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Determinants of Retailers' Economic Activity in the Roll Back of Mask Mandates During the COVID-19 Pandemic

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Determinants of Retailers' Economic Activity in the Roll Back of Mask Mandates During the COVID-19 Pandemic

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Abstract

This research paper explores the impact of an exogeneuous policy shock, which is the change of mask mandates policy, on Walmart's economic activity during the pandemic. This paper also examine the role of partisanship, trust in science in consumers' behavior in retailers through the use of panal data regression. I incorporate a dummy variable into the regression models, which takes the value 0 before the policy change and 1 after the policy change. I also incorporate two variables, vaccine hesitancy, voting share of the Republican Party into the regressions, and then interate them with the dummy variable. According to the results, people tended to go to Walmart stores more in counties with a higher vaccine hesitancy rate. The increase in the voting share of the Republican Party has a negative impact on the number of visitors in a Walmart.

JEL Classification: I18, M1

Keywords: Public policy, mask mandates, retailer

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1. Introduction

In May 2021, the US Centers for Disease Control and Prevention (CDC) made an announcement that people who have fully vaccinated against COVID-19 no longer have to wear a mask in most situations. Following the announcement from the CDC, some major national retailers made adjustments to their mask mandates policies. For example, Costco announced that in areas where there is no state or local mask mandates, people who are fully vaccinated can enter a Costco store without wearing a mask. Walmart and Sam's Club retracted their mask requirements on May 18, after the change was announced on May 14.

Ample research has been done to study the implementation of mask policy. Wright et al. (2020) introduce data collection of mask mandates at the level of the entire country, and visualize the implementation of mask mandates in the United States. Thanks to their efforts, all the data on mask mandates are available now. Using the same data, Milosh et al. (2020) show that partisanship played a heavy role in the implementation of mask policies.

Great efforts were taken by researchers to examine the impacts of mask mandates. Guy et al. (2021) find that mask mandates and prohibition of on-premises dining at restaurants helped reduce the spread of COVID-19. Betsch et al. (2020) examine the social and behavioral impacts brought by mask policies in German and put forward that mask policies could help people view each other more positively during the pandemic, but could increase social pressure associated with mask wearing and potential of polarization of attitudes towards mask policies. Knotek et al. (2020) find that consumers feel more comfortable when employees and other customers are wearing masks.

Although there has been enough research on mask mandates, there are not many studies focused on the roll back of mask mandates requirement. My research fills the gap by discovering the impact of the lifting of mask requirements on retailers' economic activity in the US. My research is important in three ways. First, it answers whether the mask mandates had a negative effect on retailer giants' business in the US. Second, it reveals how such policy shock influences consumers' behavior. Third, it takes vaccine hesitancy and partisanship into account, which provides many practical implications for policymakers dealing with common risk.

Given that the scope of the study would be too large if all major national retailers were to be considered, I will only focus on Walmart. Foot traffic (store visits) will be used to measure the economic activity of Walmart. Panel data regressions including pooled OLS model, fixed and random effects model would be used to discuss the relationship between policy shock and foot traffic. Then I use Hausman test to see whether fixed effects and random effects is the most appropriate model, and it shows that fixed effects model should be adopted. Variables such as vaccine hesitancy and republican vote share would be incorporated into the regressions in order to explore the role of partisanship and trust in science in consumers' behaviors.

The Hausman test indicates that fixed effect regression model is the appropriate model. The regression results shows that the increase in vaccine hesitancy has a positive impact on the number of daily vivistors to the Walmart stores, while the increase in the voting share of the Grand Old Party has a negative impact on the daily foot traffic of Walmart stores. The policy change itself does not exert a significant impact on the economic activity of retailers. In addition, I use two methods to check the robustness of the regression results, which are sub-sample fixed effect regression and the addition of a new control variable, estimated population of a county. The regression reults does not change too much, indicating that the results is robust.

The research contributes to the literature in such a way that it shows the impacts that non-commercial factors like trust in science, partisanship may have on the economic activity of retailer stores in the background of COVID-19 pandemic. In addition, there is not much literature trying to discover the lifting of the mask mandates requirement. As a result, my paper provides a good attempt.

Based on my main finding in this research paper, it is highly recommended that policymakers should encourage people to take vaccines against the COVID-19 by stimulating peoples' trust in medical science and informing them of the harm of the virus properly, and two parties work together to make and enforce policies. Policymakers should take factors like trust in science, partisanship into account when creating pendemic-control policies because such factors might impact the effectness of those policies.

The next section is the review of literature and the development of hypotheses. Section 3 gives a description of the dataset used in this research and the methodology adopted with equations related. Section 4 presents the main results and the robustness check. The last section describes the findings and offeres policy advice based on the results.

2. Literature Review and Hypotheses Development

Facing the urgent public health issues brought by the COVID-19 epidemic, various policies have been implemented either at the federal level or state level, which include mask mandates, social distancing, shelter-in-place orders, closure in business places, etc. Lots of research has been done about the policy responses of COVID-19. Two parts would be covered in this section, which

are literature about the effects of the public health policies during COVID-19 pandemic, and factors impacting the effectiveness of those policies.

2.1. The Effects of Policies Made in Response to COVID-19 Pandemic

Many researchers have expressed their opinions in favor of mask mandates. For example, Greenhalgh et al., (2020) point out that mask mandates need to be enforced as precautionary measures on the early stage of the pandemic where there is not sufficient knowledge on the matter. Javid et al., (2020) argue that mask mandates, alone with social distancing, should become a "new normal" during pandemic times. Kai et al., (2020) make a prediction about the effect of universal mask-wearing, and state that massive wearing of face masks is urgent.

Jacobs and Ohinmaa (2020) provide an overview of statewide mask mandates based on news reports and governors' orders. They discover that various state and local agencies were employed to make sure the enforcement of mask mandates. They show that law enforcement officers took a positive role in educating people who did not wear a mask with a reluctance to exert civil penalties against non-mask wearers, while businesses indicated their preference for government's enforcement of mask-wearing mandates. There are also research papers that explore the relationship between socio-demographic factors and mask-wearing behaviors (Fisher et al., 2020; Haischer et al., 2020), which provides useful implications for the enforcement of face mask mandates.

Great research has shown that wide mask-wearing behaviors are capable of effectively blocking the transmission route of novel virus, dramatically reducing the rate of infection of COVID-19 and mitigating the spread of virus. Gandhi et al., (2020) discover that wearing masks helped to reduce the inoculum of the novel virus to protest mask wearer. Also, wearing masks

would lead to a wider scale of community-level immunity since the rates of asymptomatic inflection would rise. Krishnamachari et al., (2020) examine the effects of school closure mandates shelter-in-place orders and mask mandates, and conclude that mask mandates are of the most importance out of these three measures. Gupta et al., (2020) shows that social distancing could greatly reduce the mobility using data collected from smart devices.

There are also studies trying to explore the impact of mask mandates policies on people's behaviors. For instance, Knotek et al., (2020) discuss a tradeoff between mask-wearing and social distancing, that some respondents are less like to follow the order of social distancing when they are wearing a mask. Yan et al., (2021) find that mask mandates would induce risk compensation behaviors. They show that people tend to spend less time at their homes and spend more time visiting commercial places like restaurants after mask mandates orders were implemented, and therefore whether risk compensation behaviors would increase or decrease the transmission of coronavirus remains unclear.

Hypothesis 1: Customers would be more likely to visit retailer stores after mask mandates were lifted.

2.2. Factors Impacting the Effectiveness of Public Health Policies During COVID-19

The researchers have identified many factors that impact the effectiveness of those policies. There are many two, which are partisanship, and trust in science.

Cornelson and Miloucheva (2020) finds that respondents are less willing to comply with social distancing policies when the state governor is in the party that respondents do not like.

Grossman et al., (2020) explore the role of partisanship in peoples' compliance with social distancing orders, and find out that recommendations from leaders in the governments are more effective in Democratic-leaning counties as compared with Republican-leaning counties. What is more, Gadarian et al., (2021) find that partisan gaps are already entrenched in peoples' responses to COVID-19 in the early stage of the pandemic, and partisanship plays a crucial role in individuals' response-making in the face of the public health crisis. Allcott et al., (2020) find that partisanship is able to shape individuals' perception and towards COVID-19 risk and response to pandemic. Painter and Qiu (2020) find that residents in Democratic counties are more likely to follow stay-at-home orders compared to their counterparts in Republican counties. Hamilton et al., (2015) shows that Democrats are more willing to believe facts backed by scientific consensus. Brzezinski et al., (2020) show that in counties with a higher concentration of climate change skeptics, the proportion of people who stay at home after the shelter-at-place policy takes effect is significantly lower.

Hypothesis 2: The effect of roll back of mask mandates is more obvious in Republican leaning states and states where there is strong vaccine hesitancy.

3. Data and Methodology

The data used in this research was extracted from three sources, which are SafeGraph repository, MIT Election Data plus Science Lab, Centers for Disease Control and Prevention (CDC). All of three dataset can be linked by FIPS code.

From the "retail" category of SafeGraph, I obtained 14 days of data on number of daily visitors to the Walmart stores before and after Walmart lifted their mask mandates requirements on May 18. The data records the foot traffic of every Walmart store in every county in the United

States during the period of four weeks, as well as FIPS code related to each county. From MIT Election Data and Science Lab, I extracted the data on 2016 presidential election voting share of the Grand Old Party and the Democratic Party in every county. From CDC, I acquired peoples' hestitancy in getting vaccinated in every county, which is used to measure residents' trust in science. Two time series plots, figure 1, and figure 2, show the average daily visitors in Walmart stores, and the average daily visitors for each state during the period of 28 days, respectively.

Panal data regression model will be used in this paper. A dummy independent variable *post* is included in the regression, which takes the value 0 before the roll back of mask mandates, and 1 after the change of mask policy. There are two other independent variables, which are *gop_share*, and *vaccine_hes*. The variable *gop_share* is the voting share of the Republican Party, whereas *vaccine_hes* measures residents' hesitancy in taking COVID-19 vaccine. The variable *post* is interacted with *gop_share* and *vaccine_hes* in the regressions. The dependent variable is every states' daily vistors, expressed as *daily_visitors*. The summary statistics for the variables *daily_visitors*, *gop_share* and *vaccine_hes* are in the table 1.

4. Results and Discussions

4.1. Main Results

My first regression is

$$Visitors_{it} = \beta_0 + \beta_1 Post_{it} + \beta_2 Hest_i + \beta_3 Gop_i + \beta_4 Post_{it} \times Hest_i + \beta_5 Post_{it} \times Gop_i + u_{it} \quad (1)$$

which is shown in the first column of Table 3. In this regression, heterogeneity among different locations are ignored since every county shares the same intercept. The coefficient on *Post* is not statistically significant. The coefficients of *Hest* and *Gop* are statistically significant at 0.1%. The interaction terms in this regression are not statistically significant.

The second regression is fixed effect regression model

$$Visitors_{it} = \beta_1 Post_{it} + \beta_2 Hest_i + \beta_3 Gop_i + \beta_4 Post_{it} \times Hest_i + \beta_5 Post_{it} \times Gop_i + \alpha_i + u_{it} \quad (2)$$

The results of which are shown in the second column of Table 3. In this regression, heterogeneity among different states is taken into consideration since each state has its own intercept, which accounts for some unobservable time-invariant effects that vary from state to state.

Similar to the first regression, the coefficient *Post* is not statistically significant. The coefficient of *Hest* is statistically significant at 0.1% level. The coefficients of two interaction terms are not statistically significant. However, the coefficient of *Gop* loses significance in fixed effect model. Note that every state's intercept is statistically significant at 0.1% level, which means that fixed effect model might be a better model to account for the heterogeneity among different states. The state Hawaii has the largest intercept, and the state Delaware has the smallest intercept, which shows that because of some state-specific unobservable time-invariant effects, Walmart stores in Hawaii tend to have the largest numbers of vivitors, while stores in Delaware tend to have the smallest daily foot traffic comparing with other states.

The coefficient of *Hest* in both regressions are economically significant, since a change of 0.1 in *Hest* will result in an increase of daily visitors by 7.47, 11.77, respectively. In addition, an increase of *Gop* by 0.1 would give rise to a decrease of daily visitors by 1.467, 0.641, which is not quite economically significant.

My third regression is the random effects regression model

$$Visitors_{it} = \beta_0 + \beta_1 Post_{it} + \beta_2 Hest_i + \beta_3 Gop_i + \beta_4 Post_{it} * Hest_i + \beta_5 Post_{it} * Gop_i + \varepsilon_i + u_{it} \quad (3)$$

In this model, I conbine the term ε_i and u_{it} together, and a composite error term is formulated. In the model, the assumption that both ε_i and u_{it} are not correlated with all the explanatory variables must hold.

Then I perform Hausman test to determine which model is the most appropriate model. Since the p-value is less than 0.05, fixed effects regression model should be adopted here.

4.2. Robustness Check

In this section, I use two methods to check the robustness of the regression results, which are sub-sample fixed effect regression and the inclusion of a new control variable. Both methods show that the regression results are quite robust, since there is not big change in the coefficients of variables.

According to previous fixed effects regression results, I find that the incerpects of different states are all statistically significant, which shows the heterogeneity among different states. Once we incorporate unobservable time-invariant effects into the fixed effect regression, the value of R^2 and Adj-R^2 increases dramatically. As a result, in this section, I use sub-sample fixed effect regressions to do the robustness check in order to capture differences among states more specifically. I divide my dataset into ten sub-samples according to geographical regions, which are Far West Area (California, Hawaii, Nevada), Greate Lakes Area (Illinois, Indiana, Michigan, Minnesota, Ohio, Wisconsin), Midsouth Area (Delaware, District of Columbia, Kentucky, Maryland, North Carolina, Tennessee, Virginia, West Virginia), Midwest Area (Iowa, Kansas,

Missouri, Nebraska, North Dakota, South Dakota), Mountain West Area (Arizona, Colorado, Idaho, Montana, New Mexico, Utah, Wyoming), New England Area (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont), Northeast Area (New Jersey, New York, Pennsylvania), Northwest Area (Oregon, Washington), South Central Area (Arkansas, Louisiana, Oklahoma, Texas), and Southest Area (Alabama, Florida, Georgia, Mississippi, South Carolina). In order to showcase heterogeneity among different state, I plot graphs which show the average number of daily visitors of different states grouped in geographical regions mentioned above. Those graphs are shown in figure 3.

The results of sub-sample fixed regression can be seen at Table 5. In Far West, Great Lakes, Midsouth, New England, Northwest, South Central and Southeast sub-samples, the coefficients of *Hest* are positive and statistically significant. In Far West, Greate Lakes, Mountain West, New England, Northwest and Southeast sub-samples, the coefficients of *Gop* are negative and statistically significant. In every sub-sample, the coefficients of Post and two interaction terms are not statistically significant. Overall, most of the sub-samples reveal the similar trend that I discover in Pooled OLS model and fixed effect regression model.

Then I add another variable into the regression to do the robustness check, which is the natural log value of the estimated population of the county.

$$\begin{aligned} Visitors_{it} = \beta_0 + \beta_1 Post_{it} + \beta_2 Hest_i + \beta_3 Gop_i + \beta_4 Post_{it} \times Hest_i + \\ \beta_5 Post_{it} \times Gop_i + \beta_6 \ln(Pop) + u_{it} \end{aligned} \tag{4}$$

The results indicates that the number of daily visitors increases as the population of the county increases. There is no major change in the coefficient of variables *hest* and *per_gop*. The results of the regression with the new variable is shown in table 6.

5. Conclusions

My paper reveals the relationship between the economic activity of a major retailer store during pandemic and non-business factors including peoples' willingness to take the vaccine against COVID-19 and the voting share of a major political party, suggesting that policymakers should take factors like partisanship, peoples' opinion towards science into consideration when making public health policies during pandemic, since such facors might compromise the effect of the policy. My paper makes an attempt to discover the potential impact that the policy reversal on mask mamdates requirement may have on a major retailer's business activity and links non-business factors to the economic activity of Walmart stores, and therefore contribute to the literature where there is little research on the topic.

The coefficient of the variable *post* is not statistically significant in every model, suggesting that the lifting of the mask mandates did not have the impact of boosting retailers' economic as one might expected, nor did it impair the retailers' business. If one indicates a strong hesitancy to take COVID vaccine, he or she tends to have not much trust in medical sicience. That is why the variable *hest* is meant to meansure peoples' trust in science. The coefficient of the variable *hest* is positive and statistically and economically significant. If a person who does not trust medical science, it is quite intuitive that he or she might underestimate the harm of the epidemic and therefore go to supermarkets or retailer stores more. Also, partisanship plays a strong role in shaping peoples' shopping behavior during pandemic. In counties more Republican-leaning, the number of daily vistors of Walmart stores are less than their Democratic-leaning counterparts.

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Figure 1 Time plot series of daily visitors

The figure below is a time series plot of average foot traffic (by day) in Walmart stores during the 28 day period.

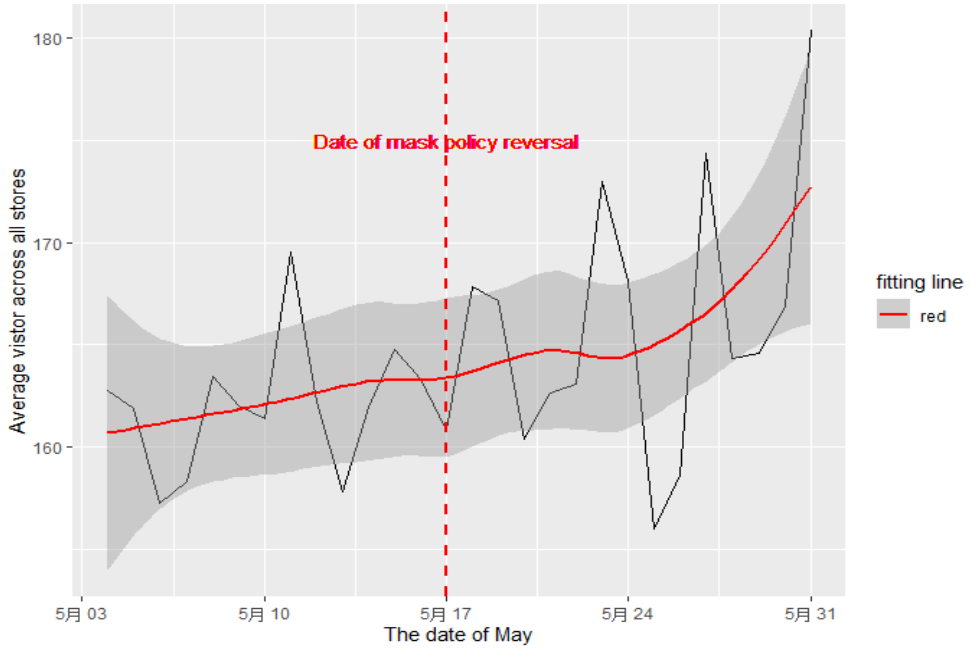


Figure 2 Time series plot of daily visitors, by state

The figure below plots the average daily visitors of a Walmart store by state against the date of May.

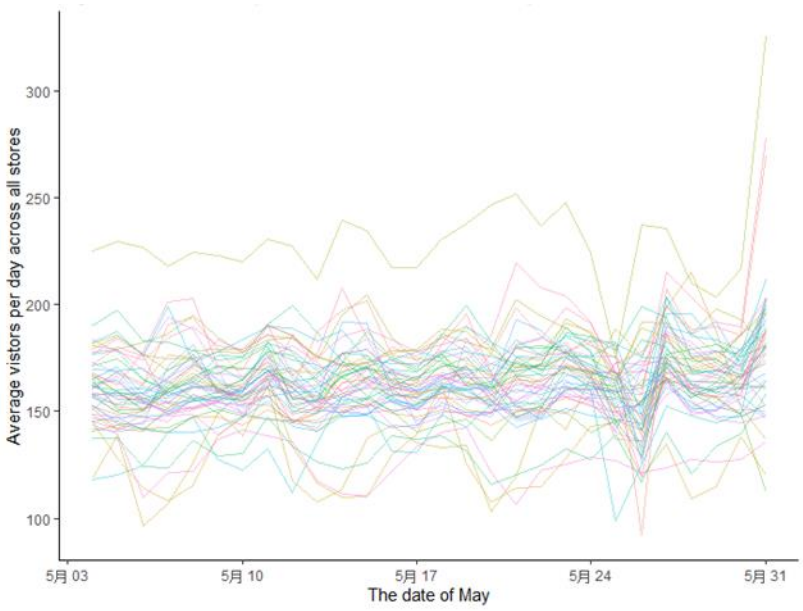
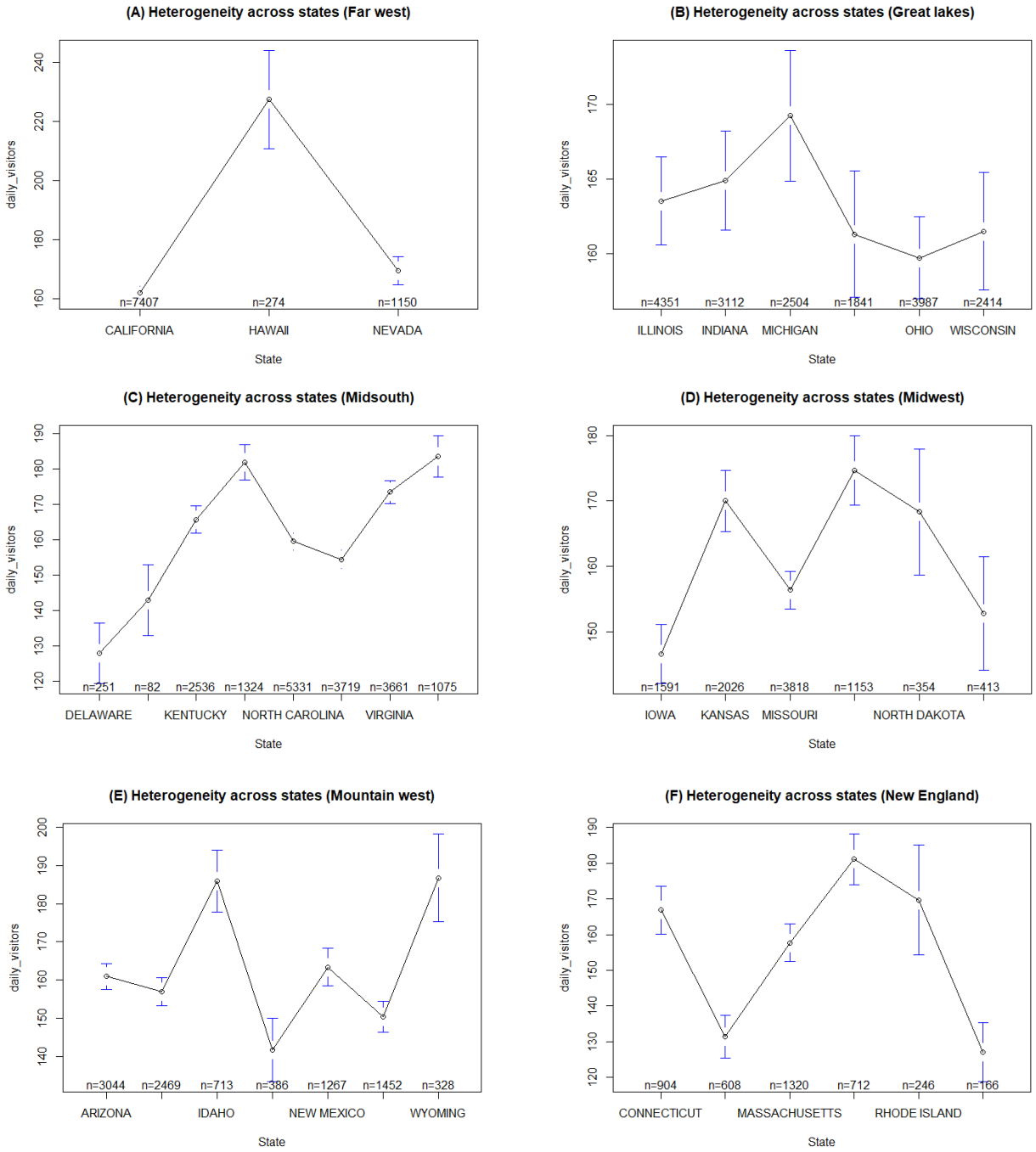
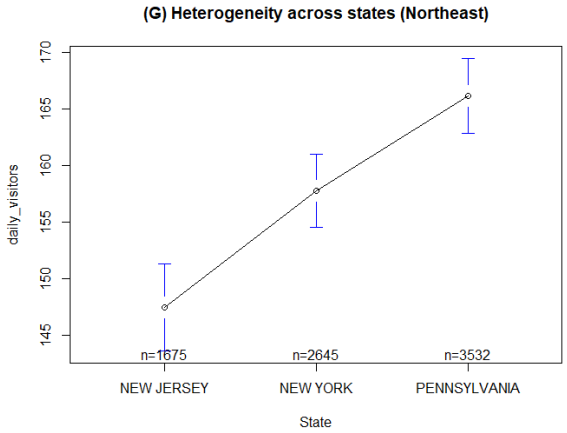
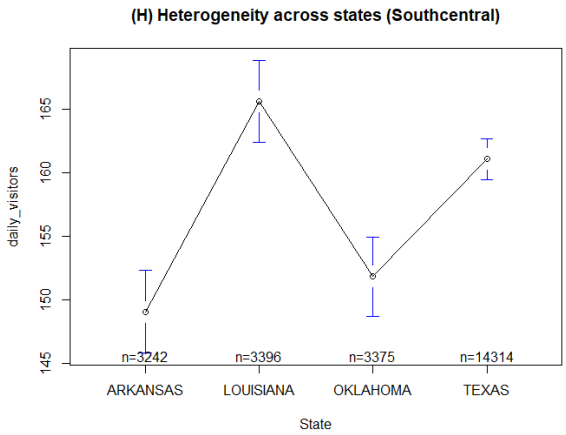


Figure 3 Heterogeneity among states

In the robustness check section, I divide the dataset into ten subsamples (Far West, Great Lakes, Midsouth, Midwest, Mountain West, New England, Southeast, Southcentral, Northeast, Northwest) and run one way fixed effect regression analysis. According to the regression results, the intercepts of various states are statistically significant, meaning that those states are heterogenous in nature. I make nine plots below in order to visualize the existing heterogeneity among different states. I compare the means of the number of Walmart store daily vivistors, and mark the confidence interval of those means on the graphs.




(G) Heterogeneity across states (Northeast)
daily_visitors
145
150
155
160
165
170
n=1675
n=2645
n=3532
NEW JERSEY
NEW YORK
PENNSYLVANIA
State


(H) Heterogeneity across states (Southcentral)
daily_visitors
145
150
155
160
165
n=3242
n=3396
n=3375
n=14314
ARKANSAS
LOUISIANA
OKLAHOMA
TEXAS
State

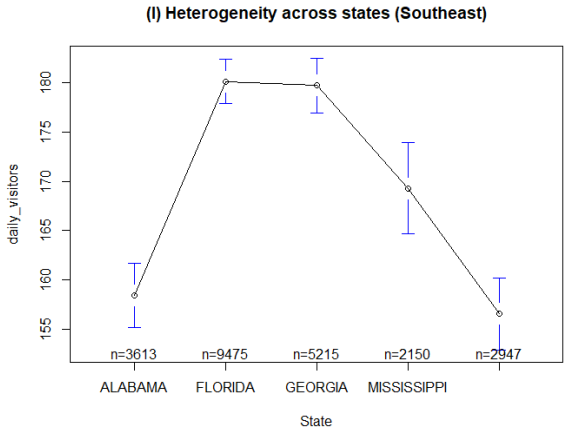

(I) Heterogeneity across states (Southeast)
daily_visitors
155
160
165
170
175
180
n=3613
n=9475
n=5215
n=2150
n=2947
ALABAMA
FLORIDA
GEORGIA
MISSISSIPPI
State

Table 1 Summary Statistics

The descriptive statistics of all the variables used in the regression are provided in the tale below. Visitors measures the daily foot traffic in a Walmart store. Gop is the proportion of voters who woted for the Repubican Party in 2016 presidential election. Hest came from CDC's data, which measures vaccine hesitancy. All missing values are omitted.

	Obs	Mean	Std. Dev	Min	25 Pct.	Median	75 Pct.	Max
Visitors	143437	163.8	97.1	0.0	94.0	148.0	214.0	1313.0
Gop	3152	0.65	0.16	0.05	0.55	0.68	0.77	0.96
Hest	3142	0.20	0.05	0.06	0.17	0.19	0.22	0.32
Pop	128800	3981	1296567	3981	64476	226486	725386	10039107

Table 2 Correlations

Correlations between the variables used in the regression can be found in the table below. *Visitors* is the daily visitors of Walmart's stores. *Post* is a dummy variable which takes binary values, which are 0 before the policy shock and 1 after the policy shock. *Hest* is CDC's meansurement of vaccine hesitancy. *Gop* is the voting share of the Republican Party in a county. *Post×Hest* and *Post×Gop* are the interaction terms with the dummy. The *p*-values of the null hypothesis such that the correlation is zero are provided in the parenthesis.

	Visitors	*Post*	*Hest*	*Gop*	*Post*Hest*	*Post*Gop*
Visitors	1.0000					
Post	0.0196	1.0000				
	(<0.0001)					
Hest	0.0244	0.0060	1.0000			
	(<0.0001)	(<0.0001)				
Gop	-0.0062	0.0038	0.1593	1.0000		
	(0.0268)	(<0.0001)	(<0.0001)			
Pos×Hest	0.0217	0.9703	0.0629	0.0297	1.0000	
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)		
Post×Gop	0.0194	0.9581	0.0365	0.0717	0.2472	1.0000
	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	

Table 3 Main Regressioin Results

The table below shows the regression results of two types of panel data regression. The column to the left is the results of pooled OLS model:

$$Visitors_{it} = \beta_0 + \beta_1 Post_{it} + \beta_2 Hest_i + \beta_3 Gop_i + \beta_4 Post_{it} \times Hest_i + \beta_5 Post_{it} \times Gop_i + u_{it}$$

The column to the right is the results of the fixed effect model:

$$Visitors_{it} = \beta_1 Post_{it} + \beta_2 Hest_i + \beta_3 Gop_i + \beta_4 Post_{it} \times Hest_i + \beta_5 Post_{it} \times Gop_i + \alpha_i + u_{it}$$

***, **, * represent the significance level of 1%, 5%, 10%, respectively.

	Pooled OLS	Fixed Effect Model
(Intercept)	157.559***	
	(1.289)	
Post	-2.415	-2.037
	(0.1725)	(0.0712)
Hest	74.740***	117.692***
	(7.287)	(16.217)
Gop	-14.084***	-6.408**
	(2.029)	(2.227)
Post×Hest	43.622	40.046
	(30.756)	(30.612)
Post×Gop	5.248	5.462
	(8.517)	(8.477)
Obs	126494	126494
Adj-R^2	0.301	0.741

Table 4 Random Effects Regression Results

The table below shows the results of random effects regression model

$$Visitors_{it} = \beta_0 + \beta_1 Post_{it} + \beta_2 Hest_i + \beta_3 Gop_i + \beta_4 Post_{it} \times Hest_i + \beta_5 Post_{it} \times Gop_i + \varepsilon_i + u_{it}$$

***, **, * represent the significance level of 1%, 5%, 10%, respectively.

	Random Effects
(Intercept)	157.559***
	(26.3889)
Post	-0.27141
	(-0.1157)
Hest	74.74**
	(2.214)
Gop	-14.083***
	(-1.500)
Post×*Hest*	41.715
	(3.170)
Post×*Gop*	1.846
	(0.506)
Obs	126494
Adj-R^2	0.325

Table 5 Robustness Check: Sub-sample Regression

The table below shows the results of ten sub-sample fixed effect regression used in the robustness check. According to the standards provided by Bureau of Economic Analysis regions in the United States, each state in the US belongs to one of the ten regions, which are Far West (California, Hawaii, Nevada), Great Lakes (Illinois, Indiana, Michigan, Minnesota, Ohio, Wisconsin), Midsouth (Delaware, District of Columbia, Kentucky, Maryland, North Carolina, Tennessee, Virginia, West Virginia), Midwest (Iowa, Kansas, Missouri, Nebraska, North Dakota, South Dakota), Mountain West (Arizona, Colorado, Idaho, Montana, New Mexico, Utah, Wyoming), New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont), Northeast (New Jersey, New York, Pennsylvania), Northwest (Oregon, Washington), South Central (Arkansas, Louisiana, Oklahoma, Texas), and Southeast (Alabama, Florida, Georgia, Mississippi, South Carolina).

***, **, * represent the significance level of 1%, 5%, 10%, respectively.

	Far West	Great Lakes	Midsouth	Midwest	Mountain West	New England	Northeast	Northwest	South Central	Southeast
Post	7.938	-18.968	4.257	-1.815	-12.617	9.743	-14.448	-70.050	24.810	11.057
	(0.380)	(-1.109)	(0.303)	(-0.060)	(-0.638)	(0.291)	(-0.533)	(-0.443)	(1.447)	(0.520)
Hest	308.953***	342.060***	91.212**	-445.258***	-4.269	1135.820***	-236.838***	1482.180***	101.181*	234.494***
	(3.932)	(7.697)	(2.596)	(-6.687)	(-0.076)	(6.398)	(-3.668)	(5.617)	(2.456)	(6.677)
Gop	-80.662***	-38.684***	38.623***	48.564***	-26.270**	-144.945***	-1.887	-191.450***	4.657	-18.179***
	(-6.511)	(-6.711)	(7.492)	(5.559)	(-3.074)	(-5.677)	(-0.184)	(-6.716)	(0.987)	(-3.546)
Post×*Hest*	-19.017	128.063	-12.846	-28.299	10.132	196.829	183.868	620.870	-101.489	-32.154
	(-0.102)	(1.342)	(-0.153)	(-0.202)	(0.096)	(0.661)	(0.795)	(0.503)	(-1.034)	(-0.337)
Post×*Gop*	-2.652	6.736	15.576	6.088	30.059	-53.152	-8.575	-70.270	3.754	18.611
	(-0.052)	(0.303)	(0.774)	(0.185)	(0.897)	(-0.509)	(-0.194)	(-0.538)	(0.197)	(0.932)
Obs	8823	18198	17966	9344	9647	3945	7844	1140	24318	23390
Adj-R^2	0.757	0.739	0.763	0.740	0.752	0.741	0.756	0.390	0.728	0.727

Table 6 Robustness Check: Adding new variable

The table below shows the regression results after the new control variable *pop* is added into the model to conduct robustness check.

$$Visitors_{it} = \beta_0 + \beta_1 Post_{it} + \beta_2 Hest_i + \beta_3 Gop_i + \beta_4 Post_{it} \times Hest_i + \beta_5 Post_{it} \times Gop_i + \beta_6 \ln(Pop) + u_{it}$$

***, **, * represent the significance level of 1%, 5%, 10%, respectively.

	Regression with new variable
(Intercept)	144.820***
	(4.2854)
Post	-2.387
	(5.482)
Hest	78.319***
	(7.377)
Gop	-9.2537***
	(2.553)
Post×*Hest*	43.572
	(30.755)
Post×*Gop*	5.213
	(8.517)
ln(*Pop*)	0.771**
	(0.247)
Obs	126492
Adj-R^2	0.371