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Time lag effects of COVID-19 policies on transportation systems: A comparative study of New York City and Seattle

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A R T I C L E I N F O

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A B S T R A C T

The unprecedented challenges caused by the COVID-19 pandemic demand timely action. However, due to the complex nature of policy making, a lag may exist between the time a problem is recognized and the time a policy has its impact on a system. To understand this lag and to expedite decision making, this study proposes a change point detection framework using likelihood ratio, regression structure and a Bayesian change point detection method. The objective is to quantify the time lag effect reflected in transportation systems when authorities take action in response to the COVID-19 pandemic. Using travel patterns as an indicator of policy effectiveness, the length of policy lag and magnitude of policy impacts on the road system, mass transit, and micromobility are investigated through the case studies of New York City (NYC), and Seattle—two U.S. cities significantly affected by COVID-19. The quantitative findings show that the National declaration of emergency had no policy lag while stay-at-home and reopening policies had a lead effect on mobility. The magnitude of impact largely depended on the land use and sociodemographic characteristics of the area, as well as the type of transportation system.

1. Introduction

One of the challenges in implementing a policy is the nature and length of the lag between policy enactment and its effects on a system. Policy lag is a well-known term in economics, in which there is often an observed delay between an economic action and a consequence. Policy lags are generally understood as unavoidable time delays. While there may exist several possible reasons for a lag, there is no general agreement on its length (Jovanovski and Muric, 2011). Similar time lags have been noticed during the COVID-19 outbreak. Nonpharmaceutical interventions (NPIs) such as social distancing policies, including emergency declarations, bans on mass gatherings, school and non-essential business closures, and stay-at-home orders were implemented. Different types of policies may

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have different levels of effectiveness on disease spread, and response to these policies is still unclear.

Travel patterns are one good indicator of the effectiveness of these NPIs. Observed changes in transportation usage may answer questions such as: how long does it take for most of a city's residents to shelter-in-place? How early is an increase in traffic volume observed in advance of the reopening of a city? Understanding the length of a policy lag (or lead) and how people react to the policies is crucial for transportation agencies to target the best timing to reduce/restore regular services, allocate resources better and ensure the transportation system's readiness. Moreover, based on different industry composition, sociodemographic characteristics, or land-use background, the length of the lag time and the degree of the effect on transportation systems can vary. There was almost no state-wide imposed stay-at-home or shelter-in-place policy implemented in natural disasters or pandemics in the past 100 years. Therefore, the behavioral changes and time effect from policies to transportation systems during COVID-19 are unpredictable and have not been previously examined.

This paper adopts the concept of "policy lags" from economics to study the relationship between the transportation system and COVID-19 related policies in different cities to 1) provide a better understanding of possible policy lag or lead time to help agencies prepare for future waves of the current pandemic or similar outbreaks, and 2) help analyze the unparalleled changes happening in terms of the road system, trip activities, mass transit, and micromobility. Two types of lags that may influence policy effectiveness are discussed:

Implementation Lag: The delay between the time when a problem is recognized and the time at which a related policy is issued. Based on (Rittenberg, 2008), implementation lag includes the time required to make a decision once a problem is identified and the time it takes to implement the corresponding policy. In the case of the COVID-19 pandemic, for example, the implementation lag of stay-at-home orders is the time delay between the observed risk of exceeding health system capacity with the first steep increase in daily hospitalization numbers, and the announcement of stay-at-home orders.

Impact Lag: The delay between the time a policy is implemented and the time that the effects of the policy can be observed.

This study develops a change point detection-based framework to identify policy lead and lag times and the degree of impacts on different transportation systems. By analyzing various time-series data, including the number of coronavirus cases, vehicular volume, mass transit ridership, and bike counts, quantitative measures are provided through case studies of two of the cities most affected by COVID-19 in the U.S., New York City (NYC) and the City of Seattle. The case studies show that our method is effective in identifying abrupt and significant changes in the performance of different transportation systems and produces lessons learned from the COVID-19 outbreak. To this end, we make the following contributions:

- We propose a change point detection-based framework to identify the length of the COVID-19 policy lags and the magnitude of the policy impacts on different transportation systems. This framework is constructed upon multiple well-known change point detection methods to detect sudden point or structural changes. These detection methods are general and may be applied in similar events in the future.
- We quantitatively estimate both the implementation lag and impact lag for major COVID-19 policy events, including social distancing and reopening in NYC and Seattle. This is achieved by investigating the changes in hospitalization rate, vehicular traffic, transit, and bike ridership for both cities. The proposed metric considers the percentage change in each dataset due to the corresponding policy.
- Our findings provide lessons for policymakers to make more informed judgments by considering potential lead and lag time and tracking the effect of various policies on transportation systems in any future pandemic. Moreover, knowing the possible length of the lag or lead time and heterogeneous changes in different systems can help transportation agencies to better allocate resources to ensure transportation system readiness for future outbreaks.

2. Literature review

Policy lag has been widely studied in the domain of economics (Friedman, 1961, Bryan, 1967, Gruen et al., 1999, Shinagawa and Tsuzuki, 2019). For example, Friedman viewed the time lag between the peak increasing rate in the money supply and the peak in economic activity as the lag between a change in monetary policy and its effect. There are two main types of lag. One is referred to as implementation lag, the time that the government needs to respond to changes in an economic environment (Yoshida and Asada, 2007). The other type of lag is lag in effect, or impact lag. This kind of lag is the time between a policy and the time at which a system begins to see difference than they would have in the absence of the policy (Culbertson, 1960).

Various studies have been conducted on the importance of the length of lags in the monetary process as well (Bryan, 1967, Yoshida and Asada, 2007). Empirical studies suggest that there are substantial lags between changes in key monetary variables such as interest rates and changes in economic activity (Bryan, 1967). The distributed lag approach, such as the distributed lag model or autoregressive distributed lag model (ADLM), has been used in many studies to analyze an economic scenario (Almon, 1965, Schmidt and Waud, 1973, Shahbaz et al., 2015). Schmidt pointed out that understating or overstating the length of a lag can be a specification error that leads to biased and inconsistent estimates (Schmidt and Waud, 1973). The length of a lag may also have an impact on the overall system. Yoshida and Asada asserted that the increase of a policy lag contributes to destabilizing the system by applying a Keynes-Goodwin model (Yoshida and Asada, 2007).

Changes in coronavirus infection, hospitalization, or death may lead to implementing a policy, and the implementation may bring changes to the transportation system. Since these changes are often not reflected immediately on mobility, but rather distributed over future periods, it is reasonable to adopt the policy lag concept into the analysis of COVID-19 research. It is also crucial to understand the delay and the proper timing of implementing policies such as NPIs. A study by Bootsma (Bootsma and Ferguson, 2007) that investigated the 1918 influenza pandemics in U.S. cities concluded that the different impacts of the autumn wave of the pandemic in different cities largely depended on the timing of public health interventions. Cities with early public health interventions achieved moderate but significant reductions in overall mortality (Bootsma and Ferguson, 2007). At the current state of the COVID-19 outbreak, Ferguson stated that optimal NPIs might reduce peak healthcare demand by 2/3 and death by half (Ferguson et al., 2020). Abouk and Heydari (Abouk and Heydari, 2020) studied the immediate effect of restriction policies on social distancing behavior and saw a steady decline in the number of daily confirmed cases 10 days after the policy was implemented, estimating a 37% reduction in the number of daily cases after 15 days.

Past studies have also shown that mobility and the effectiveness of policy have a strong correlation. The 2003 severe acute respiratory syndrome (SARS) epidemic resulted in a 50% reduction of daily underground ridership in Taipei City, compared with the loss of 80% daily ridership during the underground system's closure after Typhoon Nari (Wang, 2014). These daily loss rates dissipated in the following days with an e-folding time of about 28 days, indicating the dissipation of fear in subsequent days (Wang, 2014). The peak loss of underground ridership was 400,000 riders per day, which occurred about 10 days after the peak of daily reported SARS cases (Wang, 2014). Engle et al. (Engle et al., 2020) found that in the early stage of the outbreak in the U.S (February to early April 2020), a government order to stay at home reduces mobility by 7.87% in a county with median characteristics. A COVID-19 data dashboard developed by C2SMART Center (Zuo et al., 2020) showed that as the stay-at-home order in NYC took effect, both transit ridership and vehicular traffic in NYC experienced steep declines. The decline rates reached about 94% in peak transit ridership and 72% in vehicular traffic around the end of March 2020, compared to the same period in March 2019.

These drastic changes are not commonly seen in our transportation system. Therefore, situational awareness and the preparedness of the transportation system become critical to mitigating the negative effects of emergencies (Yoon et al., 2008). Understanding the delay effect and changes distributed over different periods can provide longitudinal perspectives on how long it took for the effect of COVID-19 policies to be reflected in various transportation systems and when, and to what degree, transportation systems should be prepared to accommodate these changes.

3. Timeline

The two U.S cities most impacted by COVID-19 in the early months of the pandemic, New York City in New York (NY) State, and the City of Seattle, the largest city in King County, Washington (WA) State were chosen as case study sites. Table 1 shows the timeline of

Table 1
Government responses timeline (as of June 2020).

Date of Action	NYC, NY	Seattle, WA
1/21/2020		The first reported case of COVID-19 in the United States was confirmed in WA
2/29/2020		Seattle reports its first death due to COVID-19
3/1/2020	NY reports its first confirmed case	
3/3/2020		Seattle Mayor declares a State of Emergency
3/5/2020		Employees whose jobs can be done remotely at companies like Amazon or Microsoft were advised to work from home.
3/7/2020	NY State of Emergency declared	
3/13/2020	US National State of Emergency declaration	
3/16/2020	NY: 50 + people gatherings banned, closure of all restaurants/bars, theaters, gyms, casinos, and K-12 schools	WA: 50 + people gatherings banned. Closure of all entertainment and recreational facilities, and restaurants/bars
3/17/2020		King County: Closure of all schools
3/22/2020	NY: "New York State on PAUSE," closure for all non-essential businesses	
3/23/2020		WA: Stay-at-home orders announced; King County Metro reduced transit services.
3/24/2020	Citi Bike launched Critical Workforce Membership Program (a free 30-day membership for essential workers)	
4/30/2020	NYC subway closures from 1 a.m. to 5 a.m. during the coronavirus pandemic to disinfect trains and stations	
5/1/2020	NYC announced Open Streets to open the first 7 miles of streets for pedestrians and cyclists	Announcement of Stay-at-home orders extension through May 31st
5/15/2020	Five regions (Finger Lakes, Mohawk Valley, North Country, Southern Tier, and Central New York) were allowed to begin Phase 1 reopening.	
6/1/2020		King County Reopening Phase 1
6/5/2020		King County Modified Reopening Phase 1
6/8/2020	NYC Reopening Phase 1	
6/19/2020		King County Reopening Phase 2
6/22/2020	NYC Reopening Phase 2	

major national, state and local government responses until the end of June 2020 that took effect in NYC and Seattle.

4. Data description

4.1. Number of coronavirus daily new cases, hospitalizations and deaths

The daily number of new COVID-19 cases, hospitalizations, and deaths in NYC and Seattle are extracted from the official website of the NYC Department of Health (www1.nyc.gov/site/doh/covid/covid-19-data.page) and King County Department of Public Health (www.kingcounty.gov/depts/health/covid-19/data.aspx).

4.2. Vehicular volume

4.2.1. NYC – Traffic volumes at all MTA bridges and tunnels

The dataset containing traffic volume is obtained from New York State's Open Data Platform (New York's Open Data Portal, 2020). This dataset is composed of the hourly traffic volume of all vehicles passing through each of the nine bridges and tunnels operated by the Metropolitan Transportation Authority (MTA). For the time series considered in this paper, we aggregated the raw data into a daily number of total vehicles, both in- and out-bound, E-ZPass and cash toll trips.

4.2.2. Seattle – Traffic volume counts

Traffic volume data for Seattle was retrieved from the Washington State Department of Transportation (WSDOT)'s TRACFLOW platform (WSDOT, 2018). TRACFLOW processes induction loop data to create performance metrics for freeways in Seattle (Wright et al., 2007). Two loop detectors are analyzed for this research, including one location at I-5 GLP (Green Lake Park), a residential area in the northern part of Seattle which usually catches commuter traffic from the north and recreational trips to the park. The SR99 loop detector is placed in the middle of Lower Queen Anne and South Lake Union. The Bill & Melinda Gates Foundation, multiple Amazon offices, the Space Needle, and the Museum of Pop Culture are near this detector.

4.3. Transit demand/ridership

4.3.1. NYC – Subway and bus ridership

The Stay-at-home orders caused an immediate direct impact on the usage of transit service. MTA is the main transit service provider in NYC and provides its systemwide ridership and traffic estimates for subways and buses. Subway ridership is determined from MetroCard and OMNY swipes and taps (MTA, 2020). Bus ridership is estimated from models that use MetroCard and OMNY swipes and taps and Automatic Passenger Counter (APC) data that is available on some MTA's bus fleet (MTA, 2020).

4.3.2. Seattle - Transit demand

The public transit demand information from the Transit App (Transit App, 2020) is used as transit ridership trends proximity for the Seattle area. This data measures public transit demand based on millions of app opens and does not represent actual transit ridership. The daily reduction in the app usage, which is the ratio of the total actual activity to expected activity based on a whole day's number of sessions, is used for this study. The usage of the app was based on four agencies: King County Metro (KCM), Community Transit, Pierce Transit, and Sound Transit.

4.4. Bike ridership

4.4.1. NYC - Citi bike

Citi Bike is the largest bike-share program in U.S., with 14,500 bikes and 950 stations across Manhattan, Brooklyn, Queens, and Jersey City (Citi Bike, 2020a). The Citi Bike trip dataset (Citi Bike, 2020b) provides relevant information such as origin and destination stations ids, names and geolocation, trip start and end dates and times, and trip duration in seconds. This data is pre-cleaned, with trips resulting from bicycles being transported by trucks for rebalancing, and false starts are eliminated.

4.4.2. Seattle – Bike counts from Seattle Department of Transportation (SDOT)

Bike counter data (SDOT, 2020) collected by SDOT at the Fremont Bridge, which is a 24/7 counter, is used in this study. Inductive loops on the east and west pathways count the passing of both personal and shared bikes traveling through Fremont Bridge regardless of travel direction (Seattle Open Data Portal, 2020). This location is selected because it is the busiest single crossing point for bike trips - different local and regional bike routes funnel to this single crossing of the Ship Canal (Seattle bike club).

5. Methodology

Change point detection aims to find abrupt changes in data when a certain property of the time series changes (Kawahara and Sugiyama, 2012). It has been implemented in various domains and applied to a broad range of real-world problems, such as medical record monitoring, speech recognition, image processing, or human activity analysis. Change point detection can be used for detecting a sudden change point, a change in states, and any changes in the structure of the data.

Fig. 1 shows the flowchart of the proposed framework applied to detect policy lags and impacts on the transportation system. Mobility and COVID-19 related raw data are acquired from the multiple data sources described in the previous section. Each dataset is cleaned and aggregated to daily numbers, so they have the same resolution. Based on the features of the input data and detection goals (e.g., offline data with multiple change points), one or more change point detection algorithms are selected.

In this study, we focus on methods that can detect both sudden change points (changes in mean and variance) and structural changes in the data, to reveal not only the short-term drop or increase in traffic mobility, but also potential long-term changes due to COVID-19. For example, the observed rise in micromobility activity, such as bike share usage, may become a long-term trend as users become familiar with alternatives to transit. These changes are often not easily explained by sudden change points, so structural changes should be considered to help understand the full picture. Thus, we apply the complementary use of 1) a likelihood ratio model with Pruned Exact Linear Time (PELT) and 2) a regression structure model with dynamic programming in this study. The former is proven to be efficient in detecting multiple sudden change points, and the latter is effective at detecting structural changes.

The detected change points are evaluated using the probability score generated from the Bayesian change point detection (BCPD) to determine if the detection result is likely to be a "true" change point. In the end, the length of the policy lags, and the percentage change of the data during the lag is quantified for each policy.

5.1. Problem formulation

Consider a multivariate non-stationary random process $y = \{y_1, \cdots, y_T\}$ that takes value in $\mathscr{R}^d (d \geq 1)$ and has T observations. The event y is assumed to be piecewise stationary, which means some features of the process change suddenly at some unknown time $t_1 < t_2 < \cdots < t_K$, and change point detection's object is estimating those time indexes, $t_k, (k = 1, 2, \cdots, K)$. Generally, change point detection can be formulated as a model selection problem that minimizes the objective function $V(\tau)$ by selecting the appropriate segmentation τ. The change point detection problem with an unknown number of change point occurrences can be considered as solving the following discrete optimization problem (Truong et al., 2020):

$$\min_{\tau} V(\tau) + penalty(\tau) \tag{1}$$

Here the objective function $V(\tau)$ is set to a sum of the cost function $c(\cdot)$ for a particular segmentation τ, and $penalty(\tau)$ is an appropriate measure of the complexity of a segmentation. Different search methods will be used to optimize $V(\tau)$.

5.2. Likelihood ratio estimation model + pruned exact linear time (PELT) method

A typical statistical formulation of change point detection is to identify a candidate data point as a change point if the probability

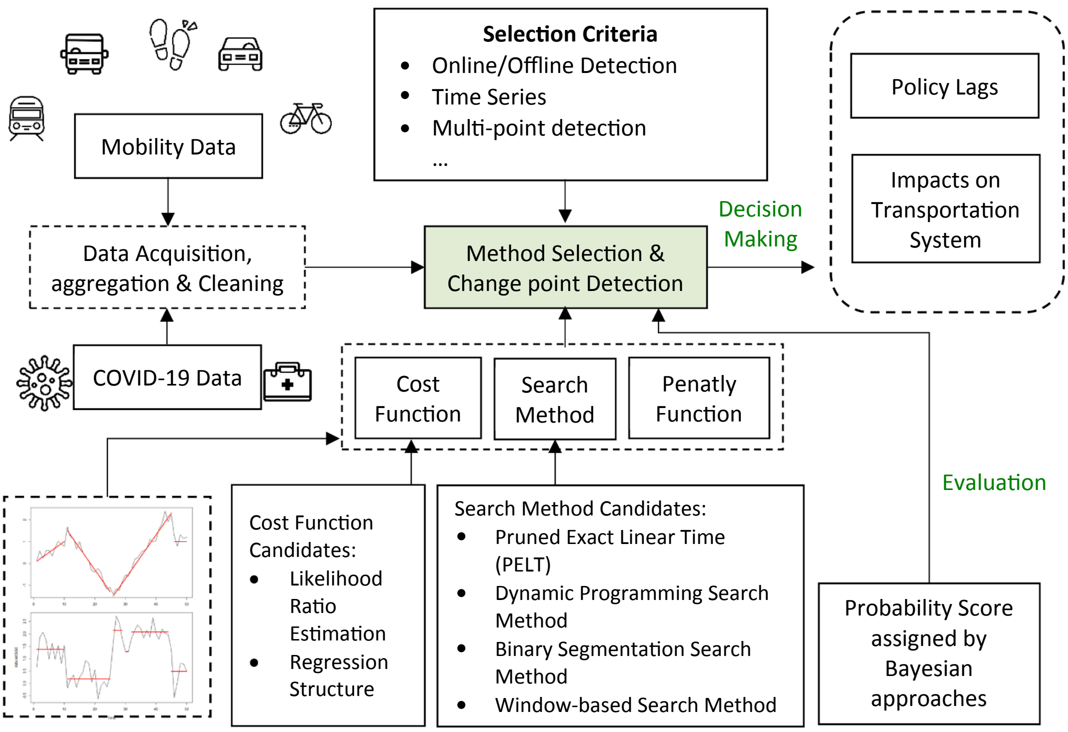


Fig. 1. Proposed change point detection-based framework for policy analysis.

distributions of data before and after this point is significantly different (Aminikhanghahi and Cook, 2017). To detect such change point in time series data, the log-likelihood ratio between two consecutive intervals is often monitored. Using likelihood ratio estimation as the cost function can detect multiple sudden change points with the help of appropriate search methods (Truong et al., 2020).

Among search methods that are compatible with likelihood ratio estimation model, we compared both exact and approximate search methods. Overall, the exact methods have greater computational complexity than approximation methods, while the exact methods are more accurate since they seek optimal results (Truong et al., 2020). For example, binary segmentation (Scott and Knott, 1974) applies a single change point method to the entire data sequence whereas window-based search method (Truong et al., 2020) measures the discrepancy between two adjacent windows. Both methods have low computational complexity ($\mathcal{O}(n\log n)$ and $\mathcal{O}(n)$) but they are less accurate than exact methods like segment neighborhood search method (Auger and Lawrence, 1989) that searches the entire segmentation space using dynamic programming approach. However, the major drawback of this latter method is its heavy computational complexity, which could be up to $\mathcal{O}(n^3)$ if the number of change points increases linearly as the observed data increases.

Thus, to find an exact search method that is also computational efficient, Pruned Exact Linear Time (PELT) algorithm, which uses a faster method called linear penalties to detect change points to minimize the costs (Killick et al., 2012) is selected. The main assumption in PELT is that the number of change points increases linearly with the size of the data and the change points are not restricted to one portion of the data (Wambui et al., 2015). When the algorithm is implemented, it is applied to the whole data set iteratively and independently to each partition until the last change point is identified. Precisely, for two indexes t and $s(t < s < T)$, the pruning rule is denoted as:

$$\textit{if} \left[\min_{\tau} V(\tau, y_{0,t}) + \beta|\tau|\right] + c(y_{t,s}) \geq \left[\min_{\tau} V(\tau, y_{0,s}) + \beta|\tau|\right] \ \textit{holds},$$
$$t \ \textit{cannot be the last change point prior to} \ T \tag{2}$$

Where $V(\tau)$ is the objective function, $\beta|\tau|$ is the penalty function, $c(y_{t,s})$ is the cost function which measures the goodness-of-fit of the sub-signal $y_{t,s}$, s and t are two indices in T samples. Under the assumption that regime lengths are randomly drawn from a uniform distribution, the algorithm has a computational cost that is linear in the number of data points.

PELT is proven to be more accurate compared to approximate search methods such as binary segmentation, and faster ($\mathcal{O}(n)$) compared to other exact search methods like segment neighborhood search method ($\mathcal{O}(n^3)$ for large datasets) or optimal partitioning $\mathcal{O}(n^2)$(Killick et al., 2012, Wambui et al., 2015). The power of the test increases with the increase in size of change (Wambui et al., 2015). However, PELT can only solve linear penalty scenarios, and cannot be directly applied to complex penalties (Truong et al., 2020). Likelihood ratio estimation is effective at detecting change points between segments having a piecewise stationary mean and variance. The disadvantage of this algorithm is that it performs poorly with trend-stationary processes (Sen and Srivastava, 1975, Truong et al., 2020). A detailed comparison of change point detection with different search methods can be found in (Truong et al., 2020). The R package “changepoint” (Killick et al., 2016) is used to implement the likelihood ratio method using PELT searching algorithm. The penalty methods include “Manual” (manual selection) and “CROPS” (predefined range of penalties). For the rest of this study, we denote this method as PELT for simplicity.

5.3. Regression structure model + dynamic programming method (Break Point (BP) detection)

The basic idea of break point detection is that the coefficients of the classical linear regression model will shift from one stable regression relationship to another at the breakpoint by assessing the deviation from stability in the regression model. Assume that there are k breakpoints, then there are $k+1$ segments that the regression coefficients are constant. We adopt the method from (Bai and Perron, 2003) for the simultaneous estimation of multiple breakpoints. Consider a multiple linear regression with k breaks and $k+1$ regimes:

$$y_t = x_t^{'}\beta + z_t^{'}\delta_j + u_t \quad t = T_{j-1} + 1, \cdots, T_j, j = 1, \cdots, k + 1 \tag{3}$$

Where, y_t is the observed dependent variable at time t; x_t and z_t are vectors of covariates; β *and* δ_j are the corresponding vectors of coefficients; u_t is the noise at time t. The purpose is to estimate the unknown regression coefficients together with the break points when t observations on (y_t, x_t, z_t) are available. The algorithm computes the optimal breakpoints given the number of breaks using dynamic programming approach based on the Bellman principle as search method. For each potential number of change point, the algorithm computes a triangular sum of squared residual (SSR) matrix, which gives the SSR for a partition starting at observation t and ending at t' where $t < t$', and the number of change points with the minimum SSR value is selected as the optimized result. In addition, the Bayesian Information Criteria (BIC) is also used as the reference for determining the optimal number of change points.

Use of regression structure model is well established in the literature for use as a cost function to detect structural changes and has been successfully applied in identifying historical, political and economic events in time-series data (Truong et al., 2020, Zeileis et al., 2003). While likelihood ratio model is good at detecting changes in mean and variance, the regression structure model (Bai and Perron, 2003) can detect both pure and partial structural changes which refer to the shifts in functional curves of the relationship between X and Y (e.g., timestamp and traffic mobility data in this study, respectively) as well as in means of time series segments, and it does not require any priori determination of the number of change points. The computational complexity of this model is acceptable ($\mathcal{O}(n^2)$)

since it is based on dynamic programming. Another benefit of this method is that it provides confidence intervals for the break points by considering the structure of the time-series data and errors across segments. The disadvantage is that it is insensitive to small changes between different partitions with a similar regression model. The R package ‘strucchange,’ which provides a suite of tools for detecting changes within linear regression models including the break point estimation above, is used for this study (Zeileis et al., 2003). For the rest of this study, we denote this method as Breakpoint (BP) for simplicity.

5.4. Probabilistic method – off-line Bayesian Change Point Detection (BCPD)

One challenge in change point detection is that ground truth information is usually very difficult to obtain. In this study, a probabilistic method, Bayesian Change Point Detection (BCPD), is selected to provide estimated prediction qualities without knowing ground truth. BCPD provides posterior probabilities of the predictions and indicates how likely a detected change point is a “true” change point. In BCPD (Barry and Hartigan, 1993), the object process is considered as a Markov chain, which is a sequence of observations $X_1, X_2, \cdots, X_n$ ordered in time, and each observation X_i being independent with a density depending on a parameter $\theta_i \in \Theta$ whose value may change from one observation to the next. The change point problem is defined as inference when there exists an unknown partition ρ of the set into contiguous blocks such that the sequence $\theta_1, \theta_2, \cdots \theta_i$ is constant within blocks. Thus, the probability of a change point at a position i is p, independent at each i. The prior distribution of μ_{ij}, i.e. the mean of the block starting at position $i+1$ and ending at position j, is $N(\mu_0, \frac{\sigma_0^2}{j-i})$.

Chandra Erdman et al., (Erdman and Emerson, 2007) presented a new model implemented Markov Chain Monte Carlo (MCMC) approximation that benefits from considering the whole blocks effect and reduces model complexity from $O(n^3)$ to $O(n)$. This model was developed into the R package ‘bcp’ (Erdman and Emerson, 2007), the package used for this study. The algorithm starts with the partition $\rho = (U_1, U_2, \cdots, U_n)$, where n is the number of observations and $U_i = 1$ represents a change point at step $i+1$, and U_i is initialized by 0. For each position i in every step of the Markov chain, a value of U_i is drawn from the conditional distribution of U_i given the data and the current partition. The transition probability, p, for the conditional probability of a change at the position $i+1$, is obtained from the simplified ratio denoted as (Erdman and Emerson, 2008):

$$\frac{p_i}{1-p_i} = \frac{P(U_i = 1|X, U_j, i \neq j)}{P(U_i = 0|X, U_j, i \neq j)}$$

$$= \frac{\int_0^{p_0} p^b (1-p)^{n-b-1} dp}{\int_0^{p_0} p^{b-1} (1-p)^{n-b} dp} \times \frac{\int_0^{w_0} \frac{w^{b/2}}{(W_1+B_1 w)^{(n-1)/2}} dw}{\int_0^{w_0} \frac{w^{(b-1)/2}}{(W_0+B_0 w)^{(n-1)/2}} dw} \quad (4)$$

Where, b is the number of blocks obtained if $U_i = 0$ conditional on U_j, for $i \neq j$. W_0 is the within-block sum of squares and B_0 is the between-block sum of squares we obtain when $U_i = 0$, W_1 and B_1 are similarity defined when $U_i = 1$, and X is the data. The parameters p_0 and w_0 are a prespecified number in [0,1], provide a restriction on the ranges of p and w to make the model effective in situations where there are few changes (when p is small), and small size of changes (when w is small). The posterior means are updated conditional on the current partition after each MCMC iteration. In this study, the time of MCMC iterations was set to 1000, and burn-in time was set to 100.

The most important advantage of BCPD is that it returns the posterior probability of a change point occurring for every observation point in the time series, which is used as a quantitative evaluation measure in this study. The BCPD-based approach also has an “online” version and is useful in modeling and prediction of time series.

5.5. Decision-making process

As mentioned in the previous section, we applied two change point detection methods (PELT and BP) to detect multiple change points among transportation mobility data and used BCPD to provide a posterior probability for every observation point in the time series. The posterior probability serves as a quantitative measure to help evaluate the performance of both PELT and BP. The steps of the decision-making process are shown below:

- Step 1: For an implemented policy, we consecutively search two candidates’ change points before the implementation date (e.g., lead change point) and two after the implementation date (e.g., lag change point) identified by PELT.
- Step 2: Repeat step 1 using BP.
- Step 3: Apply BCPD to the entire dataset and compare the posterior probabilities for each of the change points detected from PELT and BP.
- Step 4: Determine one lag change point and/or one lead change point that has the highest posterior probabilities for this policy with consideration of the policy context and BP confidence intervals.
- Step 5: Calculate the time duration between the identified lead/lag change point and the time at which the policy is implemented.
- Step 6: Repeat steps 1–5 for each policy.

6. Results and discussion

6.1. Impact lag

Change point detection results using PELT and BP methods and the corresponding Bayesian posterior probability are shown in Fig. 2 (NYC) and Fig. 3 (Seattle). The length of the lag for each policy and its impact on different transportation systems are then summarized in Fig. 4. The length of the lag is calculated by the difference between the implementation date of the policy and the date detected by our proposed change point detection algorithms. If the length of the lag is negative, the policy has a lead effect – which means the public responds before the implementation of the policy. The magnitude of impact is calculated in a before-and-after manner: it is the percentage difference of average traffic data between the two sequential detected change points. The magnitude of impact is a factor which infers how public reacts to the implementation of a single/combination of policy(s). For investigation purposes, the “lag” of the “PAUSE”/Stay-at-home order and the subway midnight closures/NYC Open Street generally represents the length of the continued effect of the policy.

6.1.1. NYC

Table 2 and Table 3 summarizes the length of a policy’s lag in days, and the magnitude of its impact on vehicular, transit, and bike traffic in NYC. The date of the selected change points determined by the aforementioned decision-making rules and the corresponding method (PELT, BP or both) used to detect them are presented as well. The State declaration of emergency had a policy lag of about 6–8 days on transportation systems in NYC, while the National declaration of emergency had almost an immediate effect that resulted in the drop of ridership, with 0 days for road and transit system and 2 days for the bike share system. The ban of gatherings of greater than 50 people, with the closure of entertainment, recreational facilities, restaurants, and K-12 schools, saw lags up to 4 days. The stay-at-home order (“PAUSE” order) had a lead effect of 2 days on the vehicular and transit system, indicating that the public responded during the weekend before the policy was officially in effect. This is highly possibly due to messaging on March 20 that the governor had signed the PAUSE order.

It is worth mentioning that because multiple social distancing restrictions were released close to each other in time, they might have a combined effect on the transportation systems. For example, the lag of a policy may be impacted by the announcement of a subsequent policy. Moreover, the impact on the transportation system can also result as a mixed effect from the lag of one policy (e.g., 50 + gather ban) and the expectations of, and early action from, the public in advance of a policy (e.g., “PAUSE”/stay-at-home order).

Two steep decreases were observed in the vehicular and transit systems during the restriction period when multiple NPIs were

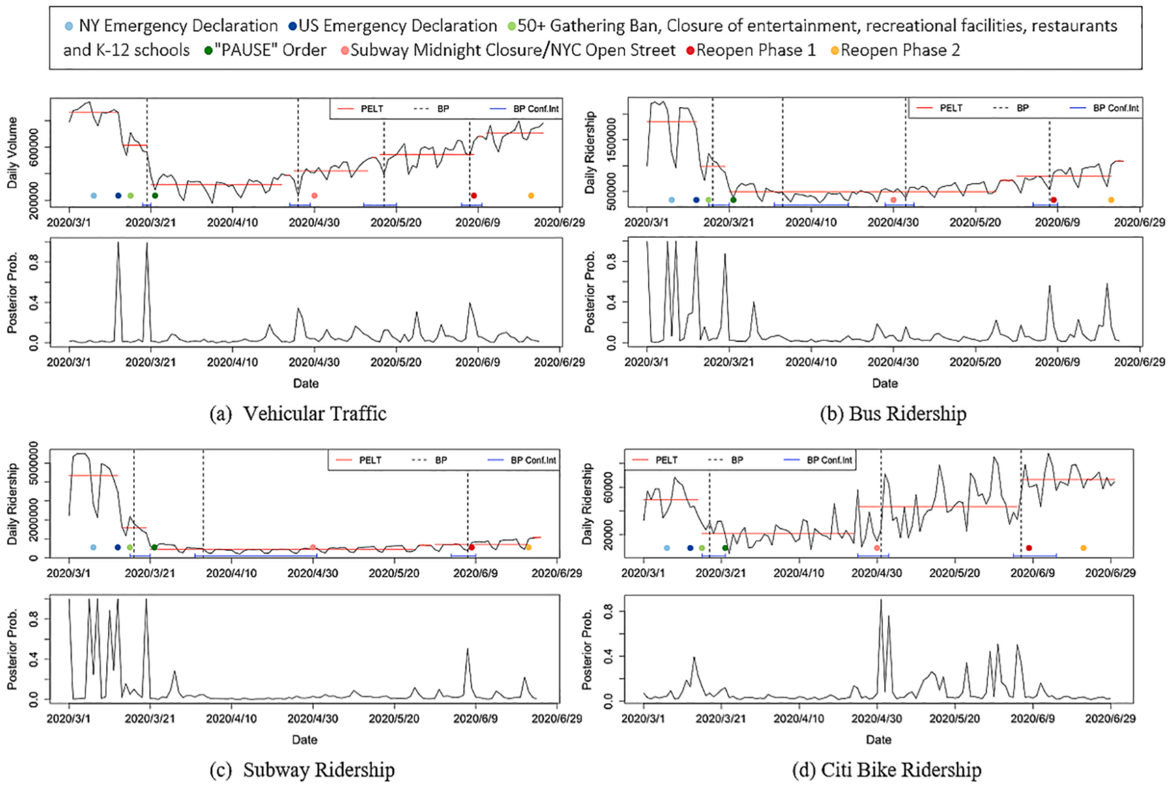


Fig. 2. Change point detection results – Impact lags (NYC).

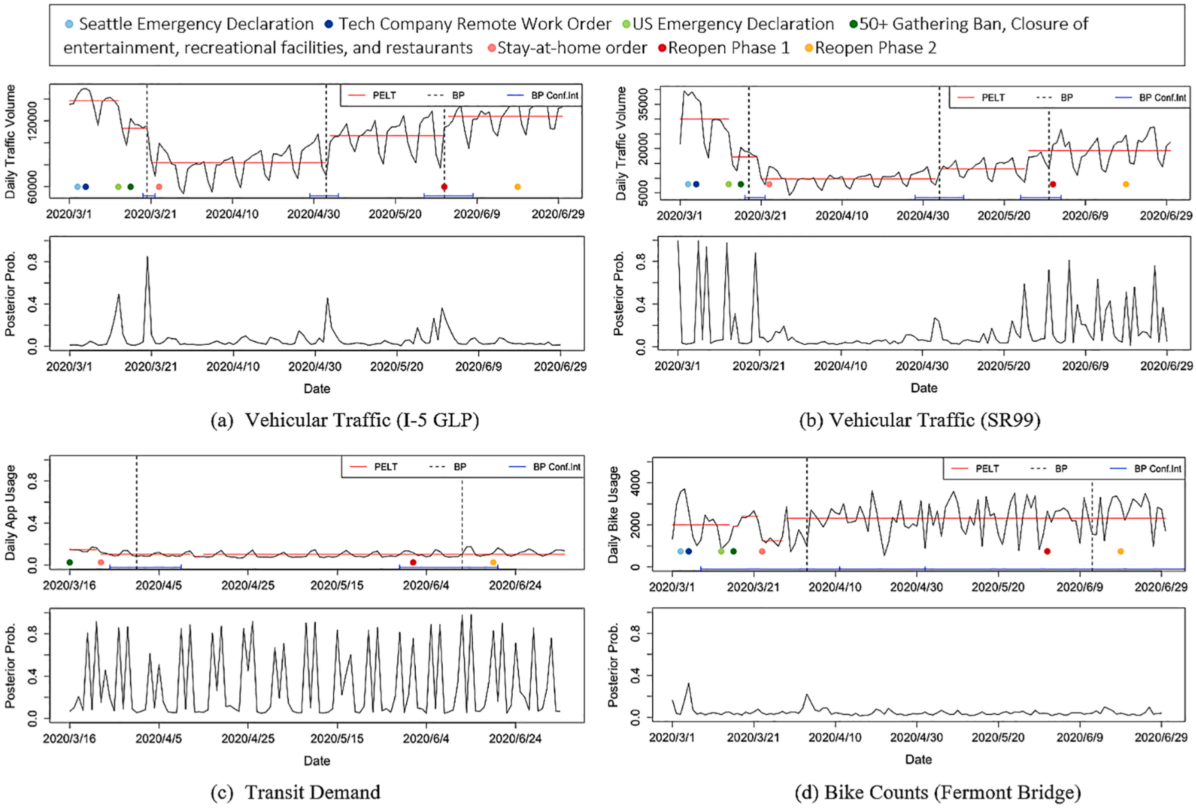


Fig. 3. Change point detection results – Impact lags (Seattle) *Transit App data starts from March 16, 2020.

announced. Vehicular traffic, bus, and subway ridership experienced a significant change in magnitude of impact, dropping of 28.92%, 46.88%, and 63.19% respectively, after the State declaration of emergency (stage 1), compared to pre-pandemic levels. These volumes continued to drop by 48.43%, 49.64%, and 71.62% respectively, compared to stage 1 levels after the announcement of the National declaration of emergency, large gathering ban with the closure of entertainment, recreational facilities, restaurants, and K-12 schools, and before the “PAUSE” order.

The “PAUSE” order had long-lasting effects that kept the transportation systems operating at low volume for a period varying in length on different systems. While the “PAUSE” order resulted in low volume in vehicular traffic and shared bike ridership for 35 days and 40 days, it had a drastic and continuous impact on the transit system for more than two months (64 days for buses and 77 days for subway). The Reopening Phase 1 of the city also had a lead effect on all transportation systems that gives useful insights on how early these transportation systems should prepare themselves to meet increasing demand. Vehicular traffic started to increase 22 days before the phase one of reopening with a 29.36% increase compared to the previous period identified by the change point detection. However, transit systems reacted almost at the same time as the phase I reopening and the impact of the increase in the transit system is relatively small (11.36% for bus and 7.26% for subway).

For vehicular traffic, both PELT and BP found a change point around May 15, although no major policies in NYC were released (Fig. 2**(a)**). This may be due to the Phase I reopening of nearby states including New Jersey and Connecticut around May 18–20 and NY state government’s announcement on May 15 that five regions of NY (not including NYC) were allowed to begin Phase 1 of the reopening. These announcements showed optimism about the crisis and possibly resulted in less fear of going out and encouraged more vehicular traffic. Another change point was detected around the end of April with the announcement of the subway midnight closure and NYC Open Streets policy which was released on the next day. Though the gradual increase in vehicular and Citi Bike ridership may indicate a mode shift, the relationship between these two modes needs further validation.

The declaration of the NY State of Emergency increased Citi Bike usage for about 8 days by more than 40%, then dropped by 57.83% over the next month and a half (Citi Bike, 2020b). The midnight closure of the subway and NYC Open Streets policy had an immediate effect on Citi Bike ridership, bringing an increase over the next 36 days up until the first phase of reopening NYC. A continued increase of 52.60% in Citi Bike usage was also observed after reopening.

6.1.2. A comparison between seattle and NYC

Table 4 and Table 5 summarizes the length of a policy’s lag in days and the magnitude of its impact on vehicular, transit and bike traffic in Seattle. In general, both NYC and Seattle experienced an initial drop in vehicular traffic after the state or city declarations of emergency, and a second drop after the national declaration of emergency and the banning of large gatherings, and the closure of

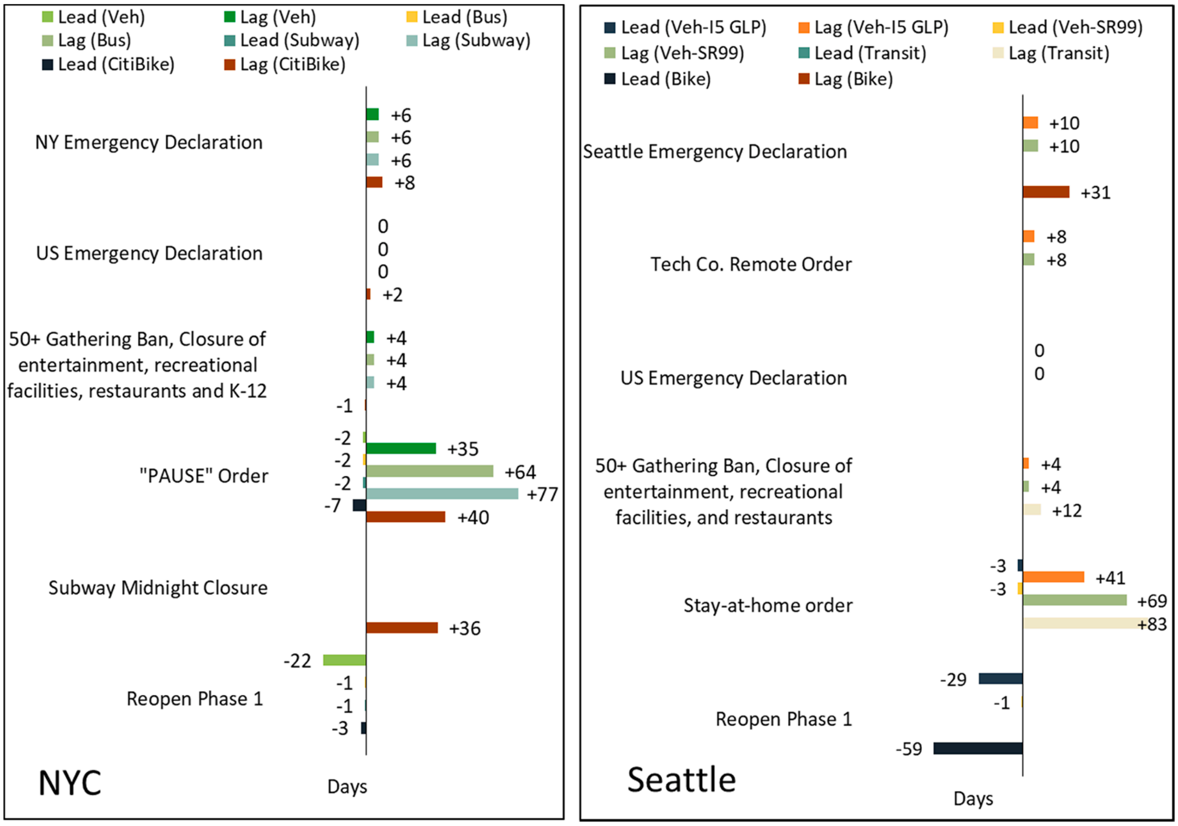


Fig. 4. Length of Policy Lags in NYC and Seattle (Negative number representing a lead time, positive number representing a lag time. *The "lag" of "PAUSE"/Stay-at-home order and subway midnight closure represents the length of the continued effect of the policy.)

Table 2
Length of policy lag/lead for NYC.

Date	Policy	Type	Vehicular traffic (#Vehicles)	Bus (#trips)	Subway (#trips)	Citi bike (#trips)
7-Mar	NY Emergency Declaration	Lag (days)	6	6	6	8
13-Mar	US Emergency Declaration	Lag (days)	0	0	0	2
16-Mar	50 + gathering ban	Lead (days)	–	–	–	1
		Lag (days)	4	4	4	–
22-Mar	"PAUSE" order	Lead (days)	2	2	2	7
		Lag (days)	35	64	77	40
30-Apr	Subway Midnight Closure	Lag (days)	–	–	–	36
8-Jun	Reopen Phase 1	Lead (days)	22	1	1	3

Table 3
Magnitude of Policy Impact on Transportation System for NYC Based on Selected Change Points Determined by the Decision-making Rules. (The magnitude of impact is calculated as the percentage change of average traffic data between the two sequential detected change points. One change point may correspond to the impact of multiple temporally proximate policies.)

Vehicular traffic (#Vehicles)		Bus (#trips)		Subway (#trips)		Citi bike (#trips)	
Change point	Magnitude of impact	Change point	Magnitude of impact	Change point	Magnitude of impact	Change point	Magnitude of impact
13-Mar (PELT)	−28.92%	13-Mar (PELT)	−46.88%	13-Mar (PELT)	−63.19%	15-Mar (PELT)	−57.83%
20-Mar (PELT&BP)	−48.43%	20-Mar (PELT)	−49.64%	20-Mar (PELT)	−71.62%	1-May (BP)	+119.32%
26-Apr (BP)	+36.38%	25-May (PELT)	+44.04%	7-Jun (BP)	+7.26%	5-Jun (BP)	+52.60%
17-May (BP)	+29.36%	7-Jun (BP)	+11.36%				

Table 4
Length of policy lag/lead for Seattle.

Date	Policy	Type	Vehicular I5-GLP (#Vehicles)	Vehicular SR99 (#Vehicles)	Transit (%App Usage)	Bike (#trips)
3-Mar	Seattle Emergency Declaration	Lag (days)	10	10	–	31
5-Mar	Tech.Co. Remote Order	Lag (days)	8	8	–	–
13-Mar	US Emergency Declaration	Lag (days)	0	0	–	–
16-Mar	50 + gathering ban	Lag (days)	4	4	12	–
23-Mar	Stay-at-home order	Lead (days)	3	3	–	–
		Lag (days)	41	69	83	–
1-Jun	Reopen Phase 1	Lead (days)	29	1	–	59

entertainment, recreational facilities, restaurants, and K-12 schools. Although Seattle showed a very similar vehicular traffic trend in terms of the length of lag from multiple restriction policies at its two data collection locations (I-5 GLP and SR99), overall, it had slightly longer lags (1–2 days) as compared with NYC. The magnitude of impact also varied in Seattle and NYC. Compared to pre-pandemic levels, City/State declarations of emergency and tech companies' remote work orders showed an 18.13% and 42.86% drop in traffic at I-5 GLP and SR99 in Seattle, compared to a 28.92% drop in NYC for the same period. The possible rationale behind these changes is the different land use and demographics. I-5 GLP, located in a residential area north of downtown Seattle, had a smaller impact from the NPIs than SR99, located in the downtown Seattle area near many office buildings and tech companies that allowed employees to work from home. NYC experienced a relatively larger impact from the restriction policies implemented before national declaration of emergency as compared to I-5 GLP (residential) and a smaller impact compared with SR99 (office and tech companies) in Seattle. A possible explanation for this might be that the vehicular traffic data collected for NYC is for all inter-borough crossings that had a "mix" of trip purposes, including residential, commute, commercial, and recreational purposes.

One interesting finding is that Seattle's declaration of emergency and tech companies remote work orders had a similar magnitude of impact as the national declaration of emergency, large gathering ban and closure of non-essential business in Seattle (I-5 GLP saw an 18.13% and 27.98% drop, SR99 saw a 42.86% and 43.36% drop), whereas the latter policy (non-essential business closure) had a much greater impact on NYC mobility (down 48.43% compared to the stage 1 drop of 28.92%). This is possibly because Seattle has several large IT companies (e.g., Amazon, Microsoft) and telework adoption began earlier and applied to all tech companies and public agencies. NYC has a higher industry share of education and health services, and financial activities (24% and 11% respectively), compared to Seattle (13% and 5%) (NYS Department of Labor, 2020; Employment Security Department, 2020), and these industries began teleworking only after the closure of schools and non-essential business. These industries also have a relatively lower tele-workable employment rate (0.54) compared to tech companies in fields like information technology (0.72) (Wang et al., 2020).

Differences were also identified in the reopening phases as traffic volume on I-5 GLP, Seattle was found to start to increase 29 days before the reopening (similar to that of 22 days in NYC), yet the traffic volume on SR99, Seattle started to increase at almost the same time as the reopening phase I (-1 day). Mass transit ridership in Seattle remained low and had not yet rebounded even after the reopening of the city. It is worth noting that Seattle's transit demand data was only available after March 16 and was generated in percentage change instead of absolute values. Thus, its change points and impact may need further validation when more data becomes available.

The observed patterns in bike counts are very different in Seattle as compared to in NYC. Multiple social distancing policies seem to have a combined lag effect on bike usage in Seattle. That is to say, the lags of different restriction policies are pointing to the same change point. It is worthwhile to mention that although PELT and BP detected multiple change points for bike demand, these points are all associated with low BCPD score, thus only one change point with relatively higher posterior probability was selected. After late March/early April, increased bike volume (+26.47%) with a steady mean value was observed. This trend continues through the end of June, the end of our observation period. A 3% and 47% increase in bike volume was observed in 2019 April and May respectively, as compared to the previous month. These numbers changed to 13% and 11% in April and May 2020, possibly due to the pandemic impact, fewer tourists, and a seasonal ridership increase (e.g., good weather). Besides the changes resulting from the subway midnight closure, the main difference of bike volume between NYC and Seattle may also be due to the different market share of personal and shared bikes.

6.2. Implementation lag

For simplicity, we only discuss the implementation lag of the stay-at-home and reopening orders. The length of the implementation lag for stay-at-home orders is defined as the delay between the time at which the first steep increase is observed in new daily hospitalization numbers and the time at which a stay-at-home order is announced. Similarly, the length of the implementation lag for reopening orders is defined as the delay between the time at which a sustained decline is observed in new daily hospitalization numbers and the time at which a reopening order is announced.

Based on the Bayesian probability, the change point results show that the implementation lags for stay-at-home and reopening orders are 13 and 9 days for NYC and 19 and 16 days for Seattle. The results indicate that if both cities' governments had acted

Table 5
Magnitude of Policy Impact on Transportation System for Seattle Based on Selected Change Points Determined by the Decision-making Rules. (The magnitude of impact is calculated as the percentage change of average traffic data between the two sequential detected change points. One change point may correspond to the impact of multiple temporally proximate policies.)

Vehicular I5-GLP (#Vehicles)		Vehicular SR99 (#Vehicles)		Transit (%App Usage)		Bike (#trips)	
Change point	Magnitude of impact	Change point	Magnitude of impact	Change point	Magnitude of impact	Change point	Magnitude of impact
13-Mar (PELT)	−18.13%	13-Mar (PELT)	−42.86%	28-Mar (PELT)	−29.48%	3-Apr (BP)	+26.47%
20-Mar (PELT&BP)	−27.98%	20-Mar (PELT)	−43.36%	28-May (BP)	−0.84%		
3-May (PELT&BP)	+30.17%	31-May (BP)	+35.66%				

immediately on early warning signs of potential risks from the coronavirus, stay-at-home orders could have been implemented 2–3 weeks earlier. There are fewer concerns about the implementation lag of the reopening as the government aimed for a safe phased reopening. The numbers presented here provide a reference for an ideal scenario with immediate government response. However, while knowing the best values that drive policy success, the dilemma exists on how to deal with tradeoffs between economics and public health considerations, especially when little is known about the virus. Furthermore, although not included in this study, other measures such as decline in deaths or hospital or ICU bed capacity can also be considered when evaluating implementation lag.

6.3. Performance of PELT, BP and BCPD

We conclude this section by discussing the performance of the three change-point detection methods implemented in this paper. Based on the empirical results from NYC and Seattle, we find that PELT is more sensitive to the fluctuation in mean and variance of the sequence data and usually detects more change points compared with BP. This is in agreement with the findings in the literature (Killick et al., 2012). For example, with respect to the vehicular traffic data in NYC (Fig. 2**(a)**), PELT detected two continuous waves of reduction in traffic volume during the announcement of a combination of social distancing orders while BP detected these two waves as one. While PELT showed a satisfactory performance, especially for the period when multiple social distancing policies were implemented, BP was found to be more effective for the post-stay-at-home period and during reopening phases (Table 3 and Table 5). For example, BP successfully detected that Citi Bike demand significantly increased after the midnight subway closure policy and the implementation of NYC Open Street policy (Fig. 2**(d)**). Another finding is that BP was able to automatically find the optimal number of change points by optimizing BIC and the residual sum of squares (RSS). BP also provided additional uncertainty information by identifying confidence intervals for each detected change point (Fig. 2 and Fig. 3).

The results of this study showed that, in most cases, BCPD scores helped determine which points detected by PELT and BP were more likely to be “true” by associating high posterior probabilities to these points. However, BCPD is overly sensitive to “smooth” data. For example, since transit demand in Seattle experienced almost no change (Fig. 3**(c)**, this dataset only includes data after mid-March), and BCPD produced too many high posterior probabilities in response to every small change in the data. BCPD is also not very useful when applied to data that is smoothed using moving averages (Fig. 5).

7. Lessons learned and implications for planning and policy

In this study, we investigated the length of the policy lag and the magnitude of impact brought by different policies on various transportation systems. The lessons learned from both NYC and Seattle showed that there is a significant interaction between released policies and the response of various traffic systems. Based on these results/lessons learned, a number of policy implications can be derived based on two aspects: length of the policy lag and the magnitude of impact on transportation systems.

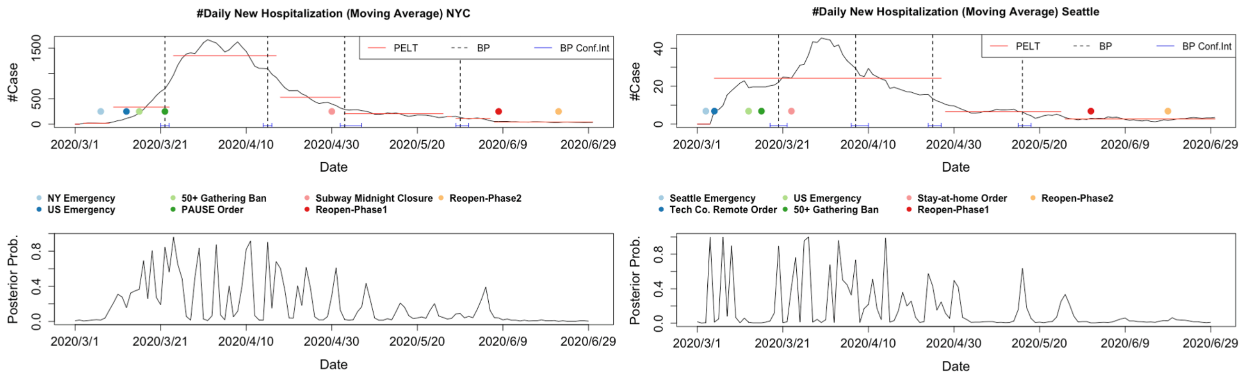
As mentioned in previous sections, multiple social distancing restriction policies that were released in a short time manner may have a combined effect on the transportation systems; they caused two dramatic drops in vehicular and transit systems. Moreover, the impact on a single transportation system may result from a mixed effect of the lag of one policy and the expectations of the subsequent policy. These lessons bring some implications for policy makers that there might be interactive effects in a combination of restriction-related policies. Moreover, public may learn lessons from previous restriction policies and react earlier to the subsequent policy. Some companies, especially the ones who are flexible on remote working may implement company-wide/industry-wide NPIs regardless of the issuance of official NPIs from city or state government.

For vehicular traffic system, both NYC and Seattle saw a significant drop due to a combination of social distancing restrictions policies released. The magnitude of impact on vehicular traffic system over the period of restriction policies can be used by policy makers to better understand and tackle the change of traffic system for future outbreaks. Moreover, during the reopening phases, vehicular traffic saw a faster recovering trend than other transportation systems. This brings the lessons that transportation agencies should allocate appropriate resources to make sure of roadway system readiness to avoid unnecessary congestion and accidents.

For public transit systems, both NYC and Seattle saw a similar steep decrease trend since the release of social distancing restrictions policies. Unparallel impact changes were observed in subway and bus system in NYC. This implies that strategies and resources should be planned and allocated differently for transit sub-systems. A reduced service with less labor for subway system, during and in the aftermath of COVID-19 or similar future outbreak, may be considered, taking into account the trade-off between system efficiency and expense. Moreover, different from the trend of vehicular traffic system, there was almost no lead effect for public transit systems during the reopening phase in both NYC and Seattle.

The observed patterns from bike counts in NYC and Seattle are very different. However, both cities saw an increase in early March while volume in other transportation systems decreased before the announcement of stay-at-home orders. Although the length of the lead time is different, increased bike volumes were also observed before and after the reopening of the cities. Micromobility has proved to be a feasible alternative travel mode in the pandemic and seems to become a part of the “new norm” in the aftermath of COVID-19. For future outbreaks, policy makers should consider spare parts inventory management for their bike share system (e.g., store certain number of additional bikes/scooters) and be prepared, both operationally and financially, for possible temporal and long-term travel mode shift. This encourages the coordination and collaboration between public and private sectors. Additionally, the difference in NYC and Seattle also implies the importance of planning different strategies depends on multiple criteria, like the market share of personal and shared bikes, station-based or dockless micromobility system, and coordination with open street projects.

Lessons learned from this analysis highlight the importance of jointly investigating both the length of policy lag and magnitude of impact. They can be useful indicators for policy makers and help them in planning appropriate and timely strategies and allocating



(a) NYC (b) Seattle

Fig. 5. Change point detection results – Implementation lags.

resources. For example, the magnitude of impact can be used as a baseline factor which helps transportation agencies to maintain the appropriate level of services in both pandemic and reopening periods.

8. Conclusions

There are understudied aspects of the length of the policy lag and the magnitude of impact brought by different policies on various transportation systems. These aspects of policy deserve more attention and can provide lessons from the aftermath of the COVID-19 pandemic.

In this paper, we developed a change point detection-based framework to explore the implementation and impact lag among government policies and transportation system in response to the COVID-19 outbreak. Cases studies were conducted for two of the U.S. cities most affected by COVID-19 in the U.S., New York City (NYC), and the City of Seattle. The case studies showed that by the complementary use of PELT, Breakpoint, and Bayesian change point detection, the proposed methodology is effective in identifying abrupt and significant changes in the performance of road, transit and bike systems.

Although a similar trend was observed in terms of the length of policy lag in both cities, especially for vehicular traffic, the magnitude of impact largely depended on the land use and sociodemographic characteristics of the area, as well as the type of transportation system. We also noticed that multiple social distancing policies had a combined effect on mobility. The National declaration of emergency was found to have no policy lag. Stay-at-home and reopening policies both had a lead effect indicating the general public responded earlier than the implementation of the policies. Transportation agencies should be aware of possible increased demand and prepare the readiness of their systems to allocate needed resources and labor. The National declaration of emergency, ban of gatherings of greater than 50 people with closure of entertainment, recreational facilities, restaurants, and K-12 schools, and stay-at-home order had the highest impact on different transportation systems.

In addition, the lag effect on bike systems varied greatly in different cities. Seattle saw an earlier rise in bike volume compared to that in NYC before the reopening of the city. The difference may be due to the different market share of personal and shared bikes in the two cities.

Given the necessity of linking mass responses and policy decisions, we hope this study provides useful insights into situational awareness and preparedness of transportation systems to help mitigate the negative effects of emergencies in future crises. Future work will concentrate on extending the current framework of online change point detection that is useful in modeling and predicting time series in real-time for similar events in the future or future major waves of the current pandemic.

CRediT authorship contribution statement

Zilin Bian: Methodology, Formal analysis, Investigation, Visualization, Writing - original draft. **Fan Zuo:** Methodology, Formal analysis, Investigation, Writing - original draft. **Jingqin Gao:** Conceptualization, Formal analysis, Visualization, Writing - original draft, Writing - review & editing, Supervision. **Yanyan Chen:** Data curation, Writing - original draft. **Sai Sarath Chandra Pavuluri Venkata:** Data curation, Writing - original draft. **Suzana Duran Bernardes:** Data curation, Writing - original draft. **Kaan Ozbay:** Conceptualization, Writing - review & editing, Supervision. **Xuegang (Jeff) Ban:** Conceptualization, Writing - review & editing, Supervision. **Jingxing Wang:** Data curation.

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