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Assessing the Influence of Health Policy and Population Mobility on COVID-19 Spread in Arkansas

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Abstract:

The outbreak of COVID-19 has created a major crisis across the world since its start in 2019, and its influence on every realm of society is undeniable. Globally, more than 500 million cases have been recorded since March 2020, with almost 6 million deaths. In the wake of this crisis, many governments and health organizations have taken steps and precautions to mitigate its spread. These steps involve public mandates of information, reducing frequency of personal contact, and use of masks to minimize the risk of transmission. Current access to mobility data released from Google detailing population movements has provided a great opportunity to quantify the correlation between COVID-19 mandates and health policies on community traveling and COVID spread. The aim of this study is to examine the relationship between population mobility and the COVID pandemic, specifically focusing on the state of Arkansas. Three main types of mobility changes and various indicators of COVID spread were examined from available data ranging from March of 2020 to March of 2022. We employed various statistical methods including discontinued regression, causality tests, and mixed regression models to better understand how implemented COVID safety polices relate to a population's aggregate mobility, and to estimate the subsequent correlation between population mobility and COVID-19 spread within counties in Arkansas.

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1. Background and Related Work

Ways to mitigate the spread of infectious disease such as in the case of COVID-19 has been an area of research for many, especially throughout the times of widespread transmission. There are studies analyzing public data to assess various measures of safety. A systematic review by Ayouni et al. (2021) examined the effectiveness of social health initiatives and non-pharmaceutical interventions for the reduction of transmission of diseases including COVID-19. Specifically, the review concluded "travel restrictions, borders measures, quarantine of travelers arriving from affected countries, city lockdown, restrictions of mass gathering, isolation and quarantine of confirmed cases and close contacts, social distancing measures, compulsory mask wearing, contact tracing and testing, school closures and personal protective equipment use among health workers" all to be effective in mitigating the spread of COVID. A study by Mukerjee et al. (2021) assessed social compliance to mitigation measures in the U.S. and investigated what degree of social compliance is required to have an effective impact on COVID spread. The study interpreted state data recording very divergent trends in infection rates, despite having similar community mitigation measures. Although conclusions were made describing compliance to mitigation measures in democratic societies as largely exogenous, major limitations of the study were mentioned. Access to quality data and effective information about the progression of the COVID outbreak has impeded analysis of population data. This study aims to address this limitation, utilizing population mobility data released from Google. The mobility data is collected through individual location tracking, utilizing the company's widespread distribution of software and devices, and consists of aggregate information on population movement trends over time. The data provides daily movement changes as a percentage (relative to baseline values) and is for community movements to distinct areas characterized as retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, or residential. According to Google, “differential privacy” was utilized to record mobility data, adding artificial noise and enabling quality results without identifying individual movements. Research has been completed analyzing mobility data in relation to mandated COVID protocols, but with differing statistical methodology and concerning different geographical areas. In a paper written by Kartel et al. (2021), the causality relationship between indicators of mobility changes and progression of COVID spread was examined. The study specifically analyzed data from the country of Turkey and focused on the use of causality tests such as the Toda-Yamamoto test to prove an econometrically causal relationship. A published review by García-Cremades et al. (2021) examined the use of artificial neural network models and ARIMA forecasting for predicting the progression of COVID in Spain, utilizing Google’s mobility data. Additionally, the use of regression in this area can be seen in a study by Wellenius et al. (2021), where the impact of social distancing policies on mobility and COVID spread in the U.S. was evaluated, through various mixed regression models. Overall, the evaluation of COVID spread and mandated polices by utilizing mobility data has already been an area of investigation, though published research pertains to differing geographical locations, methodology, and time periods of analysis.

2. Methodology

This section will introduce the methodology and development of the regression discontinuity model and linear mixed effects model for various public mandates.

2.1 Regression Discontinuity Analysis

First, to assess the associated changes in a populations mobility from mandated COVID policies and implemented public efforts, the methodology of a regression discontinuity analysis was chosen. Using regression discontinuity design was optimal in this study as the experimental analysis allows the impact of an intervention to be measured, by applying a treatment assignment threshold. Through evaluating observations on either side of the threshold, estimation of a treatment effect can be evaluated despite complete randomization. In this study, the information analyzed pertains to time series data, with every observation in direct relation. Applying a treatment threshold at a specific point in time allows this time series data to be accurately analyzed, comparing the trends evident in each created subset. Google Mobility Data was aggregated at the county level within the state of Arkansas, from March 1, 2020 to March 1, 2022. The daily data within this range includes the relative changes in average time individuals resided in residential areas, retail and recreational areas, and workplaces as the main categories of interest.

For each county's mobility data, a regression discontinuity was applied using the date of mandate implementation as the treatment threshold. The public mandates tested in this analysis include (1) March 11, 2020: The declaration of a national pandemic and nation emergency by the World Health Organization, (2) July 20, 2020: Arkansas's statewide mask mandate for public areas, and (3) July 29, 2021: Arkansas's declaration of a public health emergency. In order to account for the period of communication to each community and implementation of measures, each metric was compared using the week following the implementation, and the period 2-7 days prior to implementation. The model provided estimates of the percent change in recreation, residential, and workplace mobility from the state's implementations.

2.2 Linear Mixed Regression Model

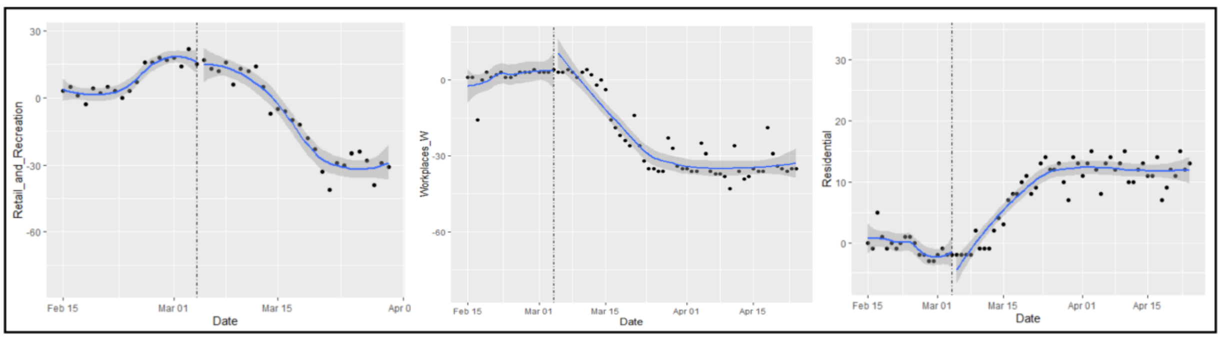
To assess the subsequent impact of variations in population mobility on COVID-19 spread in Arkansas, a linear mixed regression model was utilized. Current data detailing how the number of new COVID cases recorded daily was used for the statistical analysis, provided by the John Hopkins Coronavirus Resource Center (2022). Using this data, a daily exponential COVID growth rate was calculated as a metric COVID case progression. The metric was calculated using the difference in the log of the current cumulative COVID cases daily, and the log of cumulative COVID cases from the day prior, following the approach by Courtemanche et al. (2020). The model estimates the percent change in the daily exponential growth rate as a function of the weekly changes in mobility.

3. Results

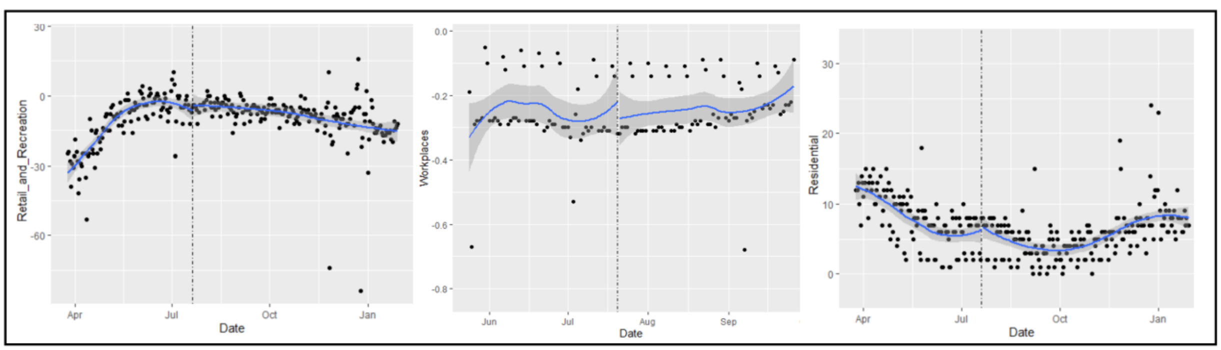
3.1 Impacts of Social Distancing Policies on Population Mobility

With regression discontinuity as the main method of analysis, three dates of major public mandates were tested as threshold values. These dates include: (1) March 11, 2020: The declaration of a national pandemic and nation emergency by the World Health Organization (2) July 20, 2020: Arkansas's statewide mask mandate for public areas, and (3) July 29, 2021: Arkansas's declaration of a public health emergency. The regression was conducted fitting a smoothing conditional means regression line to the data (Figures 1-3).

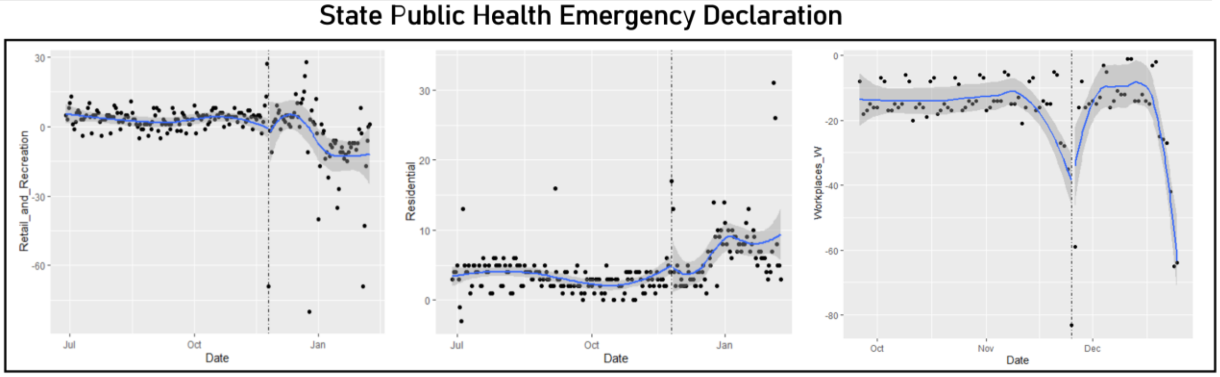
Pandemic Declaration in U.S.



State Mask Mandate



State Public Health Emergency Declaration



Figures 1-3. Discontinued regression visualizations indicating percent changes in mobility, for (1) March 11, 2020: Pandemic Declaration in U.S. , (2) July 20, 2020: State Mask Mandate, and (3) November 29, 2021: Arkansas declares a public health emergency.

The regression provides an estimate of relative mobility change for residential, retail and recreation, and workplace mobility data for each mandate. The World Health Organization's pandemic declaration was shown to correlate with a 6.4% decrease in time spent in recreational or retail areas (95% CI: (−9.2%, −3.7%)). The declaration was also associated with a 12.6% decrease in time spent at workplaces (95% CI: (−26.8%, −1.6%)), as well as a 4.6% increase in time spent in residential areas (95% CI: (−0.76%, 9.9%)). Arkansas's statewide mask mandate was associated with an 7.1% decrease of time spent in recreational areas (95% CI: (−8.2%, −5.9%)), a 24.9% decrease of time spent in workplaces (95% CI: (−27.4%, −22.3%)), and a 5.9% increase of time spent in residential areas (95% CI: (4.3%, 7.4%)). The declaring of a public health emergency was associated with a 1.5% decrease of time spent in retail or recreational areas (95% CI: (−2.3%, −0.071%)), a 19.7% decrease of time spent in workplaces (95% CI: (−20.8%, −18.6%)), and a 3.9% increase of time spent in residential areas (95% CI: 3.4%, 4.4%) (Figure 4) (Table 1).

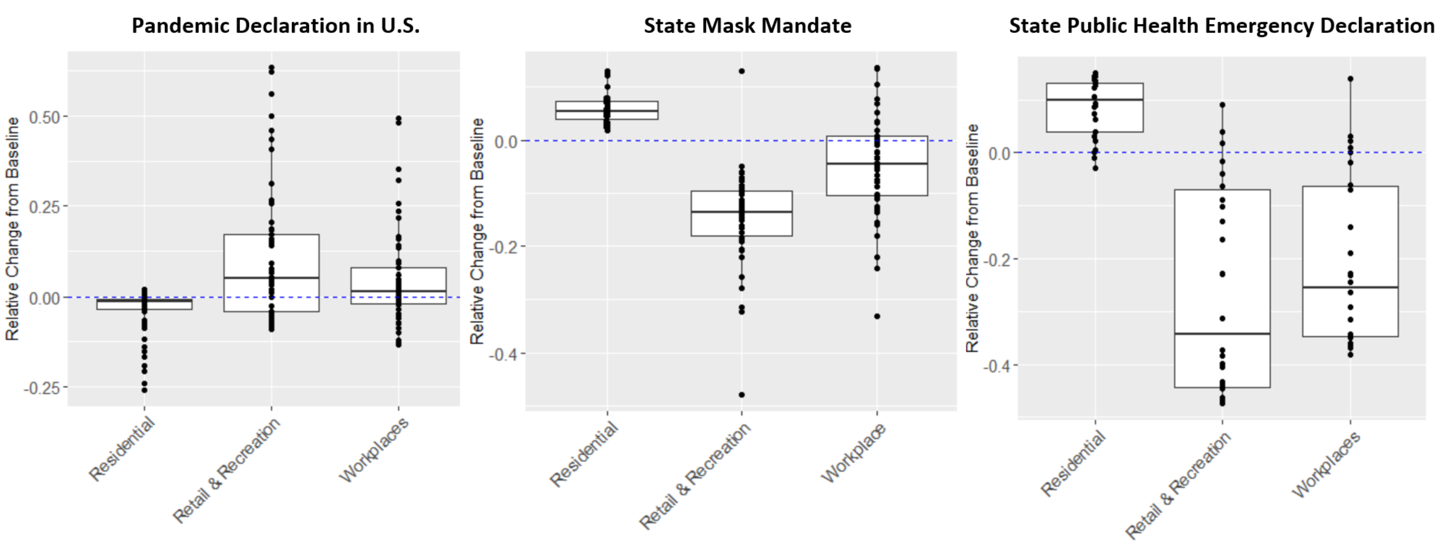


Figure 4. Average effect on residential, recreational, and workplace mobility of major public mandates.

Table 1. 95% confidence intervals of observed percent change in residential, recreational, and workplace mobility due to major public mandates.

Percent Change in Mobility (95% CI)

	Pandemic Declaration	State Mask Mandate	State Emergency Declaration
Recreation	-6.4 (-9.2, 3.7)	-7.1 (-8.2, -5.9)	-1.5 (-2.3, -0.071)
Workplace	-12.6 (1.6, -26.8)	-24.9 (-27.4, -22.3)	-19.7 (-20.8, -18.6)
Residential	4.6 (-0.76, 9.9)	5.9 (4.3, 7.4)	3.9 (3.4, 4.4)

3.2 Impact of Population Mobility on COVID-19 Case Growth

To analyze the subsequent effect mobility change has on COVID spread, a linear mixed effects model was applied. The relative mobility changes were grouped in the model at 5%, 10%, and 15% decreases for residential and recreational mobility data, as well as 15%, 25%, and 45% decreases for workplace mobility data. As mentioned, case growth was represented using a daily exponential growth rate emulating an approach by Courtemanche et al. (2020) [7]. The resulting effects on COVID growth rates were evaluated using total percent change. The model was evaluated using a lag period of 2 weeks, 3 weeks, and 4 weeks, representing the period between when the mobility was recorded and when cases were reported. The results show a 10% decrease in residential mobility was associated with 3% increase in daily exponential growth rate 2 weeks later (95% CI: (1.5%, 4.4%)), and 4.4% increase 3 weeks later (95% CI: (1.7%, 7.15%)). A 10% decrease in recreational mobility is shown to correlate with a 3.6% reduction in daily exponential growth (95% CI: (-6.3%, -0.9%)) and 6.1% decrease at 4 weeks (95% CI: (-0.09%, -11.2%)).

Additionally, A 45% decrease in workplace mobility is shown to corresponds with a 4.4% reduction at 3 weeks (95% CI: (-.7.6%, -1.5%)) and a 4.2% reduction at 4 weeks (95% CI: (-7.4%, -1.3%)) (Table 2).

Table 2. 95% confidence intervals of observed changes in daily exponential COVID growth rates, at various levels of recorded mobility changes.

		Percent Change (95% confidence interval)		
	Mobility change	2-week Lag	3-week Lag	4-week Lag
Residential	-5%	0.52 (0.39, 0.69)	0.54 (0.40, 0.68)	0.63 (0.44, 0.81)
	-10%	3.0 (1.5, 4.4)	4.4 (1.7, 7.15)	4.3 (1.59, 7.0)
	-15%	9.6 (0.55, 18.6)	8.5 (0.6, 17.7)	5.5 (2.8, 13.9)
Retail & Recreation	-5%	-2.2 (-2.7, -1.6)	-2.4 (-3.1, -1.7)	-2.8 (-3.7, -1.8)
	-10%	-2.3 (-3.5, -1.3)	-3.6 (-6.3, -0.9)	-6.1 (-11.2, -0.9)
	-15%	-3.5(-7.8, -0.79)	-5.4 (-13.0, -2.1)	-0.79 (-1.0, -0.56)
Workplace	-15%	-0.26 (-0.4, -0.18)	-0.26 (-0.3, -0.19)	-0.28 (-0.36, -0.20)
	-25%	-0.77 (-1.59, -0.1)	-0.85 (-1.1, -0.62)	-0.98 (-1.2, -0.68)
	-45%	-4.6 (-7.6, -1.5)	-4.4 (-7.4, -1.3)	-4.2 (-7.2, -1.1)

4. Discussion

To conclude, statistical testing shows an apparent relationship between the public COVID-19 mandates and reductions in mobility within Arkansas. Additionally, these reductions are shown to correspond with decreased growth in COVID cases. The statistical analysis performed demonstrates public COVID-19 mandates correlate with increased time spent in residential areas, while also reducing the overall time spent in workplace or recreational environments. Furthermore, the analysis confirmed a positive correlation between time spent in residential areas and declining COVID-19 growth rates, with time spent in retail or recreational areas contributing to increased COVID-19 growth.

Overall, when comparing the apparent effect of each public mandate, Arkansas's statewide mask order resulted in the greatest reductions in recreational and workplace mobility, as well as the greatest increases in residential mobility. Additionally, when comparing all mobility types, workplace mobility experienced the greatest changes surrounding the implementation dates. Averaging the percentage change in mobility across all mandates, workplace's saw an average of a 19% decrease in mobility, while recreational and residential experienced average mobility changes of 5.1% and 4.8% respectively. Similar analysis was conducted in a study by Wellenius et al. (2021), which utilized mobility data for the entire U.S. population. When analyzing mobility changes from a declaration of a state of emergency, there was an associated 9.9% decrease in time spent away from residential areas, an 11.4% decrease in time spent within workplaces, and a 11.5% decrease in time spent in retail or recreational areas. Therefore, the results from this study do show a greater magnitude of change in percent mobility when considering the entire U.S. when compared to similar analysis conducted within the state of Arkansas, for declarations of a state of emergency.

Subsequently, when averaging changes in exponential growth rate for all mobility variations, a lag period of 3-weeks resulted in the greatest overall change in COVID-19 growth rates for residential, recreational, and workplace mobility, exhibiting 4.6%, 3.8%, and 4.3% changes respectively. The study by Wellenius et al. (2021) exhibited similar results, with changes in mobility exhibiting stronger associations with changes in case growth when utilizing a lag period of 3 weeks, rather than with 2 weeks. Additionally, the same study saw greater changes in case growth from associated mobility variations when considering the U.S. population, with 9.2%, 20.9%, and 13% changes in residential, recreational, and workplace mobility respectively. Altogether, it is apparent that changes in mobility and COVID-19 growth rates could be experienced at greater magnitude when considering the entire U.S., compared to within the state of Arkansas. This could be contributed to areas within the U.S. that might exhibit exaggerated population movements and widespread growth of COVID-19, due to demographical variations in factors such as population size.

These results offer helpful insight into the viability of public mandates or population mobility data in the fight against COVID, though there are limitations to be considered when evaluating these results. Google mobility data observations are restricted to persons using google software or devices, not the entire population in Arkansas. Additionally, the accuracy of mobility data could vary by geographical location, as the utilization of Google location tracking could differ between locations. Another limitation to discuss involves exogenous factors within geographical locations that could affect differences in treatment responses. Data within each of Arkansas counties can vary greatly due to factors such as population, social movement, and policy acceptance. Specifically relating to the mixed regression utilized in this study, these demographical factors are not accounted for within the model, which could possibly account for some variations in case growth.

To conclude, mandates and public orders that are meant to encourage mitigation measures seem to positively affect the viewpoint of individuals' plans to quarantine, ultimately reducing the chances of COVID transmission for the Arkansas population. Aside from these conclusions, these results also emphasize the potential use of aggregate mobility data to predict COVID-19 spread in future events.

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Appendix

a. RStudio script for regression discontinuity, linear mixed regression, and related visualizations

```
rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[19])

    ggplot(rd_df, aes(x = Date, y = Retail_and_Recreation, group = mandated)) +
    geom_vline(xintercept=AR_DATA$Date[17],linetype=4) + geom_point() +
    geom_smooth()+xlim(AR_DATA$Date[1], AR_DATA$Date[45])


rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[19])

    ggplot(rd_df, aes(x = Date, y = Retail_and_Recreation, group = mandated)) +
    geom_vline(xintercept=AR_DATA$Date[19],linetype=4) + geom_point() +
    geom_smooth(method = "lm", se = FALSE)+xlim(AR_DATA$Date[1],
    AR_DATA$Date[55])

fit_1 <- lm(Retail_and_Recreation ~ mandated + Date, rd_df)

    stargazer(fit_1,

    type = "text",

    digits = 2,

    keep.stat = c("n", "rsq"))


rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[140])

    ggplot(rd_df, aes(x = Date, y = Retail_and_Recreation, group = mandated)) +
    geom_vline(xintercept=AR_DATA$Date[157],linetype=4) + geom_point() +
    geom_smooth(method = "lm", se = FALSE)+xlim(AR_DATA$Date[40],
    AR_DATA$Date[350])


rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[157])
```

```
ggplot(rd_df, aes(x = Date, y = Retail_and_Recreation, group = mandated)) +
geom_vline(xintercept=AR_DATA$Date[157],linetype=4) + geom_point() +
geom_smooth()+xlim(AR_DATA$Date[40], AR_DATA$Date[350])
```

```
fit_1 <- lm(Retail_and_Recreation ~ mandated + Date, rd_df)
stargazer(fit_1, type = "text", digits = 2, keep.stat = c("n", "rsq"))
```

```
rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[650])
ggplot(rd_df, aes(x = Date, y = Retail_and_Recreation, group = mandated)) +
geom_vline(xintercept=AR_DATA$Date[650],linetype=4) + geom_point() +
geom_smooth(method = "lm", se = FALSE)+xlim(AR_DATA$Date[500],
AR_DATA$Date[1500])
```

```
rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[650])
ggplot(rd_df, aes(x = Date, y = Retail_and_Recreation, group = mandated)) +
geom_vline(xintercept=AR_DATA$Date[650],linetype=4) + geom_point() +
geom_smooth()+xlim(AR_DATA$Date[500], AR_DATA$Date[1500])
```

```
fit_1 <- lm(Retail_and_Recreation ~ mandated + Date, rd_df)
stargazer(fit_1,  type = "text", digits = 2, keep.stat = c("n", "rsq"))
```

```
rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[19])
ggplot(rd_df, aes(x = Date, y = Residential, group = mandated)) +
geom_vline(xintercept=AR_DATA$Date[19],linetype=4) + geom_point() +
geom_smooth()+xlim(AR_DATA$Date[1], AR_DATA$Date[70])
```

```
rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[19])
ggplot(rd_df, aes(x = Date, y = Residential, group = mandated)) +
geom_vline(xintercept=AR_DATA$Date[19],linetype=4) + geom_point() +
geom_smooth(method = "lm", se = FALSE)+xlim(AR_DATA$Date[1],
AR_DATA$Date[55])
```

```
fit_1 <- lm(Retail_and_Recreation ~ mandated + Date, rd_df)

    stargazer(fit_1, type = "text", digits = 2, keep.stat = c("n", "rsq"))


rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[157])

    ggplot(rd_df, aes(x = Date, y = Residential, group = mandated)) +
    geom_vline(xintercept=AR_DATA$Date[157],linetype=4) + geom_point() +
    geom_smooth(method = "lm", se = FALSE)+xlim(AR_DATA$Date[40],
    AR_DATA$Date[350])


rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[157])

    ggplot(rd_df, aes(x = Date, y = Residential, group = mandated)) +
    geom_vline(xintercept=AR_DATA$Date[157],linetype=4) + geom_point() +
    geom_smooth()+xlim(AR_DATA$Date[40], AR_DATA$Date[350])


fit_1 <- lm(Residential ~ mandated + Date, rd_df)

    stargazer(fit_1,  type = "text", digits = 2, keep.stat = c("n", "rsq"))

rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[650])

    ggplot(rd_df, aes(x = Date, y = Residential, group = mandated)) +
    geom_vline(xintercept=AR_DATA$Date[650],linetype=4) + geom_point() +
    geom_smooth(method = "lm", se = FALSE)+xlim(AR_DATA$Date[500],
    AR_DATA$Date[1500])

rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[650])

    ggplot(rd_df, aes(x = Date, y = Residential, group = mandated)) +
    geom_vline(xintercept=AR_DATA$Date[650],linetype=4) + geom_point() +
    geom_smooth()+xlim(AR_DATA$Date[500], AR_DATA$Date[1500])


fit_1 <- lm(Residential~ mandated + Date, rd_df)

    stargazer(fit_1, type = "text", digits = 2, keep.stat = c("n", "rsq"))
```

```
rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[19])
        ggplot(rd_df, aes(x = Date, y = Workplaces_W, group = mandated)) +
        geom_vline(xintercept=AR_DATA$Date[19],linetype=4) + geom_point() +
        geom_smooth()+xlim(AR_DATA$Date[1], AR_DATA$Date[70])


rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[19])
        ggplot(rd_df, aes(x = Date, y = Workplaces_W, group = mandated)) +
        geom_vline(xintercept=AR_DATA$Date[19],linetype=4) + geom_point() +
        geom_smooth(method = "lm", se = FALSE)+xlim(AR_DATA$Date[1],
        AR_DATA$Date[55])


fit_1 <- lm(Workplaces_W ~ mandated + Date, rd_df)
stargazer(fit_1,  type = "text", digits = 2,
keep.stat = c("n", "rsq"))


rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[157])
        ggplot(rd_df, aes(x = Date, y = Workplaces_W, group = mandated)) +
        geom_vline(xintercept=AR_DATA$Date[157],linetype=4) + geom_point() +
        geom_smooth(method = "lm", se = FALSE)+xlim(AR_DATA$Date[1],
        AR_DATA$Date[800])


rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[157])
        ggplot(rd_df, aes(x = Date, y = Workplaces_W, group = mandated)) +
        geom_vline(xintercept=AR_DATA$Date[157],linetype=4) + geom_point() +
        geom_smooth()+xlim(AR_DATA$Date[1], AR_DATA$Date[800])


fit_1 <- lm(Workplaces_W ~ mandated + Date, rd_df)
        stargazer(fit_1, type = "text", digits = 2, keep.stat = c("n", "rsq"))
```

```
rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[650])

    ggplot(rd_df, aes(x = Date, y = Workplaces_W, group = mandated)) +
    geom_vline(xintercept=AR_DATA$Date[650],linetype=4) + geom_point() +
    geom_smooth(method = "lm", se = FALSE)+xlim(AR_DATA$Date[590],
    AR_DATA$Date[680])

rd_df <- as_tibble(AR_DATA) %>% mutate(mandated = Date > AR_DATA$Date[650])

    ggplot(rd_df, aes(x = Date, y = Workplaces_W,  group = mandated)) +
    geom_vline(xintercept=AR_DATA$Date[650],linetype=4) + geom_point() +
    geom_smooth()+xlim(AR_DATA$Date[590], AR_DATA$Date[680])


fit_1 <- lm(Workplaces_W~ mandated + Date, rd_df)

stargazer(fit_1,

type = "text",

digits = 2,

keep.stat = c("n", "rsq"))


lm(Retail_and_Recreation ~ mandated + Date, rd_df) %>% summary()

lm(Retail_and_Recreation ~ mandated + Date + mandated:Date, rd_df) %>% summary()

lm(Retail_and_Recreation ~ mandated + Date + I(Date^2) + mandated:Date +
mandated:I(Date^2), rd_df) %>% summary()


library(stargazer)

fit_1 <- lm(Retail_and_Recreation ~ mandated + Date, rd_df)

fit_2 <- lm(Retail_and_Recreation ~ mandated + Date + mandated:Date, rd_df)

    stargazer(fit_1, fit_2,

    type = "text",

    digits = 2,

    keep.stat = c("n", "rsq"))
```

```
fit_3 <- lm(Retail_and_Recreation ~ mandated + Date + I(Date^2) + mandated:Date + mandated:I(Date^2), rd_df)


lm_MB = lm(height~age + no_siblings, data = ageandheight) #Create a linear regression with two variables

summary(lmHeight2)


lm_MB = lm(Daily_Growth_Rate~Residential , data = AR_DATA)

summary(lm_MB)


ggplot(lm_MB, aes(x = Residential, y = Daily_Growth_Rate)) + geom_point()


*MA_1WK - RETAIL_PCT_MA*

lm_Res_MA1WK = lm(MA_1WK~Retail_PCT_MA , data = AR_DATA)

summary(lm_Res_MA1WK)

ggplot(lm_Res_MA1WK, aes(x = Retail_PCT_MA, y = MA_1WK))+geom_point()


Residential_MA_1WK = lm(MA_1WK~Retail_PCT_MA , data = AR_DATA)

ggplot(Residential_MA_1WK, aes(x = Retail_PCT_MA, y = MA_1WK))+geom_point() + coord_cartesian(xlim = c(-.5, .25), ylim = c(0, .04))

summary(Residential_MA_1WK)

stargazer(Residential_MA_1WK, type = "text", digits = 2, keep.stat = c("n", "rsq"))


lm_Res_MA2WK = lm(MA_2WK~Retail_PCT_MA , data = AR_DATA)

summary(lm_Res_MA2WK)

ggplot(lm_Res_MA2WK, aes(x = Retail_PCT_MA, y = MA_2WK))+geom_point()
```

```
lm_Res_MA2WK = lm(MA_2WK~Retail_PCT, data = AR_DATA)
summary(lm_Res_MA2WK)
ggplot(lm_Res_MA2WK, aes(x = Retail_PCT, y = MA_2WK))+geom_point()

lm_Res_MA1WK = lm(MA_1WK~Residential_PCT_MA , data = AR_DATA)
summary(lm_Res_MA1WK)
ggplot(lm_Res_MA1WK, aes(x = Residential_PCT_MA, y = MA_1WK))+geom_point()

lm_Res_MA2WK = lm(MA_2WK~Residential_PCT_MA , data = AR_DATA)
summary(lm_Res_MA2WK)
ggplot(lm_Res_MA2WK, aes(x = Residential_PCT_MA, y = MA_2WK))+geom_point()

lm_Res_MA2WK = lm(MA_2WK~Residential_PCT, data = AR_DATA)
summary(lm_Res_MA2WK)
ggplot(lm_Res_MA2WK, aes(x = Residential_PCT, y = MA_2WK))+geom_point()



grangertest(Residential ~ Daily_Growth_Rate, order = 3, data = AR_DATA)
grangertest(Residential ~ MA_1WK, order = 3, data = AR_DATA)

******************************
grangertest(Retail_PCT ~ MA_1WK, order = 3, data = AR_DATA)
grangertest(Retail_PCT_MA ~ MA_1WK, order = 3, data = AR_DATA)

Mobility %>% ggplot(aes(Mobility_Category,`Relative Change from Baseline`)) +
    geom_boxplot() +
    geom_jitter(width=0.001) +
```

```
 theme(axis.text.x = element_text(angle = 45, hjust=1)) +

theme(axis.text=element_text(size=20), axis.title=element_text(size=14,face="bold")) +
theme(axis.title.x = element_blank())
```

```
Mobility %>% ggplot(aes(Mobility_Category,`Relative Change from Baseline) +

        geom_boxplot() +

        geom_jitter(width=0.001) +

        theme(axis.text.x = element_text(angle = 45, hjust=1)) +

        theme(axis.text=element_text(size=11), axis.title=element_text(size=11)) +
theme(axis.title.x = element_blank()) + geom_hline(yintercept = 0, linetype = "dashed", col =
"blue")
```