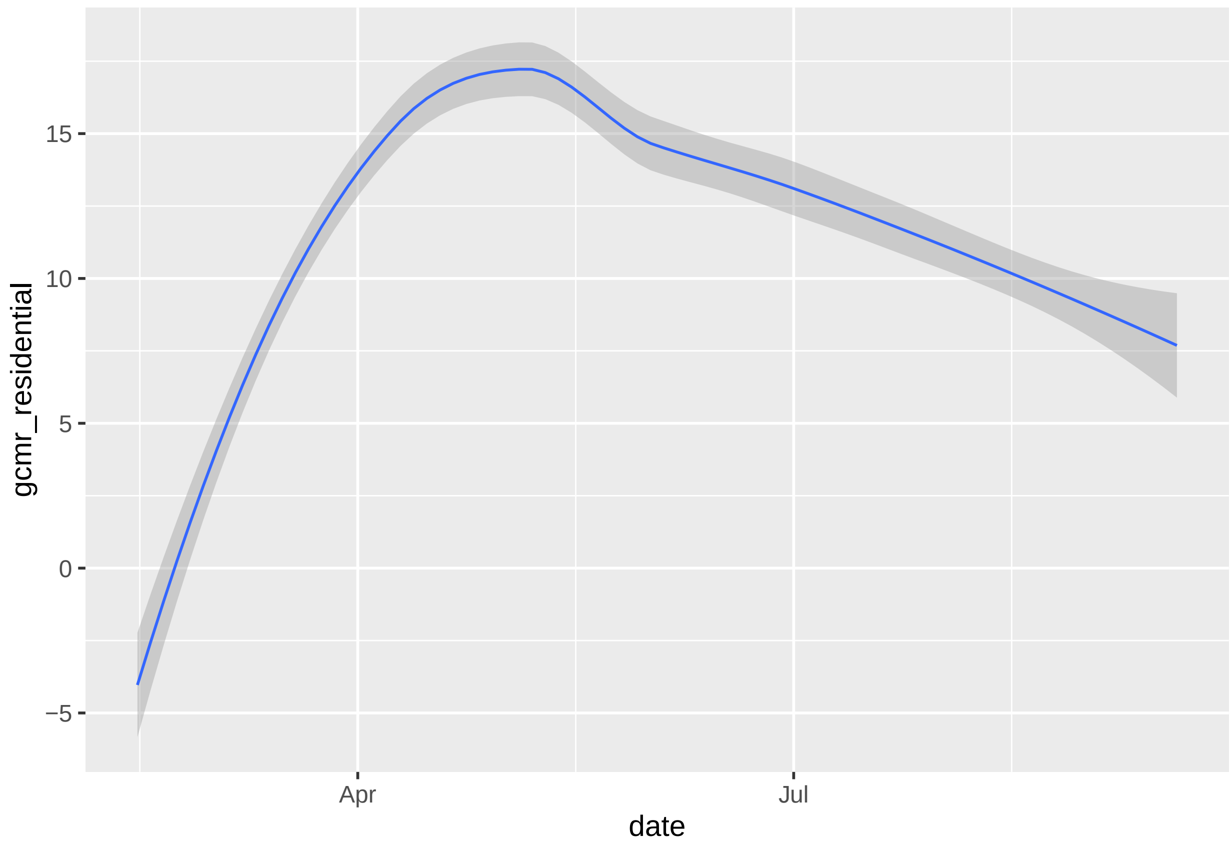



```
UKTakeoutResData <- UKTakeoutSearch
UKTakeoutResData <- UKResidentialData %>% filter(date %in% UKTakeoutSearch$date) %>% select(date, gcmr_r

UKTakeoutResData <- UKTakeoutResData %>% mutate(. = (UKTakeoutSearch %>% filter(date %in% UKTakeoutResDa
```

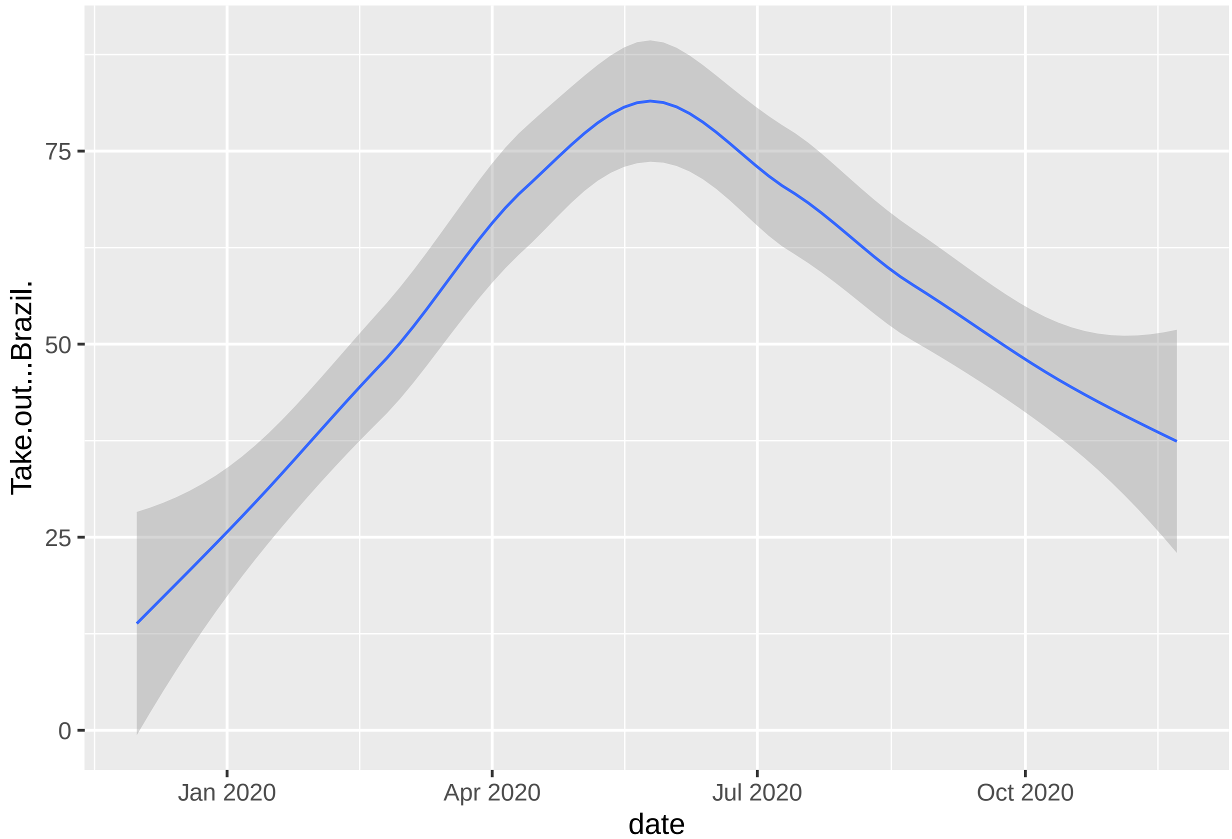
```
UKTakeoutResPlot <- ggplot(UKTakeoutResData, aes(x = gcmr_residential, y = Take.out...United.Kingdom.))


print(UKTakeoutResPlot)
```




```
BrazilResidentialData <- EuropeAmericaDataPostFeb6 %>% filter(country %in% c("Brazil"))

BrazilResPlot <- ggplot(BrazilResidentialData, aes(x = date, y = gcmr_residential)) + geom_smooth(size =
print(BrazilResPlot)
```

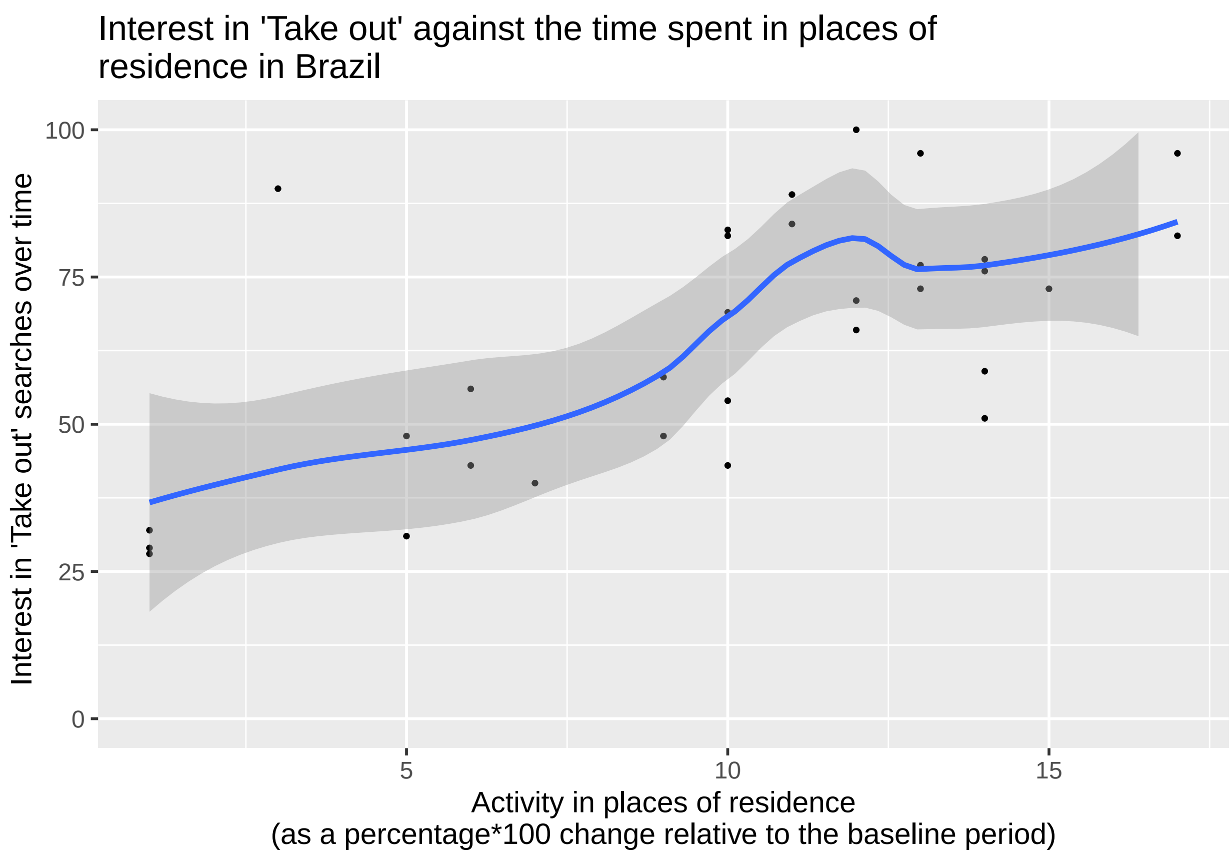



```
#Data obtained from google trends, searched terms "take-out (cuisine)" for Brazil in the past 12 months
BrazilTakeoutSearch <- read.csv("BrazilTakeoutSearchGtrends.csv")
BrazilTakeoutSearch <- BrazilTakeoutSearch %>% mutate(date = as.Date(parse_date_time(BrazilTakeoutSearc

BrazilTakeoutPlot <- ggplot(BrazilTakeoutSearch, aes(x = date, y = Take.out...Brazil.)) + geom_smooth(s

print(BrazilTakeoutPlot)
```




```
BrazilTakeoutResData <- BrazilTakeoutSearch
BrazilTakeoutResData <- BrazilResidentialData %>% filter(date %in% BrazilTakeoutSearch$date) %>% select

BrazilTakeoutResData <- BrazilTakeoutResData %>% mutate(. = (BrazilTakeoutSearch %>% filter(date %in% Br
```

```
BrazilTakeoutResPlot <- ggplot(BrazilTakeoutResData, aes(x = gcmr_residential, y = Take.out...Brazil.))


print(BrazilTakeoutResPlot)
```



After plotting the graphs for US, UK, and Brazil individually we can see some positive relationship between the interest in 'Take out' and the activity in places of residence. We will look into this further by combining these into one plot and see how they vary between the countries.

```
colnames(USTakeoutResData)[1] = "Take.Out.Interest"
USTakeoutResData <- USTakeoutResData %>% mutate(country = "United States")

colnames(UKTakeoutResData)[1] = "Take.Out.Interest"
UKTakeoutResData <- UKTakeoutResData %>% mutate(country = "United Kingdom")

colnames(BrazilTakeoutResData)[1] = "Take.Out.Interest"
BrazilTakeoutResData <- BrazilTakeoutResData %>% mutate(country = "Brazil")

USUKBrazTakeoutResData <- rbind(USTakeoutResData, UKTakeoutResData, BrazilTakeoutResData)

USUKBrazTakeoutResPlot <- ggplot(data = USUKBrazTakeoutResData, aes(x = gcmr_residential, y = Take.Out.I

print(USUKBrazTakeoutResPlot)
```

The United Kingdom implemented at least 1 lockdown measure in late March when the daily confirmed cases of COVID-19 was on the rise. Due to this, we have seen an increase in the activity in places of residence before hitting its peak in late April. We can see due to COVID-19 the interest in 'Take out' remained consistent throughout the lifetime of the pandemic. This could indicate further interest in purchasing food to eat at home. OmniCorp should facilitate this demand for "Take out" by offering food delivery services for their restaurant outlets in the United Kingdom.

Similar to the UK, the government of Brazil implemented at least 1 lockdown measure in late March. This suppressed spread of COVID-19 until July when the daily confirmed cases was on the rise. As the number of confirmed cases increased the activity in places of residence followed. We can also observe an increase in the interest for "Take out".

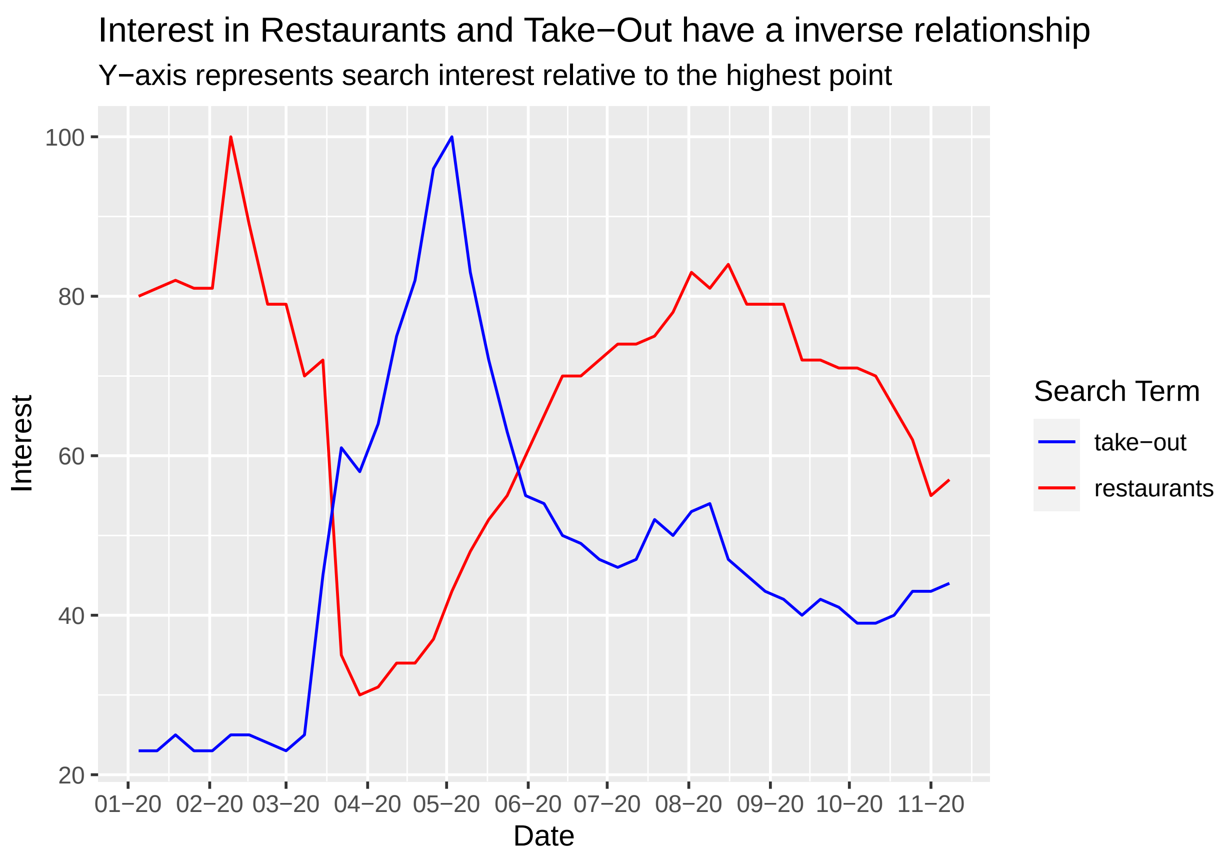
Despite the U.S. government having 0 lockdown measures in place we have seen an increase of activity in the places of residence. When the daily confirmed cases of COVID-19 in the US was at its peak, we can observe that the activity within places of residence was at a peak as well. This indicates that regardless of the lockdown measures, the people in the US were cautious and mindful of the pandemic. Due to the increased activity in residences, we have noticed a positive relationship between the activity in residences and the interest in 'Take out' searches in Google trends.

To capture the loss of business in the hospitality sector, mainly restaurants, We recommend OmniCorp to expand into delivery of food from their current hospitality businesses. This will hopefully recover the business that is lost due to COVID-19 whilst keeping the spread of COVID-19 to a minimum as customers will be eating at home. This is further supported by the following graph, showing the interest of the search terms `restaurants` and `take-out`. We will plot a graph of the average interest for these terms throughout European, North, Central and South American countries. The y axis represents search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular.

We are also interested in how the search term 'Take out' compares to 'Restaurants' globally between January

2020 to early November 2020. To observe the direction of consumer habits towards online services.

```
RestaurantTrendData <- read.csv("gt_restaurants.csv")
TakeOutTrendData <- read.csv("gt_take_out.csv")

RestaurantTrendData <- RestaurantTrendData %>%
  mutate(date = as.Date(parse_date_time(RestaurantTrendData$Week,c("d/m/y"))))
TakeOutTrendData <- TakeOutTrendData %>%
  mutate(date = as.Date(parse_date_time(TakeOutTrendData$Week,c("d/m/y"))))

plot_restaurants_trends <- ggplot(RestaurantTrendData, aes(x = date, y = interest)) +
  geom_line(aes(color='red')) +
  geom_line(data=TakeOutTrendData, aes(color='blue', labels='restaurants')) +
  xlab("Date") +
  ylab("Interest") +
  ggtitle("Interest in Restaurants and Take-Out have a inverse relationship",
          subtitle="Y-axis represents search interest relative to the highest point") +
  scale_x_date(date_breaks = "months", date_labels = "%m-%y") +
  scale_color_manual(labels = c("take-out", "restaurants"), values = c("blue", "red")) +
  guides(color=guide_legend("Search Term"))

print(plot_restaurants_trends)
```



The plot above shows that the two search terms' interests have an inverse relationship. As we can see, when lockdown and restrictions began to be imposed by governments, consumer interest in `restaurants` decreased whereas interest in `take-out` increased at a similar but opposite magnitude. This could further suggest that in lockdowns, consumers are looking to buy more food online, possibly due to sit-in restaurants being closed or people scared to go out in public. This indicates that OmniCorp should focus on online retail and hospitality when lockdown measures are introduced. It is also important to note that the interest in `restaurants` increased back to normal levels almost as fast as it fell. However, it had a smaller, more steady decrease as a second wave of restrictions took place whereas `takeout` did not have a similar magnitude of increase. This may show that take-out food is not a direct substitute for a restaurant food and hence it would not be appropriate for a complete change in online only business operations but rather a steady transition into increase online activity and presence.

Conclusion

It is clear that the lockdown and government interventions in response to the COVID-19 outbreak have had effects on the retail and hospitality sectors, as well as society as a whole. Consumer habits and attitudes have been change in a small period of time. Lockdowns generally helped slow the rate of infection within populations and reduce the impact to communities. However it brought within drastic changes. As shown, people have turned to using the internet to attempt to replace the missing gap on goods and services created by restrictions. This indicates a shift towards ecommerce and online activities. It is hard to tell if this was an already on-going process in which the COVID-19 outbreak, and subsequent government interventions, help accelerate. Either way, it is very important for OmniCorp to be aware of this change.

References

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