#198 Proactive management of mobility impact of interdependent subsurface utility and roadway construction through incentives

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1. The Problem

The U.S. civil infrastructure systems, such as bridges, are at risk from aging, leading to structural deterioration and severe challenges to public safety and the economy (Ellingwood, 2005; Shen et al., 2019). ASCE reports 39% of bridges in the U.S. are 50 years or older, exceeding their average designed lifespan of 50 years, and 9.1% of the bridges are in structurally deficient condition (ASCE, 2018).

To improve the conditions of bridges, maintenance activities are scheduled and executed. When scheduling maintenance activities, a maintenance agency needs to consider the following factors: First, to decide when to schedule maintenance activities. To be able to make that decision, it is necessary to assess the impacts of conducting maintenance (or not) on a bridge. One of those assessments is to evaluate the reduced routine maintenance expenditure on the bridge whose structural conditions are improved due to the scheduled maintenance. Once it is determined that a maintenance activity will be conducted, it is important to assess two major impacts of maintenance activities: (1) The cost of detours created due to maintenance; (2) The risk of crashes that might be generated due to work zones. In this report, we discuss three approaches to support these three decisions: (1) *a predictive infrastructure maintenance expenditure model* that predicts the reduced annual routine maintenance expenditure of one bridge whose structural conditions are improved due to scheduled maintenance; (2) *a dynamic mesoscopic traffic simulation tool* that estimates the detour cost of work zones incurred by road users in high spatial and temporal resolution (miles and minutes) in a regional traffic network; (3) *a work zone crash risk estimation model* that identifies the traffic crash risk cost attributed to the presence of work zones.

Scheduling maintenance activities involve assessing possible impacts of conducting maintenance (or not) on a bridge. The metrics evaluated in these assessments include the reduced construction cost for future routine maintenance at the improved structural conditions, and reduced repair and structural failure costs (Frangopol Dan M. et al., 1997; Frangopol et al., 2017). Although many studies have developed approaches to estimate reduced structural failure and repair costs (Yang and Frangopol, 2018; Yang et al., 2006b), the literature generally lacks approaches for predicting annual routine maintenance expenditure (AMEX) for a bridge given its structural conditions. While there are databases, such as the Indiana roadway maintenance expenditure database (Volovski, 2011), available to be utilized for predicting AMEX, the challenge is that most bridges will not get any maintenance in most years (leading to a zero value of AMEX). For example, over 92% of Pennsylvania bridges are not getting any maintenance every year from 2008 to 2017 based on data collected from Pennsylvania Bridge Management System version 2. The excess number of zero values can jeopardize the AMEX estimation model based on traditional data-driven methods, such as Ordinary Linear Squares (OLS) and random-effect linear regression models (random-effect OLS) (Volovski, 2011). Without recognizing and addressing the challenge of the excess number of zero values, OLS and random-effect OLS will fit the distribution of AMEX data poorly and underestimate the reduced AMEX due to the scheduled maintenance activities. Therefore, our first objective in this research was to develop a predictive infrastructure maintenance expenditure model that provides reliable results in cases with significant numbers of zeros in the database. In this study, we applied the Tobit model to handle the excess number of zero values in the AMEX data. We used Akaike Information Criterion (AIC) to evaluate how well the proposed model fits the data set. The baseline models are linear regression based on Ordinary Linear Squares and random-effect linear regression model. These will be discussed in detail in section 2.1 of this report.

Once a maintenance activity being scheduled, it is important to assess several impacts of conducting such activities. Examples of those are: the construction cost of the planned maintenance action, the expected time lost due to delays or detours (mobility impacts to road users) in the work zone, and possible additional accident risks in a work zone due to narrowed rights-of-way and changed daily traffic patterns (safety impacts to road users) (Aboutaha and Zhang, 2016; FHWA, 2019; Kim et al., 2016). The construction cost of one specific maintenance action is generally known, and prior studies in this area are abundant (Volovski, 2011). However, the mobility and safety impacts of maintenance actions are usually hard to measure due to the complexity of the traffic flow network and how traffic accidents occur.

The mobility impacts of work zones are usually measured in a static network or macroscopic dynamic network of traffic flow (Yang and Frangopol, 2018). The static and macroscopic traffic simulation tools used by highway agencies include QuickZone, CA4PRS, and Dynasmart-P (FHWA, 2019). However, work zones usually lead to traffic congestions, and drivers may be detoured to other roadways. Simulation tools based on dynamic traffic assignment models are needed to estimate travel times in congestion. Besides, such simulation tools need to be able to quantify possible mobility impacts (traffic delays) in high spatial and temporal resolutions (e.g. miles and minutes) and at a relatively large traffic network (e.g. regional traffic network) to capture possible effects of congestion due to work zones comprehensively. On the one hand, traffic simulation tools based on the microscopic dynamic traffic assignment model are compute-intensive. On the other hand, traffic simulation tools based on the macroscopic dynamic traffic assignment models cannot provide simulation results in a sufficient temporal and spatial resolution (e.g., miles and minutes). Therefore, our second objective in this research was to develop a dynamic mesoscopic traffic simulation tool that estimates detour costs of work zones incurred by road users in high spatial and temporal resolution (miles and minutes) in a regional traffic network**.** This study applied a mesoscopic dynamic network flow model, MAC-POSTS, to estimate road users' detour costs (Ma, Pi, and Qian 2019). The proposed traffic simulation tool can estimate traffic impact in a resolution of 5 seconds and miles within the traffic network in the Greater Pittsburgh Area. The specifics of this simulation tool are discussed in Section 2.2.

To estimate possible safety impacts of work zones, many researchers have explored the statistical associations between crash counts and work zones characterized by various deployment configurations of the corresponding work zone (e.g., Chen and Tarko, 2014; Garber and Woo, 1990; Graham et al., 1977; Khattak et al., 2002; Ozturk et al., 2013, 2014; Pal and Sinha, 1996a; Qi et al., 2005; Ullman et al., 2008; Venugopal and Tarko, 2000; Yang et al., 2013, 2015b). The deployment configurations covered in those studies include work zone length, duration, or whether fully closed lanes on the roadway. The associational research reveals sometimes strong associations among increased crashes and the presence of work zones. However, findings from statistical associations do not necessarily indicate causal relations. Moreover, without understanding causal relations, it is challenging to develop effective approaches to minimize crash risks.

It is difficult to distinguish the causes of crashes being related to work zones or roadway characteristics in associational research. Examples of roadway characteristics that might cause a crash include daily traffic volume, roadway surface conditions, and geometric design of roadways (Chen and Tarko, 2014). It is important to distinguish the crash contributing factors related to general roadway characteristics versus those related to work zones to develop effective work zone management strategies. Therefore, our third research objective was to develop a work zone crash risk estimation model that identifies the traffic crash risk cost attributed to the presence of work zones. We developed a causal inference model based on regression discontinuity design to infer the crash risk caused by the presence of work zones. By a series of placebo tests, we validated that the proposed causal inference model can estimate the crash risk caused by work zones characterized by various deployment configurations (length, duration, and light conditions of the work zones). More details on this are provided in Section 2.3.

2. The Developed Approach

2.1 Bridge annual maintenance expenditure (AMEX) prediction model.

Annual routine maintenance expenditures (AMEX), incurred by highway agencies, measure the expected future maintenance expenditure for infrastructure maintenance given a structural condition improved by maintenance actions (Volovski, 2011). The reduced value of AMEX before and after a maintenance action improving structural conditions is one of the expected benefits of proactive maintenance.

In this study, we focused on bridges specifically due to the availability of annual maintenance expenditure data for bridges. The existing data shows that most bridges will not get any maintenance in most years (leading to a large number of zero values of AMEX). This will be problematic when utilizing many data-driven estimation models, such as Ordinary Linear Regression models (Volovski, 2011). We utilized the Tobit model to manage AMEX data, which has an excess number of zero values. Tobit model (Tobin, 1958) has been widely applied to model the censored semicontinuous data. Though it has not been widely applied in analysis for civil infrastructures, the Tobit model has been widely used in economics (Keeley et al., 1978; McDonald and Moffitt, 1980; Nelson, 1977; Tobin, 1958), social science (Smith and Brame, 2003; Witte, 1980), epidemiology (Bleda and Tobías, 2002; Lubin Jay H. et al., 2004; Twisk and Rijmen, 2009), and transportation studies (NOLAN, 2003; Talley, 1995; Weiss, 1992).

The formula of our Tobit model is:

$$Y_{i(t+1)}^{*} = \beta X_{it} + \epsilon_{it} \tag{1}$$

$$\begin{cases} Y_{i(t+1)} = Y_{i(t+1)}^{*} & if\ Y_{i(t+1)}^{*} > 0 \\ Y_{i(t+1)} = 0 & if\ Y_{i(t+1)}^{*} \leq 0 \end{cases} \tag{2}$$

i represents the index of bridges, t is the index of year. $Y_{i(t+1)}$ is the Annual Maintenance Expenditure (AMEX) for bridge i at year $t+1$. $Y_{i(t+1)}^{*}$ is the latent variable representing the necessary maintenance expenditure for bridge i at year $t+1$. X_{it} represents the control variables for bridge i at year t. The control variables include bridge material information, conditions of superstructure, substructure, and deck, Average Daily Traffic (ADT), and weather information. Note that the goal of AMEX model is to predict the annual routine maintenance expenditure with the information of all control variables. If we use the AMEX and control variables in the same year, it will be hard to distinguish whether the control variables cause the changes AMEX or AMEX causes the changes of the control variables. Therefore, in our model, the control variables are extracted one year before the year of extracting AMEX to make sure we are using the control variables to predict AMEX. We choose the one-year lag between AMEX and control variables because the bridge conditions are reported every year in the National Bridge Inventory (NBI) data (FHWA, 2004).

We trained the AMEX model using maintenance data of 32,000 bridges maintained by the Pennsylvania Department of Transportation (DOT) in Pennsylvania during 2009-2017 (PennDOT, 2018a). The AMEX data are obtained from Pennsylvania Bridge Management System 2 (BMS2) (PennDOT, 2018a). Data of other control variables are collected from National Bridge Inventory (NBI) data (FHWA, 2004) and the National centers for environmental information. The original categories of condition ratings of superstructure, substructure, and deck cannot evenly represent the structural conditions of bridges. Hence, the original categories of condition ratings are reformulated to evenly represent the structural capacity of bridges using the process proposed in Yang and Frangopol (2018). In detail, the "excellent" and "very good" conditions of bridges are merged as the best category of structural condition rating due to their negligible difference in structural capacity. Similarly, the "failed", "imminent failure", and "critical" conditions are merged as the worst condition rating of bridges. Finally, the structure condition ratings in this study are encoded from 1 to 7, where a higher value represents better structural conditions of the bridge.

Our baseline model is linear regression based on Ordinary Linear Squares (OLS) (Volovski, 2011) and random-effect linear regression model (Volovski et al., 2017). Using the same notion of Equation (1) and (2), the formula of the OLS model can be represented in Equation (3).

$$Y_{i(t+1)} = \beta X_{it} + \epsilon_{it} \tag{3}$$

The OLS model assumes that each observation of AMEX is independently and randomly sampled. However, the AMEX data are extracted from a group of bridges in multiple years. The random-effect linear regression model can address the correlation of disturbance terms within the same bridge and within the same year. Using the same notion of Equation (1) and (2), the formula of the random-effect linear regression model can be represented in Equation (4).

$$
\begin{gathered}
Y_{i(t+1)} = \beta X_{it} + \mu_i + \lambda_t + \epsilon_{it} \\
\mu_i \sim N(0, \sigma_\mu^2) \\
\lambda_t \sim N(0, \sigma_\lambda^2)
\end{gathered}
\tag{4}
$$

Where μ_i represents the variance between different bridges, and λ_t represents the variance between different years.

The performance metric is the fitting statistics of the given model, Akaike Information Criterion (AIC) (Lee and Lemieux, 2010). For a given set of data, suppose we have a model f with k estimated parameters, and the log-likelihood of f on the given set of data is LL. Then AIC of f can be defined as:

$$AIC(f) = 2k - 2LL \tag{5}$$

If one model's AIC value is smaller than 2 of the other model, we say that the former model fits the data better than the later model (Burnham and Anderson, 2004).

2.2. Mesoscopic dynamic traffic assignment model

The Mesoscopic Dynamic Traffic Assignment model is used in the traffic simulation tool to estimate the detour cost of work zones incurred by road users. We used a dynamic network flow model, MAC-POSTS, to estimate road users' detour costs (Ma, Pi, and Qian 2019). The travel demands are calculated based on actual travel count and speed observations in the Pittsburgh region. Assuming that every road user (car or truck) tends to minimize their travel time for their trips, we simulated the traffic flow in 5 seconds. Emissions are calculated based on miles traveled by vehicles and time spent on their trips.

In this study, we modified the roadway network as the input of the MAC-POSTS to investigate the mobility impacts of proposed roadwork. The roadway network is modified by changing the traffic capacity from the full capacity to zero capacity at the road segment where the proposed roadwork is performed. Then by simulating the traffic flow on the modified roadway network, we obtained the total travel time, total emissions, and total travel distance for all the car users and truck users in the Pittsburgh region. The output from the modified roadway network is compared with the output from the original roadway network to reflect the mobility impact of roadwork on road users.

2.3. Work zone crash risk estimation model

We developed a model based on regression discontinuity design (RDD) to infer the work zone deployment configurations' effect on work zone crash risk.

RDD is a quasi-experimental analysis method accounting for unobserved heterogeneity and confounding problems, allowing causal inference with non-randomized observation (Moscoe et al., 2015; Nørgaard et al., 2017). It has been applied to investigating the causal effect of light conditions on the traffic crash rate (Uttley and Fotios, 2017). Their essential idea is that factors affecting the crash occurrence rate, such as habitual travel behavior, are continuous. Only the ambient light condition changes immediately before and after the daylight-saving time changes. Therefore, by observing the traffic crash rate difference immediately before and after the daylight-saving time changes, it is possible to get the crash rate affected only by the ambient light condition changes. Similarly, in this paper, our intuition is that consecutive weekly observations of crash risk on one specific road segment(s) are "continuous" if no work zone was deployed. By using "continuous," we mean that the observations of crash risk over weeks can be described as a single continuous function. With this assumption, we obtain the "realized outcome" – the number of crashes that occur on the road segments of work zones, and the "potential outcome" – the number of crashes that would occur on the same road segments and time of day if they had not been exposed to the presence of work zones. These definitions are used to obtain the number of crashes caused by the presence of work zones.

The work zone crash risk estimation model in this study focuses on estimating the crashes caused by the presence of work zones. The number of crashes caused by the presence of work zones is the delta value of the numbers of observed crashes and the number of crashes caused by factors affecting crash risk other than work zones, such as roadway characteristics. The number of crashes caused by the presence of work zones is obtained through the proposed RDD method utilizing "potential outcome" and "realized outcome." In detail, we obtained a "potential outcome" – the number of crashes that would occur on the same road segments and time of day if they had not been exposed to the presence of work zones. The number of crashes on road segments with the presence of work zones is the "realized outcome" corresponding to the presence of work zone. We assume the road segments immediately before and after the shock are expected to be similar to the road segments during the presence of work zone in terms of road characteristics that affect the crash risk. The only difference is whether there is roadwork on the road segment. Therefore, RDD constructs counterfactual scenarios as if "there were no roadwork" on the road segments experienced roadwork in reality. The difference between the number of crashes observed (realized outcome) and the number of crashes estimated in the counterfactual scenario (potential outcome) is the quantitative measurement of work zones' safety impact. The formula of our RDD model is:

$$logit(C_{jt}) \sim \alpha_1 W_{jt} + \alpha_2 R_{jt} + \beta X_{jt} + \epsilon_{jt} \tag{6}$$

j denotes the index of road segments. t denotes the index of time. C_{jt} is the crash occurrence during time t at road segment j. If a crash occurs, C_{jt}=1, else C_{jt} =0. W_{jt} denotes whether the roadwork is performed on road segment j during time t. If there is roadwork, W_{jt}=1, else W_{jt} =0. R_{jt} is the running variable, representing the weeks before, during, or after the roadwork. X_{jt} denotes control variables, include work zone deployment configurations (work zone duration, length, whether performed during nighttime, and whether performed during weekdays), road characteristics (road class, number of intersections, lane counts, and speed limit), and weather changes (wind speed, temperature, and precipitation). The coefficient of W_{jt} represents the value of crash risks caused by the presence of work zones, characterized by the roadway characteristics, work zone deployment configurations, and weather changes. Since weather conditions can change quickly, the given data sets' temporal resolution is set as 30 minutes to capture the effect of weather conditions on crash risk.

Our model is trained with crash data from 2015 to 2017 in Pennsylvania. The data of crashes is extracted from PennDOT Crash Data on all roadways from 2015 to 2017 (PennDOT, 2018b). The information of work zones is extracted from Road Condition Reporting System (Commonwealth Pennsylvania, 2018). The data of other control variables are extracted from PennDOT open-source roadway network data (Pennshare, 2018) and Federal Aviation Administration weather data (Pennsylvania State Climatologist, 2020).

Our proposed model is validated by temporal and spatial placebo tests. The placebo tests are designed to demonstrate that the desired causal effect should not exist when the data did not capture the presence of work zones. Each placebo test has a hypothesis that could challenge the validity of the causal effect identified in the model expressed in Equation (6). For each hypothesis, we designed corresponding placebo tests to prove that the hypothesis is not valid. By doing this, we can falsify the hypothesizes and further validate the causal effect identified in Equation (6). We listed the hypothesis and the corresponding placebo design.

- Temporal placebo test:
    - Hypothesis: Perhaps the locations of work zones are unique and cause the observed crashes. If it is true, the coefficient of W_{jt} in Equation (6) would represent the causal effect of the road segments selected as work zones on crash risk.
    - Placebo: We assigned the placebo treatment on road segments with roadwork, but not on the time that roadwork occurs. Instead, we assigned the placebo treatment one week prior and one week after the week when roadwork occurs.
- Spatial placebo test:
    - Hypothesis: Perhaps the times of work zones are unique and cause the observed crashes. If it is true, the coefficient of W_{jt} in Equation (6) would represent the causal effect of the times when performing work zones on crash risk.
    - Placebo: We assigned the placebo treatment on road segments that are randomly selected from the roadway network of Pennsylvania and on the time when there is one roadwork on road segments in Pennsylvania other than the selected road segment.

We expect the placebo treatment variable to be insignificant in both the temporal and spatial placebo tests. Then, we can falsify those hypothesizes and validate the identified causal effect in our model Equation (6).

3. Findings

3.1. Findings from the bridge annual maintenance expenditure (AMEX) prediction model

The results of these OLS, random-effect linear regression model, and Tobit model are shown in Table 1. The dependent variable is the log-transformed value of AMEX.

Firstly, the Tobit model performs better for fitting the given data set than the OLS model and random-effect linear regression model. It is because the Tobit model has a much smaller Akaike Information Criterion (AIC) compared with OLS (87,112 vs. 130,920) model and random-effect linear regression model (87,112 vs. 124,786).

Secondly, the coefficients of the bridge superstructure and substructure conditions are statistically significant. These coefficients can be used to estimate how much AMEX will be reduced if the condition rating of the bridge is improved. For example, the coefficient of the Superstructure condition is 0.20. It means that if the inspectors find the superstructure condition rating is one unit better than the condition rating inspected one year before, the AMEX of bridges is expected to be associated with a decrease of 22.1% (the calculation process is: $(\exp(0.20) - 1)$) than one year before, controlling all the other variables. Other variables can be interpreted similarly. Therefore, the Tobit model helps a maintenance agency estimate how much AMEX will be reduced if they improve the superstructure condition ratings or substructure condition ratings.

Overall, the proposed Tobit model estimates the reduced AMEX once the maintenance agency scheduled a maintenance to improve structural condition ratings of one bridge. By addressing the excessive number of zeros in the AMEX data, the proposed Tobit model fit the data much better than the baseline models (the OLS model and random-effect linear regression model) with a smaller value of Akaike Information Criterion, as shown in Table 2. The proposed Tobit model helps maintenance agencies schedule maintenance activities by estimating the reduced AMEX due to the scheduled maintenance.

Table 1 Results for bridge annual maintenance expenditure model. The coefficients of the variables at each model are shown with the stars to demonstrate their statistical significance, where "" means p<0.1; "**" means p<0.05; and "***" means p<0.01; Standard errors of the estimated coefficients for each variable at each model are shown in parentheses*

	OLS	***Random-effect***	***Tobit***
	(1)	(2)	(3)
Age	0.02^{***}	0.02^{***}	0.06^{***}
	(0.001)	(0.002)	(0.01)
Main span material- others, compared with concrete	0.02^{***}	0.02^{***}	0.14^{***}
	(0.005)	(0.01)	(0.05)
Main span material- steel, compared with concrete	0.02^{***}	0.02^{***}	0.20^{***}
	(0.002)	(0.003)	(0.03)
Superstructure condition (larger value represents worse conditions)	0.02^{***}	0.02^{***}	0.20^{***}
	(0.002)	(0.002)	(0.02)
	0.02^{***}	0.02^{***}	0.27^{***}

Substructure condition (larger value represents worse conditions)	(0.002)	(0.002)	(0.02)
Deck condition (larger value represents worse conditions)	0.01***	0.01***	0.26***
	(0.002)	(0.002)	(0.02)
Average Daily Traffic (ADT)	-0.01***	-0.01***	-0.01
	(0.001)	(0.001)	(0.01)
Truck percentage of ADT	0.01***	0.01***	0.19***
	(0.001)	(0.001)	(0.01)
Minimum Temperature	0.32***	0.32***	5.92***
	(0.05)	(0.05)	(0.59)
Maximum Temperature	0.30***	0.30***	6.32***
	(0.05)	(0.05)	(0.59)
Precipitation	0.01***	0.01***	0.23***
	(0.002)	(0.002)	(0.02)
Average Temperature	0.19*	0.22**	-1.07
	(0.10)	(0.10)	(1.06)
Cooling degree days	-0.19***	-0.19***	-2.31***
	(0.02)	(0.02)	(0.24)
Heating degree days	0.64***	0.67***	9.09***
	(0.07)	(0.07)	(0.81)
Palmer Drought Severity Index	-0.01***	-0.02***	-0.31***
	(0.004)	(0.004)	(0.04)
Palmer Modified Drought Index	0.002	0.01	0.33***
	(0.004)	(0.004)	(0.04)
Palmer Z-Index	-0.002	-0.002	-0.26***
	(0.002)	(0.002)	(0.02)
Deck area	-0.004***	-0.004***	0.04***
	(0.001)	(0.001)	(0.01)
Scour rating	0.01***	0.01***	-0.02
	(0.001)	(0.001)	(0.01)
Constant	0.07***	0.07***	-3.44***
	(0.001)	(0.002)	(0.03)
Bayesian information criterion (BIC)	131 125	124 982	87 318
Akaike information criterion (AIC)	130 920	124 786	87 112

Note: When "p<0.01", we say the corresponding variable are identified as statistically significantly associated with the AMEX of the bridge; The coefficients of the bridge superstructure and substructure conditions can be used to estimate how much AMEX will be reduced if the condition rating of the bridge is improved. E.g., if the inspectors find the superstructure condition rating is one unit better than the condition rating inspected one year before, the AMEX of bridges is expected to be associated with a decrease of 22.1% (the calculation process is: (exp(0.20)-1)) than one year before, controlling all the other variables

Table 2 Goodness of fit for AMEX prediction model.

Model name	***OLS***	***Random-effect***	***Tobit***
Akaike information criterion (AIC)	130 920	124 786	87 112

3.2. Findings from mesoscopic dynamic traffic assignment model.

We performed case studies in Pittsburgh. We selected the road segments under the bridge carrying State Road 28 over Bridge street. This bridge has low under-clearance and is more likely to be lifted. Hence, a work zone is possible to be performed on the selected road segments. We assumed that the vehicles would be blocked during the roadwork. We run MAC-POSTS to simulate the traffic flow changes if there is roadwork on selected road segments, considering all trucks and cars in Great Pittsburgh Area. The results show that trucks all over the Great Pittsburgh area will experience 1,133 additional hours of travel time and produce 157.5 kg additional CO_2 to complete their daily traffic demand. The cars all over the Great Pittsburgh area will experience 34,495 additional hours of travel time and produce 222.6 kg additional CO_2 to complete their daily traffic demand. The proposed Mesoscopic Dynamic Traffic Assignment model can help maintenance agencies to evaluate the mobility impact of scheduled maintenance in high temporal and spatial resolution.

3.3. Findings from work zone crash risk estimation model

The results of the causal inference model for work zone deployment configurations' effects on crash risk are shown in Table 33.

Firstly, this model explains the crash risk caused by the presence of work zones. The odds of crashes occur in roadways with the presence of work zones are 1.47 (calculated by $\exp(0.376)$) times higher than the ones without work zones, controlling all the other variables. Secondly, this model also explains the association between the crash risk and other covariates. For example, a 1% increase in traffic volume (AADT) is associated with $\exp(0.01 \times 0.764) = 1.008$ times higher crash occurrence odds, controlling other road characteristics and weather changes. These interpretations can be extended to other statistically significant variables (p<0.01), such as numbers of interactions near the work zone, length of the work zone, and whether the roadwork is performed during daytime.

The results of placebo tests are in line with our expectations. In other words, our model falsified the hypothesizes that the designed model captured the causal effect on the crash risk of the times of work zones only or locations of work zones only. Therefore, we can validate that our proposed model captures the causal effect of the presence of work zones.

Overall, the proposed work zone crash risk estimation model distinguishes the crash risk caused by the presence of work zones and the crash risk caused by the other covariates. It can help maintenance agencies to estimate the crash risk caused by the presence of scheduled maintenance activities.

Table 3 Results for work zone crash risk estimation model. The coefficients of the variables at each model are shown with the stars to demonstrate their statistical significance, where "" means p<0.1; "**" means p<0.05; and "***" means p<0.01; Standard errors of the estimated coefficients for each variable at each model are shown in parentheses.*

	Crash occurrence
Roadwork (W)	0.376***
	(0.119)
WeekN (R)	0.019*
	(0.010)
Duration (s; log)	-0.023
	(0.056)
Length (m; log)	0.543***
	(0.049)
Weekday of week	-0.165
	(0.119)
Daytime of day	0.766***
	(0.099)
Roadwork closure type	-0.443
	(0.628)
AADT (log)	0.842***
	(0.056)
NHS major roads	-1.897*
	(0.999)
Number of intersections (log)	0.354***
	(0.047)
Lane counts = 1	-0.146
	(0.173)
Speed limit	-0.020***
	(0.003)
Average wind speed (mph)	0.022***
	(0.007)
Average temperature (F)	0.005
	(0.004)
Average precipitation (inch)	-0.141
	(0.627)
Constant	-19.482***
	(1.016)
Monthly Dummies	Y
Yearly Dummies	Y
Observations	2,210,443

R2	0.114
chi2	1,754.004*** (df = 29)

Note: "WeekN" means weeks before, during, or after the roadwork; "NHS" means National Highway System. This model explains the crash risk caused by the presence of work zones. The odds of crashes occur in roadways with the presence of work zones are 1.47 (calculated by $\exp(0.376)$) times higher than the ones without work zones, controlling all the other variables.

4. Conclusions

It is a great challenge to maintain the deteriorating civil infrastructure systems, such as bridges. This study aims to assist maintenance agencies in scheduling maintenance activities when assessing the impacts of conducting maintenance on a bridge and the cost of the detour, and the risk of crashes during the presence of the maintenance activity.

Firstly, we build a predictive infrastructure maintenance expenditure model that predicts the reduced annual routine maintenance expenditure of one bridge whose structural conditions are improved due to the scheduled maintenance. It helps highway agencies to predict the reduced value of AMEX due to a scheduled maintenance activity improving structural conditions. The proposed Tobit model solves the excessive number of zero values in the data of maintenance costs by introducing a latent variable representing the necessary maintenance expenditure. The Tobit model fits the data better than the baseline models with a smaller value of the Akaike Information Criterion.

Secondly, we applied a mesoscopic dynamic traffic assignment model to estimate the detour cost of work zones incurred by road users in high spatial and temporal resolution (miles and minutes) and a regional traffic network. It helps highway agencies to predict the mobility impact of one scheduled maintenance activity in a high temporal and spatial resolution. We performed our case study on one real-world bridge in Pittsburgh. The simulated results provide an estimation of detour cost incurred by road users, including travel time and $\mathrm{CO_2}$ emissions.

Thirdly, we proposed a causal inference model based on RDD to estimate the traffic crash risk caused by the presence of work zones. The model distinguishes the crash risk caused by the presence of work zones and the crash risk caused by the other factors. It helps highway agencies to predict the safety impact of one scheduled maintenance activity.

In summary, this study helps maintenance agencies scheduling and assessing the potential impacts of maintenance activities on bridges. Due to data availability, we only implemented and evaluated our model based on data in Pennsylvania. In future studies, it would be good to test the methodologies proposed in this study on the data in other states. With that, it would be possible to compare the potential impact of maintenance activities across states.

Reference:

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