Exploring the impacts of travel-implied policy factors on COVID-19 spread within communities based on multi-source data interpretations

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ABSTRACT

The global Coronavirus Disease 2019 (COVID-19) pandemic has led to the implementation of social distancing measures such as work-from-home orders that have drastically changed people's travel-related behavior. As countries are easing up these measures and people are resuming their pre-pandemic activities, the second wave of COVID-19 is observed in many countries. This study proposes a Community Activity Score (CAS) based on inter-community traffic characteristics (in and out of community traffic volume and travel distance) to capture the current travel-related activity level compared to the pre-pandemic baseline and study its relationship with confirmed COVID-19 cases. Fourteen other travel-related factors belonging to five categories (Social Distancing Index, residents staying at home, travel frequency and distance, mobility trend, and out-of-county visitors) and three social distancing measures (stay-at-home order, face-covering order, and self-quarantine for out-of-county travels) are also considered to reflect the likelihood of exposure to the COVID-19. Considering that it usually takes days from exposure to confirming the infection, the exposure-to-confirm temporal delay between the time-varying travel-related factors and their impacts on the number of confirmed COVID-19 cases is considered in this study. Honolulu County in the State of Hawaii is used as a case study to evaluate the proposed CAS and other factors on confirmed COVID-19 cases with various temporal delays at a county-level. Negative Binomial models were chosen to study the impacts of travel-related factors and social distancing measures on COVID-19 cases. The case study results show that CAS and other factors are correlated with COVID-19 spread, and models that factor in the exposure-to-confirm temporal delay perform better in forecasting COVID-19 cases later. Policymakers can use the study's various findings and insights to evaluate the impacts of social distancing policies on travel and effectively allocate resources for the possible increase in confirmed COVID-19 cases.

1. Introduction

The Coronavirus Disease 2019(COVID-19) has spread rapidly across the globe since its first identified case in Wuhan, Hubei Province, China (Jiang et al., 2020). It is a respiratory illness that spread mainly from person-to-person in close contact (within about 6 feet or 1.8 m) with an infected person through his or her respiratory droplets (e.g., coughing, sneezing, and talking) that land in the mouths or noses of uninfected people (CDC, 2020). The World Health Organized declared the COVID-19 outbreak as a pandemic on March 11, 2020, with countries such as the United States, Brazil, and India being hit the hardest. At present (August 19, 2020), over 22 million people worldwide have been

infected by COVID-19, and more than 783,000 people have lost their lives (The New York Times, 2020). Several studies have shown that the low-income population and/or minorities (e.g., African Americans and Hispanics) are affected the most by COVID-19 in the U.S. (Amram et al., 2020).

To slow down the spread of COVID-19, numerous countries (e.g., China, Italy, and Spain) have introduced *social distancing measures* to limit close social contact and reduce COVID-19 exposure. These measures can range from aggressive measures like mandatory work-from-home orders and travel restrictions to less restrictive ones such as reducing the number of seats in indoor facilities. These measures and other COVID-related health measures such as contact tracing and rapid

diagnosis are effective in many countries such as South Korea and Spain. The main goal of these measures is to "flatten the curve" of the COVID-19 pandemic (i.e., slow the spread of the epidemic so that the peak number of people needing care at a time is reduced) to reduce the burden of the healthcare system (Park et al., 2020; Saez et al., 2020). These measures profoundly impacted travel-related decisions as many people were asked to work-from-home and most non-work-related activities were canceled. These travel-related decisions can include mode choice, route choice, trip frequency, travel distance, non-work-related destinations, etc. Several studies have shown that there were drastic drops in car traffic, public transit ridership (often caused by reduced service frequency and mandatory face-covering for transit riders), and airline passengers in many countries (Saez et al., 2020; Yeli and Khan, 2020; Engle et al., 2020; Gao et al., 2020; Wen et al., 2020; Sobieralski, 2020; de Haas et al., 2020; Hadjidemetriou et al., 2020).

With these initial successes in combating COVID-19 spread, many countries and regions have gradually lifted or relaxed various social distancing and other COVID-related health measures, and most people returned to their travel and different types of activity routines in May 2020 (Guo and Peeta, 2020; Yang et al., 2020). The second wave of COVID-19 (some suggested that many countries are still in the middle of the first wave) has been observed across the world, particularly in some states in the U.S., such as California, Texas, and Florida (Strzelecki, 2020; Xu and Li, 2020). Despite some efforts taken recently at city and state levels to curtail the second wave, many states, business owners, and individuals are against drastic social distancing measures such as lockdowns and restaurant closure (Bonaccorsi et al., 2020; Atkeson, 2020). Several studies have shown that these lockdown measures have long-term economic, physiological, and phycological impacts on millions of people (Yin et al., 2020; Pakenham et al., 2020). The compliance with and the willingness to comply with these measures may also deteriorate as the duration of the measures increases and can be influenced by people's perceptions and beliefs (Briscese et al., 2020; Painter and Qiu, 2020). Arkansas, California, Florida, Montana, Oregon, and Texas all recorded record single-day coronavirus deaths on July 28, 2020, as many states across the U.S. started to reopen (World Economic Forum, 2020). The surge of COVID-19 cases across the U.S. suggests that the total number of confirmed cases will continue to rise as long as there are still a large number of people infected by COVID-19, most people don't change their activity routines, the implementation of social distancing measures are limited, the compliance rate with social distancing measures is low, and COVID-19 vaccines are not widely available.

This study seeks to (i) propose a Community Activity Score (CAS) based on inter-community traffic characteristics (in and out of community traffic volume and travel distance) to capture the current travel-related activity level compared to the pre-pandemic baseline, (ii) understand the relationship among CAS and other travel-related factors, social distancing measures, and confirmed COVID-19 cases to study the possible connection between the likelihood of exposure to confirmed infections, (iii) capture the exposure-to-confirm temporal delays between possible COVID-19 exposure and confirmed COVID-19 cases, and (iv) evaluate the potential of using travel-related factors and policy factors to predict COVID-19 cases in coming days. Honolulu County in the State of Hawaii is used as a case study to evaluate the proposed CAS and other factors on confirmed COVID-19 cases with various exposure-to-confirm temporal delays. All the data used in this study has been converted to county-level data. Considering the nature of the data, four types of models were considered, including Poisson, Negative Binomial, Zero-inflated Poisson, and Zero-inflated Negative Binomial models. The Negative Binomial modeling approach was used based on Vuong test and overdispersion parameter (α) t statistics, and its model estimation results were used for interpretation. The case study results show that CAS and other travel-related factors can be used to predict confirmed COVID-19 cases later so that policymakers can allocate resources for the possible increase in confirmed COVID-19 cases.

The remainder of the paper is organized as follows. The next section describes the existing literature related to travel and infectious disease spread, and COVID-19 spread. The following section discusses the method and data used to quantify CAS, other travel-related factors, and policy factors. After that, the study region's details and the descriptive statistics of all the variables are presented. The econometric model results and the prediction power of models with different exposure-to-confirm temporal delays are presented. In section 6, policy insights based on the model estimation results are highlighted. The last section provides some concluding comments and future research directions.

2. Literature review

Global pandemics, dating back to the Black Death (occurred in Asia and Europe in the 14th century) and the more recent example of the severe acute respiratory syndrome (SARS) pandemic in 2003, can significantly increase the mortality rate over large geographic areas that can cause drastic social, economic, and political disruption (Madhav et al., 2017). The World Health Organization (WHO) has designed specific standards that compel its member states to prepare, detect, report on, and respond to compact such infectious diseases after the SARS pandemic (Katz, 2009). Such standards potentially enable the WHO to lead a more coordinated effort to combat global pandemics which it successfully did in combating a 2009 influenza outbreak.

It has long been established that travel plays a significant role in the spread of infectious diseases. Cliff and Haggett (2004) analyzed three examples, including importing measles into Fiji, behavior changes in Iceland after a measles epidemic, and changes in the spread of cholera within the U.S. They argued that the development of transportation technologies promoted massive increases in personal mobility and the speed of infectious disease transfer. Mangili and Gendreau (2005)and Findlater and Bogoch (2018) also warned that the increasing ease and affordability of air travel plays a critical role in spreading many infectious diseases as air travel contributed significantly to the SARS pandemic in 2003. Hence, one of the most common practices to slow down the spread of contagious disease is to limit entry points (e.g., airports and border checkpoints) to reduce the possibility of virus traveling (Sun et al., 2020). It requires constant communication, information sharing, and coordination among people, communities, states, and countries.

Unfortunately, COVID-19 has quickly evolved from an isolated case of unknown origin in Wuhan, China to a global pandemic, partly due to insufficient information communication and sharing, and coordinated effort among countries. Its carriers may not show symptoms, only show mild symptoms that people may treat as a common cold, or have lagged symptoms that may only appear 2–14 days after exposure to the virus. COVID-19 has spread relatively easily spread among people (CDC, 2020). Chinazzi et al. (2020) concluded that the epidemic progression was only delayed by 3–5 days within China, despite a drastic effort by the Chinese government to implement a travel quarantine of over 10 million people in Wuhan after January 23, 2020. They also found that travel bans restricting travel from China were only partially effective for some countries. For example, Linka et al. (2020) found that banning air travel from outside Canada could be more efficient in managing the COVID-19 pandemic than border reopening and quarantining 95% of the incoming population. At the start of April, at least 90% of the population lived in a country with some form of travel restriction on people arriving from other countries regardless of their citizenship (Devi, 2020). These travel restrictions, along with various types of social distancing and self-isolation measurements, have various socioeconomic implications (Nicola et al., 2020). Reduced workforce and job opportunities can lead to reduced income and living standards for workers, particularly in the air travel and tourism industries. Schools shutting down and moving educational activities online can lead to children with special needs falling behind. The demand for commodities and manufactured products has decreased, and panic-buying and stockpiling of

food products have been observed worldwide. People under travel restrictions, social distancing, and self-isolation measurements also experience tremendous psychological burden. Morgul et al. (2020)found that over 60% of the participants experienced psychological fatigue in a cross-sectional study conducted in Istanbul, Turkey, between March and June 2020.

The U.S. government introduced its travel ban for some countries very early. Still, other COVID-19 countermeasures within the country are largely uncoordinated at the federal level, and the enforcement level varies among states (Sun et al., 2020). Widespread COVID-19 misinformation, inconsistency in CDC guidelines, and collective exhaustion with COVID-19 related restrictions have emerged as formidable adversaries for government to implement and enforce these restrictions (Meichtry et al., 2020). Furthermore, people's needs to complete their essential travel (e.g., visiting grocery stores, pharmacies, and hospitals) and craving to attend activities outside of the home such as sports, entertainment, and family gatherings have also driven many states to lift or ease COVID-19 related restrictions when many people believed that the peak in coronavirus cases might have passed around June 2020.

The lift or ease COVID-19 related restrictions, along with the reopening of the economy and people's desire to travel and connect, can be partly reflected in the increase in air and road travel. According to Transportation Security Administration (TSA), the number of people going through TSA checkpoints has increased from around 100 thousand people in April to approximately 800 thousand people daily in December (TSA, 2021). Simultaneously, the number of COVID-19 cases surged across the U.S. since June 2020, varying between different states. These observations show a clear correlation among travel-related factors, social distancing measures, and confirmed COVID-19 cases. Despite some attempts to quantify some travel-related factors, it is still challenging to methodically quantify travel-related factors for a community and how they are connected to confirmed COVID-19 cases. Furthermore, some of the models used by Chinazzi et al. (2020) and Linka et al. (2020) also rely on high-resolution data availability which can be challenging for some communities.

One of the more recent examples of connecting travel and confirmed COVID-19 cases is the Social Distancing Index (SDI) developed by the Maryland Transportation Institute (2020). It is calculated as a weighted sum of six county-level mobility metrics, including the percentages of people staying at home, reduction in all trips, reduction in work trips, reduction in non-work trips, reduction in out-of-county trips, and reduction in travel distance. It is an integer (between 0 and 100) that reflects the extent to which residents and visitors are practicing social distancing, where 0 indicates no social distancing is observed, and 100 shows all residents are staying at home and no visitors are entering the county. However, it is not clear to the authors how the weights are calculated. The same weights were also assigned to each county across the U.S., limiting its ability to reflect the potential travel pattern differences among different counties. For example, the overwhelming majority of out-of-county travel for counties such as Honolulu is through the air which can be easily controlled, while most of the out-of-county trips for counties such as Los Angeles County is through land which cannot be easily controlled. It is not reasonable to assign the same weight to the percentage reduction of out-of-county trips for these two types of counties when calculating SDI. Furthermore, limited studies have been done to understand (or model) the relationship among travel-related factors, social distancing measures, and confirmed COVID-19 cases.

To address these limitations, this study seeks to (i) propose a CAS to quantify current car travel-related activity compared to a pre-pandemic baseline and (ii) use econometric models to understand its relationship, along with the relationship between other travel-related factors, and social distancing measures, with confirmed COVID-19 cases while accounting for the potential temporal delays due to the lag between COVID-19 exposure and COVID-19 infection confirmation. Finally, the estimated models with different exposure-to-confirmation temporal

delays will also be evaluated to see if they can be used to predict the number of confirmed COVID-19 cases in the coming days.

3. Methods and data description

In this section, the quantification methods and data sources for 15 travel-related independent variables considered belonging to six categories (CAS, SDI, *residents staying at home, travel frequency and distance, mobility trend,* and *out-of-county visitors*), 3 policy factors, and one dependent variable (daily confirmed COVID-19 cases) are presented. Furthermore, the description of four possible modeling approaches is also presented and the final modeling approach selection process is also described. It is important to note that only one modeling approach was used for result interpretation.

3.1. Quantifying CAS

The number of people traveling to and away from a community and miles traveled by these people daily have been used to reflect the community's mobility level, accessibility level, activity patterns, neighborhood built environment, etc. (Wellman, 2005; Cervero and Murakami, 2010; Zhang et al., 2012; Ding et al., 2017; Guo and Peeta, 2020). In the context of a global pandemic, it can also reflect how many possible contacts were made with people outside the community and the community activity level compared to the pre-pandemic baseline. CAS is a quantification method proposed in this study to capture the current travel-related activity level compared to the *pre-pandemic baseline* based on inter-community traffic characteristics (traffic volume and travel distance). The pre-pandemic baseline is defined as the median value for that day of the week from a 4-week period before the week of the first identified COVID-19 case. CAS can be calculated as follows,

$$A_{mn} = \left(a \frac{I_{mn} D_{mn}}{I_{m0} D_{m0}} + b \frac{O_{mn} D_{mn}}{O_{m0} D_{m0}} \right) * 100 \tag{1}$$

where A_{mn} is the activity score of community m on day n during the pandemic.

a and b are predetermined coefficients, and a + b = 1,
I_{mn} is the incoming traffic volume of the community m on day n,
I_{m0} is the average incoming traffic volume of the community during the pre-pandemic baseline,
O_{mn} is the outgoing traffic volume of the community m on day n,
O_{m0} is the average outgoing traffic volume of the community during the pre-pandemic baseline,
D_{mn} is the average travel distance of the community m on day n,
D_{m0} is the average travel distance of the community during the pre-pandemic baseline.
As CAS is a relative activity level compared to the pre-pandemic baseline, the baseline value for CAS is 100. In this study, a = b = 0.5.

The average travel distance data (D_{mn} and D_{m0}) used to calculate CAS in Eq. (1) is collected through Descartes Labs (2020). The traffic volume data was collected from the Hawaii Department of Transportation (HDOT, 2020). Considering that the travel distance data (as well as most other travel-related data and COVID-19 data) is only available at the county-level at the time of the study, CAS is converted from community-level to county-level. Hence, county-level CAS is calculated as follows,

$$A_n = \sum_{m=1}^{M} w_m A_{mn} \tag{2}$$

where A_n is the county activity level on day n, w_m is the weight of community m in the County, and M is the total number of communities in the County. In this study, each community's weight, w_m, is proportional to its total population within the county.

3.2. Quantifying other factors

The data of SDI was collected from Maryland Transportation Institute (2020), which can be calculated as follows,

$$SDI = 0.8 * [H + 0.01 * (100 - H) * (0.1 * T + 0.2 * W + 0.4 * NW + 0.3 * D) + 0.2 * O \quad (3)$$

where H is the percentage of people staying at home (traveled less than one mile from their residence).

T is the percentage change in the number of trips made compared to the pre-pandemic baseline. A trip is defined as movements that include a stay of longer than 10 min at an anonymized location away from home,
W is the percentage change in the number of work trips made compared to the pre-pandemic baseline,
NW is the percentage change in the number of non-work trips made compared to the pre-pandemic baseline,
D is the percentage change in the daily travel distance compared to the pre-pandemic baseline,
O is the percentage change in out-of-county trips made compared to the pre-pandemic baseline.

The authors were unable to identify the methods used to assign weights to different travel-related factors.

Apart from CAS and SDI, the rest of the 13 travel-related factors can be classified into three categories. "Travel frequency and distance" category includes percentage of people staying at home from USDOT (2020), the daily trip frequency from USDOT (2020), estimated mode usage frequency (walking, driving, and using transit) from Apple (2020), and median maximum travel distance compared to the pre-pandemic baseline (Descartes Labs, 2020). Factors belonging to the "mobility trend" category include six variables, including the number of visits to retail/recreation (restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters), grocery/pharmacy (grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies), parks, transit stations, places of work, and places of residence compared to the pre-pandemic baseline from Google (2020). Considering Honolulu County's nature, the only out-of-county people were coming from the airport during the study period. Table 1 summarizes the descriptions and data sources of one dependent variable and fifteen travel-related independent variables considered.

Three policy factors related to social distancing measures are considered including mandatory stay-at-home order (i.e., if there is a mandatory stay-at-home order), mandatory traveler self-quarantine order (i.e., mandatory 14-day self-quarantine order after arriving in Hawaii), and mandatory face-covering order (i.e., mandatory face-covering request for all essential business order). Mandatory traveler self-quarantine order is a unique policy implemented at a state level among all the states in the U.S. At the same time, the other two have been applied in many states throughout the pandemic.

3.3. Data modeling

Before conducting data modeling, the first two steps are removing variables with possible high strong correlation and multicollinearity among independent variables. Pearson correlation analysis was conducted among independent variables to identify the potential strong correlation (i.e., the absolute value of the correlation coefficient is higher than 0.5). Then, multicollinearity tests were conducted using variance inflation factors (VIFs).

Considering the dependent variable (daily COVID-19 cases) is a count variable, four types of econometric modeling methods for modeling count data were considered in this study, including Poisson,

Table 1
Travel-related variable description and data sources.

Variables	Data description	Data source
COVID	Daily confirmed cases of COVID-19	The New York Times (2020)
CAS	Proposed Community Activity Score (CAS)	HDOT (2020)
SDI	Social Distance Index: ranging from 0 (no social distancing is observed) to 100 (everyone staying at home and no visitors are entering the county)	Maryland Transportation Institute (2020)
Travel frequency and distance		
Home	Percentage of people traveling less than 1 mile away from their residence place compared to the pandemic baseline.	USDOT (2020)
Trip	The number of trips made per day compared to the pandemic baseline. A trip is defined as movements that include a stay of longer than 10 min at an anonymized location away from home.	USDOT (2020)
Drive	Daily Volume of driving directions requests compared to the pandemic baseline.	Apple (2020)
Transit	Daily Volume of transit directions requests compared to the pandemic baseline.	Apple (2020)
Walk	Daily Volume of walking directions requests compared to the pandemic baseline.	Apple (2020)
Distance	The maximum travel distance to a point from the initial point of the day (i.e., the max-distance mobility) compared to the pandemic baseline.	Descartes Labs (2020)
Mobility trend		
Retail	The number of visits to restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters compared to the pandemic baseline.	Google (2020)
Grocery	The number of visits to grocery markets, food warehouses, farmers' markets, specialty food shops, drug stores, and pharmacies compared to the pandemic baseline.	Google (2020)
Park	The number of visits to national parks, public beaches, marinas, dog parks, plazas, and public gardens compared to the pandemic baseline.	Google (2020)
Stations	The number of visits to national parks, public beaches, marinas, dog parks, plazas, and public gardens compared to the pandemic baseline.	Google (2020)
Work	The number of visits to places of work compared to the pandemic baseline.	Google (2020)
Residences	The number of visits to places of residence compared to the pandemic baseline.	Google (2020)
Out-of-county visitors		
Airport	The number of people through Hawaii airport (hundreds).	Hawaii Tourism Authority (2020)

Negative Binomial (NB), Zero-inflated Poisson (ZIP), and Zero-inflated Negative Binomial (ZINB) models. Overall, NB models outperform Poisson models because the Poisson distribution restricts the mean and variance to be equal. In an NB model, the probability of day n having c_n cases of confirmed COVID-19 cases is given by (Washington et al., 2020):

$$P(c_n) = \frac{EXP(-\lambda_n)\lambda_n^{c_n}}{c_n!} \quad (4)$$

where $P(c_n)$ is the probability of day n having c_n cases of confirmed COVID-19 cases and λ_n is the parameter which can be estimated as a function of explanatory variables which can be written as,

$$\lambda_n = EXP(\beta x_n + \varepsilon_n) \quad (5)$$

where x_n is a vector of explanatory variables and β is a vector of a parameter.

Unlike most counties in the U.S., Honolulu County has 31 days out of 166 days without any confirmed COVID-19 cases throughout the pandemic period. The data may belong to two-state regimes (normal-count and zero-count states). Zero-inflated models were also considered for model estimation. The model formulation details can be found in Washington et al. (2020).

The data modeling process and model selection process consist of two steps: (i) Vuong test and overdispersion parameter (α) t statistics are used to select among four possible modeling methods (Shankar et al., 1997). Table 2 presents the model selection guideline based on Shankar et al. (1997). This means that only one of the four modeling method is going to be selected based on the results of this step; and (ii) various goodness-of-fit methods were used to evaluate the different models for each modeling process, including the McFadden pseudo-R^2, the Akaike Information Criterion (AIC), and the corrected Akaike Information Criterion (AICc). Models with higher values of McFadden pseudo-R^2, and lower values of AIC and AICc are considered to have better statistical fits.

3.4. Evaluating the performance of models with different exposure-to-confirm temporal delays

Studies by the CDC have shown that the COVID-19 symptoms may appear 2–14 days after people's exposure to COVID-19, and it may take days between testing and confirming COVID-19 infections (CDC, 2020). The exposure-to-confirm temporal delay between the time-varying travel-related factors, social distancing measures, and their impacts on the number of confirmed COVID-19 cases are considered in this study. Up to 14-day temporal delay to no delay were considered, and their performances were compared based on model prediction accuracy. Hence, 15 dependent variables are considered for model estimation. These dependent variables are daily confirmed COVID-19 cases with 0–14 days of temporal delay. These various temporal delays are used to capture the temporal delays from exposure (which connects to travel-related factors) to confirmed infection. For example, with n day of temporal delay, the independent variable values are from the day i, and the dependent variable value (i.e., confirmed COVID-19 cases) is from day $i + n$. To evaluate the performance of model results with different temporal delays, the final model with each temporal delay was used to forecast the number of COVID-19 cases for the next 22 days (i.e., between August 17, 2020 and September 7, 2020). A model with a higher prediction power may suggest that the model can better reflect the community's actual exposure-to-confirm temporal delay.

4. Honolulu COUNTY'S COVID-19 response and descriptive statistics

4.1. Study area description

Honolulu County in the State of Hawaii is selected as the case study region. First, unlike most counties in the U.S., most of the traffic coming in and out of the county is through the airport. The State of Hawaii introduced travel restrictions early during the pandemic to the airport's traffic and enforce out-of-state mandatory 14-day quarantines. Second, Hawaii introduced relatively strict social distancing measures, and the testing capacity gap (i.e., ability to provide enough tests based on World Health Organization-recommended positive test rate proxy) remains relatively low, suggesting the state has sufficient testing through the pandemic (The COVID Tracking Project, 2020). Finally, the authors have access to the traffic volume data from all the sensors in Honolulu County.

Fig. 1 shows zones in Honolulu County and Table 3 summarizes some of each community's key characteristics using American Community Survey 5-year estimates in 2015 (USCB, 2016). Downtown Honolulu is located in Zone 9 and most of the tourist attractions were located in the Waikiki region (Zones 11 and 12). It is important to note that zone (community) boundaries are set based on a combination of zip code boundaries and traffic volume sensors' locations across the county. Other than traffic volume data, all the travel-related data is at the county-level.

4.2. Honolulu County's COVID-19 response and policy factors

The first COVID-19 infection in Honolulu County was confirmed on Friday, March 6, 2020. The *pre-pandemic period* for Honolulu County is set between February 3, 2020, to March 1, 2020 (one month before the first confirmed COIVD-19 infection on March 6th, 2020). The *study period* is set between March 9, 2020 (Monday) and August 16, 2020 (Sunday) (the following week after the first confirmed COVID-19 case). It includes 161 days or 23 weeks. Fig. 2 shows the daily COVID-19 cases in Honolulu County and some of the study period's important policies. The *forecasting period* is set between August 17, 2020, and September 7, 2020, to evaluate the model's prediction power with different exposure-to-confirm temporal delays.

Fig. 3 shows the daily traffic volumes (in and out of) for each zone. As shown in Fig. 3, a clear pattern can be observed for each zone that the weekend volume is often way lower than weekday volume. It also can be observed that after initial traffic volume reduction in March and April, the traffic volume for each zone has recovered to around 80 to 90 percent of the pre-pandemic baseline. Another interesting observation is the sharp traffic volume increase after June 12, 2020, in Zone 9. A possible reason is that Zone 9 contains downtown Honolulu and Chinatown, both of which were hit the hardest during the COVID-19 pandemic. People in that zone recovered the slowest among all the people in Honolulu County. Furthermore, many government offices are also located in Zone 9, with most of them reopened in June. To further illustrate the traffic volume differences across different days of the week, Fig. 4 presents the monthly average traffic volume for each day of the week throughout the study period.

Table 4 summarizes some of the Hawaii government's important policies during the pandemic, and the information is based on the Hawaii Governor Office and various news websites. Many of these policies were still being used at the time of the study (i.e., 8/23/2020). Hawaii remains one of the states with the lowest COVID-19 cases per capita (8215 cases per one million people compared to the national average of 20,712 cases per one million people) in the U.S. However, Hawaii is experiencing a surge in cases after its decision to gradually opening up the economy.

Based on the policy response, three policy factors are introduced, and all of them are indictor variables. First, *no mandatory stay-at-home order factor* is an indicator variable. It equals one when no mandatory stay-at-home order is in place (between September 3, 2020 and 3/22/2020 and between May 5, 2020 and 8/16/2020) and otherwise equals zero. Second, the *traveler self-quarantine order factor* is an indicator variable, where it equals one when there is a mandatory 14-day self-quarantine order (between 3/26/2020 and 8/16/2020) and otherwise equals zero. The last one is the *mandatory mask order factor*. It is also an indicator variable. It equals one when there is a mandatory face-covering order for people going to most businesses (between 4/21/2020 and 8/

Table 2
Decision guidelines for model selection among Poisson, NB, ZIP, and ZINB.

		t statistic of the NB overdispersion parameter α	
		$< |1.96|$	$> |1.96|$
Vuong statistic for ZINB and NB comparison	$< |1.96|$	ZIP or Poisson	NB
	$> |1.96|$	ZIP	ZINB

Fig. 1. Communities in honolulu county.

Table 3
Zip code-based Communities in Honolulu County.

Zone ID	Zip code	Population (2015)	Zone land size (km^2)	Density (person/km^2)
1	96712, 96717, 96730, 96731, 96762, 96786, 96791, 96792, 96857, 96759	129,220	768.22	168.20
2	96734, 96744, 96763, 96795, 96825	146,672	698.54	209.97
3	96706, 96707	112,917	169.19	667.38
4	96797, 96782, 96789	169,991	213.17	797.43
5	96701	39,270	50.95	770.69
6	96818, 96860, 96853	59,717	40.14	1487.61
7	96859, 96819	55,177	66.67	830.10
8	96817	57,405	25.25	2273.24
9	96813	22,391	9.55	2344.30
10	96822	45,979	21.23	2165.61
11	96826	31,143	2.81	11084.54
12	96815	18,680	4.33	4307.18
13	96816	78,190	34.76	2249.25
14	96821	18,914	31.09	608.36
Total		985,666	2135.73	461.51

16/2020) and otherwise equals zero.

4.3. Travel-related behavioral changes during the study period

Table 5 presents the weekly average values of all travel-related variables for each week during the study period. There are five key observations. First, in terms of CAS and SDI, the results show that travel-related community activities experienced a sharp decrease during the mandatory shut down period (Week 3 to Week 8). At the end of the study period, both measures show that the community activity and social distancing practice returned close to the pre-pandemic baseline (i.e.,

close to 100). Second, the percentage of people staying at home (i.e., people who did not travel longer than one mile away from home) has increased significantly due to a combination of the implementation of social distancing measures, many people that were working from home, and the rising unemployment rate which increased from 2.7% in February to 13.1% in July with the unemployment rate peaked at 23.8% in April (U.S. Bureau of Labor Statistics, 2020). Third, people traveled less frequently, within a shorter range, driving, using transit, and walking less frequently. Traveling by bus reduces the most (about 80% reduction compared to the pre-pandemic baseline) due to a multitude of reasons such as reduced travel needs, mandatory wearing a face mask on the bus after April 21, 2020, and people's worry of COVID-19 spread in a closed environment. Fourth, people visited places such as retail stores, grocery stores, parks, workplaces, and transit stations less frequently in terms of the mobility trend. Visits to grocery stores reduce the least among the mobility trend (maintained at over 70% of the pre-pandemic visits). This may suggest that going to grocery stores was considered essential for many people in Honolulu County. Last but not least, the number of passengers through the airport dropped significantly from 200 to 300 thousand per day to 10–20 thousand per day after the pandemic outbreak and the mandatory 14-day quarantine order. Over 90% of the GDP in the State of Hawaii depends on the service and tourism industries, and this likely contributed to the increasing unemployment rate in Hawaii.

5. Results

5.1. Multicollinearity tests and modeling method selection

Using the first two steps of the independent variable selection process in section 3.4, 12 out of the 18 possible variables are removed due to high correlations with other variables and multicollinearity. The remaining variables include 4 travel-related variables and two policy variables. The travel-related variables are travel-related factors,

Table 4
COVID-19 responses by state of Hawaii.

Date	COVID-19 Responses
3/5	Gov. David Ige issued an **emergency proclamation** that aims to prevent, contain, and mitigate the spread of COVID-19, and to provide emergency relief if necessary.
3/6	The **First** confirmed COVID-19 case in Hawaii.
3/9	The first Monday after the First confirmed COVID-19 cases in Hawaii.
3/13	The **30-day federal ban on flights from Europe** except the United Kingdom began. The Hawaii Department of Health recommends **large, crowded gatherings, or public events** that include 100 people or more be **postponed or canceled**.
3/15	The Hawaii State Department of Education is **extending its spring break** for all public and charter school students.
3/20	The County of Honolulu has **mandated the closure of restaurants, parks, and nightclubs** for indoor service.
3/23	The County of Honolulu has issued **stay-at-home, work-at-home orders**.
3/26	Governor David Ige has ordered that all persons entering Hawaii to **self-quarantine for 14 days or for the duration of their stay** in Hawaii, whichever is shorter.
3/30	Governor Ige announced that **anyone traveling between islands will now be required to self-quarantine** in their home or other lodgings for 14 days.
4/17	Governor David Ige is encouraging everyone to **wear cloth face masks** whenever in public places with the exception of exercising outside, as long as social distancing requirements are maintained. Governor David Ige **closes all state beaches** to sitting, standing, lounging, lying down, sunbathing, and loitering, including restrictions on boating, fishing, and hiking.
4/21	Everyone **must wear a mask** in most city settings, including on the city bus, visiting businesses, or ordering from the drive-thru.
5/5	The Stay-at-Home order is now referred to as the **Safer-at-Home** order. Selected Hawaii **State Parks re-opening** for hiking and beach access but not gatherings
5/7	**Phase One Businesses reopen.**
5/15	**Retail stores and shopping** malls in the County of Honolulu can reopen under the Safer-At-Home order.
5/18	Hawaii Moves into "**Acting with Care**" Phase
5/22	**Major stores** such as Macy, Apple, and Ross **reopened** in the County of Honolulu.
5/29	Reopening of some tourist attractions (Zoo, Kualoa ranch, Wet and wild Hawaii, etc.).
6/5	Reopening of **dine-in restaurant services.**
6/25	Gov. David Ige announced that the **reopening of Hawaii tourism** would be August 1, 2020, and tourists with a valid negative COVID-19 test can enter Hawaii without self-quarantine.
7/10	The Pearl Harbor National Memorial reopened.
7/14	Gov. David Ige announced that the reopening of Hawaii tourism would be **postponed** until September 1, 2020.
7/18	Honolulu County Public School announced that the public schools would be opened to students on August 4, 2020.
7/28	Public school reopening day was postponed until August 17, 2020.
7/29	The Governor announced he would take action to "**reinstate some of the measures** we've relaxed over the last few weeks" in the fight against COVID-19 in Hawaii.
8/6	Starting Saturday, August 8, 2020, **all State Parks on the island of Oahu will be closed** until September 4, 2020.
8/18	Honolulu County announced the order "**Act Now Honolulu: No social Gatherings**" to shut down beaches, parks, and bars. The reopening of Hawaii tourism would be **postponed** until October 1, 2020. New "**Stay-at-home**" order was expected in the coming days.

including *CAS* (the proposed community activity index), *park* (i.e., number of visits to national parks, public beaches, marinas, dog parks, plazas, and public gardens compared to the pandemic baseline), *trip* (number of trips made per day compared to the pandemic baseline), and *walk* (daily Volume of walking directions requests compared to the pandemic baseline). The two policy variables are the *mask order* (if there is a mandatory face-covering order for people going to most businesses) and *no stay home* (no mandatory stay-at-home order is in place).

These six variables are used to construct Poisson, NB, ZIP, and ZINB models. Using Vuong test and overdispersion parameter (α) *t* statistics under the guideline highlighted in Table 2. Overdispersion parameter (α) *t* statistics shows that NB performs better than Poisson but the Vuong test show that NB and ZINB are indistinguishable. Hence, only NB is used to illustrate model estimation results.

5.2. Modeling results

Table 6 presents the model estimation results with different exposure-to-confirm temporal delays using Negative Binomial regression models. All the independent variables that were found to have statistically significant correlations ($z \geq 1.96$ or statistically significant

at 0.95 level of confidence) were included in the final models. It is important to note that if a variable is not included in the final models because of its statistical significance, it does not mean that it is not correlated with the dependent variable. It can have a weak correlation with the dependent variable and/or the models with this independent variable have a lower goodness-of-fit compared to the final model.

5.3. Modeling prediction power

To evaluate NB models with different exposure-to-confirm temporal delays, it is important to evaluate whether these models can be used to predict the number of COVID-19 cases in coming days and how accurate these models are in predicting COVID-19 cases in the coming days. For example, suppose the estimated model has 0 temporal days. In that case, the model can only be used to predict the number of COVID-19 cases on the same day by using that day's travel-related data. If the estimated model has 14 temporal days, the model can only be used to predict the number of COVID-19 cases 14 days later using that day's travel-related data.

Table 7 illustrates the prediction results of all 15 models (from no delay to 14-day delay) for forecasting daily COVID-19 cases between
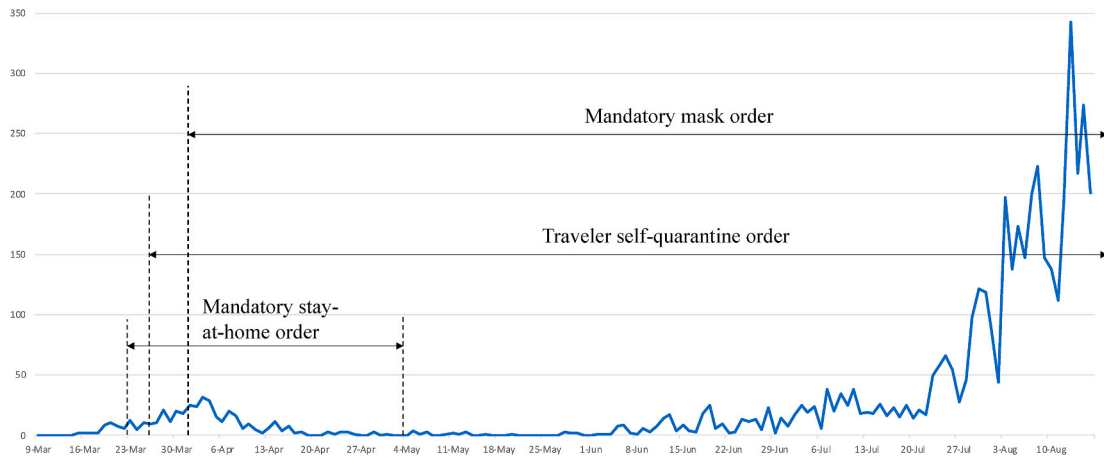
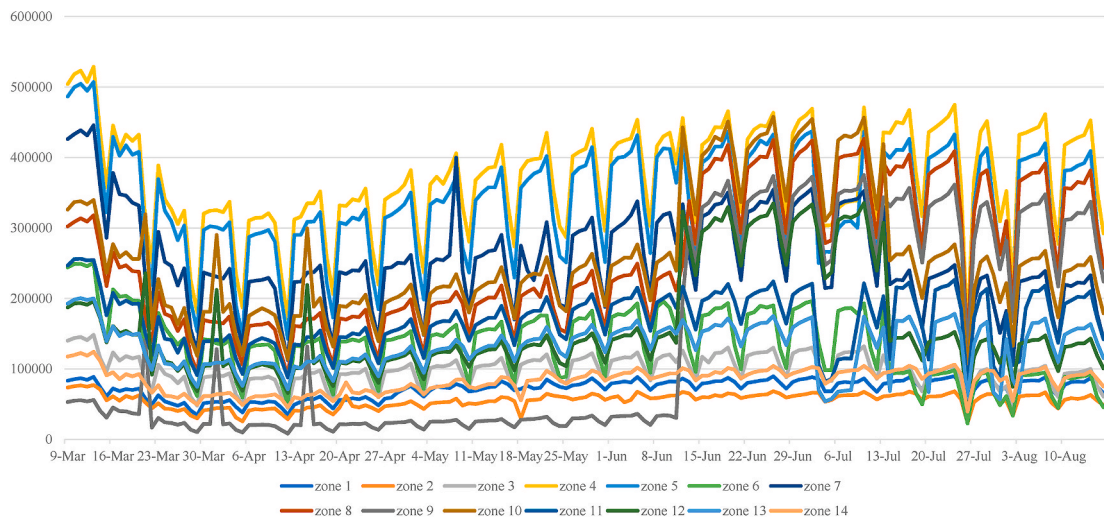**Fig. 2.** Daily COVID-19 cases and important policies.

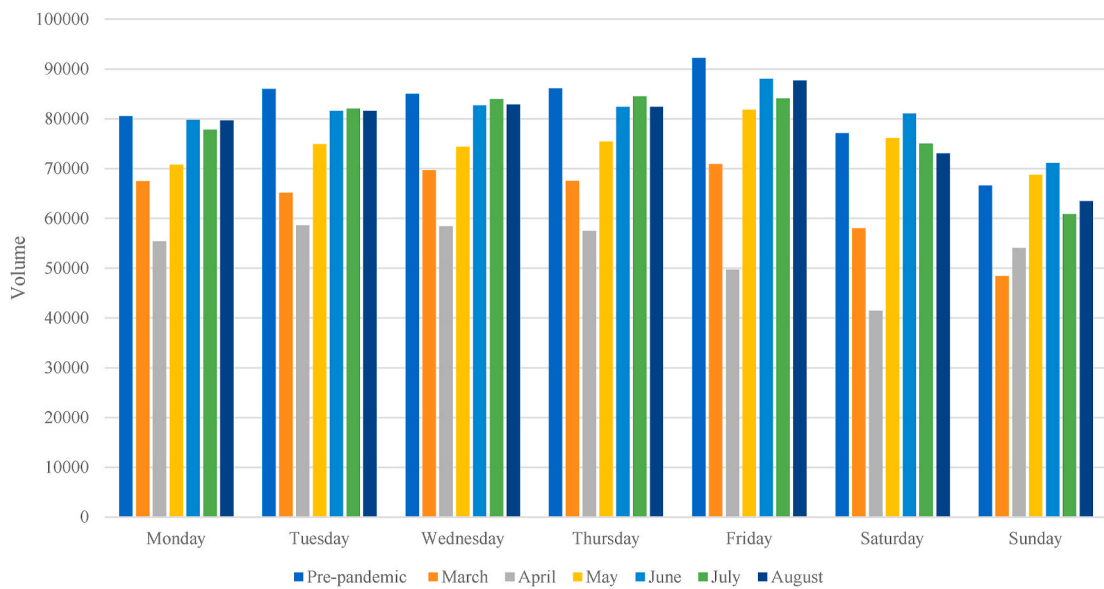**Fig. 3.** Daily traffic volume (in-and-out of the zone) for each zone during the study period.

Fig. 4. Weekly traffic volume (in-and-out of the zone) for Zone 1.

Table 5
Weekly average of COVID-19 cases and travel-related factors.

	COVID	CAS	SDI	Home	Trip	Drive	Transit	Walk	Distance	Retail	Grocery	Park	Station	Work	Residence	Airport
1	0.3	95.1	*21.6*	*104.5*	**82.5**	**92.9**	**79.6**	**94.4**	**95.8**	**96.0**	**105.1**	**94.3**	**89.7**	**98.7**	*101.6*	**165.6**
2	5.3	64.1	42.3	142.7	66.8	61.0	**39.8**	**54.1**	54.4	**74.9**	**98.0**	64.4	**67.6**	**74.1**	112.7	**82.7**
3	11.1	32.7	66.4	148.5	*54.9*	34.5	15.1	21.6	18.8	52.9	*72.9*	*39.1*	41.3	55.4	121.7	17.9
4	23.1	*28.6*	69.4	148.1	*56.0*	*33.0*	12.0	*19.9*	16.8	52.6	74.7	40.1	34.4	52.4	122.1	5.3
5	9.9	*26.8*	71.9	**151.8**	58.6	*31.9*	**11.1**	19.0	*13.4*	49.3	73.7	37.4	*32.1*	49.0	**123.3**	4.8
6	4.7	28.6	70.1	142.8	65.2	34.9	**11.2**	20.0	17.6	*50.1*	74.9	41.1	*33.3*	52.3	**122.3**	4.8
7	1.6	31.8	67.7	146.4	63.7	36.4	11.4	20.3	17.8	51.9	75.4	44.6	33.9	53.4	121.7	*4.3*
8	*0.6*	37.6	63.0	145.1	64.0	40.5	12.6	22.3	24.6	54.9	79.3	53.0	36.1	55.6	119.0	5.8
9	1.3	42.4	58.7	143.0	64.7	46.0	14.1	25.1	*11.0*	58.1	85.7	61.0	38.4	58.4	118.4	7.2
10	1.0	43.4	57.4	136.5	67.5	50.1	14.2	27.7	25.0	57.7	82.1	65.1	38.1	59.7	117.9	8.6
11	*0.1*	46.4	54.3	*118.6*	67.3	57.2	17.8	32.0	42.0	62.1	87.3	70.0	39.6	61.6	116.7	9.7
12	1.0	58.8	51.9	134.6	65.3	59.4	19.5	33.9	42.2	63.7	86.9	77.3	41.0	60.6	116.6	10.2
13	2.9	70.5	45.4	130.9	68.0	63.6	21.9	38.4	49.8	66.9	88.6	76.0	43.1	68.4	114.0	14.2
14	7.4	76.4	45.7	135.7	65.9	65.0	21.9	39.2	53.9	68.3	85.0	76.4	42.3	67.0	113.7	14.7
15	10.4	80.0	43.3	140.3	65.2	68.7	22.7	40.9	54.9	69.7	85.9	75.4	45.0	69.1	112.6	14.4
16	10	91.6	39.6	139.0	64.5	70.0	23.4	42.2	57.1	69.7	83.3	**77.9**	45.3	69.3	112.3	14.4
17	15.4	79.3	43.1	149.1	61.1	70.2	22.1	45.0	54.6	70.9	88.9	77.1	44.4	63.1	113.0	19.0
18	25.6	72.8	44.3	143.3	58.5	69.6	22.6	43.8	**59.0**	70.0	86.0	74.7	46.6	68.9	112.1	21.3
19	20.3	**102.9**	43.9	145.4	60.1	70.6	21.9	44.2	46.1	71.3	84.1	76.3	44.7	68.7	*112.0*	20.0
20	40	94.1	44.6	151.2	58.1	65.9	20.8	41.4	37.9	68.0	86.9	66.4	41.9	65.9	113.6	17.6
21	77.3	95.9	40.3	148.3	58.2	**70.6**	20.9	43.6	34.6	69.3	80.0	71.1	43.3	67.0	113.0	23.8
22	**175**	95.6	45.4	**148.7**	59.7	68.7	20.3	43.9	35.2	67.7	83.6	61.7	43.3	67.4	113.1	23.9
23	**211.4**	**97.8**	*38.1*	137.3	68.2	67.1	19.7	44.3	31.0	65.7	80.3	44.1	41.9	66.0	114.4	19.2

Note: The highest and the second-highest value of each variable are bold, and the lowest and the second-lowest value of each variable are italic during the study period.

Table 6
Model Estimation Results ($N = 161$). D represents exposure-to-confirm temporal delays.

	Constant	CAS	Park	Trip	Walk	Mask	No Stay-home
D0	11.636	0.034**	−0.059**	0.022**	−0.144*	–	0.978**
D1	11.656	0.040**	−0.063**	0.029**	−0.149**	–	0.707*
D2	8.979	0.042**	−0.051**	–	−0.104**	–	0.859*
D3	9.801	0.042**	−0.051**	–	−0.117**	–	0.929**
D4	8.424	0.040**	−0.045**	–	−0.100**	–	0.953**
D5	6.840	0.039**	−0.036**	–	−0.078**	–	0.915**
D6	7.154	0.038**	−0.033**	–	−0.083**	−0.743*	1.565**
D7	8.618	0.046**	−0.035**	–	−0.111**	−0.854**	1.421**
D8	7.968	0.043**	−0.043**	–	−0.094**	−0.887**	1.806**
D9	7.895	0.046**	−0.039**	–	−0.097**	−0.872**	1.593**
D10	8.132	0.046**	−0.035**	–	−0.104**	−0.893**	1.552**
D11	5.209	0.046**	−0.029**	–	−0.063**	–	0.755**
D12	5.098	0.040**	−0.023**	–	−0.064**	–	1.111**
D13	7.273	0.033**	−0.028**	0.025**	−0.104**	–	1.326**
D14	6.251	0.037**	−0.030**	0.028**	−0.091**	–	1.186**

* significant at 0.05 level.
** significant at 0.01 level.
– not significant in the model.

August 17, 2020, and September 7, 2020, not included in model estimation. Two criteria are used to evaluate the forecasting power of each model: (i) mean absolute percentage error (MAPE) and (ii) the root-mean-square deviation (RMSD). MAPE is one of the most common measures to quantify forecast error. RMSD is calculated as the square root of the second sample moment of the differences between predicted values and observed values or the quadratic mean of these differences (Zwillinger, 2002). A model's forecasting results with a lower MAPE and/or RMSD suggest that the model has a higher forecasting power compared to those with a higher one. Table 7 shows that the 11-day exposure-to-confirm temporal delay model has the highest predicting power with the lowest RMSD and the second-lowest MAPE. This illustrates the potential exposure-to-confirm temporal delays that exist in the relationship between travel and COVID-19 spread. It is also possible that such temporal delay may vary among different counties due to differences in testing capability, government policy, etc. Fig. 5 shows COVID-19 prediction results of models with no temporal delay, 4-day, 11-day, and 14-day compared to observed COVID-19 cases to better illustrate the results.

6. Discussion

The proposed CAS was found to be positively correlated with confirmed COVID-19 cases across all 15 models. This suggests that the proposed CAS is a good indicator to capture the possible exposure to COVID-19 in the community and can be used to predict the potential increase in confirmed COVID-19 cases up to 14 days. Also, it can also be used to capture the effectiveness of the COVID-related policies in restricting people's movement throughout the pandemic. A lower CAS suggests that people's movement within the community is minimal, and a higher CAS (close to 100) indicates that people's movement within the community is returning to normal. Apart from the CAS proposed by the authors to capture the relationship between travel-related factors and COVID-19 spread, several studies have also provided some interesting variables such as SDI (Gao et al., 2020; Zhang et al., 2020) and Community Social Risk Estimator (the probability of people meeting potential cases in public places such as grocery stores, gyms, libraries, restaurants, coffee shops, offices, etc.) by Sun et al. (2020). SDI is removed because of its high correlation with other variables and multicollinearity. Additional studies are needed to compare these two

Table 7
Model forecasting results.

	D0	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14	Observed
17-Aug	204	145	133	31	89	199	91	84	216	281	87	55	173	89	139	163
18-Aug	147	251	149	135	33	95	185	85	111	218	284	58	59	169	97	124
19-Aug	95	177	214	157	127	38	87	219	112	109	198	221	69	64	177	233
20-Aug	104	114	162	222	146	136	36	85	245	110	94	204	207	156	64	229
21-Aug	29	120	119	165	197	150	125	28	107	257	95	131	174	322	123	207
22-Aug	105	30	113	117	152	198	142	132	38	104	233	133	110	142	314	259
23-Aug	493	126	27	113	115	160	181	163	159	36	92	262	112	81	154	225
24-Aug	266	587	109	26	108	130	145	207	179	160	31	112	214	83	99	150
25-Aug		333	421	110	28	117	118	157	247	187	142	43	99	186	102	201
26-Aug			291	498	106	33	106	122	191	250	173	174	42	93	217	244
27-Aug				307	392	116	31	106	148	193	222	191	146	45	106	289
28-Aug					265	330	107	23	134	152	169	248	165	144	51	232
29-Aug						259	323	110	33	133	134	204	201	139	173	263
30-Aug							237	479	132	30	116	181	167	187	155	174
31-Aug								290	460	134	26	146	149	148	222	107
1-Sep									334	490	119	38	124	119	178	157
2-Sep										344	477	150	37	110	148	301
3-Sep											307	368	129	39	132	190
4-Sep												330	314	125	45	236
5-Sep													260	358	149	190
6-Sep														231	358	146
7-Sep															274	89
RMSD	148.98	185.9	112.66	115.34	99.15	107.96	121.17	147.84	142.94	128.7	101.53	92.77	109.35	121.41	115.29	
MAPE	62.43	79.91	41.89	44.43	43.00	38.08	46.29	65.31	60.88	52.29	47.96	38.59	39.72	49.57	52.93	

variables in other counties and other regions. Additional studies are needed to use the proposed CAS method to compare CAS and other methods, such as SDI and Community Social Risk Estimator.

The model estimation results also show that the daily confirmed COVID-19 cases increase as the number of trips increases, while the daily confirmed COVID-19 cases decrease when the walking frequency increases. It shows that the increased trip frequency contributes to increased COVID-19 cases after the economy opens up. The increased walking can potentially reduce COVID-19 case because COVID-19 is less likely to spread in an outdoor environment while walking (Feng et al., 2020; Morawska et al., 2020), and the increased exercises through walking may benefit people as shown in Feng et al. (2020) that people with more physical exercises have a lower risk of contracting COVID-19. It is also important to note that trip frequency and walking frequency are from different data sources. Trip frequency is based on mobile phone location information that shows a person moves away from home and stays at a different location for at least 10 min. The walking frequency is based on Apple Maps information that captures the number of route requests by walking. The walking frequency may only represent a person's desire to travel to a different by walking. Additional studies are needed to validate the relationship between route requests and trips made by walking.

The model estimation results also show that the increasing visits to locations such as parks and beaches contribute negatively to the daily confirmed COVID-19 cases. Numerous studies suggest that the decreased physical activities during quarantine and the closure of gyms contribute to the increased risk of COVID-19. It is crucial to maintain a certain level of physical activity level during the pandemic (Hammami et al., 2020; Mattioli et al., 2020). The increasing visits to parks and beaches suggest that the recovery of physical activity level to the pre-pandemic baseline can potentially lower the risk of COVID-19 and the risk of contracting COVID-19 is also low in an outdoor environment. However, Honolulu County closed most parks and beaches after the surge of COVID-19 cases since July, and this may contribute positively to the increasing COVID-19 cases in Honolulu county.

Regarding the policy implications, the modeling results show that both mandatory face-covering policy and mandatory work-from-home policy contribute positively toward reducing COVID-19 infection in Honolulu County. These results highlight the importance of using various social distancing measures to reduce COVID-19 spread. For example, the likelihood of infection can be reduced if face-covering is required, even if the travel behavior remains the same.

In terms of the model prediction results using various exposure-to-confirm temporal delays in Section 5.3, the results not only highlight the importance to factor such temporal delay in the modeling process the relationship between various factors and the confirmed COVID-19 cases but also suggest that if the COVID-19 related health policies remain the same, when the travel-related activates increase, the confirmed COVID-19 cases are expected to increase a few days after such increase.

7. Conclusions

This study explores the relationship between travel-related and policy factors and COVID-19 cases spread in the community with various exposure-to-confirm temporal delays at a county-level. Community Activity Score (CAS) is proposed in this study to capture the current travel-related activity level compared to the pre-pandemic baseline based on inter-community traffic characteristics. CAS and thirteen other travel-related factors are used to study the relationship between travel and COVID-19 spread in the community. The exposure-to-confirm temporal delay between the time-varying travel-related factors and their impacts on the number of confirmed COVID-19 cases are also considered. A Honolulu County-based case study is used to evaluate the proposed CAS and its relationship with confirmed COVID-19 cases. The NB model results show that CAS can be used as an indicator to study
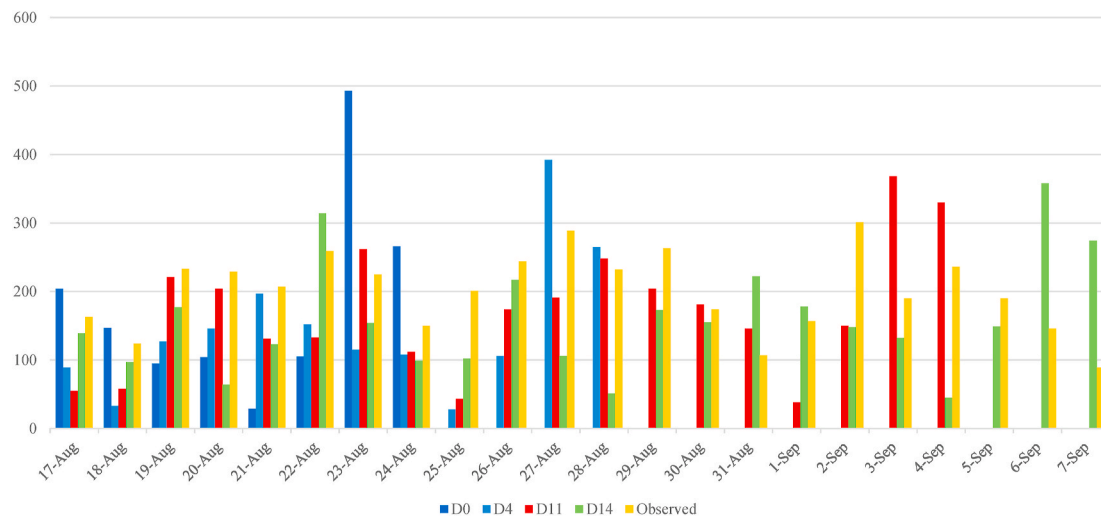
Fig. 5. COVID-19 prediction results of models with no temporal delay, 4-day, 11-day, and 14-day compared to observed COVID-19 cases.

the social distancing measures' effectiveness and predict a potential increase in the community. Furthermore, models with different exposure-to-confirm temporal delays are used to forecast COVID-19 cases to illustrate the importance of including exposure-to-confirm temporal delays when evaluating the impacts of travel-related factors and policy factors on COVID-19 spread.

This study has a few limitations. First, the study relies on data from various sources, and only CAS is independently verified by the authors using the raw data. The reliability of the modeling results depends on the accuracy of these data sources and the authors are planning to revisit this study once such raw data is available. Second, Honolulu County is relatively unique compared to most of the counties in the U.S. as most of its out-of-county travels are through the airport. This makes it easier for the county to control COVID-19 cases imported from other counties. Additional studies are needed to evaluate the potential of using the proposed Community Activity Score to monitor the potential increase in COVID-19 cases in other counties. Third, data such as mobility trends and mode usage frequency may not accurately reflect the total visits to different locations and mode usage frequency. For example, mobility trends reflect the total visits to various sites for users with Google Maps and the location tracking on and many people may have neither. Mode usage frequency can only reflect the total number of route requests for different modes of transportation through Apple Maps. It cannot represent the mode usage frequency of all the county population or whether these trips were made. Fourth, most of the social distancing measures in Honolulu County remains the same throughout the pandemic. It can be challenging to evaluate these policies' real impacts as people's compliance to these policies and the enforcement levels can vary significantly throughout the pandemic. Fifth, some of the other factors found by some studies related to neighborhood built environment (Mitra et al., 2020) were not included in this study due to the unavailability of the data and other modeling methods such as spatial data analysis methods (Cuadros et al., 2020; Harris, 2020) was not used due to the nature of studying only one county. Last but not least, most of the existing data is at the county-level, and it is important to acquire higher resolution data for additional analysis.

Future studies have been planned to address some of the limitations. First, Honolulu County is used as a case study to illustrate the relationship between proposed CAS and other travel-related factors and COVID-19 spread in the communities. Additional studies are planned to use the proposed method to evaluate CAS in other counties. Second, in terms of the modeling method and data used, different types of advanced models that can capture unobserved heterogeneities in the data can be used, and the model estimation can be improved with more high-

resolution data. Third, a more comprehensive comparison between CAS and other mobility indexes should be conducted to evaluate the potential of using CAS to assist decision-makers in combating COVID-19 spread within the communities. Last but not least, future studies can analyze data from multiple counties/communities and capture the potential spatial autocorrelation among them.

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