Impacts of COVID-19 on the Operational Performance of Express Lanes and General-Purpose Lanes

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Abstract
The COVID-19 pandemic outbreak brought significant changes in the travel behavior and operational characteristics of transportation systems. Express lanes (ELs) are among the transportation facilities that are affected by this pandemic. These facilities are built adjacent to existing general-purpose lanes (GPLs), providing drivers additional lanes that are dynamically priced in response to changing traffic conditions. This research investigated the impacts of COVID-19 on the operational performance of ELs and GPLs based on field data from a 5.5 mi corridor on I-95 in Miami, Florida, U.S. The traffic flow parameters, which include speed, traffic flow, and occupancy, were used to describe the traffic conditions before and during COVID-19 (i.e., March–June 2019 and March–June 2020, respectively). The travel time reliability measures, coefficient of variation of travel time, and planning time index, were used to measure user satisfaction. These metrics were derived from a multivariate Bayesian additive regression model that was developed to calibrate the traffic conditions on the study corridor. Overall, the model results indicated that both ELs and GPLs have less variation in travel time, thus making the travel time more reliable during COVID-19 than before. This may be attributed to the decline in the traffic volume observed during the pandemic. The results further showed that COVID-19 had more impact on the GPLs compared with the ELs. The results from this research could assist transportation agencies in understanding the impacts of the COVID-19 pandemic on ELs and GPLs in relation to traffic operations.

Keywords
operations, managed lanes, express lanes

The first half of 2020 was remarkable for the global “war” against the enemy known as the COVID-19 pandemic. The novel COVID-19 pandemic emerged in December 2019 in Wuhan, China, and eventually spread widely across the globe. Following the outbreak of the COVID-19 pandemic, the world experienced unprecedented phenomena. In March 2020, COVID-19 was declared as a pandemic by the World Health Organization (WHO), and emergency measures were internationally implemented as the outbreak continued to threaten public health. As of September 30, 2020, there were almost 35 million worldwide confirmed cases of COVID-19, with the U.S. accounting for more than 7 million cases, which was equivalent to about 20% of the overall cases worldwide (1). As the novel COVID-19 pandemic was found to spread rapidly from around the globe, various nonpharmaceutical interventions were considered to slow down the spread of the disease. These interventions aimed to limit person-to-person interaction, which is the main cause of the spread of the virus. The nonpharmaceutical

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interventions imposed to limit the spread of the COVID-19 pandemic included social distancing, quarantine of exposed persons, contact tracing, school closures, business closures, teleworking, restaurant and bar closure, and stay-at-home orders. For example, in Florida, the first executive order was signed on March 1, 2020, directing the Florida Department of Health to issue a public health emergency following the COVID-19 outbreak. On March 9, 2020, the Governor declared a state of emergency for the entire state, and stay-at-home orders came into effect on April 1, 2020 (2).

The measures imposed to slow down the spread of the disease dramatically changed peoples’ lives and led to a decrease in economic activities, therefore reducing the number of trips that individuals usually made (3). The decrease in the number of person trips following the travel restrictions and stay-at-home order led to a rapid drop in traffic demand. The COVID-19-induced drop in traffic demand eased congestion, and this was intuitively expected to result in low travel time and high travel speed (4–8). The increase in average travel speeds was observed in several states across the U.S. While some states, such as California and North Carolina, reported only a slight increase in travel speeds, several other states, including New York and Minnesota, reported a high increase in travel speeds, especially on freeways (6–8).

In summary, the novel COVID-19 pandemic brought unprecedented changes in traffic patterns and travel behavior and their impact on the operational performance of the transportation network is not yet clear. Express lanes (ELs), being the facilities that are generally used to respond to changes in traffic conditions in real-time, were not immune to the impacts of the pandemic. It is unclear how people’s responses and reactions to the crisis affected the operational performance of the ELs. This study focuses on quantifying the impacts of the COVID-19 pandemic on ELs and general-purpose lanes (GPLs). To achieve the stated objectives, the study developed a data-driven approach to assess the impacts of the COVID-19 pandemic based on travel time reliability and traffic flow parameters.

The study explored the response of the ELs’ performance characteristics to the drop in traffic flow resulting from the COVID-19 pandemic. This study presented another example of how real-time macroscopic traffic data could be utilized to address transportation-related problems. Specifically, the real-time traffic data such as speed, traffic flow, and density (in relation to detector occupancy) were integrated with the ELs’ operational data, for example, toll prices and the ELs’ operational status (i.e., open or closed). Furthermore, the Bayesian approach that was used to fit the model incorporates uncertainty in parameter estimates, improving the prediction accuracy and reliability of the outcome. Also, the model accounts for the possible correlation between the three traffic flow parameters, that is, speed, flow, and density.

Travel time reliability was assessed based on both statistical measures, that is, coefficient of variation (CV) of travel time, and index-based measures, that is, planning time index (PTI). In this study, March through June 2019 was considered as the “before” period, while March through June 2020 was considered to be “during” the COVID-19 pandemic. The analysis was based on the 5.5 mi section of interstate 95 (I-95) in Miami, Florida, U.S. The study results could assist agencies in understanding the impacts of the COVID-19 pandemic on ELs and GPLs in relation to traffic operations and could potentially be useful in operational and strategic planning for other catastrophic events that result in the decline of traffic flow.

Data Description

Data Collection

The real-time traffic data (traffic volume and traffic speed) aggregated at a 5 min interval were retrieved from the Regional Integrated Transportation Information System (RITIS). The travel time data were derived from the traffic speed and corridor length. The analysis included only the northbound direction, since the southbound direction had missing traffic volume data. To reduce variations in the data resulting from different operating characteristics associated with days of the week, only typical weekdays, that is, Tuesday, Wednesday, and Thursday, were considered in the analysis.

The ELs’ operational data were requested from the Florida Department of Transportation (FDOT) operational office. This data includes the status of the ELs (i.e., whether the ELs were closed or open, etc.), and the toll amount. Dates and times when the ELs are closed were excluded from the analysis. Thus, the data included in the analysis comprise three status, that is, time of day, dynamic zero tolls, and manual. Toll rates on the I-95 are based on the traffic conditions of the ELs only and not on the conditions of the GPLs. Thus, the toll prices vary based on the level of congestion on the ELs only. As ELs become congested, toll rates increase, whereas toll rates decrease as the congestion goes down. Generally, ELs are operated to maintain a free flow of traffic at a speed of 45 mph or greater.

Table 1 shows a summary of the toll amount in the study period. As indicated in the table, the toll amount in 2019 was higher than in 2020. On average, the toll amount when the ELs are operational was $1.87 in 2020 and $2.39 in 2019.
Site Description

The study corridor includes 5.5 m of I-95 in Miami, Florida. As indicated in Figure 1, the corridor spans from NW 81st Street to NW 159th Street. The corridor has five on-ramps, six off-ramps, two ELs, and four GPLs in the northbound direction. The speed limit along the study corridor is 60 mph.

Real-Time Traffic Data Characteristics

Figure 2, a to d, show the characteristics of the real-time traffic flow rate along the study corridor during the analysis period. Figure 2, a and b, show the time series of the traffic flow rate data along the ELs in the study corridor before and during the COVID-19 outbreak, respectively. As indicated in the plot, there was a drop in the traffic volume amid the outbreak compared with the regular times (i.e., before the outbreak of the pandemic). A similar drop in the traffic flow rate was also observed in the GPLs during the COVID-19 outbreak, as presented in Figure 2d. This was expected, especially after the stay-at-home order was declared on April 1, 2020, thus reducing the traffic demand on the transportation network.

Furthermore, as the traffic flow rate dropped amid the COVID-19 pandemic, an increase in the travel speed on both ELs and GPLs was expected, as presented in Figure 3, b and d.

Methodology

This research developed a flexible statistical regression based on the generalized additive model (GAM) to investigate the impact of COVID-19 on the operational performance of the study corridor. To calibrate the time-series pattern accurately, GAM uses a set of finite functions (9, 10). The finite functions can be of any form appropriate to the data characteristics, which range from linear to non-linear models. In the present study, the traditional GAM is modified to incorporate the estimation of the critical point that separates the traffic flow characteristics data before and during the pandemic. Because there are dependencies between traffic speed, flow, and occupancy, a multivariate function was used to account

| Month | Before COVID-19 (2019) | During COVID-19 (2020) |
|-------|------------------------|------------------------|
| Mean  | Standard deviation     | Mean                   | Standard deviation     |
| March | $2.44 $2.82            | $2.10 $2.60            |
| April | $2.19 $2.68            | $1.28 $2.52            |
| May   | $2.52 $2.99            | $1.44 $2.34            |
| June  | $2.42 $2.90            | $1.76 $2.28            |
| Overall | $2.39 $2.85         | $1.87 $2.49            |

Table 1. Toll Amount Summary Between 2019 and 2020
for the correlation among the three variables. Suppose that the travel speed, flow, and occupancy records at time $t$ are denoted by $S_t$, $F_t$, and $O_t$, respectively, the modifying GAM can take the following form:

$$
\begin{pmatrix}
S_t \\
F_t \\
O_t
\end{pmatrix}
\overset{\text{MVNormal}}{\sim}
\begin{pmatrix}
\mu_{1t} \\
\mu_{2t} \\
\mu_{3t}
\end{pmatrix},
\Sigma
$$

(1)

The typical smoothening function, with a Fourier series of 3rd order, was used to estimate the speed pattern (Equation 2). Higher order of Fourier series can also be used to fit the data characteristics. A similar function was set for flow and occupancy variables in the multivariate model in Equation 1.

$$
\begin{aligned}
\mu_{1t} &= \begin{cases}
\beta_{10} + \sum_{n=1}^{3} \beta_{1n} \cos(n \omega_{n} x_t) + \phi_{1n} & \text{if } x_t < \lambda \\
\beta_{20} + \sum_{n=1}^{3} \beta_{2n} \cos(n \omega_{n} x_t) + \phi_{2n} & \text{if } x_t \geq \lambda
\end{cases} \\
\beta_{10}, \beta_{1n}, \beta_{20}, \phi_{2n} &\sim N(0, 100) \\
\omega_{n} &\sim Gamma(1, 1) \\
\phi_{2n} &\sim Uniform(-\pi/2, \pi/2) \\
\lambda &\sim DiscreteUniform(t_1, t_n)
\end{aligned}
$$

(2)

where $\Sigma$ = the covariance matrix, $\theta = \{\beta_{10}, \beta_{1n}, \omega_{1n}, \phi_{1n}, \beta_{20}, \beta_{2n}, \omega_{2n}, \phi_{2n}\}$ are regression parameters, $\lambda$ = the critical date that separates before and during the COVID-19 traffic flow characteristics, and $t_1$ and $t_n$ = begin and end times of the study period.

To account for the stochastic characteristics of traffic flow data, the Markov Chain Monte Carlo (MCMC) simulation, which is also referred to as the Bayesian inference, was used to calibrate the modified GAM. It is worth stating that the stochastic characteristics of traffic flow data can be attributed to many factors, such as drivers’ behavior, vehicle composition, and weather conditions, among other factors. With the Bayesian inference, the estimation of the posterior distributions’ model parameters requires two major terms to be defined before the analysis: prior distributions of all parameters and the likelihood function (Equation 3).

$$
Posterior\ distribution,\ P(\theta|d) \propto prior,\ P(\theta) \times likelihood,\ L(\theta|d)
$$

(3)

where $P(\theta) =$ prior distribution of the parameter, $L(\theta|d)$ = likelihood function, and $P(\theta|d)$ = posterior distribution.
The prior distributions of these parameters are also presented in Equation 2. These distributions represent the probability of each parameter before data are observed (11). These probabilities can be obtained from the previous findings or non-informative priors (11). Since there is no study which has a similar set of analysis as the current study, the authors selected non-informative priors in the estimation of parameters. This approach has also been used in previous studies (12–18). The non-informative priors have a negligible influence on the estimates (11). In other words, these priors do not dominate the likelihood function. These include the Gaussian distribution for regression coefficients, half-normal for the standard deviations, discrete uniform distribution for critical value, gamma, and uniform distribution for the parameters in the Fourier series function. Note $t_1$ and $t_n$, which correspond to the first and last date of study period in the dataset. Using this set of prior parameters provides equal probability of the critical date to be at any recorded date (19).

The developed model was implemented in Python programming language using a Pymc3 package with No-U-Turn Sampling (NUTS) (20). The sampling step applied includes the initial burn-in phases set to 20,000 iterations and, subsequently, 10,000 iterations were used for making an inference. As with the Bayesian inference, the model convergence was evaluated using the Gelman-Rubin diagnostic statistic. For the model to achieve convergence, the difference between chain variances, which is the Gelman-Rubin diagnostic statistic, has to be equal to 1 (21). Moreover, visual diagnostics based on the autocorrelation plot, density, and trace plot of each parameter were used in the assessment.

### Travel Time Reliability Estimation

As stated earlier, travel time reliability was assessed based on the CV of travel time and the PTI. The CV of travel time represents the ratio of the standard deviation of the travel time to the mean travel time. It is a useful statistic for comparing the degree of variation of travel time along the study corridor. It best quantifies the variation of travel times along the study corridor. The PTI is computed as the 95th percentile travel time divided by the free-flow travel time. PTI represents how much total time a traveler should allow to ensure on-time arrival. The CV of travel time and the PTI were estimated using Equations 4 and 5, respectively.

$$CV = \frac{SD}{Mean \ TTPD} \times 100\% \quad (4)$$

**Figure 3.** Real-time travel speed along express lanes (ELs) and general-purpose lanes (GPLs): (a) time series of travel speed for ELs before COVID-19, (b) time series of travel speed for ELs during COVID-19, (c) time series of travel speed for GPLs before COVID-19, and (d) time series of travel speed for GPLs before COVID-19.
The CV of travel time was retrieved from the multivariate travel time before and during COVID-19, respectively. The second term mainly fits the daily data fluctuation. These reliability indices (i.e., CV of travel time and PTI) were computed using the estimated posterior distributions calibrated using the MCMC simulation. In particular, from the fitted regression model (Equation 6), the first coefficients \( \beta_{10} \) and \( \beta_{20} \) represent the average travel time before and during COVID-19, respectively. The second term mainly fits the daily data fluctuation. The CV of travel time was retrieved from the multivariate distribution for the travel time data. The estimate of \( \beta_{10} \) and \( \beta_{20} \) and the standard deviations were used in travel time reliability computation.

\[
\mu_{17} = \begin{cases} 
\beta_{10} + \sum_{n=1}^{3} \beta_{11} \cos(n \omega_n x_i + \varphi_{1n}) & \text{if } x_i < \lambda \\
\beta_{20} + \sum_{n=1}^{3} \beta_{21} \cos(n \omega_n x_i + \varphi_{2n}) & \text{if } x_i \geq \lambda 
\end{cases}
\]

(6)

**Results and Discussion**

This section discusses the model results from the modified GAM regression. It starts by presenting the posterior predictive checks (PPCs) investigating the accuracy of the fitted model. Then, the impacts of COVID-19 on travel time reliability and traffic parameters with their comparison of the posterior distribution estimated from the model are discussed.

**Modified GAM Model Assessment**

Several approaches can be used to assess the prediction accuracy of the model in Bayesian data analysis. The popular methods for model evaluation include the use of information criteria, mean square error, mean absolute error, and root mean square error, among others. However, these metrics work best when two or more models are compared in the analysis, because a model with the lowest error value or information criterion best predicts the data (22). Another methodology that can be used to diagnose the fitness of the model is the use of PPCs. A PPC provides a visual comparison of the posterior predicted distribution of simulated data derived from model parameters on the actual data (21, 23, 24).

The main assumption of PPCs is that, if a model better fits the dataset, the generated or simulated data from the calibrated parameters should resemble the actual data characteristics (24). The replicated data from the posterior distributions for predictive checks can be computed using Equation 7.

\[
p(\hat{y}|y) = \int p(\hat{y}|\theta)p(\theta|y)d\theta
\]

where \( \hat{y} \) = the predicted data, \( \theta \) = the model parameters, and \( y \) = observed data, travel time.

Figure 4 provides a PPC by plotting actual data and posterior predicted lines of the simulated data. The predicted trends of the posterior predicted lines follow the actual data pattern closely in all analyzed traffic parameters for the ELs, as illustrated in Figure 4. Note that a similar trend was also observed in the traffic parameters for the GPLs. It is necessary to understand that PPC is a qualitative analysis that focuses on investigating the visual graphics of actual data and replicated by observing the important features on the trend. In this case, 10,000 simulated samples for each average trend were estimated. These samples were used to compute the travel time reliability indices, that is, CV of travel time and PTI.

**Impacts of COVID-19 on Travel Time Reliability**

Travel time reliability was used as the measure of effectiveness to assess the impacts of the COVID-19 pandemic on the study corridor. As stated earlier, travel time reliability, as the measure of user satisfaction, was quantified based on both statistical measures, that is, CV of travel time, and index-based measure, that is, PTI. Figure 5, a and b, present the results of the travel time reliability indices estimated from the model.

As illustrated in Figure 5a, the CV of travel time was 15.96% and 15.35% before and during the pandemic, respectively, for the ELs. The lower values of the CV of travel time during COVID-19 indicated that travelers experienced less variation in travel time compared with a corresponding period under normal situations. Similarly, the PTI was found to be 1.29 and 1.23 before and during the pandemic, respectively, for the ELs. This suggested that, during the pandemic, travelers generally set less time to ensure the on-time arrival compared with the corresponding period before the pandemic.

Figure 5b presents the distribution of the CV of travel time and PTI for before and during COVID-19 on the GPLs. The CV of travel time before and during the pandemic was found to be 21.03% and 18.05%, respectively, indicating that there was less variation in travel time amid the COVID-19 outbreak. Furthermore, the PTI...
was 1.68 and 1.42 before and during COVID-19, respectively, indicating that travelers experienced more reliable times amid the outbreak of the COVID-19 pandemic. Both ELs and GPLs were found to have less variation in travel time during the pandemic. This lower variation in travel time along the study corridor may be attributed to the decline in traffic flow as a result of the stay-at-home orders and social distancing imposed to limit the spread of the virus.

In summary, the travel time reliability indices estimated from the model indicated that during the COVID-19 outbreak, there was less variation in travel time, thus making travel time more reliable. This may be attributed to the reduction in traffic volume observed during the pandemic. As expected, when there was less traffic flow on the roadway network, drivers tended to drive at free-flow speed leading to on-time arrival. However, the analysis showed that the pandemic had more impacts on travel time in GPLs compared with ELs. This was expected, because the operational performance of the ELs before the pandemic was higher than the GPLs. Thus, the significant changes in the traffic flow characteristics following the occurrence of the pandemic affected the GPLs more.

Figure 6, a and b, present the comparison of the posterior distribution of the travel time reliability indices before and during COVID-19 for the ELs and GPLs with the probability indicating the direction of the effect. As illustrated in Figure 6a, the mean of the difference between the CV of travel time before and during the

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**Figure 4.** Posterior predictive checks (PPCs) for ELs

*Note: HPD = Highest posterior density.*
Figure 5. Travel time reliability indices: (a) express lanes (ELs) and (b) general-purpose lanes (GPLs).
Note: CV = coefficient of variation.

Figure 6. Comparison of posterior distributions of travel time reliability indices: (a) express lanes (ELs) and (b) general-purpose lanes (GPLs).
Note: CV = coefficient of variation; CV\text{Before} = CV of travel time before COVID-19; CV\text{During} = CV of travel time during COVID-19; PTI = planning time index; PTI\text{Before} = PTI before COVID-19; PTI\text{During} = PTI during COVID-19.
The novel COVID-19 pandemic caused unprecedented impacts on several sectors, transportation being one of them. The nonpharmaceutical interventions to lessen the pandemic was 0.65 with the probability of 56% for the ELs. This indicates that before the outbreak of the COVID-19 there was more variation in travel time, with 56% of the data indicating higher variation compared with the variation observed amid the pandemic. A similar trend was observed in the difference between the PTI before and during COVID-19, with 57% of the data indicating higher variation in the before period. For the GPLs, the mean of the difference between the CV of travel time before and during COVID-19 was 3.007 with a probability of 68%. Similarly, the mean difference between the PTI before and during COVID-19 was 0.261 with a probability of 69%. This result indicates that COVID-19 affected travel time on the GPLs more than on the ELs.

Impacts of COVID-19 on Flow Rate and Occupancy

The variation in travel time is mainly influenced by the traffic flow on the roadway section among all other factors. Understanding that, it is necessary to determine the impacts of COVID-19 on the traffic flow and occupancy as the factors influencing travel time reliability. Note that, in this study, occupancy refers to the percentage of time that the detector is occupied by the vehicle in a defined time period. Figure 7a presents the distribution of the traffic flow rate and occupancy before and during COVID-19 for the ELs. As shown in Figure 7a, traffic flow and occupancy were lower amid the outbreak of the pandemic compared with the corresponding period under normal situations. A similar lower trend of traffic flow and occupancy was observed in the GPLs, as presented in Figure 7b.

Figure 8, a and b, present the comparison of the posterior distribution of traffic flow and occupancy before and during COVID-19 for the ELs and the GPLs, respectively. As illustrated in Figure 8a, the mean of the difference between the traffic flow before and during COVID-19 was 368.857 with the probability of 78% for the ELs. This indicates that before the COVID-19 outbreak there was a higher traffic flow with 78% of the data indicating higher traffic flow. A similar trend was also observed for occupancy, as presented in Figure 8a.

For the GPLs, the mean of the difference between the traffic flow before and during COVID-19 was 276.378 with a probability of 96%. Similarly, the mean difference between occupancy before and during COVID-19 was 3.373 with a probability of 79%. This result indicates that the COVID-19 outbreak had a greater impact on the GPLs compared with the ELs.

Conclusions

The novel COVID-19 pandemic caused unprecedented impacts on several sectors, transportation being one of them. The nonpharmaceutical interventions to lessen the
spread of this pandemic, for example, stay-at-home orders, resulted in significant changes in the travel behavior and operational characteristics of transportation systems. Compared with other unforeseen events, such as hurricanes, COVID-19 was one of the few disastrous events that did not induce an increase in traffic. Before COVID-19, it was difficult to imagine a drop in traffic volume to this extent and for this long. Transportation systems management and operations (TSMO) strategies such as ELs were introduced to better manage the flow of traffic on existing facilities. These strategies work on the principle of meeting traffic demand. The significant drop in traffic during the pandemic took the demand out of the equation. In general, the novel COVID-19 pandemic has given transportation researchers a rare chance to evaluate the operation of transportation systems under low traffic demand.

This research investigated the response of the ELs’ performance characteristics to the drop in traffic flow resulting from the COVID-19 pandemic. The performance measure of user satisfaction, that is, travel time reliability, was used to quantify the difference in the travel times/travel speeds before and during the pandemic. Specifically, two performance measures, including the CV of travel time and the PTI, were considered the performance measures for travel time reliability. Besides travel time reliability, other traffic flow parameters, such as traffic flow and occupancy, were also used to illustrate the difference in the operational characteristics of the ELs and GPLs between the two time periods. This study presented another example of how real-time traffic data could be utilized to address transportation-related problems.

The study was based on 5.5 mi of I-95 in Miami, Florida. March through June 2019 was considered as the before period, while March through June 2020 was considered to be during COVID-19. To achieve the study objective, real-time traffic flow data from the RITIS platform were fitted using the multivariate Bayesian GAM. This model accounts for the possible correlation between the three traffic flow parameters, that is, speed, traffic flow, and density (in this study, represented by detector occupancy). Furthermore, the fitted Bayesian model incorporates uncertainty in parameter estimates, therefore improving the prediction accuracy and reliability of the outcome. The model can estimate time and location experiencing significant traffic patterns changes. This is essential information for traffic operators and planners.

Figure 8. Comparison of posterior distributions of flow and occupancy: (a) express lanes (ELs) and (b) general-purpose lanes (GPLs).

Note: Flow\textsubscript{Before} = traffic flow before COVID-19; Flow\textsubscript{During} = traffic flow during COVID-19; Occupancy\textsubscript{Before} = occupancy before COVID-19; Occupancy\textsubscript{During} = occupancy during COVID-19.
travel time amid the pandemic than before the pandemic. A similar trend was observed on the PTI, meaning that, during the pandemic, travelers generally set less time to ensure on-time arrival compared with the corresponding period before the pandemic. The differences in both the CV of travel time and PTI for the GPLs were observed to be higher than those of the ELs. This observation implies that COVID-19 had a greater impact on the GPLs compared with the ELs.

Among all other factors, the variation in travel time is mainly influenced by traffic flow and occupancy on the roadway section. Therefore, it is necessary to determine the impact of COVID-19 on traffic flow and occupancy as the factors influencing travel time reliability. Thus, in addition to comparing the traffic flow condition before and during COVID-19, the distributions of the traffic flow rate and occupancy before and during COVID-19 were also compared. The traffic flow rate and occupancy were lower during the pandemic compared with the corresponding period before the pandemic for both the ELs and the GPLs. The reduction in the traffic flow following the COVID-19 outbreak eases congestion, therefore there is reduction of travel time, leading to more reliable time as suggested by the computed travel time reliability indices. This means that travelers experienced more reliable travel time during COVID-19.

Overall, the comparison of the travel time reliability indices, traffic flow rate, and occupancy estimated from the model indicated that, during COVID-19, there was less variation in travel time, thus making travel time more reliable. This may be attributed to the decline in traffic volume observed during the pandemic. However, the analysis showed that COVID-19 had a greater impact on travel time reliability in the GPLs than in the ELs. This was expected, because ELs are usually used to improve traffic operational, thus, even with the drop in the traffic flow, there was less improvement in travel time reliability in the ELs compared with the GPLs. The fact that travel time reliability continued to improve on the ELs compared with the GPLs, even amid the pandemic and the reduced toll prices during the pandemic, could articulate the lower percentage reduction in traffic in the ELs compared with in the GPLs. This implies that reduction in traffic demands should not adversely affect the operations of the ELs. Transportation agencies could use these results to justify the continuous use of ELs, even with low traffic demand. Further, the results may assist agencies in understanding the impacts of the COVID-19 pandemic on ELs and GPLs in relation to traffic operations. Also, the study findings may further, potentially, be helpful in operational and strategic planning for other catastrophic events that will result in significant low traffic flow.

Author Contributions
The authors confirm contribution to the paper as follows: study conception and design: J. Kodi, A. Kitali, E. Kidando, P. Alluri; data collection: J. Kodi; analysis and integration of results: J. Kodi, A. Kitali, E. Kidando, P. Alluri; draft manuscript preparation: J. Kodi, A. Kitali, E. Kidando, P. Alluri. All the authors reviewed the results and approved the final version of the manuscript.

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