Stimulus Checks and Consumer Spending

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9/2/2021

Note: We are using tidyverse, lubridate libraries for our analysis. Make sure, before knitting report these libraries are installed on your system.

See this session info for more insights on the packages we are using. If you are not able to knit the report then you might consider to update your packages to the below versions.

```
sessionInfo()
```

```
## R version 4.1.1 (2021-08-10)
## Platform: aarch64-apple-darwin20 (64-bit)
## Running under: macOS Big Sur 11.5.1
##
## Matrix products: default
## BLAS:   /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/lib/
    libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/4.1-arm64/Resources/lib/
    libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
## [1] knitr_1.33
##
## loaded via a namespace (and not attached):
##  [1] compiler_4.1.1    magrittr_2.0.1    tools_4.1.1       htmltools_0
    .5.1.1
##  [5] yaml_2.2.1        stringi_1.7.3     rmarkdown_2.10    stringr_1.4.0
##  [9] xfun_0.25         digest_0.6.27     rlang_0.4.11      evaluate_0.14
```

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Questions of Interest

1.We want to know whether or not the stimulus checks sent out by the US government have had a positive impact on the economy (using consumer spending as a proxy for how healthy the economy is).

2.We also want to know if unemployment checks sent out by US government effects the unemployment levels.

Unemployment checks protects workers incomes after layoffs, improving their long-run labor market productivity, and stimulating the economy during recessions. But, giving out unemployment checks in large nummber can also discourage job searching.

Why Should YOU Care How Healthy the US Economy Is?

Why should we care about consumer spending? It seems like a big picture idea that won't really effect any of us specifically, right? Wrong. When the economy is healthy, there are more jobs available. Those jobs also pay more. As graduate students, we all want to get good paying jobs as Data Scientists, and that will be more likely to happen more quickly if the economy is healthy.

This analysis will help us understand how stimulus checks effect the US economy, and therefore, indirectly, the analysis will also help us understand whether or not stimulus checks will help us get good-paying jobs quickly after graduation.

There is also a long-standing debate between the liberal and conservative political ideologies in the US over whether or not the increase in consumer spending caused by stimulus checks is actually worth the debt incurred by the government when sending out the checks. While this analysis doesn't cover that, this would be an interesting topic for future research using this dataset.

Data Sources

All of our data was aggregated by Opportunity Insights at https://github.com/OpportunityInsights/EconomicTracker. In this analysis, we use spending data provided by Affinity Solutions, job postings data from Burning Glass Technologies, COVID data from the CDC, GPS mobility reports from Google, unemployment claims from the Department of Labor, and employment levels from Paychex, Intuit, Earnin and Kronos.

Primary Reference:

"The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data", by Raj Chetty, John Friedman, Nathaniel Hendren, Michael Stepner, and the Opportunity Insights Team. November 2020. Available at: https://opportunityinsights.org/wp-content/uploads/2020/05/tracker_paper.pdf

Read Data

from Opportunity Insights GitHub Repository

In this code chunk, we read the columns that we're interested in from the datasources. We could use all of the data in the datasources, but we choose not to, since not all of the features will be helpful in answering the question of whether or not the stimulus checks have boosted the economy.

```
move_daily_df <- read_csv("https://raw.githubusercontent.com/
    OpportunityInsights/EconomicTracker/main/data/Google%20Mobility%20-%20
    State%20-%20Daily.csv",show_col_types = FALSE, col_select = c(year, month,
     day, statefips, gps_retail_and_recreation))

affinity_daily_df <- read_csv("https://raw.githubusercontent.com/
    OpportunityInsights/EconomicTracker/main/data/Affinity%20-%20State%20-%20
    Daily.csv", show_col_types = FALSE, col_select = c(year, month, day,
    statefips, spend_all))

affinity_national_df <- read_csv("https://raw.githubusercontent.com/
    OpportunityInsights/EconomicTracker/main/data/Affinity%20-%20National
    %20-%20Daily.csv", show_col_types = FALSE, col_select = c(year, month, day
    , spend_all, spend_all_q1, spend_all_q4))

job_listings_weekly_df <- read_csv("https://raw.githubusercontent.com/
    OpportunityInsights/EconomicTracker/main/data/Burning%20Glass%20-%20State
    %20-%20Weekly.csv", show_col_types = FALSE, col_select = c(year, month,
    day_endofweek, statefips, bg_posts))

employment_daily_df <- read_csv("https://raw.githubusercontent.com/
    OpportunityInsights/EconomicTracker/main/data/Employment%20-%20State
    %20-%20Daily.csv", show_col_types = FALSE, col_select = c(year, month, day
    , statefips, emp))

employment_national_df <- read_csv("https://raw.githubusercontent.com/
    OpportunityInsights/EconomicTracker/main/data/Employment%20-%20National
    %20-%20Daily.csv", show_col_types = FALSE, col_select = c(year, month, day
    , emp_incq1, emp_incq4))

ui_claims_weekly_df <- read_csv("https://raw.githubusercontent.com/
    OpportunityInsights/EconomicTracker/main/data/UI%20Claims%20-%20State
    %20-%20Weekly.csv", show_col_types = FALSE, col_select = c(year, month,
    day_endofweek, statefips, contclaims_rate_combined))

state_id <- read_csv("https://raw.githubusercontent.com/OpportunityInsights/
    EconomicTracker/main/data/GeoIDs%20-%20State.csv",show_col_types = FALSE)
```

Data Cleaning and Transformation

For National Level Data

First, let's prepare national level data for visualization.

We need date column with 'date" datatype for our further analysis and visualization, so let's create one using year, month, and day columns.

```
# https://tidyr.tidyverse.org/reference/unite.html
affinity_national_df <- affinity_national_df %>% unite("date", day:month:year,
    remove = FALSE, sep = "-")

## Warning in x:y: numerical expression has 2 elements: only the first used

employment_national_df <- employment_national_df %>% unite("date", day:month:
    year, remove = FALSE, sep = "-")

## Warning in x:y: numerical expression has 2 elements: only the first used
```

Change data type of date column to "date"

```
# https://lubridate.tidyverse.org/reference/ymd.html
affinity_national_df <- affinity_national_df %>% mutate(date = dmy(affinity_
    national_df$date))
employment_national_df <- employment_national_df %>% mutate(date = dmy(
    employment_national_df$date))
```

We also need week column for our analysis and visualization. In below code chunk we are creating one in both dataframes.

```
affinity_national_df <- affinity_national_df %>% mutate(week = epiweek(date))
employment_national_df <- employment_national_df %>% mutate(week = epiweek(
    date))
```

Now, let's take look at a summary of the data to see if there are problems

```
glimpse(affinity_national_df)

## Rows: 967
## Columns: 8
## $ date         <date> 2019-01-07, 2019-01-08, 2019-01-09, 2019-01-10,
    2019-01-~
## $ year         <dbl> 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019, 2019,
    201~
## $ month        <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
    1, ~
## $ day          <dbl> 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20,
    21, ~
## $ spend_all    <chr> ".", ".", ".", ".", ".", ".", ".", ".", ".", ".", ".",
     ".~
## $ spend_all_q1 <chr> ".", ".", ".", ".", ".", ".", ".", ".", ".", ".", ".",
     ".~
## $ spend_all_q4 <chr> ".", ".", ".", ".", ".", ".", ".", ".", ".", ".", ".",
     ".~
## $ week         <dbl> 2, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 4, 4, 4, 4, 4,
    4, ~
```

```
glimpse(employment_national_df)

## Rows: 557
## Columns: 7
## $ date      <date> 2020-01-14, 2020-01-15, 2020-01-16, 2020-01-17,
    2020-01-18,~
## $ year      <dbl> 2020, 2020, 2020, 2020, 2020, 2020, 2020, 2020, 2020,
    2020, ~
## $ month     <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2,
    2, ~
## $ day       <dbl> 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27,
    28, ~
## $ emp_incq1 <dbl> -2.23e-03, -1.26e-03, -2.48e-04, 6.96e-04, 1.49e-03, 2.17
    e-0~
## $ emp_incq4 <dbl> 1.22e-03, 6.94e-04, 2.16e-04, -2.00e-04, -5.59e-04, -8.67
    e-0~
## $ week      <dbl> 3, 3, 3, 3, 3, 4, 4, 4, 4, 4, 4, 4, 5, 5, 5, 5, 5, 5, 5,
    6, ~
```

After taking closer look at above output we realized the Spend_all, spend_all_q1, spend_col_q4, etc. columns have char datatype insetad of dbl. let's change their data type to dbl.

```
df_national <- affinity_national_df %>%
  select(date, year, month, day, week, spend_all, spend_all_q1, spend_all_q4)
    %>%
  mutate(
    spend_all_q1 = as.double(spend_all_q1),
    spend_all_q4 = as.double(spend_all_q4),
    spend_all = as.double(spend_all)
  ) %>% filter(date > ymd("2020-01-15"))

## Warning in mask$eval_all_mutate(quo): NAs introduced by coercion

## Warning in mask$eval_all_mutate(quo): NAs introduced by coercion

## Warning in mask$eval_all_mutate(quo): NAs introduced by coercion

emp_national <- employment_national_df %>%
  select(date, year, month, day, week, emp_incq1, emp_incq4) %>%
  mutate(
    emp_incq1 = as.double(emp_incq1),
    emp_incq4 = as.double(emp_incq4),
  ) %>% filter(date > ymd("2020-01-15"))
```

For First Regression Model

Now, let's prepare data for our first regression model

```
consumer_spending <- affinity_daily_df
visits_to_retail <- move_daily_df
employment <- employment_daily_df
```

Join the dataframes.

Here we join the datasets of interest based on a shared date and state of measurements.

```
regression1_df <- left_join(consumer_spending, visits_to_retail, by = c("year"
    , "month", "day", "statefips"))
regression1_df <- left_join(regression1_df, employment, by =c("year", "month",
     "day", "statefips"))
```

We need date column with 'date" datatype for our further analysis, so let's create one using year, month, and day columns.

```
regression1_df <- regression1_df %>% unite("date", day:month:year, remove =
    FALSE, sep = "-")
```

```
## Warning in x:y: numerical expression has 2 elements: only the first used
```

```
regression1_df$date <- dmy(regression1_df$date)
```

Adding Stimulus Check Data

Here we add in the data for the COVID stimulus checks. We do this by creating a feature encoding for each check, where the value for that check is **0** before the check is sent out, then $1200 for two weeks after the first check, then zero, then $600 for two weeks after the second check, then zero, then $1400 for two weeks after the third check, and then zero.

```
regression1_df<- regression1_df%>% mutate(
  stimulus_checks = ifelse (date < ymd("2020-04-15"), 0,
                                ifelse (date < ymd("2020-05-01"), 1200,
                                          ifelse (date < ymd("2021-01-04"),0,
                                                    ifelse (date < ymd("2021-01-19")
                                                        ,600,
                                                              ifelse (date < ymd("
                                                                  2021-03-17"),0,
                                                                        ifelse (date < ymd
                                                                           ("2021-04-01")
                                                                           ,1400, 0))))))
                                                                           )
```

Dealing with missing values

To fix the **NA** values found in our dataset, we replace them all with **0**. We could have handled them many other ways, like replacing them with the column mean, median, mode, or by training a regression model to fill them based on the rows that were not missing those values. For this dataset, though, we found that **NA**s are frequently used when the there was no interesting data to report (in other words, the value for the feature was zero). This can be seen particularly in columns like new_death_count and new_case_count from the CDC COVID dataset.

We also drop rows that have 0 spending data because this value is not realistic. Also, we need the spend_all column to be clean because we will be using it for plotting and training a regression model later on.

```
regression1_df$spend_all <- ifelse(regression1_df$spend_all == ".", NA,
    regression1_df$spend_all)
regression1_df$spend_all <- as.double(regression1_df$spend_all)

regression1_df$emp <- ifelse(regression1_df$emp == ".", NA, regression1_df$emp
    )
regression1_df$emp <- as.double(regression1_df$emp)

#glimpse(regression1_df)
```

For Second Regression Model

In last, We will prepare data for our second regression model

Here we repeat the cleaning and transformation steps that we did for the first linear model, except now we're doing it on weekly data instead of daily data.

```
visits_to_retail_weekly <- move_daily_df
visits_to_retail_weekly <- visits_to_retail_weekly %>% unite("date", day:month
    :year, remove = FALSE, sep="-")

## Warning in x:y: numerical expression has 2 elements: only the first used

visits_to_retail_weekly$date = dmy(visits_to_retail_weekly$date)
visits_to_retail_weekly <- mutate(visits_to_retail_weekly,week =isoweek(date))
visits_to_retail_weekly <-  visits_to_retail_weekly %>% group_by(year, week,
    statefips) %>% summarise(gps_retail_and_recreation = mean(gps_retail_and_
    recreation), date =max(date))

## `summarise()` has grouped output by 'year', 'week'. You can override using
    the `.groups` argument.

unemployment_claims <-  ui_claims_weekly_df
unemployment_claims <- unemployment_claims %>% unite("date", day_endofweek:
    month:year, remove = FALSE, sep="-")

## Warning in x:y: numerical expression has 2 elements: only the first used

unemployment_claims$date <- dmy(unemployment_claims$date)
unemployment_claims$contclaims_rate_combined <- as.double(unemployment_claims$
    contclaims_rate_combined)

## Warning: NAs introduced by coercion

job_postings <-  job_listings_weekly_df
job_postings <- job_postings %>% unite("date", day_endofweek:month:year,
    remove = FALSE, sep="-")

## Warning in x:y: numerical expression has 2 elements: only the first used

job_postings$date <- dmy(job_postings$date)
job_postings$date <- job_postings$date+1
job_postings$day_endofweek <- job_postings$day_endofweek+1

regression2_df <- left_join(unemployment_claims, job_postings, by =c("date", "
    statefips", "month", "year", "day_endofweek"))
regression2_df <- regression2_df %>% mutate(week = isoweek(date))
regression2_df <- left_join(regression2_df, visits_to_retail_weekly, by = c("
    week","statefips", "year"))
regression2_df <- left_join(regression2_df, state_id, by = c("statefips"))
regression2_df <- rename(regression2_df, c(visits_to_retail_and_recreation = "
    gps_retail_and_recreation", date = "date.x"))
```

Adding Unemployment check values

As we know, many states stopped giving out pandemic unemployment checks early. Our data is super helpful for comparing states that continued with pandemic benefits vs those states which cut benefits off early. Below is a list of states that cut off benefits early.

```
states_which_stopped_early_benefits <- c("Arizona", "Indiana", "Maryland", "
    Tennessee", "Alaska", "Iowa", "Mississippi", "Missouri", "Alabama", "Idaho
    ", "Nebraska", "New␣Hampshire", "North␣Dakota", "West␣Virginia", "Wyoming"
    , "Arkansas", "Florida", "Georgia", "Ohio", "Oklahoma", "South␣Carolina",
    "South␣Dakota", "Texas", "Utah", "Montana")
```

Now, let's add Unemployment checks data

```
regression2_df <- regression2_df %>% mutate(unemployment_checks =
                                    ifelse((date >= ymd("2020-03-29") & date<= ymd("2020-07-31")
                                        ), 600,
                                    ifelse ((date >= ymd("2020-07-26") & date<=ymd("2020-09-05")
                                        ), 300,
                                    ifelse ((date >= ymd("2020-12-26") & date<=ymd("2021-03-13")
                                        ), 300,
                                    ifelse ((date >= ymd("2021-03-14") & date <= ymd("2021-06-21
                                        ") &
                                          (statename %in% states_which_stopped_early_benefits))
                                               ,300,
                                    ifelse((date >= ymd("2021-03-14") & date <= ymd("2021-09-04"
                                        ) &
                                          !(statename %in% states_which_stopped_early_benefits)),
                                               300, 0))))))
```

Dealing with missing values

Here we replace missing values (such as ".") with NA.

```
regression2_df$contclaims_rate_combined <- ifelse(regression2_df$contclaims_
    rate_combined == ".", NA, regression2_df$contclaims_rate_combined)
regression2_df$contclaims_rate_combined <- as.double(regression2_df$contclaims
    _rate_combined)
```

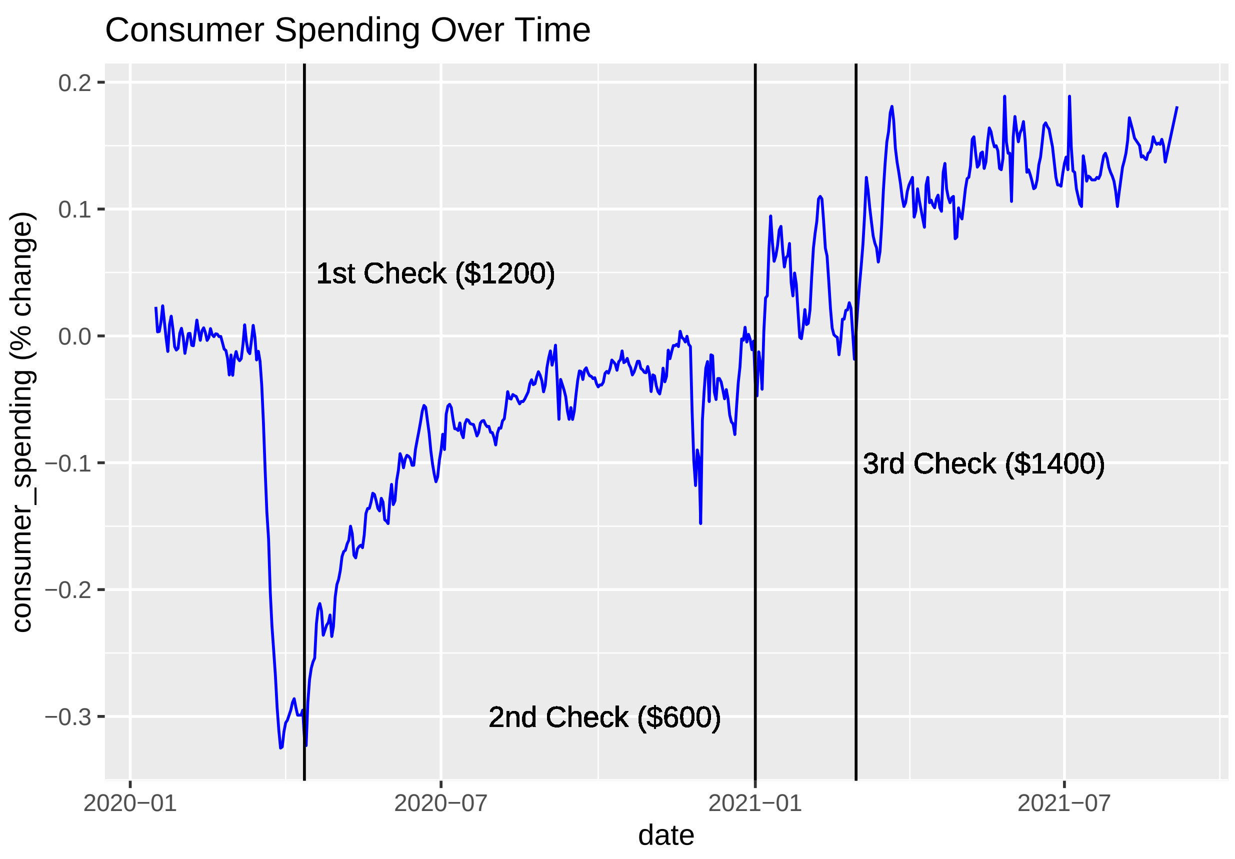
Analysis and Visualization

Now, let's understand the national level data through visualizations

National Spending Over Time

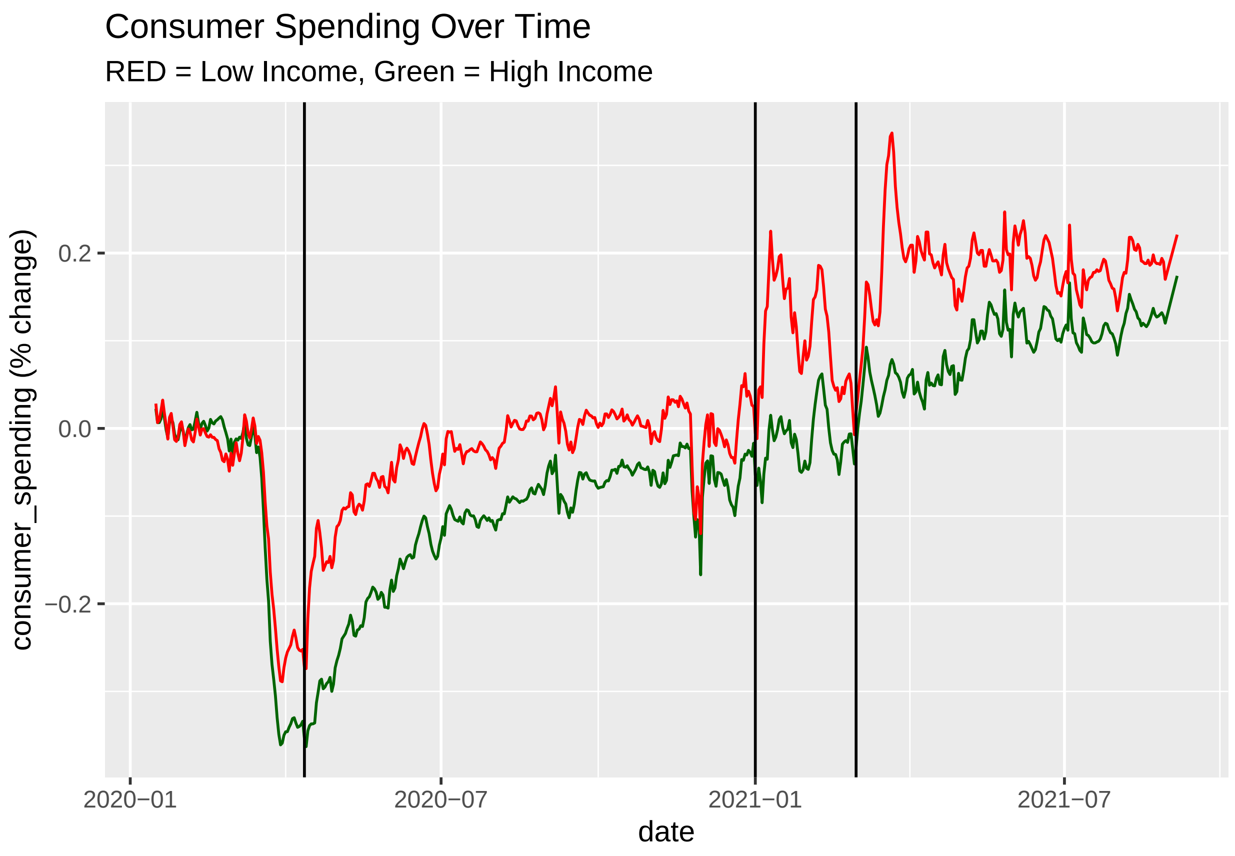
(The dates for the stimulus checks were approximated from this article.)

```
ggplot(df_national, aes(x = date, y = spend_all)) +
  geom_line(color="blue") +
  geom_vline(xintercept = as.Date("2020-04-12")) +
  geom_vline(xintercept = as.Date("2021-01-01")) +
  geom_vline(xintercept = as.Date("2021-03-01")) +
  geom_text(aes(x = as.Date("2020-06-28"), label = "1st Check ($1200)"),
    color = "black", angle = 0, y = .05
  ) +
  geom_text(aes(x = as.Date("2020-10-05"), label = "2nd Check ($600)"),
    color = "black", angle = 0, y = -.3
  ) +
  geom_text(aes(x = as.Date("2021-05-15"), label = "3rd Check ($1400)"),
    color = "black",
    angle = 0, y = -.1
  )+
  ylab("consumer_spending (% change)") +
  labs(title = "Consumer Spending Over Time")
```



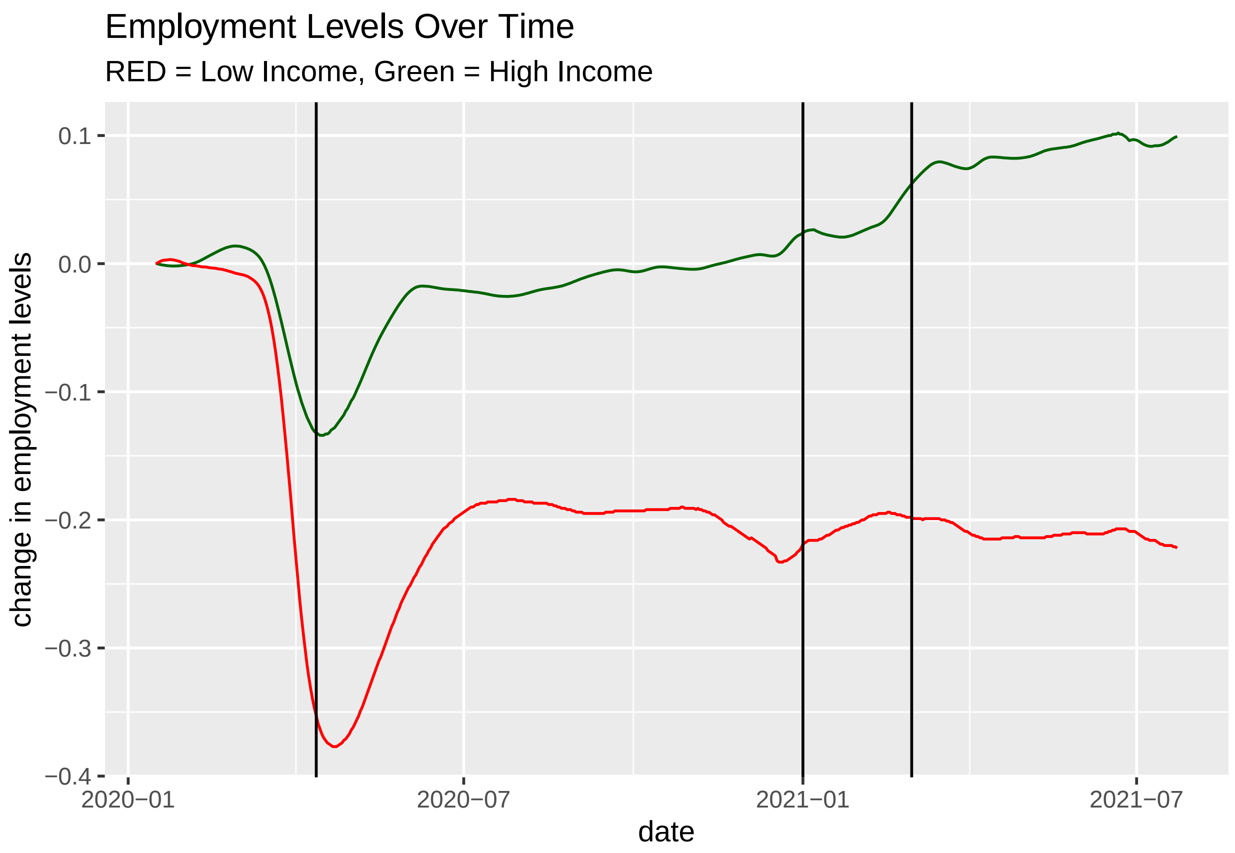
National Spending Over Time (Split by Income)

```r
ggplot(df_national, aes(x = date, y = spend_all_q1)) +
  geom_line(aes(y = spend_all_q4), color="dark␣green") +
  geom_line(color="red") +
  geom_vline(xintercept = as.Date("2020−04−12")) +
  geom_vline(xintercept = as.Date("2021−01−01")) +
  geom_vline(xintercept = as.Date("2021−03−01"))+
  ylab("consumer_spending␣(%␣change)") +
  labs(title = "Consumer␣Spending␣Over␣Time", subtitle = "RED␣=␣Low␣Income,␣
      Green␣=␣High␣Income")
```



National Unemployment Rate Over Time (Split by Income)

```
ggplot(emp_national, aes(x = date, y = emp_incq1)) +
  geom_line(aes(y = emp_incq4), color="dark␣green") +
  geom_line(color="red") +
  geom_vline(xintercept = as.Date("2020-04-12")) +
  geom_vline(xintercept = as.Date("2021-01-01")) +
  geom_vline(xintercept = as.Date("2021-03-01")) + ylab("change␣in␣employment␣
      levels") +
  labs(title = "Employment␣Levels␣Over␣Time", subtitle = "RED␣=␣Low␣Income,␣
      Green␣=␣High␣Income")
```



Spending Regression Model

Training the First Linear Model on Our Data

In this code chunk, we fit a linear model to the *gps_retail_and_recreation*, *emp*, and *stimulus_checks* features, with the goal of predicting the *spend_all* variable. The working assumption here is that *spend_all* is a dependent variable, and the others are independent variables.

The reason we chose these three input variables is that *stimulus_checks* are directly relevant to our analysis. We are trying to identify if these features had a positive or negative effect on the economy. These two features, *gps_retail_and_recreation* and *emp*, were added to help account for change in spending that could not necessarily be accounted for by the *stimulus_checks*. We chose not to include any other input features because we believe that *gps_retail_and_recreation* and *emp* account for much of the possible variance without over-complicating our linear model.

```
spending_regression <- lm(spend_all ~ gps_retail_and_recreation + emp +
    stimulus_checks, regression1_df)
```

Summarize Spending Regression Model

```
summary(spending_regression)
```

```
##
## Call:
## lm(formula = spend_all ~ gps_retail_and_recreation + emp + stimulus_checks,
##     data = regression1_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.33348 -0.07187 -0.00643  0.06591  0.57687
##
## Coefficients:
##                            Estimate Std. Error t value Pr(>|t|)
## (Intercept)               7.981e-02  1.003e-03   79.54   <2e-16 ***
## gps_retail_and_recreation 2.000e-01  7.927e-03   25.23   <2e-16 ***
## emp                       8.467e-01  1.409e-02   60.10   <2e-16 ***
## stimulus_checks           5.551e-05  2.139e-06   25.95   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1038 on 22536 degrees of freedom
##   (8468 observations deleted due to missingness)
## Multiple R-squared:  0.4067, Adjusted R-squared:  0.4067
## F-statistic:  5150 on 3 and 22536 DF,  p-value: < 2.2e-16
```

Based on the information displayed above, all of the variables we are regressing on are statistically significant for predicting the overall spending. The positive coefficient for the *stimulus_checks* variable in the linear model seems to indicate that *stimulus_checks* are positively correlated with overall consumer spending (the variable we're predicting with our linear model).

Our model is fairly limited in how accurately it predicts overall consumer spending because it is a linear model, and because we've limited ourselves to regressing on three variables for the sake of model simplicity, rather than the 30+ that we could've regressed on.

Future analysis could be done using neural networks, gradient boosted decision trees, or recurrent neural networks. We believe that all of these would be able to learn the nuances of our dataset better than a linear model could.

Unemployment Regression Model

Training the Second Linear Model on Our Data

In this code chunk, we fit a linear model to the *visits_to_retail_and_recreation*, *unemployment_checks*, and *bg_posts* features, with the goal of predicting the total continued unemployment claims variable. The working assumption here is that *contclaims_rate_combined* is a dependent variable, and the others are independent variables.

Again, we chose only these three variables to regress on for the sake of model simplicity.

```
unemployment_regression <- lm(contclaims_rate_combined ~ bg_posts + visits_to_
    retail_and_recreation + unemployment_checks, regression2_df)
```

Summarize the Unemployment Model

```
summary(unemployment_regression)
```

```
##
## Call:
## lm(formula = contclaims_rate_combined ~ bg_posts +
    visits_to_retail_and_recreation +
##     unemployment_checks, data = regression2_df)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.908   -4.027   -1.171    2.924   57.707
##
## Coefficients:
##                                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       5.744725   0.181844   31.59   <2e-16 ***
## bg_posts                         -4.937473   0.488912  -10.10   <2e-16 ***
## visits_to_retail_and_recreation -12.011443   0.828006  -14.51   <2e-16 ***
## unemployment_checks               0.008454   0.000505   16.74   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.608 on 3872 degrees of freedom
##   (612 observations deleted due to missingness)
## Multiple R-squared:  0.2401, Adjusted R-squared:  0.2395
## F-statistic: 407.9 on 3 and 3872 DF,  p-value: < 2.2e-16
```

Once again, all of the variables we are regressing on are statistically significant for predicting the change in unemployment since the pre-pandemic baseline. The positive coefficient for the *umemployment_checks* variable in the linear model seems to indicate that *unemployment_checks* are positively correlated with overall unemployment rates. This is a rather odd way of saying that unemployment checks are correlated with high unemployment.

This model is also fairly limited for a couple of reasons: we're using linear modeling and only regressing on a small set of features for the sake of model interpretability and simplicity.

As with the other model, future analysis could be done using neural networks, gradient boosted decision trees, or recurrent neural networks. We believe that all of these would be able to learn the nuances of our dataset better than a linear model could.

Biases

Model Biases

We were expecting to find that the stimulus checks all had a positive impact on consumer spending, because this is the only outcome that makes any economic sense, as far as we can tell. This effected how we encoded our stimulus check data into feature variables, and it effected how accurate we thought any given model was. If a model said that a stimulus check caused a decrease in consumer spending, we considered that model to be almost certainly highly inaccurate.

Data Biases

Our data contains several potential biases that could skew our results. For example, we use movement data from Google. This data was likely pulled from android phones, not Apple products. Imagine, then, that more affluent people tend to purchase Apple products. If this is true, our movement data will be skewed away from affluent people who may be more likely to spend more, more casually.

Conclusion

The coefficients of our first linear model seem to indicate that, unsurprisingly, giving out stimulus checks is correlated with an increase in overall consumer spending.

Additionally, our second linear model seems to indicate that giving out extra stimulus checks is correlated with higher unemployment levels for low income households.

Therefore, *if* high consumer spending is correlated with a healthier economy, then it seems reasonable to conclude that giving out stimulus checks is also good for the economy, and if they are good for the economy, they are also good for our chances of getting jobs that pay well post-graduation.

The "if" at the beginning of the previous sentence is a big one, though. If the government has to go further into debt to send out stimulus and unemployment checks, then is the net effect of these checks really good for the economy? We don't know, and this analysis has not considered the effect of increased government debt on the economy. This would be an interesting topic for future analysis.