COVID-19 POLICIES AND RECREATION BEHAVIOR: AN ECONOMIC ANALYSIS

by

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A thesis

submitted in partial fulfillment

of the requirements for the degree of

Master of Science in Economics

Boise State University

May 2022

BOISE STATE UNIVERSITY GRADUATE COLLEGE

DEFENSE COMMITTEE AND FINAL READING APPROVALS

of the thesis submitted by

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Thesis Title: COVID-19 Policies and Recreation Behavior: An Economic Analysis

Date of Final Oral Examination: 10 March 2022

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The final reading approval of the thesis was granted by Lee Parton, Ph.D., Chair of the Supervisory Committee. The thesis was approved by the Graduate College.

ACKNOWLEDGMENTS

I would not be at this point without the support of my committee. Dr. Parton guided me through every step of this research over the past year and a half. Without him, I do not know where I would be. Dr. Islam encouraged me to explore the Master of Science program through my final years of undergrad. She saw something in me that I did not see in myself. Her initial push to the program is why I am in it now. Dr. Paudel and Dr. Islam taught my favorite set of courses in the program. I am grateful for their kind demeanors and fascinating lectures. Guido Giuntini's support when I decided to join the program was integral to my success here. He connected me with the right people, answered my questions, and was a joy to work with throughout my time at Boise State.

I have worked harder through this program than I've ever worked before. This would not have been nearly as enjoyable without the support of my friends and family. Weekly walks, words of encouragement, and other ways to check-in kept me sane. I could not be successful without all of the people in my corner. Thank you.

ABSTRACT

A number of studies have examined park visitation patterns and consumer preferences using available national and state park visitation data (Kupfer et al., 2021; Volenec et al., 2021; Wood et al., 2013; Yan et al., 2021a). However, municipal park visitation remains largely understudied due to the difficulty and costliness associated with data collection and analysis. This study utilizes high frequency mobile device location data to measure changes in municipal and state park visitation caused by COVID-19 response policies. We exploit spatial and temporal variation in COVID-19 mandates at the county level in the U.S. state of Idaho and at the state level in the United States to identify the causal effect of mandates on park visitation. The research finds that people were more likely to recreate in, and come from, areas with less restrictions. One may expect the same people that preferred regions without mandates to come from areas with mandates as a way to avoid strict at-home measures. However, it would seem the opposite is true. Visitation rates were about seven percent lower in areas with a mask mandate than would be expected if no policies were in place. Our research brings insight on the behavioral response to restrictions and on recreational choice behavior. Estimates of visitation patterns based on visitors' origin states indicate that of the people who recreate in Idaho, a state with limited COVID-19 response, the from out-of-state visitation rate was 21 percent less for visitors from states with mask mandates than that of visitors from states without mask mandates.

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CUSP	COVID-19 US State Policy
DID	Difference-in-Differences
IRR	Incidence Rate Ratio
LM	Lagrange Multiplier
LR	Likelihood Ratio
NB	Negative Binomial

CHAPTER ONE: INTRODUCTION

Idaho has experienced noteworthy population growth (Associated Press, 2021; DePietro, 2021), with this came an increase in Idaho park visitation (Figure 1). Over 7,500,000 people went to Idaho state parks in 2020 (Figure 1). The change in visitor counts from 2019 to 2020 was over 300 percent of the average growth in visitation experienced from 2016 to 2019.

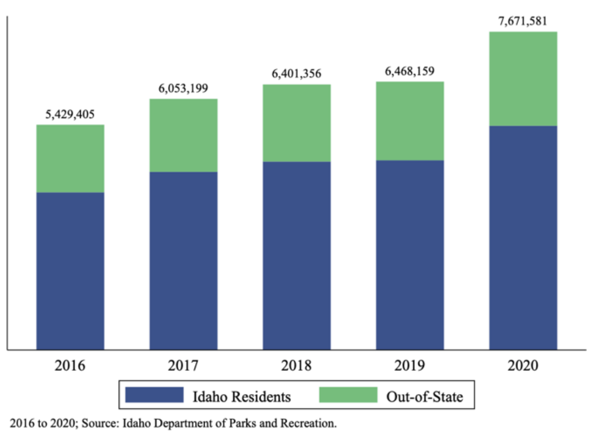

Figure 1 Total State Park Visitation, by Residency

This begs a few questions. How did the visitation patterns in 2020 differ across the state? Did COVID-19 response policies influence rates of park visitation in Idaho?

Studies attribute the COVID-19 pandemic to increased outdoor activity, but it’s not yet clear how policies influence recreation behavior (Dingfelder, 2020; Morse et al., 2020; Zaveri, 2020). Idaho provides a unique landscape for us to answer this question.

In 2020, Idaho Governor Brad Little deferred mask mandate institution to county commissioners. 14 of the 44 counties in Idaho instituted a mask mandate in 2020 (county ordinances[1]). While annual visit data are available for Idaho State Parks, a robust analysis of the recreation response to COVID-19 policies is not feasible with data measured at this scale. Use of mobile device location data from SafeGraph mitigates this issue.

Across disciplines, mobile device data is increasingly used to assess human behavior (Geng et al., 2020; Kupfer et al., 2021; Volenec et al., 2021; Wood et al., 2013; Yan et al., 2021a; Zhang et al., 2020). The data are used to study risk compensation in response to mask mandates, western migration due to the pandemic, and general social distancing patterns (Dimke et al., 2021; Yan et al., 2021a; Yan et al., 2021b).

There's growing literature that studies the effect of the COVID-19 pandemic on recreation patterns (Geng et al., 2020; Kupfer et al., 2021; Landry et al., 2020; Volenec et al., 2021; Wood et al., 2013; Yan et al., 2021). Landry et al. (2020) used survey data to construct demand models of recreation desires before and during the COVID-19 pandemic. The authors estimated risk perceptions in response to COVID-19 spread prevention measures to study recreation trips and values throughout the pandemic. Other authors have used mobile device tracking data via social media (Volenec et al., 2021; Wood et al., 2013), Google (Geng et al., 2020), or SafeGraph (Kupfer et al., 2021; Yan et al., 2021).

Social media crowd sourcing is a common method in this research field. Authors used user-generated location data to estimate visitation rates. In research from Wood et

[1] This includes: Ada County Order (2020); Eastern Idaho Public Health's Board (2020); Order of the District Board of Health. (2020). Eastern Idaho Public Health, State of Idaho. 3 September; Order of the District Board of Health. (2020). Eastern Idaho Public Health, State of Idaho. 10 August; Order of the District Board of Health. (2020). Eastern Idaho Public Health, State of Idaho. 14 September. https://www.co.fremont.id.us…; Order of the District Board of Health. (2020). Eastern Idaho Public Health, State of Idaho. 14 September. https://eiph.idaho.gov…; Order of the Board of Health (2020); Ordinance No. 2020-05 (2020); Valley County Face Covering Order (2020).

al. (2013), the locations of flickr photographs are used to determine location origins. The authors found location check-ins on social media to be an accurate estimator of visitation rates. Volenec et al. (2021) used Instagram geotagged posts to quantify recreation. This method of visitation tracking is reliant on user accounts' privacy settings. If someone posts a picture on Instagram, tags herself at a location, but has a private account, this person's data would not be accessible to crowd source social media check-ins. Even if they have a public profile, they will only be counted if they post a picture and tag themselves at the location.

Kupfer et al. (2021) used SafeGraph data to track visitation to U.S. National Parks during COVID-19. The authors validated their results against the National Parks Service survey data and found SafeGraph data "provided greater temporal resolution" than other visitation measurement methods and allowed for "a more nuanced view of changing visitation patterns" (Kupfer et al., 2021. p. 13).

Previous literature on recreation throughout the COVID-19 pandemic estimate broad patterns. There is a global analysis of municipal park visitation (Geng et al., 2020), a study of national park visitation (Kupfer, 2021) and an estimation of park visitation in response to a state-level shutdown (Volenec et al., 2021). This paper provides a novel way to measure municipal park visitation, assesses the impact of indoor mask mandates on nearby outdoor activities, and uses Idaho parks to evaluate the influence of origin-state regulations on destination-state behaviors.

The paper is structured as follows. The next section, chapter two, describes the and the other variables included to accurately estimate park visitation. Chapter three outlines the empirical methods used in this paper, justifies the use of the negative binomial model for these data, and discusses the quasi-experimental design used. Chapter four details the results. Chapter five includes the robustness checks for the models. Chapters six and seven further elaborate on the models, their implications, and future research opportunities.

CHAPTER TWO: DATA DESCRIPTION

The visitation information used in this study came from SafeGraph mobile device tracking data. A visitor is counted if the mobile device is at the location for at least four minutes (SafeGraph Docs, 2022). The data contains visit information for over 4.5 million places of interest (POIs) across the United States, Canada, and Great Britain (SafeGraph Docs, 2022). This research focuses on POIs within Idaho from January 2019 to June 2021. The visits are aggregated by month and have been filtered to include recreation sites. SafeGraph has descriptive variables for each location including latitude and longitude, census block group, and category. POIs classified as “Nature Parks and Other Similar Institutions” were used in this analysis, which yielded 597 sites and a panel of 16,991 site-month observations. Figure 2 shows the spatial distribution of POIs across Idaho and which counties instituted mask mandates on or before November 2020.[2] Figure 3 shows statewide mask mandate distribution across the United States.

[2] All mandates were issued in Idaho on or before November 2020. If a mandate was not issued by this time one was not instituted at the county level.

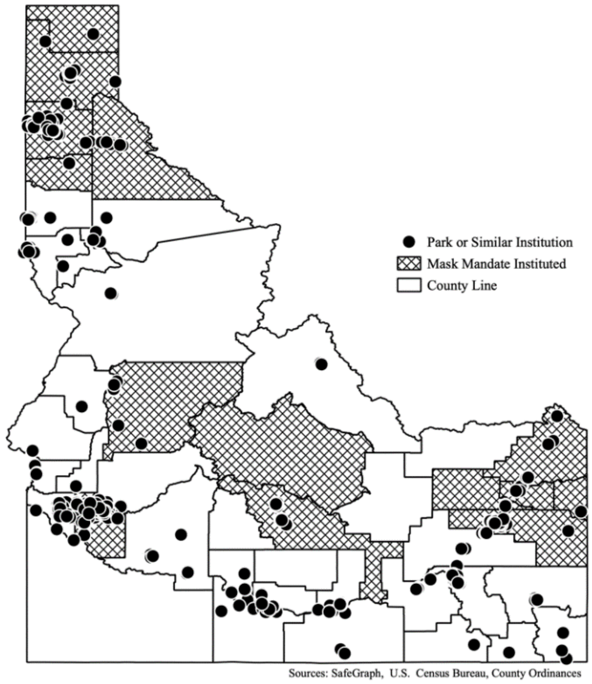

Figure 2 Mask Mandate and Recreation Areas in Idaho

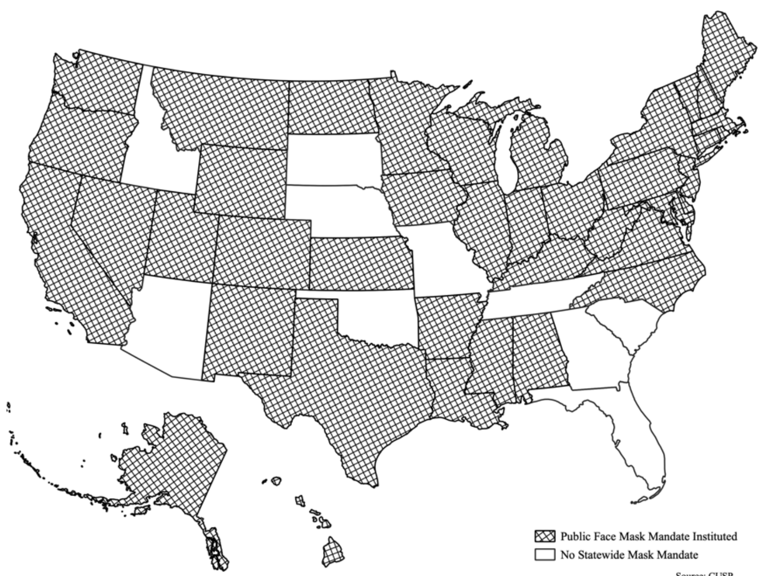

Figure 3 U.S. Statewide Mask Mandates

The primary question in this study is: did mask mandate institution influence recreation patterns in Idaho? Mandate information was gathered from ordinances available on county public websites and CUSP, a COVID-19 state-policy database (Raifman et al., 2020). Using variation in mask mandates in conjunction with park location and visitor home states, we can estimate how people were pushed or pulled to recreate in Idaho.

Since the data is gathered via cell phone connection, there is a limitation to how this research can be conducted. A space is considered to have reliable cell phone coverage if a user has 4G LTE service at a minimum speed of five megabits per second (Federal Communications Commission). Phone carrier companies that SafeGraph includes are Verizon Wireless, AT&T, T-Mobile, Sprint, Altice, and C-Spire (SafeGraph Docs, 2022). The methods of collection and aggregation were consistent across the set of 30 months of data.[3] Thus, it is valid to use the data to look at changes over time within this period.

Data on precipitation and temperature come from the PRISM Climate Group from Oregon State University (PRISM).[4] The weather data included in the regressions in this paper are monthly mean temperature, mean weekend temperature, total precipitation, and mean daily precipitation.

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[3] SafeGraph provides historical data in a backfills folder when current or recent data is downloaded. An algorithm is used to identify home census block groups. Within the data used in this paper, the same algorithm is used from January 2019 through May 2020, then a new algorithm is used from May 2020 to present. Although the algorithm changes, SafeGraph reports that the results are equally reliable for monthly patterns (SafeGraph Docs, 2022).

[4] The data were originally created in 2014 and are updated regularly to provide accurate climate data (PRISM). They undergo a quality assessment and, after six months, are considered final. For this reason and when the analyses were run in this paper, weather data after February 2021 is provisional, though still reliable.

CHAPTER THREE: METHODS

Negative Binomial Model

Two models are used to explore the effect, if any, mask mandate institution had on recreation patterns. The typical ordinary least squares model would likely produce biased results, since the dependent variable in each model is visitation counts. A Poisson model or negative binomial model is recommended to estimate count data (Cameron and Trivedi, 2013). The Poisson model requires equality between the mean and variance. In cases where the data are overdispersed (i.e., the variance is greater than the mean), a Poisson model is not recommended (Cameron and Trivedi, 2013; Lee et al., 2012; Negative). A negative binomial (NB) model is determined to be the best tool to model the patterns studied in this paper. The NB model is a cross-disciplinary research tool (Lee et al., 2012; Parton and Dundas, 2020) "designed to model overdispersed Poisson count data," and its use is considered "a foremost method of analyzing count response models" (Hilbe, 2011. pp. xi, 12).

The marginal NB distribution is given by: $Prob[Y = y_i|x_i] = \frac{\Gamma(\theta+y_i)r_i^{\theta}(1-r_i)^{y_i}}{\Gamma(1+y_i)\Gamma(\theta)}$, where $y_i = 0,1,\ldots,\theta > 0$ and $r_i = \theta/(\theta + \lambda_i)$ (Greene, 2008. p. 586). The exponential mean parameter assumption permits the use of the NB model to estimate count data in difference-in-differences analyses. That is, $\mu_i = \exp(x_i'\beta)$, where β is the vector of coefficients including the average treatment effects modeled in Equation 1.

The first model, “Visits-To”, uses destination conditions to explain park visitation. To control for cross-park and month-to-month effects, a panel model is used. Parks serve as the panel variable and the time variable is month. Park-specific fixed effects are included to control for time invariant unobserved characteristics. The data are unbalanced since there are not values for every month-park combination. The missing data is random to locations when no visitor was recorded, about 5.6 percent (between 33 and 34) parks per month.

The second model, “Visits-From”, uses home-state conditions to explain park visitation from out-of-state visitors.[5] Information on origin-state policy come from the COVID-19 US State Policy (CUSP) database, a free-access repository of state policy response to COVID-19 led by researchers at Boston University and Johns Hopkins University (Raifman et al., 2020). Mask mandate information comes from CUSP and was merged with the visit data to determine at-home restrictions of Idaho park visitors. Weather data come from the PRISM Climate Group at Oregon State University and describe conditions at the destination park.

The models are estimated using Equation 1. The explanatory variables in Equation 1 are location (i) and time (t) variant. *ParkVisits* represents the number of visits park i received in month t. *MaskMandate* equals one if the location of interest (destination county or origin state) issued a mask mandate. *PostTreatment* equals one if t is after the designated treatment period (median month of mask mandates for the population). S identifies season, a factor variable where winter is from December to

[5] The use of mask-mandate as the primary variable of interest is imperfect as it does not incorporate county-level mandates, but it captures the statewide response to the pandemic.

February, spring is from March to May, summer is from June to August, and fall is from September to November. Fall is omitted from the regression and is the base variable. W represents a vector of weather variables of temperature and precipitation values.

$$Park\ Visits_{it} = \beta_0 + \beta_1(MaskMandate_i) + \beta_2(PostTreatment_t) + \beta_3(MaskMandate_i \times PostTreatment_t) + \beta_4 S_t + \beta_5 W_{it} + \epsilon_{it}$$

Equation 1 Model Specification

The difference in mean values between the treated and control groups and between before and after the treatment indicate that time and treatment are reasonable predictors of visitation. Table 1 gives mean monthly visits by park. Table 2 gives mean visits by origin-state. Treated indicates that a mask mandate was in place. For Visits-To, treated means a park is in a county with a countywide mask mandate. For Visits-From, treated means a visitor is coming from a state with a state-wide mask mandate.

Table 1 Visits-To Mean Monthly Visits

Visits-To	Pre-Treatment	Post-Treatment
Treated	347.277	300.021
Control	360.486	256.375

Table 1 Visits-From Mean Monthly Visits

Visits-From	Pre-Treatment	Post-Treatment
Treated	283.646	232.835
Control	92.094	106.633

Overdispersion Tests

Data are overdispersed if the variance of the dependent variable is greater than the mean (Cameron and Trivedi, 2013). While the difference between the mean and variance of the visit counts indicates overdispersion (Table 3), tests for overdispersion following methodology from Cameron and Trivedi are used to verify that the NB model is appropriate.

Table 3 Summary Statistics of Raw-Visit Counts

	Mean	Variance	Observations
Visits by Destination	332.1337	1,827,963	16,991
Visits by Origin County	7.355652	968.2564	44,940

From January 2019 to June 2021. Source: SafeGraph.

The three tests for overdispersion are as follows: a likelihood ratio test, a Wald test, and a Lagrange multiplier test.[6] To begin, the Poisson and NB models are run. The likelihood ratio (LR) test calculates a test statistic using the log-likelihood value (Equation 2).

$$LR\ Test\ Statistic = 2 * (LogLikelihood_{Poisson} - LogLikelihood_{NB})$$

Equation 2 LR Test Statistic Formula

This test is against the null hypothesis that the LR test statistic is zero. Computations for either model are in Figure 4 and Figure 5.

$$LR\ Test\ Statistic_{Visits-To} = 2 * (541643.94 - 49786.17) = 98713.54$$

Figure 4 Evaluation of Visits-To LR Test Statistic

$$LR\ Test\ Statistic_{Visits-From} = 2 * (297451.5 - 102232.47) = 390438.06$$

Figure 5 Evaluation of Visits-From LR Test Statistic

[6] See the appendix for the Lagrange multiplier test for both models.

Cameron and Trivedi (2013) assert that, due to the probability mass of the asymptotic distribution of the LR test statistic, the value can be tested against $\chi^2_{.98}(1)$ which is equal to 5.41.[7] For either model, the LR test statistic is greater than the critical value of 5.41, so we reject the null hypothesis and move on to the Wald test. The Wald test evaluates the chi-squared parameter (or Wald test statistic) in the NB model to determine if the parameter is statistically significant. The Wald test statistics for Visits-To and Visits-From are 1,686.65 and 182.43, respectively. These have a p-value of zero or near zero,[8] so they are statistically significant.

We reject the null hypothesis that the data are Poisson distributed; the NB model is determined to be the best approach.

Difference-in-Differences

Of particular interest is if, after the institution of mask mandates, there was a significant difference, between groups, in where people chose to recreate. This is determined using difference-in-differences NB models. The difference-in-differences (DID) model is commonly used to estimate the average treatment effect on the treated group in the absence of "truly experimental data" (Abadie, 2005. p. 1). In the typical DID model there are two groups, a treated and a control, and two time periods, a before and an after. The treated group is subject to treatment while the control group serves as a counterfactual to assess treatment impacts. The DID rests on the core assumption of parallel trends in the pre-treatment period (Abadie, 2005). If trends were similar between the two groups before the treatment, we can assume that they would have continued to be

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[7] Due to the nature of count data, the dependent variable observations can only be positive. Cameron and Trivedi recommend one-sided distributions for determination of critical value.
[8] The exact value of the Wald statistic p-value in Visits-From is 7.314×10^{-34}.

similar had the treatment not occurred. In this paper, there are two groups – counties, or states, with a mask mandate (treated) and those without (control). The treatment event is the median date of implementation of a mask mandate across that group.

The effect of the treatment on the treated can be evaluated as:

$$
\begin{aligned}
&E[Y^1(1) - Y^0(1)|X, D = 1] \\
&\qquad = \{E\{Y(1)|X, D = 1] - E[Y(1)|X, D = 0]\} \\
&\qquad - \{E[Y(0)|X, D = 1] - E[Y(0)|X, D = 0]\}.
\end{aligned}
$$

Equation 3 Average Treatment Effect Evaluation

Where *Y(1)* is the pre-treatment group, *Y(0)* is post-treatment, and *X,D* indicates if the parameter is in the treated group (*X,D=1*) or the control group (*X,D=0*) (Abadie, 2005). The average treatment effect of the treated group ($E[Y^1(1)-Y^0(1)|X,D=1]$) is found through the differences of mean values between the treated and control groups and the pre- and post-treatment groups. We can use this to estimate the average treatment effect mask mandate institution (treatment) had on parks in counties with mandates (treated group).

Identification

A parallel trends test is run using a DID model in the pre-treatment period to test for group specific differences before treatment. The mean values in Table 4 indicate commonality in visitation patterns in parks across Idaho. This is an initial confirmation that a DID approach is an appropriate tool to assess the impact mask mandates had on recreation patterns in Idaho, though other tests are needed to confirm this.

Table 4 Summary Statistics of Visits to Idaho Parks

	Mean	Variance	Observations
Visits to Counties with a Mask Mandate	333.3808	1,353,171	10,498
Visits to Counties without a Mask Mandate	330.1172	2,595,935	6,493
Visits from States with a Mask Mandate	7.567692	1,076.18	40,219
Visits from States without a Mask Mandate	5.549248	45.22559	4,721

From January 2019 to June 2021. Sources: SafeGraph, CUSP, and county ordinances.

Since this is a non-linear model, an empirical test is needed to determine if parallel trends exist before the treatment. The NB model is run in the pre-treatment period with the explanatory variables, mask mandate, and location interacted against time variables. Seasonal and weather variables were included to control for outdoor recreation patterns that would change based on time of year, temperature, and precipitation patterns.

In the Visits-To model, the treatment event is September 2020, the median date of initial mask mandate implementation for counties in Idaho (county ordinances). In Visits-From, the treatment event is July 2020, the median date of initial statewide mask mandate implementation in the U.S. (Raifman et al., 2020). The primary coefficient of interest is the interaction between the treatment (mask mandate) and the time variable (trend). This is bolded in Table 5. The null hypothesis in this model is that, prior to the treatment, there is no significant difference in trends between treated and control parks. The coefficients of interest are insignificant, so we fail to reject the null hypothesis. Thus, in both models, prior to the treatment, we can assume parallel trends exist.

Table 5 Trends Tests

	Visits-To Model	Visits-From Model
	Coefficients	Coefficients
MaskMandate	0.986	-2.024
	(1.416)	(2.900)
Trend	-0.000136**	-0.000313**
	(0.0000548)	(0.0000732)
MaskMandate # Trend	**-0.0000352**	**0.000113**
	(0.0000648)	(0.000135)
Observations	6669	22425
Wald	1207.4	355.4
Log-Likelihood	-35746.1	-70031.7

Robust standard errors are in parentheses. Pre-treatment period. Fixed effects used in visits-to model. *MaskMandate* is descriptive of the destination county's policy in the visits-to model; it describes policy in the origin state in the visits-from model. * $p < 0.10$, ** $p < 0.05$

CHAPTER FOUR: RESULTS

Visit Analysis

This model uses characteristics of the destination park to explain patterns, so it is called “Visits-To”. The dependent variable is visits to an Idaho park. A visit is counted if a mobile device is recorded within a park’s boundary for more than four minutes. Although mask mandates varied in length, all counties that did institute a mandate put one in place in 2020. Weather data comes from the PRISM Climate Group at Oregon State University. The weather data describes the conditions of the destination. Results are in Table 6.

Table 6 Visits-To Results

	Visits	
	Coefficients	IRR
MaskMandate	0.204**	1.226**
	(0.0321)	(0.0394)
PostTreatment	0.0591**	1.061**
	(0.0193)	(0.0205)
MaskMandate # PostTreatment	0.0747**	0.928**
	(0.0237)	(0.0220)
Spring	0.0175	1.018
	(0.0148)	(0.0151)
Summer	-0.0146	0.985
	(0.0204)	(0.0201)
Winter	0.0808**	1.084**
	(0.0216)	(0.0234)
Average temperature, in Celsius	0.0321**	1.033**
	(0.00288)	(0.00297)
Average weekend temperature, in Celsius	-0.00614**	0.994**
	(0.00283)	(0.00281)
Monthly total precipitation, in millimeters	0.0228**	1.023**
	(0.00352)	(0.00360)
Average daily precipitation, in millimeters	-0.699**	0.497**
	(-0.106)	(0.0526)
Constant	1.030**	2.810**
	(0.0309)	(.0865)
Observations	9154	
Wald	1686.7	

	Visits	
	Coefficients	IRR
Log-Likelihood	-49786.2	
Standard errors in parentheses; Model uses fixed effects; Treatment is September 2020, the median date of countywide mask implementation in Idaho; * $p < 0.10$, ** $p < 0.05$		

The incidence rate ratio (IRR) (Equation 4) estimates the expected effect an input has on the dependent variable in comparison to the reference group (Hilbe, 2011).

$$IRR_{\beta_n} = \exp\left(\beta_n\right)$$

Equation 4 Incidence Rate Ratio Calculation

In this case, the reference group is parks located in counties that did not implement a mask mandate. After September of 2020, parks in counties with mask mandates had an expected visitation rate of about 7 percent less than that of the reference group. In other words, visitation to parks in counties with mask mandates was 7.2 percent less than what would be expected given the rates experienced in other counties. This indicates that people were pulled to recreate in areas without mask mandates.

Counties with high tourist levels, e.g., Ada County, which contains Idaho's capital and largest city, and Teton County, which is adjacent to Grand Teton National Park, implemented mask mandates as a proactive method to prevent rapid spread within their community. For example, Valley County, home to the Payette National Forest, Lake Cascade, Ponderosa State Park, and other recreation sites cited the popularity of its amenities as a reason for the mandate, saying "[m]any Ada County residents commute to Valley County weekly to recreate and … frequent private businesses and public spaces in Valley County" (Valley County Face Covering Order, 2020). Counties that implemented mask mandates realized a decrease in tourism as compared to the control group.

Visitor Analysis

Table 7 Visits-From Model Results

	Visits	
	Coefficients	IRR
MaskMandate	0.447^{**}	1.563^{**}
	(0.178)	(0.278)
PostTreatment	0.101^{**}	1.106^{**}
	(0.0388)	(0.0429)
MaskMandate # PostTreatment	-2.31^{**}	0.793^{**}
	(0.0755)	(0.0599)
Spring	0.0343	1.035
	(0.0291)	(0.0301)
Summer	-0.155	0.857
	(0.120)	(0.103)
Winter	0.288^{*}	1.333^{*}
	(0.158)	(0.211)
Average temperature, in Celsius	-0.0218	0.978
	(0.0241)	(0.0235)
Average weekend temperature, in Celsius	0.0401	1.041
	(0.0364)	(0.0379)
Monthly total precipitation, in millimeters	-0.0257^{*}	0.975^{*}
	(0.015)	(0.0146)
Average daily precipitation, in millimeters	0.787^{*}	2.197^{*}
	(0.418)	(0.919)
Constant	1.436^{**}	4.204^{**}
	(0.135)	(0.5678)

	Visits	
	Coefficients	IRR
Observations	33179	
Wald	182.4	
Log-Likelihood	-102232.5	

Robust standard errors in parentheses and clustered at state-level; Treatment is July 2020, the median date of statewide mask mandate implementation in the U.S.; Model clustered at origin-state level; Weather is descriptive of park conditions; Only includes out-of-state visitors. $^{*}\ p < 0.10$, $^{**}\ p < 0.05$

The reference group for this model is visits from states that did not institute a statewide mask mandate. After July of 2020, the visitation rate from states with mask mandates was approximately 21 percent lower than what would have been expected. This indicates that although people were pulled to recreate in less restrictive areas, they weren't necessarily pushed from areas with COVID-19 related restrictions. Given the results from the visits-to model, this outcome is unexpected. One would think that the same people that preferred regions without mandates would come from areas with mandates as a way to avoid strict at-home measures. However, it would seem the opposite is true.

These results provide insight into cross-state regulations. In a growing world, transit between states is normal. People utilize no sales tax in Oregon, legal gambling in Nevada, or recreation sites in Idaho, an area with few statewide COVID-19 restrictions, during the peak of the pandemic.

CHAPTER FIVE: ROBUSTNESS CHECKS

A placebo treatment is imposed in the pre-treatment period to test for any unobserved events that could influence Idaho park visitation. In Visits-To, the placebo treatment is in November 2019, halfway through the time period (January 2019 to September 2020). With 21 months in the pre-treatment period, *placebo* equals 1 when *trend* is greater than or equal to 10.[9] In Visits-From, the placebo treatment is implemented in September 2019. There are 19 months before treatment in this model, so *placebo* equals 1 when *trend* is greater than or equal to 10. The null hypothesis is that the placebo treatment does not have a significant influence on park visitation. This would indicate that there were group specific unobserved differences in recreation patterns across treated and control groups prior to mask mandates. The placebo variable interacted with mask mandate produces an insignificant coefficient in both models. Thus, we fail to reject the null hypothesis that there were not any unobserved group specific differences in visitation before countywide mask mandates were imposed.

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[9] The regressions are run in the pre-treatment period, when *trend* is less than or equal to 0.

Table 8 Placebo Tests

	Visits-To Model	Visits-From Model
	Coefficients	Coefficients
MaskMandate	0.236**	0.416**
	(0.0395)	(0.177)
Placebo	-0.0317	-0.126**
	(0.0199)	(0.0253)
MaskMandate # Placebo	**-0.0370**	**0.0574**
	(0.0242)	(0.0520)
Observations	6669	22425
Wald	1213.7	356.1
Log-Likelihood	-35744.4	-70032.0

Robust standard errors are in parentheses. Pre-treatment period. Fixed effects used in visits-to model. *MaskMandate* is descriptive of the destination county's policy in the visits-to model; it describes policy in the origin state in the visits-from model. * $p < 0.10$, ** $p < 0.05$

CHAPTER SIX: DISCUSSION AND IMPLICATIONS

This research informs who most uses these parks (Idaho residents), the spillover effect of statewide policies in other parts of the nation, and how people respond to those policies. Idaho's population, like other western states, is growing rapidly (DePietro, 2021; Dimke et al., 2021). People often cite Idaho's recreation opportunities as the reason for their move to Idaho. Parks and other public spaces create opportunity for recreation and community with fellow residents. They are often free and thus are an increasingly needed accessible outdoor space for people. The research here modeled how people are using parks more than before.

Recreational opportunities like hiking, fishing, biking, or skiing connect Idaho residents and visitors to the land. Parks and other public spaces create opportunity for recreation and community with fellow residents. Research shows that people connected to the land will engage more in conservation (Mackay and Schmitt, 2019). Connection to nature may indirectly cause pro-environmental behavior by influencing feelings of empathy or moral duty to protect, and even identification with activist groups. As more people engage in outdoor spaces, they are more likely to also engage in actions and contribute to initiatives that could protect the environment.

Research has shown that time outdoors contributes to quality of life, is useful in coping with a crisis, and benefits physical health; each of these factors contribute to overall well-being (Morse et al., 2020; Zaveri, 2020). Parks are an increasingly needed, utilized, and accessible outdoor space for people. Results from the paper showed the dramatic increase in visitation to recreation spaces. The research in this paper is integral to understanding the value of amenities in a post-pandemic world, when recreation patterns continue to be shaped by persisting variants and the threat of future pandemics (Dingfelder, 2020; Penn, 2021).

CHAPTER SEVEN: CONCLUSION

The data used in this study are imperfect by virtue of the collection method. Not everyone has a cell phone. A consumer group of municipal park amenities (play structures, swings, etc.) is a young population. They likely do not have cell phones and thus will not be identified as a visitor to a given location. One can't go back in time to measure the quantity of children that visited parks in June of 2020, for example. However, one could create a model for predicted number of children at a park given the number of visitors tracked in SafeGraph. This could estimate total visitors, including those without mobile devices. A vast, thorough, and likely costly study would be needed to create an accurate estimation tool.

Government response to COVID-19 varied, in some cases, within states. This study uses origin-state mandates as a proxy for general pandemic response within counties. Future research could refine this paper's work. A non-arbitrary system could be used to identify a county's level of response to the pandemic before August of 2020. Counties without a mandate would be assessed a score based on their distance from the nearest region with a government COVID response. This would allow a more refined analysis than this paper.

People came from regions without restrictions to recreate in regions also without restrictions. This was an unexpected finding and would be interesting to explore further. Perhaps people from states with mandates did not feel in their best interest to come to Idaho, a state with relatively limited COVID-19 response. Maybe those from states without mandates in place wanted to recreate somewhere similar to from where they came. They might not have wanted to adjust their comfort zone to wear a masks when they typically would not.

Another area of interest is a nationwide park analysis. The literature review made clear that the research on United States National Parks is rich. What is unstudied, though, is visitation at state and municipal parks across the nation. Expanding this research to all parks in the nation would be novel. Were behavioral responses to government policies consistent between different kinds of parks? How does the elasticity of visitation pattern differ between instate, border state, and cross-country visitors? At a grander scale, these research questions exponentially increase the size of the dataset. The already developed methods used in this paper open the door for any number of variations in the research questions mentioned.

A third model that was explored but determined to not be robust and thus omitted from the paper is a distance traveled analysis. The data have origin location at the census block group level. This could be incorporated with the mask mandate data to see how far people were willing to travel throughout the pandemic and if that differed based on home policy. As restrictions ease, it would be of interest to study Americans' travel patterns before, during, and after statewide mask mandates were in place. Understanding how the value of these amenities has changed is of great interest to policy makers and is an avenue for future research.

Counties that instituted mask mandates experienced less visitation than would have occurred had the mandate not been enacted. Fewer visitors came from states with mask mandates than would have otherwise been expected. This showed the widespread impact of countywide decisions. A policy made by county commissioners may initially only directly impact those within the county, but that policy likely will have spillover effects into nearby counties and states. When considered through a lens beyond that of recreation or COVID-19 policy, countywide and statewide regulations are far more than independently effective in that region; they have reverberating impacts across the nation.

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APPENDIX

Poisson Models

Table A.1 Poisson Model Results

	Visits-To	Visits-From
Mask Mandate	0.886**	0.453**
	(0.0405)	(0.184)
Post-Treatment	0.0166**	0.100**
	(0.00252)	(0.0388)
Mask Mandate # Post-	-0.108**	-0.233**
Treatment	(0.00300)	(0.0727)
Spring	-0.117**	0.0349
	(0.00176)	(0.0378)
Summer	-0.120**	-0.165
	(0.00227)	(0.120)
Winter	-0.0322**	0.312*
	(0.00259)	(0.189)
Average temperature,	0.0481**	-0.0155
in Celsius	(0.000377)	(0.0186)
Average weekend temperature,	-0.0170**	0.0354
in Celsius	(0.000362)	(0.0322)
Monthly total precipitation,	0.0242**	-0.0279*
in millimeters	(0.000444)	(0.0152)
Average daily precipitation,	-0.762**	0.860**
in millimeters	(0.0133)	(0.431)
Constant		1.406**
		(0.168)
Observations	9154	33179
Log-Likelihood	-541643.9	-297451.5
Robust standard errors in parentheses. Visits-To model uses fixed effects. * $p < 0.10$, ** $p < 0.05$		

Lagrange Multiplier Test

The Lagrange Multiplier (LM) test statistic uses an OLS regression with fitted values from the Poisson model. After generating predicted visit counts, lambda, from the Poisson model, those values are used for an auxiliary OLS regression with results from Equation 5.

$$\frac{(y_i - \hat{\mu}_i)^2 - y_i}{\hat{\mu}_i} = \alpha + u_i$$

Equation 5 Calculation for LM Test Statistic[10]

Results from the LM test for both models are in Table 10.

Table A.2 Lagrange Multiplier Test Results

	Visits-To	Visits-From
Lambda	134.744**	0.878**
	(4.931)	(0.024)
Robust standard errors in parentheses. Visits-To model uses fixed effects. * p < 0.10, ** p < 0.05		

The t-statistic for lambda from the visits-to regression is 27.32 and 36.00 for the visits-from regression. These are statistically significant since they are greater than the critical value of $z_{0.99} = 2.33$.

[10] This comes directly from *Regression Analysis of Count Data* by Cameron and Trivedi.