COVID-19 and Visitation to Central Park, New York City

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Abstract

Central Park is an iconic feature in New York City, which was the first and one of the hardest hit cities in the United States by the Coronavirus. State-level restrictions in New York on travel and social distancing, as well as the publics' personal concerns regarding exposure to the virus, led to reduced Central Park visitation. Utilizing cellphone tracking data we estimated a difference-in-difference model of demand for Central Park visitation. The analysis indicates the pandemic reduced visitation by 59%, resulting in a more than $300 million loss of annual consumer surplus. We also observed a rebound in visitation after the initial outbreak of the pandemic that was influenced by changing government policy, weather conditions, holidays, and personal characteristics.

Keywords

Covid-19; Central Park, New York City visitation; Urban park visitation modeling; Difference-in-difference identification; Consumer surplus welfare loss

Highlights

- The COVID-19 pandemic reduced visitation to the iconic Central Park in New York City by 56%.
- After the initial onset of the pandemic, visitation slowly rebounded but did not recover to pre-pandemic visitation from 2019.
- Overall, and the reduced visitation resulted in a loss of more than $300 million in annual consumer surplus.
- Rebound effect exist during the pandemic periods.

1. Introduction

The Coronavirus (COVID-19) pandemic created unprecedented challenges on societies worldwide. Among all sectors of the economy, tourism (local and nonlocal) was one of the hardest hit (Crespí-Cladera et al., 2021; Hu et al., 2021). Yet, participation in outdoor recreation may have been an important means for people to navigate the stresses of the pandemic.

In response to the public-health threat, national and local governments around the world declared various kinds of lockdown and social-distancing policies to slow the spread of the disease. These measures affected the use of public areas if they restricted travel or limited visitation. At the same time, the pandemic affected peoples' personal choices about travel and being in public areas, leading to voluntary avoidance behavior (Zenker et al., 2021). These policy and personal actions reduced air travel to distant tourism sites. Such tourism impacts have been associated with SARS-CoV-1 (Zeng et al., 2005), Ebola (Cahyanto et al., 2016) and the H1N1 influenza (Lee et al., 2012).

It is an open question of how the pandemic may have affected visitation to local parks. Offsetting the negative impacts noted above, these parks may provide a way to break the routine of living and working from home and people may have chosen outdoor recreation in nearby parks as a safe way to navigate pandemic risks. Urban parks are close to where people live and work, providing important recreational opportunities and bringing social and psychological benefits to visitors (Chiesura, 2004; Bertram et al., 2017; Zhang and Zhou, 2018).

Two studies have conducted large special-scale investigations of park visitation during COVID-19. Landry et al. (2020) conducted a national study in the USA looking at the impact of COVID-19 on recreation trips and found diminished participation and lost economic value. Day (2020) investigated visitation to green spaces in England and found a shift of visitation to available greenspaces during lockdown.

In the current study we investigate the impacts of COVID-19 on visitation to a specific urban park, Central Park in New York City, USA. The iconic Central Park may have been appealing for visitation due to its size for social distancing and accessibility due to multiple modes of transportation in the city. However, New York City suffered the brunt of the initial onslaught of the COVID-19 pandemic in the United States, which could have dampened visitation. The governor of the New York declared a state of emergency where one of the actions was to limit park access to ensure social distancing.[1] Simultaneously, travel restrictions for both domestic and foreign tourists significantly reduced visits to New York City and, thereby, Central Park.

We utilize cellphone mobility data to investigate the impact of COVID-19 on Central Park visitation and lost economic value. We investigate the effect at the outbreak of the pandemic and as the pandemic progressed. We also consider the lost consumer surplus due to decreased visitation. Weekly cellphone mobility data from January 2019 through December 2020 allows identification of the pandemic effect by considering pre-pandemic and within-pandemic visitation.

Several key findings emerge from our analysis. First, there was a sharp decrease in visitation at the pandemic outbreak and the implementation of New York state stay-at-home orders. This was followed by a gradual rebound in visitation that started several weeks after the initial outbreak. Yet, within-pandemic visitation did not rebound to pre-pandemic levels during the period of our analysis. Overall, we find a 56% decrease in Central Park visitation and an over $300 million loss in annual consumer surplus. While these results are specific to Central Park in New York City, the qualitative insights may apply to large, iconic parks in other global cities.

[1] *"N.Y.C. May Limit Entry to Parks to Prevent Crowds". The New York Times. May 7, 2020. ISSN 0362-4331*

2. Related Literature

Several studies have found that tourism is sensitive to large-scale crises, especially when the occurrence and scale of the crisis are unexpected (Aliperti et al., 2019; Ritchie and Jiang, 2019). As noted above, these events can affect site availability and peoples' risk perceptions associated with the site, which can impact site demand (Kozak et al., 2007; Kock et al., 2016).

For example, Rittichainuwat, (2011) found that Chinese and Thai tourists are likely to avoid tsunami-hit sites because of fear over the perceived supernatural phenomena believed to be associated with disasters. Wang (2009) examined four major crises in Taiwan and found that safety-related crises, earthquakes, and the SARS outbreak negatively affected tourism demand. Kuo et al. (2008) found that the number of SARS cases had a significant impact on affected countries while the relatively mild Avian Flu did not have an effect. Page et al. (2012) found that the swine flu pandemic had a significant negative effect tourism demand in the United Kingdom (UK). Even without actual cases, a serious epidemic, such as Ebola, can have consequences on tourism for countries geographically proximity to infected areas (Novelli et al., 2018).

Zenker et al. (2021) developed a scale to measure tourist's anxiety and found that COVID-19 significantly increase the risk perception of potential tourists. This increased risk perception could lead people to adopt self-protection actions by avoiding infected areas and changing activities (Widmar et al., 2017; Wang et al., 2019). For example, Wang and Ackerman (2019) found that people avoid crowed environments. There can be offsetting positive impacts such as tourists visiting sites near affected areas to support the local tourism sector (Kock et al., 2019; Romagosa 2020).

Overall, for urban parks, these insights suggest the government policies and personal choices may lead to avoidance behaviors that suppress visitation, but there may be some offsetting impacts that dampen the visitation diminution.

3. Study Site and Cellphone Data

3.1 Study Site

Central Park, located in the heart of Manhattan within New York City, attracted over 40 million visitors in 2019 and has been regarded a model for the world's urban parks (Lange, 2020). It is the most visited urban park in the United States (Kelleher, 2019). Central Park is a renowned tourist site as well as a daily activity space for local residents. Like other major urban parks in metropolitans, a large share of the visits (70%) are made by people who live in New York City. New Yorkers' share of visits is highest in winter (77%) and lowest in summer (63%) with summer being the most popular season to visit the Park (Central Park Conservancy, 2011). In short, Central Park is typical of large urban parks metropolitan areas around the world.

The pandemic changed local and non-local travel in NYC dramatically. In the spring of 2020, NYC suffered heavily in the early stages of the pandemic. The park remained open after New York Governor Cuomo issued a "New York State on PAUSE" executive order (also known as "stay-at-home order") on March 20, 2020, but access was limited to prevent overcrowding and to promote social distancing (COVID-19 Updates, n.d.).

3.2 Cellphone Data

We use cellphone data to identify weekly visits of New Yorkers to Central Park from January 2019 to December 2020. The data were provided by SafeGraph, a company that records the location and movement of over 45 million mobile devices in the United States, which covers 10% of the cellphone mobility patterns in the United States. The SafeGraph data has been widely used in the literature to trace mobility patterns during COVID (Allcott et al. 2020; Chang et al. 2020, Jay et al. 2020, Weill et al. 2020).

The original dataset is listed by point of interest, which is defined as the place where people spend time or money. Due to the large geographic area of Central Park, there are multiple points of interests within the geographic range of Central Park, thus we aggregate data for all the points of interest to get the total number of visitors for the Central Park area. SafeGraph also provide the home block group information for each visitor, which allow us to collect and analyze Central Park visitation from each block group in New York City by week.[2]

We scale up the original number of visitors in the SafeGraph data with adjustments on market share of the mobile service company and the percentage of U.S. citizens with smart phones to reflect the total number and trend for the visitors. Specifically, the number of visitors is calculated using the following equation:

$$V_t = N_t/M \tag{1}$$

Where V_t is the adjusted number of visitors in each week t, N_t is the original number of visitors from SafeGraph data, M is the adjustment indictor, which is a multiplier of market share of mobile service company (10%) and the percentage of U.S. citizens with smart phones (81%).

3.3 Overview of the Visitation to Central Park

We observe similar number of visitors in weeks 1-11 in 2019 and 2020, which suggests parallel visitation patterns between the two years in the absence of the pandemic (Figure 1, Panel A). In 2019, the number of visitors increased thereafter, peaking in weeks 26-30, which exhibits the same pattern as the Central Park Conservancy's data (Central Park Conservancy, 2011). Conversely, in 2020, we observe a sharp decrease of number of visitors in week 12. The decrease is no doubt due to the fast-growing number of COVID-19 cases and "stay-at-home" order issued on March 20. NYC was logging

[2] Visitor home location is identified by the data vendor, referred as the home census block groups of the visitors. SafeGraph determine the home census block group by analyzing 6 weeks of data during nighttime hours (between 6 pm and 7 am).

2,000 cases per day during week 12, and the number grew thereafter. The stay-at-home order banned all non-essential gatherings. As shown, after the initial decline, there is a gradual rebound. By week 48, visitation in 2020 had returned to its 2019 level but, then again, began to decline in the final weeks of the year. In aggregate, our cell phone data show a 67% decline in 2020. These data, based on visual inspection, suggest a large COVID impact on Central Park visitation.

4. Empirical Analysis

4.1 Difference-in-difference Design

We use a quasi-experimental design to identify visitation impacts. We incorporate a difference-in-differences (DID) design in a recreation-demand model to control for unobservable factors that might confound the treatment effects of interest.

DID is typically used to estimate the effect of a specific treatment by comparing the changes in outcomes between control and treated conditions. In our case, the pandemic is the treatment (on visitation in 2020) and visitation in 2019 is the control. Weeks 1-11 in 2020 are the pre-pandemic period and weeks 12-52 are the pandemic period. To reflect the number of visitors from different zones and to examine welfare changes due to COVID-19, we use a classical zonal travel cost demand model (ZTCM) (citation). We use neighborhood tabulation areas (NTAs) as our zones. NTAs are designations used by the New York Department of City Planning for small area population projections. Within New York City, there are 195 NTAs with a minimum population of 15,000 in each area. Our data includes visits by residents and non-residents (e.g., visitors staying at hotels). To reflect this possibly, we calculate the total population as the sum of census population in each zone and the number of hotel visits.[3]

[3] Information of hotel visits also comes from SafeGraph cellphone dataset and has been adjusted using the same way with number of visitors. The trend of hotel visitors and visitation rates are illustrated in panel (b) and panel (c) of figure 1. Similar to the number of Central Park visitors, we also observe a decrease in visitors in week 12.

The ZTCM establishes a relationship between visit rate and a set of explanatory variables believed to influence visitation. The visitation rate of each zone is

$$VR_{it} = \frac{V_{it}}{pop_i} \tag{2}$$

where V_{it} is the number of visitors from zone *i* in week *t*, and pop_i is the total population of zone *i*. Our econometric model then is specified as:

$$ln(VR_{iwt}) = \alpha + \beta ln(TC_{iwt}) + \gamma TreatmentWeek_w + \delta TreatmentYear_t + \theta TreatmentWeek_w * TreatmentYear_t + \rho Policy_{wt} + \sigma X_{iwt} + \varphi T_w + \varepsilon_{iwt} \tag{3}$$

where $ln(VR_{iwt})$ is the log form of visitation rate, $ln(TC_{it})$ is the log form of the average travel cost to visit Central Park, $TreatmentWeek_w$ takes a value of one if visits occur at week 12 or later and zero otherwise, $TreatmentYear_t$ is one if the visitation occurs in 2020 and zero otherwise, $\text{Policy}_{\boldsymbol{wt}}$ takes a value of one for weeks when the "New York State on PAUSE" was in effect, $\boldsymbol{X}$ is a vector of socio-demographic characteristics, weather and holiday variables (e.g., median household income, median age, and percentage of people with high school diploma by NTA; average precipitation, average daily maximum temperature by county, and week with national holidays); $\boldsymbol{T}$ represents monthly fixed effects; *i* is an index for research zone (NTA), *w* is an index for week, and *t* is an index for year.[4]

The cost of a visit is the round-trip cost to Central Park from visitors' NTA, calculated as the sum of driving costs and time costs. For driving costs, we multiple operating costs per mile with travel distance from visitors' home place to central park. Estimation of the average operating cost are provided by American Automobile Association (AAA), or 20 cents per mile is used in the calculation[5]. For time costs, we calculate per minute cost of time based on per capita income and then multiple it with travel

[4] We choose the log-log form as the specification since the AIC and BIC favor the nonlinear and the coefficient of interest are robust to specification to TC and lnTC in both the log and linear specifications of the dependent variable.
[5] Due to the data limitation, we cannot observe the actual transportation (private car, bus, subway, etc.) the visitors are using to visit the park. Thus, we use the unified drive cost to proxy the expenditure of the visitors on transportation, which is also the common practices for similar studies (Kubo et al., 2020).

time from visitors' home location to central park.[6] Travel distance and travel time are calculated using OpenStreetMap, an open source tool which provides similar function to Google Maps. In the calculation, we assume visitors would travel by car, with the consideration of road distances and speed limits of the road.

We obtain socio-demographic data from the American Community Survey (2016) 5-year estimate on the Census Block Group level, and then aggregate block group level data to NTAs. Covid and weather-related data are constructed at borough level. We retrieve all the covid data through Badr et al. (2021), including cases, hydromet and policy related information. We obtain daily weather estimates from GRIDMET, and then aggregate daily level weather data by week.[7]

Our DID strategy compares changes in recreation behavior before and after the onset of the pandemic in 2020 with recreation behavior before the pandemic in 2019. The parameter γ captures how both groups (control year 2019 and treatment year 2020) are affected before and after week 12. If γ is positive and significant, it indicates that, in general, visitation would go up after week 12. The parameter δ captures the differences between control year and treatment year,

which indicates what would have happened to the treatment year (year 2020) in the absence of the pandemic. Our main interest in the treatment effect, which is represented by θ. If θ is negative and significant, it indicates that pandemic negatively impacted Central park visitation.

4.2 Event Study Design

The estimation results provide strong evidence that the pandemic has affected visitation to Central Park. To examine the effects dynamically, we compare weekly visitation rates between 2019 and year 2020 as follows:

[6] The value of time (per minute) is calculated annual per capita income/(2080*60), where 2080 is the number of working hours per year.

$$\ln(VR_{iwt}) = \alpha + \beta \ln(TC_{iwt}) + \delta TreatmentYear_t + \sum_{w=1}^{w=52} \theta_w * W_w * TreatmentYear_t + \sigma X_{iwt} + \varepsilon_{iwt} \tag{4}$$

The equation (4) is an extension of our basic DID analysis in equation (3), where VR_{iwt}, TC_{iwt}, $TreatmentYear_t$ have the same meaning and definition as equation (3). In the event study, W_w is an indicator for week, θ_w is our coefficient of interests, which capture the differences in visitation rates in the same week between the control year (year 2019) and the treatment year (year 2020). Since we are exploring variation across weeks, there are less control variables in equation (4), X_{iwt} includes median household income, median age, percentage of people with high school diploma, average precipitation level and average maximum temperature of the day.

4.3 Consumer Surplus Calculations

Using the estimated coefficients in equation (3), we also calculate the average weekly per visitor consumer surplus for four time periods (2019 week 1-11, 2019 week 12-52, 2020 week 1-11, and 2020 week 12-52), the average weekly consumer surplus for all NYC visitors for the same four periods, and the aggregate consumer surplus for year 2019 and 2020 (scaled up to total number of visitors).

Consumer surplus is

$$CS_i = \frac{pop_i}{1{,}000} e^{\widehat{\beta}_0} \int_{TC_i}^{CP_i} TC^{\widehat{\beta}_1} dTC, \tag{5}$$

where CP_i represents chock price of and $\hat{\beta}_0 = \alpha + \gamma TreatmentWeek_{it} + \delta TreatmentYear_{it} + \theta TreatmentWeek_{it} * TreatmentYear_{it} + \rho \text{Policy}_{it} + \boldsymbol{\sigma X_{it}} + \boldsymbol{\varphi T_t}$. For each period, we take the average values of $TreatmentWeek, Treatment\ Year, Policy, \boldsymbol{X}\ and\ \boldsymbol{T}$ in each zone. Due to the nature of a logarithmic function, it is not possible to obtain a zero level of visitation. Thus, we identified the chock prices at the point where the level of visitation reached one.

We calculate the average weekly per visitor consumer surplus by adding up the weekly consumer surplus in each zone and then divided by the weekly number of visitors. Utilizing the per visitor consumer surplus and the fact that our data covers 6.3% of the NYC visitors to Central Park, we also calculate average weekly consumer surplus for all NYC visitors and the aggregate consumer surplus per year.

5. Results

5.1 Descriptive Evidence

Summary statistics for number of visitors, visitation rates, travel cost, sociodemographic, weather, policy and other control variables are presented in Table 1. We present results separately for the time period before and after the pandemic as well as for the treatment and control year. Overall, the summary statistics highlight substantial changes in visitation rates between control group and treatment group. Due to seasonal effects, number of visitors would increase in week 12-52 of year 2019, For our econometric analysis, this suggest that controlling for a number of observed and unobserved time-varying changes are likely needed to identify the impact of pandemic on recreational demand.

For each NTA, the average number of visitors in weeks 1-11, 2019 was 124 (sd=341); in weeks 12-52, the average number is 201 (sd=489). In 2020, before the pandemic (weeks 1-11), the average number of visitors is 108 (sd=262), which is similar to the number in year 2019; while after pandemic (weeks 12-52), the average number drops to 50 (139).

5.2 Impact of COVID-19 on Visitation

Table 2 reports the estimation results for linear-linear, linear-log, log-linear, and log-log functional forms of our main regression model, specified in Equation (2). Based on adjusted R^2, AIC, and BIC, the log-log model is our preferred specification. Thus, the functional form of log-log is chosen for further discussion and analysis.

The overall empirical evidence on recreational demand suggest that the pandemic has reduced visitation rates significantly. From the log-log form model, the estimated results show that the pandemic has reduced the visitation rates by 59%. The estimates are significant at all functional forms and when control variables are included.

The travel cost coefficients are negative and significant for all the four models, indicating that higher travel costs-including both driving costs and opportunity costs-lead to a lower recreational demand. In our preferred log-log specification, a 1% increase in travel costs results in a corresponding 1.227% decline in the number of visits to central park per 1,000 zonal population.

There are other factors which would affect recreational demand. We find significant negative coefficient for shelter-in-place policy, which results in a 47% decrease in visitation rates. A positive and significant coefficients of median household income and median age suggests that zones with a higher level of income and higher age, are associated with a higher demand to visit Central Park. Conversely, a negative and significant coefficient of percent of high school degree indicates that zones with higher education level would lead to a lower recreational demand. Weather also plays an important role - we find prepetition levels would decrease visitation rates, while temperature would increase visitation rates. In addition, people travel more on national holidays due to the decrease of opportunity costs.

5.3 Adaptation Effects

Figure 2 depicts the coefficient estimates of θ_w. Before the pandemic (week 6 to week 10), the coefficients are insignificant, which provides another evidence to support the parallel trend assumption. We start to observe a significant negative coefficient in week 11, which indicates a decrease in visitation rate. Although the shelter-in-place policy did not begin in week 11, in week 11 of year 2020, the CDC started to recommend no gatherings of 50+ in the U.S. and the public school in New York City have started to close, those restrictions provided early signal of the shelter-in-policy policies and raised New

Yorker's awareness of the pandemic. In week 12, our results suggest a significant negative coefficient of -1.284, which indicates that a 72% decrease in visitation rates in year 2020 (compared to year 2019). The decreasing of visitation rates (negative weekly coefficient) would continue till week 37, where we start to have insignificant coefficient estimates, which means that the visitation rates in year 2020 has no significant difference compared with the visitation rates in year 2019. Although in some week, there are fluctuations, in general, the rebound of visitors continued till week 51. The underlying reason for rebound effects could contribute to two channels: first, as time goes by, New Yorkers are getting familiar with the new normal and are able to adaptive to the pandemic; Second, urban park could serve as a good place to alleviate the stress from the pandemic and people start to value more about the value of urban parks.

5.4 Economic Impacts

We use change of consumer surplus to evaluate the economic impacts of COVID-19. The consumer surplus estimates are presented in Table 3. The average weekly per visitor consumer surplus are $14.3, $15.6, $15.8, $14.4 for 2019 (week 1-11), 2019 (week 12-52), 2020 (week 1-11), 2020 (week 12-52), respectively. Considering the change in total number of visitors, for the pre-treatment periods, on average, we find a 4% decrease in the weekly consumer surplus when compared the treatment year with the control year, for the post-treatment period, on average, our result indicates a 58% of decrease of consumer surplus per week. Overall, when compared the treatment year with the control year, our results indicate a 67% decrease of total welfare.

6. Discussion and Conclusion

Considering the overwhelming impact of COVID-19 outbreak on tourism industry, it is important to access the impacts of pandemic on recreational demand. Utilizing the iconic Central Park as a study site, our analysis benefit from a large cellphone mobility dataset, which enables us to explore how the COVID-19 pandemic changed how New Yorkers' engaged with Central Park and impacted on the economic value they derived from those interactions.

In this paper, we integrate the big cellphone mobility data along with a DID analysis framework and the traditional economic valuation approach, ZTCM, to estimate a timely fine-scale human welfare and economic values associated with the pandemic. Our results highlight that how enormously the recreation activities in urban parks by the COVID-19 pandemic, with 59% visitation decrease and $305 million decrease in annual consumer surplus. Even though there exist some rebound effect after a couple of months, the loss is still significant.

As one of the first empirical studies estimating the economic impact of COVID-19 on tourism, our study provides the up-to-date estimation for the non-market services provided by urban park. The results shed light on the magnitude of the hidden loss caused by the pandemic. Existing relief programs, to individual or small business, may fail to capture these losses and underestimate the damage of the pandemic to the residents.

Our study provides several important policy implications for urban park and offers a valuable guidance to help the park and recreation administration around the global to design and enact the proper and up-to-date recovery policy for the post-pandemic era.

. First, our study provides objective basis for the federal and local governments deciding the priority. Given the huge size of the recreation value loss, policy makers should carefully design effective and innovative methods to increase the experience of tourists to regain the lost benefits of these urban parks. Second, our dynamic analysis suggest that people are beginning to adapt to the pandemic. Thus, instead of encouraging more visitation, the park managements should focus on assure the safety of the current visitors to avoid further public-health incidents. This conclusion echoed the results from Landry et al., (2021). Lastly, both park managers and policymakers should work together to develop a comprehensive plan to manage potential abrupt systemic crisis in the future. It does not mean there will be no losses but a well-prepared solution could minimize the damage at a reasonable level.

Our study also illustrates the opportunity to combine mobile big data and conventional travel cost model in the crisis impact estimation. This framework is an applicable and cost-effective way of monitoring the recreational value of outdoor sites over a long period and large spatial coverage. Combining the big data with the present approach could help to analysis the post-crisis travel behavior change and the monetarize valuation of tourism sites, especially the urban recreation sites (Zenker, 2020).

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Table 1. Descriptive Statistics of key variables

Variable	Control Year (2019)		Treatment Year (2020)	
	Week 1-11	Week 12-52	Week 1-11	Week 12-52
Number of Visitors per NTA	124 (341)	201 (489)	108 (262)	50 (139)
Population	44,581 (43,726)	52,406 (42,309)	44,122 (43,237)	27,568 (41,638)
Visitation Rates per 1000 population	1.61 (4.15)	2.57 (5.65)	1.40 (2.87)	0.63 (1.62)
Travel cost ($)	15.28 (8.30)	15.14 (8.24)	15.25 (8.39)	15.37 (8.37)
Stay at home Policy	-	-	-	0.39 (0.49)
Median household income ($)	63,525 (25,606)	63,525 (25,606)	63,525 (25,606)	63,525 (25,606)
Median age	37.14 (4.51)	37.14 (4.51)	37.14 (4.51)	37.14 (4.51)
Percent of high school degree (%)	21.3% (6.6%)	21.3% (6.6%)	21.3% (6.6%)	21.3% (6.6%)
Precipitation (mm)	3.07 (1.66)	3.97 (3.24)	1.67 (1.43)	3.53 (2.87)
Maximum daily temperature (degrees F)	41.73 (4.68)	67.94 (14.38)	47.68 (5.75)	68.44 (14.10)
Week with national holidays	0.18 (0.39)	0.15 (0.35)	0.18 (0.39)	0.15 (0.35)
Number of weeks after pandemic	-	-	-	21 (11.83)

Note: This table reports the mean and standard deviation (in parentheses) of the variables of interest in each period. Week 1-11 represents the pre-pandemic weeks, and week 12-52 represents the post-pandemic weeks. Visitation Rates per 1000 population is the dependent variable in our econometric model.

Table 2: Estimation Results

Variable	Coefficients	Standard Error
ln(Travel cost)	-1.227***	0.0189
Treatment week (= 1)	0.184***	0.0627
Treatment year (= 1)	-0.148***	0.0407
Treatment week*Treatment year (=1)	-0.883***	0.0473
Stay at home policy (=1)	-0.640***	0.0377
Median household income	2.13e-05***	5.29e-07
Median age	0.0238***	0.00233
Percent of high school degree	-2.482***	0.189
Precipitation	-0.0130***	0.00324
Maximum daily temperature	0.0151***	0.00196
Week with national holidays (=1)	0.169***	0.0286
Constant	0.242***	0.116
Monthly FE	Yes	
Observations	20,072	
R-squared	0.410	
AIC	64,827	
BIC	65,008	

Note: This table examines the visitation rate change as a result of the pandemic, following equation (1), we group NTA level weekly observations of 2019-2020 into four periods: 2019 week 1-11 (Treatment week=0, Treatment year=0), 2019 week 12-52 (Treatment week=1, Treatment year=0), 2020 week 1-11 (Treatment week=0, Treatment year=1), 2020 week 12-52 (Treatment week=1, Treatment year=1). The dependent variable in columns (1)-(2) is in linear form, and the dependent variable in column (3)-(4) is in log form. Monthly fixed effects are included in all the models. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Estimation of Consumer Surplus (CS)

	(1) CS Per Visitor (Per Week)	(2) Aggregate CS of NYC Visitors Per Week	(3) Aggregate CS of NYC Visitors Per Year
2019			$452,980,596
Week 1-11	$14.3	$5,450,921	
Week 12-52	$15.6	$9,585,865	
2020			$147,385,304
Week 1-11	$15.8	$5,230,644	
Week 12-52	$14.4	$2,191,420	

Note: Column (1) represents the average per week per visitor consumer surplus for each period; Column (2) represents the total per week consumer surplus of all New York City visitors, Column (3) represents the annual consumer surplus of all New York City visitors.

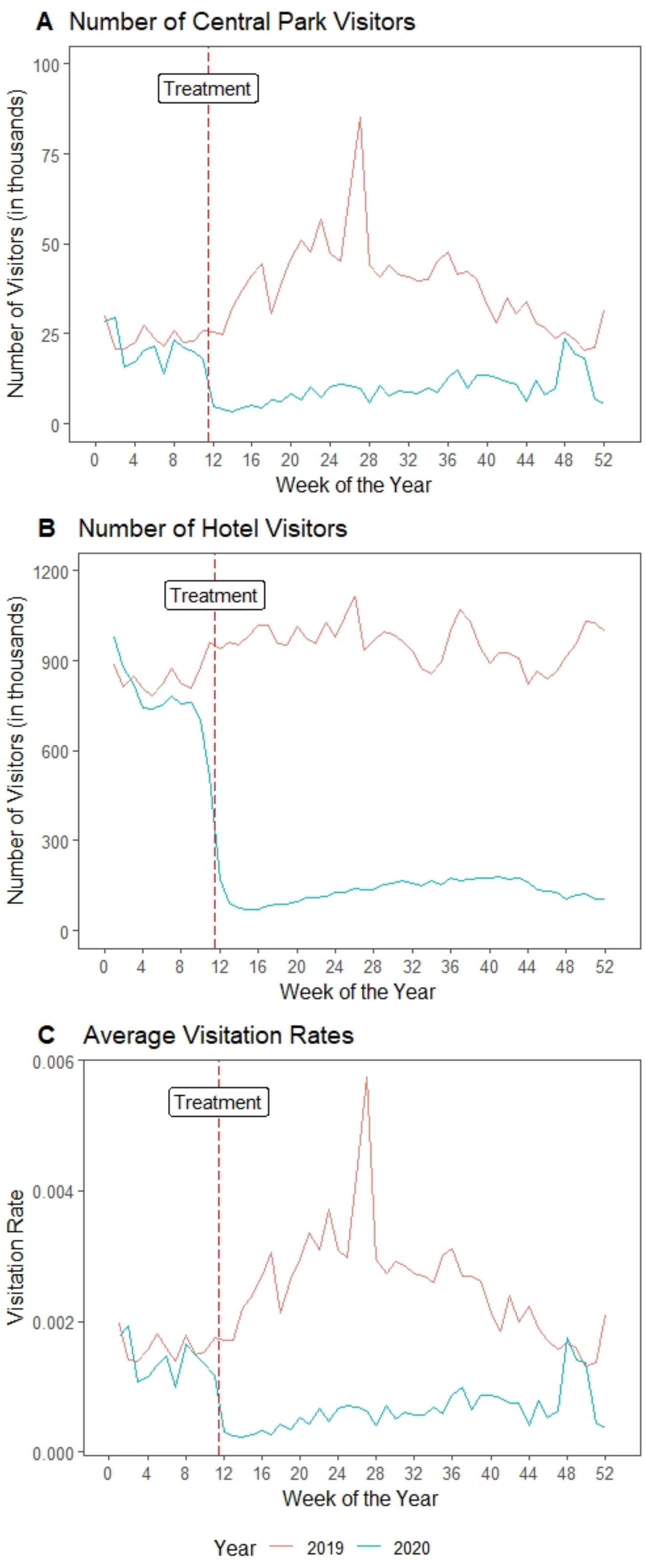

Figure1： Number of Central Park Visitors, Number of Hotel Visitors, and average of NTA Visitation Rates in 2019-2020.

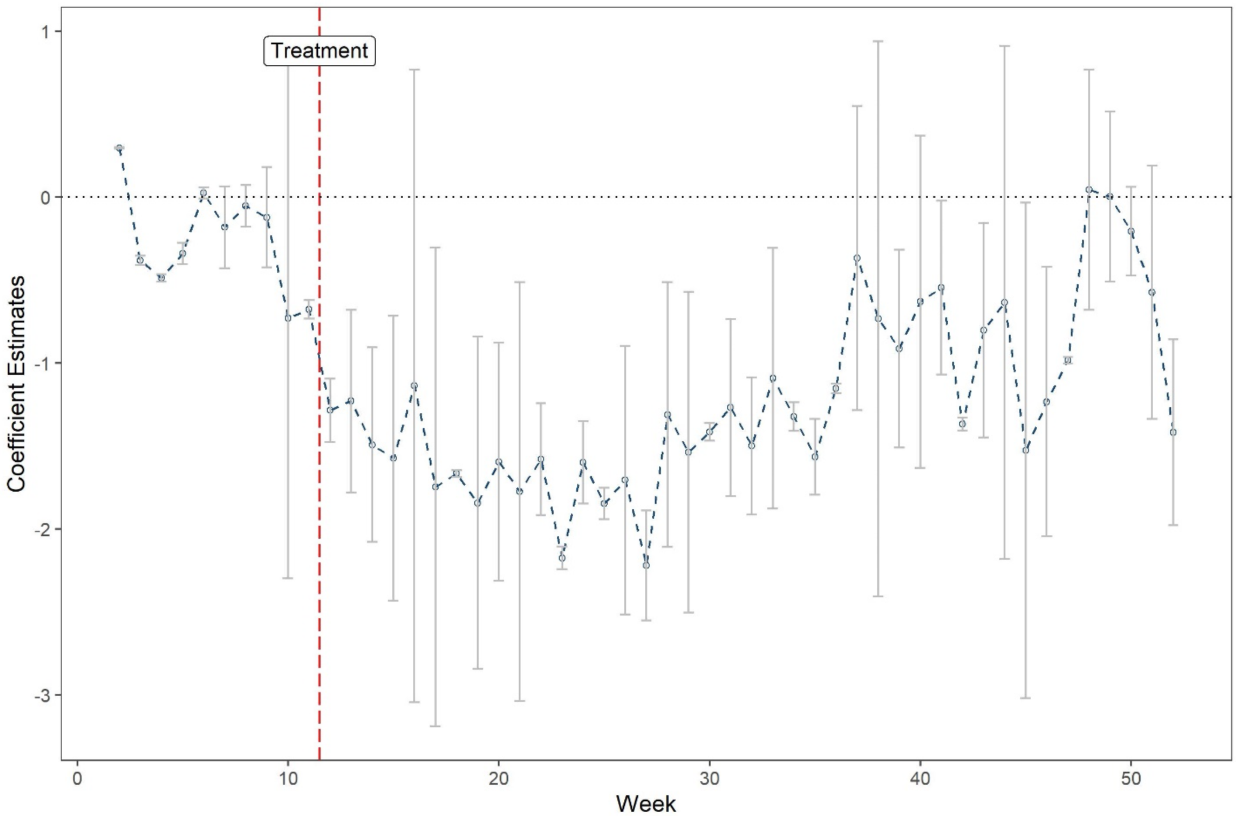

Figure 2: Plot of event-study coefficients
Note: This figure plots θ_w in equation (3), which indicates the estimated effects of visitation rates changes in 2020 relative to 2019. Percentage changes could be calculated using (exp(θ_w)-1)*100%. 95% confidence intervals are shown in grey lines.

Appendix 1: Robustness Check of Different Functional Forms

Variable	(1) Linear-linear	(2) Linear-log	(3) Log-linear	(4) Log-log
Travel cost	-0.219***		-0.0787***	
	(0.00657)		(0.00143)	
ln(Travel cost)		-3.329***		-1.227***
		(0.0950)		(0.0189)
Treatment week (= 1)	0.529***	0.557***	0.174***	0.184***
	(0.162)	(0.161)	(0.0636)	(0.0627)
Treatment year (= 1)	-0.411***	-0.421***	-0.144***	-0.148***
	(0.102)	(0.101)	(0.0415)	(0.0407)
Treatment week*Treatment year (=1)	-1.284***	-1.278***	-0.886***	-0.883***
	(0.120)	(0.119)	(0.0482)	(0.0473)
Stay at home policy (=1)	-0.786***	-0.821***	-0.627***	-0.640***
	(0.115)	(0.114)	(0.0384)	(0.0377)
Median household income	7.81e-05***	7.74e-05***	2.11e-05***	2.13e-05***
	(2.58e-06)	(2.44e-06)	(5.50e-07)	(5.29e-07)
Median age	0.0729***	0.0841***	0.0192***	0.0238***
	(0.00532)	(0.00543)	(0.00235)	(0.00233)
Percent of high school degree	-3.596***	-3.127***	-2.805***	-2.482***
	(0.463)	(0.487)	(0.194)	(0.189)
Precipitation	-0.0333**	-0.0378***	-0.0115**	-0.0130***
	(0.0114)	(0.0114)	(0.00328)	(0.00324)
Maximum daily temperature	0.0226***	0.0201***	0.0160***	0.0151***
	(0.00592)	(0.00586)	(0.00200)	(0.00196)
Week with national holidays (=1)	0.392***	0.399***	0.167***	0.169***
	(0.0953)	(0.0945)	(0.0290)	(0.0286)
Constant	-2.888***	1.994***	-1.508***	0.242***
	(0.340)	(0.288)	(0.122)	(0.116)
Monthly FE	Yes	Yes	Yes	Yes
Observations	20,072	20,072	20,072	20,072
R-squared	0.329	0.344	0.391	0.410
AIC	107,513	107,064	65,486	64,827
BIC	107,695	107,246	65,668	65,008

Note: This table examines the visitation rate change as a result of the pandemic, following equation (1), we group NTA level weekly observations of 2019-2020 into four periods: 2019 week 1-11 (Treatment week=0, Treatment year=0), 2019 week 12-52 (Treatment week=1, Treatment year=0), 2020 week 1-11 (Treatment week=0, Treatment year=1), 2020 week 12-52 (Treatment week=1, Treatment year=1). The dependent variable in columns (1)-(2) is in linear form, and the dependent variable in column (3)-(4) is in log form. Monthly fixed effects are included in all the models. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1