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Performance of US Concrete Highway Bridge Decks Characterized by Random Parameters Binary Logistic Regression

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ABSTRACT

This study employs a random parameters binary logistic regression (LR) to characterize the impact of environmental and structural parameters on concrete highway bridge deck deterioration nationwide. Two specific gaps in the literature are addressed: the use of a nationwide dataset for analysis and the implementation of a methodology to account for unobserved heterogeneity. A total of 3,262 bridge deck deterioration observations derived from the authors' Nationwide

Concrete Highway Bridge Deck Performance Inventory (NCBDPI) database were used in this study. Deterioration rate (DR) was computed as the decrease in the concrete bridge deck condition rating (CR) over time. Bridge decks with deterioration rates (DR) below a certain threshold were categorized as the lowest deteriorated bridge decks (“lowest DR”) and decks with DR above a certain threshold were considered among the highest deteriorated (“highest DR”). The following variables were found to be significant in the final model: average daily truck traffic (ADTT), climatic region, distance from seawater, bridge deck area, age of bridge, type of design and/or construction, structural material design, deck protection, type of membrane, type of wearing surface, and maintenance responsibility. The results show that bridge decks with a high ADTT, age of bridge, bridge decks located in cold regions, and those that are close to seawater are associated with the “highest DR” group of bridge decks. Furthermore, type of design and/or construction and maintenance responsibility play a role in deck being associated with “highest DR”.

Keywords: Highway bridge deck, concrete, performance, deterioration, National Bridge Inventory, database, random parameters binary logistic regression.

INTRODUCTION AND BACKGROUND

Over 600,000 bridges across all states represent critical components of the US transportation system, ensuring network continuity. The highest costs in bridge superstructure repair and rehabilitation are incurred through maintenance, repair, and replacement of concrete bridge decks (Li and Zhang, 2001). Understanding the causes of bridge deck deterioration is therefore central to asset management. Bridge decks, which are exposed to freeze and thaw cycles, deicers, and

heavy traffic loads, are a bridge's most susceptible element. Concrete bridge deck deterioration is also a leading cause for structural deficiency (Russell 2004). According to the Federal Highway Administration (FHWA), two billion dollars are spent annually for maintenance and capital costs for concrete bridge decks (ASCE, 2013). As a direct consequence, Departments of Transportation (DOT) and the FHWA are interested to determine the reasons behind concrete bridge deck deterioration.

Previous work has attempted to model bridge condition ratings (CR) by using various deterministic and stochastic models, such as simple regression (Morcous and Hatami, 2011), multiple regression (Reardon, 2015, Tae-Hoon et al., 2006; Bolukbasi et al., 2004), Markov models (Agrawal et al., 2010; Morcous, 2006, Madanat, 1995), and Bayesian models (Attoh-Okine and Bowers, 2006). Although these methods have been used to model bridge CR, the most commonly used and widely accepted method across civil engineering disciplines is logistic regression (LR). In the transportation field, LR has been widely used to model injury severity of crashes (Dissanayake and Lu, 2002; Harb et al., 2008; Donnell and Mason, 2004; Al-Ghamdi, 2002; Mannering and Bhat, 2014; Anderson and Hernandez, 2017; Al-Bdairi et al., 2018) and route/mode choice (Abdel-Aty and Abdalla 2004; Bierlaire et al. 2010; Dalumpines and Scott 2017; Mai et al. 2015; Mishra et al. 2013; Tan et al. 2015; Vidana-Bencomo et al. 2018; Washington et al. 2009). In construction management, LR has been used to model contractors' bids and worker safety (Lowe and Parvar, 2004; Hwang and Kim, 2016; Alomari et al., 2017), disputes (Diekmann and Girard, 1995; Cheung et al., 2010), contractors performance (Wong, 2004), and risk analysis (Ozdemir, 2016; Mwesige et al., 2016; Smith and McCarty, 2009). Lastly, in structural engineering, LR models have been used to study the performance of beam-column connections (Mitra et al., 2011; Kang and Mitra,

2012) and failure mode of reinforced concrete interior beam column joints under seismic loading (Vandana and Bindhu 2017).

More closely related to this study, Ariaratnam et al. (2001) used LR to study the performance of local sewer systems in Edmonton, Canada. Age, diameter, material, waste type, and average depth of cover were modeled as the independent variable. Salman and Salem (2012) applied three different regression models, including multinomial and binary logistic regression to establish deterioration models for wastewater collection lines. Shan and Lewis (2016) used a binary LR to characterize deficient steel bridges with concrete cast-in-place deck and multibeam/girder designs based on the NBI data. The best model consisted of eight independent variables (average daily traffic (ADT), structure length, length of maximum span, bridge roadway width, state code, owner, and age), two of which, owner and state code, were insignificant. In addition to these studies, there have been recent works that use LR to study material behavior. This has included evaluating the splitting tensile strength in plain and steel fiber-reinforced concrete based on compressive strength (Behnood et al. 2015), reproducing the stiffness degradation curve of asphalt specimens during fatigue testing (Mateos et al. 2017), analysis of asphalt fatigue test results (Mateos et al. 2015), and comparing low-temperature crack intensity on pavements with high modulus asphalt concrete and conventional asphalt concrete (Rys et al. 2017).

Directly related to the current study, statistical analysis and modeling of concrete bridge deck condition data has been performed by several researchers. For example, Madanat, et al. (1995) used an ordered probit model to estimate Markovian transition probabilities from deck condition ratings contained in the Indiana Bridge Inventory (IBI), a subset of the NBI. Using the same data

93 set, Mauch and Madanat (2001) introduced a semiparametric hazard rate model and stochastic
94 duration models (Mishalani and Madanat, 2002) to study bridge deck condition transition
95 probabilities. Using NBI data for the State of Wisconsin, Tabatabai, et al. (2011) evaluated
96 different distributions for analysis of condition rating data. More, a number of published studies
97 have specifically investigated the effects of chloride penetration on deck performance (e.g.,
98 Williamson, 2007; Lounis, 2000; Wedding et al., 1983).

99
100 While some published work has focused on concrete bridge deck CR, no attempts have been made
101 to use a nationwide dataset. Some studies have used subsets of a nationwide dataset, but focus on
102 a disaggregated picture (i.e., state or region). In addition, since these works have been completed,
103 the NBI dataset has substantially grown and provides researchers with more information for
104 analysis. A nationwide model can provide a holistic view of variables that impact bridge deck
105 deterioration. More, using region-specific indicators (i.e., climatic characteristics), the nationwide
106 model can potentially help in identifying problematic regions regarding bridge deck deterioration.
107 This, in turn, can lead to more focused analyses based on needs, as well as define regions based
108 on such characteristics. As it pertains to structural and bridge engineering applications, as well as
109 applications to concrete bridge decks, the LR analyses do not address what has become a prevalent
110 issue in today's datasets: unobserved heterogeneity (i.e., unobservables). As such, the current study
111 distinctively fills these gaps in the literature. To the best of the authors' knowledge, this is the first
112 attempt at modeling NBI data on a nationwide scale and the first attempt at overcoming a key
113 limitation within the NBI data by utilizing a random parameters estimation approach to account
114 for unobserved heterogeneity.

Objective and Motivation

The objective of this study was to characterize the effect of various environmental, structural, construction, climatic, and traffic related parameters on concrete bridge deck performance. Specifically, the focus was on two extreme groups: bridges that have experienced the highest and lowest levels of deterioration. A random parameters binary LR framework was developed to quantify the impact of various parameters on the likelihood of a bridge deck being associated with the group of highest and lowest deterioration rates (DR), while also accounting for a key limitation within the data: unobserved heterogeneity. This method uniquely fills a gap in literature with its application to bridge deck deterioration.

DATASET

The authors have created a Nationwide Concrete Bridge Deck Performance Inventory (NCBDPI) database (Ghonima et al., 2018) with the specific goal of adopting a more statistical and data mining approach to understanding concrete highway bridge deck performance. The primary source of information for the NCBDPI database is the National Bridge Inventory (NBI) database (FHWA, 2017). For this research, a number of NBI items were extracted and complemented with additional parameters such as climatic region, distance to seawater, bridge age, and deterioration rate (DR). One of the key performance metrics available in the authors' NCBDPI database is the DR, which is defined as follows (Ghonima et al., 2018):

$$DR = (CR' - CR'') / TICR \quad (Eq. 1)$$

where CR' and CR'' are the bridge deck condition ratings (CR) at the beginning and end of a series of consecutive CR, and TICR (= time-in-condition rating) is the duration in years, as illustrated in Fig. 1. Deterioration is referred to as the observed decrease in CR. Also, maintenance is used to refer to any deck improvement action that increases the CR, similar to many published materials in the past. Note that the DR could only be calculated when $CR' > CR''$, i.e. when deterioration occurred. For the sample deck shown in Fig. 1, one fully observable cycle of deterioration occurs. DR was employed in this analysis as the independent variable because of its ability to capture the rate of change of CR, which TICR cannot. This emerged from discussions with a number of stakeholders involved in the overall research (Ghonima et al., 2018), in particular from bridge inspectors that have found some bridge decks to deteriorate much faster than others.

Fig. 1. Sample concrete bridge deck condition rating (CR) with computed independent variables.

Note: A decrease and an increase in the assigned CR is considered deterioration and maintenance, respectively. Data considered in this analysis include years 1992 to 2014.

This study regarded concrete bridge decks with $DR \leq 0.056$ as the group with the lowest deterioration rate (“lowest DR”) with a total of 1,569 observations. $DR = 0.056$ means that a bridge deck was assigned the same CR for approximately 18 years, i.e. $TICR = 18$, before experiencing a one-unit CR decrease. Concrete bridge decks assigned a $DR \geq 2$ were considered as part of the group associated with the highest deterioration rate (“highest DR”) with a total of 1,693 observations. $DR = 2$ means that the bridge was assigned the same CR for one year, i.e. $TICR = 1$, before a two-unit CR decrease occurred. The thresholds of 0.056 and 2 were selected after careful analysis and discussing with practitioners, bridge engineers from two state DOTs, and the FHWA what might be a reasonable TICR before a bridge deck is assigned a lower CR. While ideally, a physics-based classification would be applied to select boundaries, this is not possible here given that the CR are based on qualitative visual inspection results that include a number of deterioration mechanisms. As can be observed, using this approach produced two groups with similar numbers of samples.

The lowest and highest DR groups were coded as binary variables and assigned 0 and 1, respectively. The reason behind taking these values was to make a clear distinction between the best and worst performing concrete bridge decks.

Table 1 presents a summary of the variables included in the study and/or their frequencies. Refer to Ghonima, et al. (2018) for more details. Following are some observations: The average ADTT on the bridges in the dataset is nearly 1000. A significant majority of the bridges has cast-in-place decks. In terms of structural material and/or design, close to 80% of the bridge decks are part of either a simple or continuous span concrete or prestressed concrete bridge system. Close to 75%

of the bridges have no deck protection and more than 75% of the bridges have no membrane. A majority of the bridge decks captured in the sample were in rural areas. Finally, a state highway agency was responsible for the maintenance of nearly two-thirds of the bridges.

Table 1. Summary statistics and counts for the bridge deck variables included in this study.

Continuous variables	Minimum	Mean	Maximum
Distance from Seawater (km)	0	5,655	16,619
Deck Area (ft ²) – computed from NBI Items 49 and 51	2370	74,304	4,080,000
Average Daily Truck Traffic (ADTT) – NBI Item 109	0	983	25,432
Bridge Age (years) – computed from NBI Items 27 or 106	0	39.8	122
Number of Lanes (-) – NBI Item 28	1	1.45	11
Categorical variables	Categories	Frequency	Percentage
Deck Structure Type – NBI Item 107	Cast-in-Place	2,899	88.0
	Concrete Precast Panels	397	12.0
Structural Material/Design – NBI Item 43a	Concrete – simple span	764	23.2
	Concrete – continuous	454	13.8
	Prestressed concrete – simple	872	26.5
	Prestressed concrete – continuous	515	15.6
	Steel – simple span	554	16.8
	Steel – continuous	137	4.2
Climatic Region (IECC)	Very Hot	215	6.5
	Hot	919	27.9
	Average	553	16.8
	Cold	1,045	31.7
	Very Cold (VC)	444	13.5
	Extremely Cold (EC)	33	1.0
	Average Marine (AM)	38	1.2
	Hot Marine (HM)	49	1.5
Deck Protection – NBI Item 108c	None	2,421	73.5
	Epoxy-Coated Reinforcing	487	14.8
	Galvanized Reinforcing	16	0.5
	Other Coated Reinforcing	4	0.1
	Cathodic Protection	2	0.1
	Polymer Impregnated	11	0.3
	Internally Sealed	1	0.0
	Unknown	329	10.0
	Other	25	0.8
Type of Membrane – NBI Item 108b	None	2,566	77.9
	Built-up	106	3.2
	Preformed Fabric	99	3.0
	Epoxy	23	0.7
	Unknown	403	12.2
	Other	99	3.0

Table 1. (Continued)

Type of Wearing Surface – NBI Item 108a	None	207	6.3
	Monolithic Concrete	1,239	37.6
	Integral Concrete	248	7.5
	Latex Concrete or Similar Additive	131	4.0
	Low-Slump Concrete	59	1.8
	Epoxy Overlay	36	1.1
	Bituminous	1,160	35.2
	Timber	88	2.7
	Other	128	3.9
Functional Classification of Inventory Route – NBI Item 26	Rural	2,339	71.0
	Urban	957	29.0
Type of Design and/or Construction – NBI Item 43b	Slab	664	20.1
	Stringer/multi-beam or girder (SB)	1,628	49.4
	Girder and floor beam system	60	1.8
	Tee beam (TB)	275	8.3
	Box beam or girders – multiple (BBM)	387	11.7
	Box beam or girders – single or spread (BBS)	36	1.1
	Frame	17	0.5
	Truss – through	60	1.8
	Arch-deck	17	0.5
Maintenance Responsibility – NBI Item 21	Channel beam (CB)	152	4.6
	State Highway Agency	2,134	64.7
	County Highway Agency (CHA)	838	25.4
	Town or Township Highway Agency	139	4.2
	City of Municipal Highway Agency (CMHA)	140	4.2
	State Toll Authority (STA)	45	1.4

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185 **ANALYSIS**186 **Logistic Regression**

187 Logistic (or logit) regression (LR), a modeling approach that describes the occurrence probability
188 of an outcome or event, is a method of fitting a regression curve to determine the outcome
189 probability of said outcome or event as a function of covariates (i.e., independent variables). In the
190 case of binary logistic regression, in which the outcomes are binary (i.e., 0 or 1), the probability
191 that the outcome takes on the value 1 is determined through a set, or function, of covariates (Train
192 2009; Washington et al. 2011; Greene 2018). Covariates can be continuous, categorical, or both.

For the current study, the outcome being modeled is bridge deck deterioration rate (DR), where concrete bridge decks associated with the two groups “lowest DR” and “highest DR” were coded as 0 and 1, respectively. Because some of the independent variables are categorical, several indicator variables were created to differentiate the different categories. But, to avoid multicollinearity issues, only $k-1$ indicators from the same categorical variable could be included in the final model specifications (Yannis, et al., 2011). For example, the variable category Climatic Region (Table 1) consists of 8 different sub-categories; therefore, at most, seven indicator variables indicating climatic region can be included in final model specifications.

Fig. 2. S-shape probability function used in binary logistic regression (LR).

The probability function of a logit model that describes a dependent variable in terms of independent variables can be represented as an S-shape function (Fig. 2), where the logit probability is represented as (McFadden 1981; Train 2009):

$$P_n(i) = \frac{e^{(\beta_i X_{in})}}{\sum_{\forall i} e^{(\beta_i X_{in})}} \quad (\text{Eq. 2})$$

where $P_n(i)$ is the probability of observation n having outcome i , β_i is a vector of estimable parameters indexed by outcome i , and X_{in} is a vector of explanatory variables (e.g., climatic region, wearing surface, etc.) used to determine the outcome probability. Now, by satisfying the alternative-specific-constant rule in logit modeling (see Train (2009) for a full discussion), normalizing one of the outcomes to utilize a binary logit framework for the current study results in the following (Train 2009; Washington et al. 2011; Hensher et al. 2015; Greene 2018):

$$P_n(i) = \frac{e^{\hat{\beta}_i}}{1 + e^{\hat{\beta}_i}}, \text{ where } \hat{\beta} = \beta_0 + \beta_1 X_{1,n} + \dots + \beta_i X_{i,n} + \varepsilon_{in} \quad (\text{Eq. 3})$$

where ε_{in} is a Type I Extreme Value distributed error term and all other terms have been defined previously. The error term attempts to capture unobservables within the data; that is, attributes that are unobserved by the analyst (variables not included or collected in the data). In the case of the current study, each and every variable that contributes to the deterioration of a bridge deck is likely not included in the utilized data. This could be a result of several factors, such as the data is unavailable or the data is not collected. Therefore, these variables not included in the data are considered unobservables. These unobservables can result in unobserved heterogeneity, which if not accounted for, can result in biased estimates, incorrect inferences, and inaccurate recommendations. In addition, unobserved heterogeneity can be a result of variation within an existing variable due to unobserved characteristics. For instance, climatic regions are available, but no information on weather irregularities are included. This unobservable can be “embedded” in climatic region variables; therefore, resulting in unobserved heterogeneity (the reader is referred to Mannering et al. (2016) for a full discussion on methods and implications as it pertains to unobserved heterogeneity in econometric analyses).

As such, the current study attempts to account for these unobservables by estimating a model with random parameters. As opposed to a traditional logit model, in which coefficient estimates are assumed to have the same sign (or effect) across all observations, a random parameters model allows beta estimates to vary across observations based on a distribution defined by the analyst (i.e., beta will be negative for a proportion of observations and positive for the remainder, or vice-versa). To estimate such a model, a mixing distribution is introduced to the binary logit formulation in Eq. (2) (Greene 2016a; McFadden and Train 2000; Train 2003; Washington et al. 2011):

$$P_n(i | \phi) = \int_x \frac{e^{(\hat{\beta})}}{1 + e^{(\hat{\beta})}} f(\hat{\beta} | \phi) d\hat{\beta} \quad (\text{Eq. 4})$$

where $P_n(i | \phi)$ is now the weighted outcome probability of $P_n(i)$ taking on the value 1 conditional on $f(\hat{\beta} | \phi)$. In particular, $f(\hat{\beta} | \phi)$ is the density function of $\hat{\beta}$ with distributional parameter ϕ . The density function, $f(\hat{\beta} | \phi)$, is what allows parameter estimates to vary across observations so as to permit $\hat{\beta}$ to account for observation-specific variations of the effect of X on $P_n(i | \phi)$ (Washington et al. 2011). In general, the density function is specified to be normally distributed and is the distribution assigned to $f(\hat{\beta} | \phi)$ in the present study (Greene 2016b; Hensher et al. 2015).

Due to difficulties in computing the probabilities in such a model, a simulation-based approach is applied to estimate parameters. To simulate, previous work has shown that Halton draws provide a preferred alternative to merely random draws; therefore, Halton draws are used in the current study (Bhat 2003; Halton 1960; Train 2000). Using Halton draws, the simulated probabilities are

inserted into the log-likelihood function of the logit model, thus providing a simulated log-likelihood (Train 2009; Washington et al. 2011):

$$SLL = \sum_{n=1}^N \sum_{i=1}^I \delta_{in} \ln[P_n(i | \phi)] \quad (\text{Eq. 5})$$

where N is the total number of observations, I is the total number of outcomes, δ_{in} is equal to 1 if the observed outcome for observation n is i and zero otherwise, and all other terms have been defined previously. Using Halton draws, $P_n(i | \phi)$ are approximated by drawing values of β from the density function (given values of the distribution parameter ϕ) and used to estimate the logit probability shown in Eq. (2). This is done many times and the computed logit probabilities are then summed and averaged to obtain the simulated probability, $P_n(i | \phi)$.

LR differs from multiple linear regression with respect to the interpretation of the coefficients of the independent variables. In multiple linear regression, the beta estimates can be interpreted as a marginal effect (i.e., the effect on a dependent variable due to a one-unit increase in explanatory variable, X). However, this is not the case with LR models. In some cases, LR coefficients are interpreted using the log of the odds (i.e., odds ratios). However, odds ratios are most often seen in the statistics literature (Ramsey and Schafer 2012), whereas pure econometrics analyses almost exclusively consist of marginal effects to interpret parameter estimates (Greene 2018; Greene and Hensher 2010; Hensher et al. 2015). Therefore, the current study uses marginal effects to interpret estimates from the LR model.

As described previously, marginal effects measure the impact of an explanatory variable, due to a one-unit increase, on the probability that the outcome takes on the value 1. For continuous explanatory variables, marginal effects are computed as (Greene 2016a, 2018):

$$\frac{\partial P_n(i)}{\partial X_{ink}} = [1 - P_n(i)]P_n(i)\beta_{n(i)} \quad (\text{Eq. 6})$$

where $\frac{\partial P_n(i)}{\partial X_{ink}}$ is the derivative of the probability of observation n having deterioration outcome i . However, for indicator variables, marginal effects are computed differently. For indicator variables (the majority of variables used in the present study), marginal effects are defined as the difference of the estimated probabilities when indicator variable X_{ink} changes from zero to one while all other variables remain equal to their means (remain constant) (Greene 2018):

$$M_{X_{ink}}^{P_n(i)} = \Pr[P_n(i) = 1 | X_{(X_{ink})}, X_{ink} = 1] - \Pr[P_n(i) = 1 | X_{(X_{ink})}, X_{ink} = 0] \quad (\text{Eq. 6})$$

where $X_{(X_{ink})}$ is the mean of all other variables (the variables that are being held constant) while X_{ink} changes from zero to one.

Logistic Regression Coefficients

This study began by generating several indicators from the categorical variables and creating natural logarithm variables from variables that had large values, as this would result in marginal effects of essentially zero (marginal effects are discussed in the coming sections) (i.e., ADTT, deck area, distance from seawater, etc.). Using a stepwise procedure, in which the model was built-up

from just the constant, Table 2 shows that 25 variables were found to have a statistically significant impact on bridge deck deterioration. In addition, as anticipated, model estimates show that the data is susceptible to large amounts of heterogeneity (i.e., unobservables). This is observed by the 9 variables with normally distributed estimated random parameters. That is, these 9 variables have heterogeneous effects on bridge deck deterioration.

Table 2. Random parameters binary logit model specifications.

Variable	Coefficient	Std. Error	t-statistic	Marginal Effects
Constant	4.660	0.686	6.79	
Natural Logarithm of Deck Area [DA]	-0.472	0.064	-7.42	-0.117
Natural Logarithm of ADTT [ADTT]	0.320	0.025	12.58	0.079
Natural Logarithm of Distance to Seawater [SW]	-0.255	0.028	-9.23	-0.063
Age of Bridge [AGE]	-0.028	0.003	-9.62	-0.007
<i>(Std. Dev. Of Normally Distributed Random Parameter)</i>	<i>(0.038)</i>	<i>(0.002)</i>	<i>(17.89)</i>	
Structural Material Design				
1 if Continuous Concrete, 0 Otherwise [CONCR]	0.545	0.184	2.97	0.135
<i>(Std. Dev. Of Normally Distributed Random Parameter)</i>	<i>(3.266)</i>	<i>(0.269)</i>	<i>(12.13)</i>	
1 if Simple Prestressed Concrete, 0 Otherwise [SMPCR]	1.856	0.164	11.33	0.459
1 if Continuous Prestressed Concrete, 0 Otherwise [CONPCR]	1.045	0.200	5.23	0.258
<i>(Std. Dev. Of Normally Distributed Random Parameter)</i>	<i>(3.417)</i>	<i>(0.268)</i>	<i>(12.77)</i>	
1 if Simple Span Steel, 0 Otherwise [SMSTL]	0.923	0.167	5.54	0.228
<i>(Std. Dev. Of Normally Distributed Random Parameter)</i>	<i>(1.357)</i>	<i>(0.165)</i>	<i>(8.25)</i>	
1 if Continuous Steel, 0 Otherwise [CONSTL]	0.525	0.254	2.07	0.130
Climatic Region				
1 if Very Hot, 0 Otherwise [VH]	-1.694	0.238	-7.13	-0.419
1 if Average, 0 Otherwise [AVG]	-0.778	0.133	-5.84	-0.193
<i>(Std. Dev. Of Normally Distributed Random Parameter)</i>	<i>(0.886)</i>	<i>(0.169)</i>	<i>(5.23)</i>	
1 if Extremely Cold, 0 Otherwise [EXCLD]	4.252	0.571	7.44	1.052
1 if Hot Marine, 0 Otherwise [HMAR]	1.252	0.482	2.60	0.310
Deck Protection				
1 if Epoxy-Coated Reinforcing, 0 Otherwise [EPOX]	2.273	0.254	8.94	0.563
<i>(Std. Dev. Of Normally Distributed Random Parameter)</i>	<i>(6.187)</i>	<i>(0.488)</i>	<i>(12.67)</i>	
1 if Polymer Impregnated, 0 Otherwise [POLY]	3.444	1.213	2.84	0.852

Table 2. (continued)

Type of Membrane				
1 if Built-Up Membrane, 0 Otherwise [BUM]	0.911	0.219	4.16	0.226
Type of Wearing Surface				
1 if No Wearing Surface, 0 Otherwise [NOSUR]	1.735	0.241	7.18	0.429
<i>(Std. Dev. Of Normally Distributed Random Parameter)</i>	<i>(2.218)</i>	<i>(0.345)</i>	<i>(6.42)</i>	
1 if Integral Concrete, 0 Otherwise [ICON]	1.947	0.250	7.79	0.482
1 if Latex Concrete or Similar Additive, 0 Otherwise [LATEX]	0.730	0.232	3.14	0.181
1 if Low-Slump Concrete, 0 Otherwise [LSLMP]	1.866	0.306	6.10	0.462
Type of Design and Construction				
1 if Girder and Floor Beam System, 0 Otherwise [GFBS]	2.307	0.410	5.62	0.571
1 if Tee Beam, 0 Otherwise [TB]	1.346	0.198	6.80	0.333
1 if Truss (Through), 0 Otherwise [TRS]	1.991	0.381	5.22	0.493
Maintenance Responsibility				
1 if County Highway Agency, 0 Otherwise [CNTY]	1.089	0.150	7.26	0.270
<i>(Std. Dev. Of Normally Distributed Random Parameter)</i>	<i>(3.393)</i>	<i>(0.215)</i>	<i>(15.76)</i>	
1 if City of Municipal Highway Agency, 0 Otherwise [CITY]	0.404	0.259	1.56	0.100
<i>(Std. Dev. Of Normally Distributed Random Parameter)</i>	<i>(2.183)</i>	<i>(0.384)</i>	<i>(5.68)</i>	
Model Statistics				
Number of Observations	3,262			
Log-Likelihood at Zero	-1,953.98			
Log-Likelihood at Convergence	-1,484.24			
McFadden Pseudo R-Squared	0.24			

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304 Referring to Table 2, final model specifications show that significant variables were found in the
 305 following categories: Maintenance Responsibility, Type of Design and/or Construction, ADTT,
 306 Climatic Region, Distance to Seawater, Deck Area, Age of Bridge, Structural Material Design,
 307 Deck Protection, Type of Membrane, and Type of Wearing Surface. Those variables were chosen
 308 through a stepwise procedure based on (1) their statistical significance and (2) were assumed to
 309 play a role in bridge deck performance.

310

311 The beta estimates and independent variables from the final model specifications can now be
 312 substituted into the right-hand side of Eq. 3 to give:

$$\begin{aligned}
& \log\left(\frac{P_n(i)}{1-P_n(i)}\right) = 4.660 - 0.472 \cdot \ln(\text{DA}) + 0.320 \cdot \ln(\text{ADTT}) - 0.255 \cdot \ln(\text{SW}) - 0.028 \cdot \text{AGE} + \\
& 0.545 \cdot \text{CONCR} + 1.856 \cdot \text{SMPCR} + 1.045 \cdot \text{CONPCR} + 0.923 \cdot \text{SMSTL} + 0.525 \cdot \text{CONSTL} - \\
& 1.694 \cdot \text{VH} - 0.778 \cdot \text{AVG} + 4.252 \cdot \text{EXCLD} + 1.252 \cdot \text{HMAR} + 2.273 \cdot \text{EPOX} + 3.444 \cdot \\
& \text{POLY} + 0.911 \cdot \text{BUM} + 1.735 \cdot \text{NOSUR} + 1.947 \cdot \text{ICON} + 0.730 \cdot \text{LATEX} + 1.866 \cdot \text{LSLMP} + \\
& 2.307 \cdot \text{GFBS} + 1.346 \cdot \text{TB} + 1.991 \cdot \text{TRS} + 1.089 \cdot \text{CNTY} + 0.404 \cdot \text{CITY} \quad (\text{Eq. 7})
\end{aligned}$$

As mentioned previously, the more common way to interpret parameter estimates in an econometric analysis is to look at marginal effects (see Table 2). Taking the natural log of ADTT (continuous variable) as an example, and holding all other variables equal to their means (held constant), increasing the natural logarithm of ADTT by unity significantly increases the probability of high bridge deck deterioration by 7.9%. Interpretation of marginal effects on log-transformed variables follows that of Haleem and Abdel-Aty (2010). While the interpretations are similar for the indicator variables, they are relative to “otherwise.” This indicates that inference can be made relative to all other categories, or inference can be made directly on the indicator variable. A full discussion of significant variables and their effects on bridge deck deterioration probability is provided in the discussion of significant variables.

Variable Importance

To assess the relative importance of the individual predictors in the model, the absolute value of the t -statistic for each model variable can be used to obtain variable importance. All measures of importance were scaled to have a maximum value of 100. As can be seen in Fig. 3, ADTT, simple prestressed concrete, age of the bridge, and distance to seawater are the most influential variables.

Fig. 3. Relative importance of model parameters based on *t*-statistic (scaled to 100).

Variable Elasticities for Continuous Variables

In addition to interpreting estimates through marginal effects, an alternate method consists of using elasticities to interpret parameter estimates. In cases where the explanatory variables have large values (e.g., ADTT, deck area, distance to seawater), the effect of a 1% increase on the probability of the outcome taking on the value 1 may be more intuitive (Ulfarsson and Mannering, 2004). Consider a one-unit increase in ADTT to a 1% increase in ADTT, for example. Using elasticities can provide a unit-less measure to choice sensitivity to each independent variable (Yannis et al., 2011; Broach, 2012). However, the calculations for elasticities is different. In NLOGIT, elasticities of the probability are computed as (Greene 2016b):

$$\frac{\partial \log E[y | X]}{\partial \log X_{ink}} = \frac{X_{ink}}{E[y | X]} \times M_{X_{ink}}^{P_n(i)} \quad (\text{Eq. 8})$$

A naïve pooling method was used where elasticities for each observation were calculated and the mean of all cases was taken as the elasticity (Hensher et al., 2015) (Table 3).

Table 3. Elasticities for continuous variables.

Continuous Variable	Elasticity
Natural Logarithm of ADTT	0.731
Natural Logarithm of Deck Area	-2.724
Natural Logarithm of Distance to Seawater	-1.089

As can be seen in Table 3, following the interpretation from Wooldridge (2010) and Greene (2018), the elasticity of the natural log of ADTT means that a 1% increase in the natural log of ADTT results in an increase of bridge deck deterioration probability by 73.1%. On the other hand, a 1% increase in deck area and a 1% increase in distance to seawater (their natural logarithms) result in a decrease in bridge deck deterioration probability by 272% and 109%, respectively. These results suggest that bridge deck area and distance to seawater have a significant impact on bridge deck deterioration.

Statistical Evaluation of the Final Model

To evaluate the statistical fit of the LR model, a log-likelihood ratio test was performed. In a binary LR, a model having more predictors is expected to provide a better fit to the data than a model having fewer predictors. A log-likelihood ratio test estimates the overall explanatory power of a model to determine if the independent variables chosen for the model improve the overall model

fit. In the case of the current study, being that a model with random parameters was estimated, the log-likelihood ratio test determines if the log-likelihood of the random parameters model is of more significance than the log-likelihood with fixed parameters (model not accounting for data unobservables). Therefore, the log-likelihood ratio test is computed as follows (Washington et al. 2011):

$$\chi^2 = -2[LL(\beta_{\text{Fixed}}) - LL(\beta_{\text{Random}})] \quad (\text{Eq. 9})$$

where $LL(\beta_{\text{Fixed}})$ is the log-likelihood at convergence of the fixed parameters model, $LL(\beta_{\text{Random}})$ is the log-likelihood at convergence of the random parameters model, and χ^2 is a chi-square statistic with degrees of freedom equal to the number of estimated random parameters in β_{Random} . In the log-likelihood ratio test, the null hypothesis is that the fixed parameters model is true and the alternative hypothesis is that the random parameters model is true. Thus, if the p -value for the log-likelihood ratio test is statistically significant, there is evidence that the random parameters model is preferred and the null hypothesis can be rejected (Washington et al. 2011) (Table 4).

Table 4. Likelihood ratio test results.

Model	Parameters	Log-Likelihood	Degrees of Freedom	χ^2	p -value
Fixed	28	-1,953.98	-	-	-
Random	28	-1,484.24	9 (Estimated Random Parameters)	939.48	0.000

As seen from Table 4, the null hypothesis that the fixed parameters model is preferred is rejected. In particular, the overall model fit of the random parameters model is of more significance with

well over 99% confidence. Moreover, when comparing the log-likelihood at zero (estimated with only the constant) to the log-likelihood at convergence of the random parameters model, a McFadden Pseudo R-Squared value of 0.24 is obtained. A model with a McFadden Pseudo R-Squared value of this magnitude is considered to have an “exceptional” fit (McFadden 1973, 1977, 1981).

DISCUSSION OF SIGNIFICANT VARIABLES

To ease discussion, a synthesis of significant variables will be done by variable category as defined in Table 2. To begin, the variables not related to a specific category will be discussed (ADTT, distance to seawater, and deck area have been discussed previously): age of bridge. Both of these variables are significant and have heterogeneous effects (i.e., they have normally distributed random parameters). As it pertains to the age of the bridge, model estimations show an estimated parameter mean of -0.028 and an estimated standard deviation of 0.038. Based on these estimations, the normal distribution curve indicates that the estimated parameter mean is greater than zero for 23.1% of bridge decks and less than zero for 76.9% of bridge decks. In other words, as bridge age increases, 23.1% are more likely to have high deterioration and 76.9% are less likely. The heterogeneous effects here may be attributed to corrosion. In regards to corrosion, it has been proposed that corrosion rate decreases with age (Tabatabai and Lee 2006; Vu and Stewart 2000). Therefore, as age increases, it may be less likely to observe high deterioration. However, some environments are more severe than others and the natural protection from corrosion due to the high alkalinity of cement-based materials can be reduced (Bien et al. 2007; Gucunski et al. 2011). For the latter, this occurs due to chloride ingress, which upon reaching the rebar will destroy the

passivity layer. In such a case, corrosion as a result of age can lead to an increase in likelihood of high deterioration.

Structural Material/Design (NBI Item 43A)

Five variables related to structural material/design, which describes the bridge superstructure material and whether it is simple-span or continuous, are found to be significant. The assumption here is that when the bridge is considered continuous, so is the deck, and vice versa. Of these five variables, three have heterogeneous effects on deterioration probability. The first structural material/design variable with heterogeneous effects is: concrete continuous. Referring to model estimations, this parameter has an estimated mean of 0.545 and an estimated standard deviation of 3.266. Using the normal distribution curve, these estimates indicate that 43.4% of concrete continuous decks are less likely to have high deterioration and 56.7% are more likely. Being that cracking can lead to bridge deck deterioration by allowing water and chemicals to penetrate the deck, this random parameter may be attempting to capture unobservables related to cracking (Schmitt and Darwin 1995). Specifically, cracking is greater in continuous span decks due to the negative bending moment regions at the interior supports (Grace et al. 2004). In addition, it has been shown that the severity of cracking is directly correlated with the severity of vibrations (Alampalli et al. 2002). Therefore, the proportion of continuous concrete bridge decks that are less likely to have high deterioration may be experiencing fewer vibrations at a lesser severity, in addition to less cracking (the bridges have shorter spans that result in less cracking). Also with a normally distributed estimated random parameter is the indicator for continuous prestressed concrete. Referring to model estimations, the estimated parameter mean of 1.045 and estimated standard deviation of 3.417 indicate that 38% of bridge decks supported by a continuous

434 prestressed concrete bridge superstructure are less likely to have high deterioration and 62% are
435 more likely. The non-homogenous nature in this variable may also be attributed to cracking. That
436 is, prestressed concrete without longitudinal cracks reduces the likelihood of deterioration due to
437 corrosion and/or freeze-thaw cycles. However, if transverse cracking takes place (i.e., parallel to
438 the transverse prestressing), there is a high likelihood of early deck deterioration, as well as
439 exposed tendons that can be prone to corrosion (Poston et al. 1989). This random parameter may
440 be capturing these differences in cracking among decks supported by prestressed concrete bridge
441 superstructures.

442
443 The third variable, also with a normally distributed random parameter, is the indicator for concrete
444 bridge decks supported by simple-span steel bridge superstructures. With an estimated parameter
445 mean of 0.923 and a standard deviation of 1.357, 24.8% of bridge decks supported by simple span
446 steel bridge superstructures are less likely to experience high deterioration and 75.2% are more
447 likely to experience high deterioration relative to decks supported by simple span concrete
448 superstructures. The heterogeneous nature of this variable may be linked to end restraints of steel
449 superstructures and shrinkage (Russell 2004). In addition, concrete deck cracking is observed more
450 in curved bridges than in straight bridges and more cracking is observed as restraint increases, steel
451 configuration, girder depth, or close girder spacing (Russell 2004). These attributes impacting
452 bridge deck deterioration are unobserved in the NBI data; therefore, the randomness in this
453 parameter may be accounting for these unobservables that can result in varying effects across
454 bridge decks.

455

Deck Protection (NBI Item 108C)

For deck protection variables, two are found to be significant. Of the two variables, the first with a normally distributed random parameter is epoxy-coated reinforcing bars. Therefore, with an estimated parameter mean of 2.273 and a standard deviation of 6.187, 35.7% of decks protected by epoxy-coated reinforcing bars are less likely to experience high deterioration and 64.3% of decks are more likely to experience high deterioration. The heterogeneous nature of this variable is likely related to the location of deck deterioration. For instance, Lawler et al. (2011) found that bridge decks with epoxy-coated reinforcing bars have less than 0.15% corrosion-induced deterioration. However, Lawler et al. (2011) also observed deterioration in bridge decks with epoxy-coated reinforcing bars, specifically at cracks or construction joints. This finding shows that a large proportion of bridge decks with epoxy-coated reinforcing may have considerable deterioration stemming from cracks and/or construction joints, suggesting that these locations be investigated further for such bridge decks.

Type of Membrane (NBI Item 108B)

Of the several variable categories, type of membrane is the only category to have just one significant variable. In particular, bridge decks with a built-up membrane have a 22.6 percentage point increase in probability of suffering from high deterioration, according to marginal effects. This finding may be attributed to this type of membrane being popular in the 1960s and, in nearly all cases, having been discontinued (Manning 1995). For built-up membranes, two layers are used: glass fabric and coats of coal-tar pitch emulsion (Hagenbuch 1971; Manning 1995). However, over time, condition surveys showed that the glass fabric being used in built-up membranes was rotting (Manning 1995). These findings suggest that built-up membranes increase the probability of being

associated with high deterioration as a result of built-up membrane characteristics being prone to rotting, specifically the glass fabric.

Type of Wearing Surface (NBI Item 108A)

Four wearing surfaces have significant impacts on high deck deterioration probability, including integral concrete, latex concrete, low-slump concrete, and no wearing surface. Of the four significant wearing surfaces, one is found to have deck-specific variation based on a normal distribution: bridge decks with no wearing surface. Specifically, with a mean of 1.735 and a standard deviation of 2.218, 21.7% of bridge decks with no wearing surface are less likely to be associated with high deterioration and 78.3% of bridge decks with no wearing surface are more likely. A plausible explanation for no wearing surface decreasing the likelihood of deterioration on some decks may be linked to limit states or specific climatic regions. Another plausible reason may be attributed to the use, or non-use, of de-icers on bridge decks with no wearing surface (this would also correspond to climate regions).

Type of Design and/or Construction (NBI Item 43B)

Three variables related to design and/or construction are found to significantly affect the probability of high deck deterioration. For these variables, there are no heterogeneous effects across bridge decks. Although, each of these variables have considerable impacts on deck deterioration according to marginal effects, with one having larger effects on deck deterioration compared to the others. To be specific, based on marginal effects, girder and floor beam systems increase the probability of deck deterioration by 57.1 percentage points. A plausible explanation for the increase in probability may be attributed to the type of bridge. For example, tied arch

bridges experience web-gap fatigue in the connections of girder and floor beam systems (National Academies of Sciences, Engineering, and Medicine 2013). Another plausible explanation may be linked to bridges that have not been retrofitted or repaired in regards to web-gap fatigue cracks (Dexter and Ocel 2013).

Maintenance Responsibility (NBI Item 22)

For this category, just two variables are found to be significant, both of which have non-homogenous effects on bridge deck deterioration. The first of these variables is the indicator for county highway agency (i.e., maintenance responsibility is that of a county highway agency). Turning to model estimates, the indicator for county highway agency has an estimated parameter mean of 1.089 and an estimated parameter standard deviation of 3.393. Based on a normal distribution, these estimates indicate that 37.4% of bridge decks under the maintenance responsibility of a county highway agency are less likely to have high deterioration. On the other hand, however, 62.6% of bridge decks under the maintenance responsibility of a county highway agency are more likely to have high deterioration. The second variable, also with a normally distributed random parameter, is city or municipal highway agency being responsible for deck maintenance. With an estimated parameter mean of 0.404 and an estimated standard deviation of 2.183, 42.7% of bridge decks under the maintenance of a city or municipal highway agency are less likely to have high deterioration and 57.3% of bridge decks are more likely to have high deterioration. A plausible explanation for the heterogeneous nature in these two variables may be linked with funding for bridge deck maintenance. For instance, routine maintenance is not eligible for federal funds (FHWA 2018). Therefore, the varying effects of these two variables could be a result of limited or available funding at the county-specific level or the city- and municipal-specific

level. With the Highway Bridge Program giving state DOTs discretion in regards to funding bridge rehabilitation, replacement, and several preservation activities (FHWA 2018), Strategic Highway Research Program et al. (2018) suggest that DOTs must design and build new bridges to have the longest potential service life. In doing so, this can free up funds for bridge preservation, bridge maintenance, and repairs (Strategic Highway Research Program et al. 2018).

IECC Climatic Region

The final set of variables found to be significant on the probability of bridge deck deterioration are climatic indicators. In this study, climate regions according to the International Energy Conservation Code (IECC) were adopted (International Code Council 2012). Inherently, these indicators serve as surrogates for region-specific climates and can help guide future work in defining specific regions to be considered for region-specific bridge deterioration models. With that in mind, four climatic indicators are significant, one of which has heterogeneous effects on bridge deck deterioration: average climate. Referring to model estimations, the indicator for average climate has an estimated parameter mean of -0.778 and an estimated standard deviation of 0.886. Therefore, based on the normal distribution curve, 19.0% of bridge decks located in the average climatic region are more likely to be associated with high deterioration and 81.0% of bridge decks in the average climatic region are less likely to be associated with high deterioration. These varying effects may be explained by weather irregularities, such as harsh winters or extreme summers. Specifically, Kesiraju (2017) found some correlation between bridge deck deterioration and climate change, where climate change may be a primary source of weather irregularities (Huybers et al. 2013).

As for the remaining three climatic variables, very hot climates, extremely cold climates, and hot marine climates impact the probability of bridge deck deterioration. First, according to marginal effects, there is a 41.9 percentage point decrease in the probability of bridge deck deterioration for bridge decks in very hot climates. This follows the findings of Ghonima et al. (2018), where as climate becomes colder bridge decks are more likely to be associated with high deterioration, while hotter climates are less likely. The next climatic variable is related to extremely cold climates. Pointedly, marginal effects show that bridge decks in extremely cold climates have a 105.2 percentage point increase in the probability of high deterioration. This finding is in-line with several previous works, as specific aspects in extremely cold climates can lead to bridge deck deterioration. Bridge decks in extremely cold climates will be susceptible to a large number of freeze-thaw cycles that accelerate deterioration (Hema et al. 2004). Specifically, cold climates use de-icing methods, where chlorides from de-icing salts can penetrate the bridge deck and eventually “depassivate” the reinforcing steel initiating corrosion (Gong et al. 2013; Njardardottir et al. 2005). More, de-icers can have negative reactions with the cement paste and/or aggregates in the bridge deck; therefore, increasing the likelihood of deterioration (Xie and Shi 2015). The final climatic indicator is for hot marine climates, in which marginal effects show a 31.0 percentage point increase in the probability of bridge deck deterioration. As it pertains to marine climates, bridge decks can be exposed to sulfate ions from seawater. These sulfate ions can then attack components of the cement paste in the bridge deck inducing deterioration (Hema et al. 2004). In addition, marine climates have other sulfates, such as sodium and magnesium, that can also induce deterioration (Hema et al. 2004).

Table 5. Summary of significant variables and effects on deck deterioration probability.

Category	Variable	Effect on Probability
Continuous Variables	Deck Area	↓
	ADTT	↑
	Distance to Seawater	↓
Structural Material Design	Age of Bridge	↑↓
	Continuous Concrete	↑↓
	Simple Prestressed Concrete	↑
	Continuous Prestressed Concrete	↑↓
	Simple Span Steel	↑↓
Deck Protection	Continuous Steel	↑
	Epoxy-Coated Reinforcing	↑↓
	Polymer Impregnated	↑
Type of Membrane	Built-Up Membrane	↑
Type of Wearing Surface	No Wearing Surface	↑↓
	Integral Concrete	↑
	Latex Concrete or Similar Additive	↑
Type of Design and Construction	Low-Slump Concrete	↑
	Girder and Floor Beam System	↑↓
	Tee Beam	↑
	Truss (Through)	↑
Maintenance Responsibility	County Highway Agency	↑↓
	City or Municipal Highway Agency	↑↓
Climatic Regions	Very Hot	↓
	Average	↑↓
	Extreme Cold	↑
	Hot Marine	↑

↓ = Decrease in Bridge Deck Deterioration Probability

↑ = Increase in Bridge Deck Deterioration Probability

↑↓ = Heterogeneous Effects on Bridge Deck Deterioration Probability

SUMMARY AND CONCLUSIONS

The objective of this study was to examine how environmental and structural parameters affect the performance of concrete bridge decks by means of random parameters binary logistic regression (LR) modeling. The model is used to compute the likelihood for a concrete bridge deck being associated with the “highest deterioration rate (DR)” group, which is the worst performing set of bridge decks, while also accounting for unobservables in the data. The random parameters LR model development is based on 3,262 observations extracted from a nationwide database, which

was developed by the authors previously (Ghonima et al., 2018). In the final model, the DR was used as the dependent variable, while ADTT, Climatic Region, Distance from Seawater, Type of Design and/or Construction, Bridge Age, Bridge Deck Area, Structural Material Design, Deck Protection, Type of Membrane, Type of Wearing Surface, and Maintenance Responsibility characteristics were used as independent variables. A log-likelihood test was performed to show that the random parameters model is preferred over the traditional binary model, where results indicated with well over 99% confidence that the random parameters model is statistically preferred (several variables were found to have statistically significant random parameters). Significant bridge deck deterioration variables were ranked in order of their relative importance in the model. Based on marginal effects and elasticities, as presented in Table 5, it was found that bridge decks 1) with higher ADTT, 2) extremely cold climate, 3) hot marine climate, and 4) with no wearing surface are all associated with an increase in “highest DR” group probability. On the other hand, 1) deck area, 2) distance to seawater, 3) age of bridge, and 4) very hot climates are associated with a decrease in “highest DR” group probability. Some of these variables were also found to be heterogeneous across observations, as detailed in the discussion.

In the future, additional variables could be added, such as structural design characteristics (e.g., minimum deck thickness, reinforcement bar size, bar spacing), construction practice (e.g., concrete temperature, placement procedure, curing practice), specifications (e.g., water-to-cement ratio and minimum cementitious material content), and other notable variables (e.g., application of deicers and freeze-thaw cycles). By adding additional data (i.e., potential bridge deck deterioration variables), data-heterogeneity is mitigated by reducing the number of unobservables (i.e., there are more observed characteristics to be used by the analyst). In addition, it is recommended that future

studies utilize this methodology to model those additional variables to determine their significance and impacts on bridge deck deterioration.

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REFERENCES

- Abdel-Aty, M, Abdalla, M.F., 2004. Modeling Repeated Multinomial Route Choices Under Advanced Traveler Information System: Generalized Estimating Equations with Polytomous Logit Function. Transportation Research Record: Journal of the Transportation Research Board 1882, 61–69.
- Agrawal A. K., Kawaguchi A., and Chen Z. (2010). Deterioration rates of typical bridge elements in New York. Journal of Bridge Engineering, 15(4), 419-429.
- Al-Bdairi, N.S.S., Hernandez, S., Anderson, J., 2018. Contributing Factors to Run-Off-Road Crashes Involving Large Trucks under Lighted and Dark Conditions. Journal of Transportation Engineering, Part A: Systems 144 (1), 1–9.
- Al-Ghamdi, A. S. (2002). Using logistic regression to estimate the influence of accident factors on accident severity. Accident Analysis and Prevention, 34, 6, 729-741.

625 Alampalli, S., Owens, F. T., and Sandhu, D. (2002). "A Qualitative Study of Correlation between
626 Bridge Vibration and Bridge Deck Cracking." *81st Annual Meeting of the Transportation*
627 *Research Board*, Washington, DC.

628 Alomari, K., Gambatese, J., and Anderson, J., 2017. Opportunities for Using Building
629 Information Modeling to Improve Worker Safety Performance. *Safety* 3 (1), 7.

630 Anderson, J., Hernandez, S., 2017. Roadway Classifications and the Accident Injury Severities
631 of Heavy-Vehicle Drivers. *Analytic Methods in Accident Research* 15, 17–28.

632 Ariaratnam, S. T., El-Assaly, A., & Yang, Y. (2001). Assessment of Infrastructure Inspection
633 Needs Using Logistic Models. *Journal of Infrastructure Systems*, 7, 4, 160-165.

634 ASCE (2013). Report Card for America's Infrastructure. Retrieved September 23, 2014, from
635 <http://www.infrastructurereportcard.org/a/#p/bridges/overview>.

636 Attoh-Okine, N. O., & Bowers, S. (2006). A Bayesian belief network model of bridge
637 deterioration. *Proceedings of the Institution of Civil Engineers - Bridge Engineering*, 159, 2,
638 69-76.

639 Behnood, A., Verian, K.P., Modiri Gharehveran, M., 2015. Evaluation of the Splitting Tensile
640 Strength in Plain and Steel Fiber-Reinforced Concrete Based on the Compressive Strength.
641 *Construction and Building Materials* 98, 519–529.

642 Bhat, C.R., 2003. Simulation Estimation of Mixed Discrete Choice Models Using Randomized
643 and Scrambled Halton Sequences. *Transportation Research Part B: Methodological* 37 (9),
644 837–855.

645 Bien, J., Elfgrén, L., and Olofsson, J. (Eds.). (2007). *Sustainable Bridges: Assessment for Future*
646 *Traffic Demands and Longer Lives*. Dolnoslaskie Wydawnictwo Edukacyjne.

647 Bierlaire, M., Hurtubia, R., Flötteröd, G., 2010. Analysis of Implicit Choice Set Generation
648 Using a Constrained Multinomial Logit Model. Transportation Research Record: Journal of
649 the Transportation Research Board 2175, 92–97.

650 Bolukbasi, M., Mohammadi, J., & Arditi, D. (2004). Estimating the future condition of highway
651 bridge components using national bridge inventory data. Periodical on Structural Design and
652 Construction, 9(1), 16-25.

653 Broach, J. (2012). Discrete Choice Modeling: Theoretical Assumptions and Transportation
654 Applications. Retrieved February 28, 2017, from
655 <https://drive.google.com/file/d/0B8GGT7br4AVqRWplaEhDbHlGUnM/view>.

656 Cheung, S. O., Yiu, T. W., & Chan, H. W. (2010). Exploring the Potential for Predicting Project
657 Dispute Resolution Satisfaction Using Logistic Regression. Journal of Construction
658 Engineering and Management, 136, 5, 508-517.

659 Dalumpines, R., Scott, D.M., 2017. Determinants of Route Choice Behavior: A Comparison of
660 Shop Versus Work Trips Using the Potential Path Area - Gateway (PPAG) Algorithm and
661 Path-Size Logit. Journal of Transport Geography 59, 59–68.

662 Dexter, R. J., and Ocel, J. M. (2013). *Manual for Repair and Retrofit of Fatigue Cracks in Steel*
663 *Bridges*. McLean, VA. Federal Highway Administration. Report No. FHWA-IF-13- 020.

664 Diekmann, J. E., & Girard, M. J. (1995). Are Contract Disputes Predictable?. Journal of
665 Construction Engineering and Management, 121, 4, 355-363.

666 Dissanayake, S., & Lu, J. (2002). Analysis of Severity of Young Driver Crashes: Sequential
667 Binary Logistic Regression Modeling. Transportation Research Record, 1784, 108-114.

668 Donnell, E., & Mason, J. (2004). Predicting the Severity of Median-Related Crashes in
669 Pennsylvania by Using Logistic Regression. *Transportation Research Record: Journal of the*
670 *Transportation Research Board*, 1897, 55-63.

671 FHWA. (2018). *Bridge Guide Preservation: Maintaining a Resilient Infrastructure to Preserve*
672 *Mobility*. Washington, DC.

673 FHWA. (2017). National Bridge Inventory (NBI). Federal Highway Administration. Retrieved
674 March 8, 2017, from <https://www.fhwa.dot.gov/bridge/nbi>.

675 Ghonima, O., Schumacher, T., Unnikrishnan, A., and Fleischhacker, A. (2018). Advancing
676 Bridge Technology, Task 10: Statistical Analysis and Modeling of US Concrete Highway
677 Bridge Deck Performance - Internal Final Report. Portland State University Library. URL:
678 https://pdxscholar.library.pdx.edu/cengin_fac/443.

679 Gong, J., Huang, J., Wang, S., and Soltesz, S. (2013). "Potential Deicer Effects on Concrete Bridge
680 Decks: Developing Exposure Maps." *Symposium of Climatic Effects on Pavement and*
681 *Geotechnical Infrastructure*, American Society of Civil Engineers, Fairbanks, AK.

682 Grace, N., Hanson, J. L., and AbdelMessih, H. I. (2004). "Inspection and Deterioration of Bridge
683 Decks Constructed Using Stay-in-Place Metal Forms and Epoxy-Coated Reinforcement."
684 *Jim L. Hanson*, 11.

685 Greene, W.H., 2016a. LIMDEP Version 11 Econometric Modeling Guide. Plainview, NY:
686 Econometric Software, Inc.

687 Greene, W.H., 2016b. NLOGIT Reference Guide. 6th ed. Plainview, NY: Econometric Software,
688 Inc.

689 Greene, W.H., 2018. *Econometric Analysis*. 8th ed. New York, NY: Pearson.

690 Greene, W.H. and Hensher, D.A., 2010. Modeling Ordered Choices. New York, NY: Cambridge
691 University Press.

692 Gucunski, N., Romero, F., Kruschwitz, S., Feldmann, R., and Parvardeh, H. (2011).
693 *Comprehensive Bridge Deck Deterioration Mapping of Nine Bridges by Nondestructive*
694 *Evaluation Technologies*. Ames, IA. Iowa Department of Transportation. Report No. SPR-
695 NDEB(90)--8H-00.

696 Hagenbuch, J. J. (1971). "Bay State Considers Alternative Bridge Deck Repairs." *Public Works*,
697 102(10), 68–69.

698 Haleem, K. and Abdel-Aty, M., 2010. Examining Traffic Crash Injury Severity at Unsignalized
699 Intersections. *Journal of Safety Research* 41 (4), 347–357.

700 Halton, J.H., 1960. On the Efficiency of Certain Quasi-Random Sequences of Points in
701 Evaluating Multi-Dimensional Integrals. *Numerische Mathematik* 2 (1), 84–90.

702 Harb, R., Yan, X., Pande, A., Radwan, E., & Abdel-Aty, M. (2008). Freeway work-zone crash
703 analysis and risk identification using multiple and conditional logistic regression. *Journal of*
704 *Transportation Engineering*, 134, 5, 203-214.

705 Hema, J., Guthrie, W. S., and Fonseca, F. S. (2004). *Concrete Bridge Deck Condition*
706 *Assessment and Improvement Strategies*. Salt Lake City, UT. Utah Department of
707 Transportation. Report No. UT-04-16.

708 Hensher, D.A., Rose, J.M., and Greene, W.H., 2015. Applied Choice Analysis. 2nd ed.
709 Cambridge, United Kingdom: Cambridge University Press.

710 Huybers, P., Kuang, Z., and Farrell, B. (2013). "Extreme Weather and Climate Change: An
711 Interview With Harvard Climate Scientists." *Environment@Harvard*, 5(1), 18–21.

- Hwang, J.-S., & Kim, Y.-S. (2016). A bid decision-making model in the initial bidding phase for overseas construction projects. *KSCE Journal of Civil Engineering*, 20, 4, 1189-1200.
- International Code Council. (2012). International Energy Conservation Code (IECC). Retrieved May 15, 2019 from: <https://bascc.pnnl.gov/resources/2012-iecc-international-energy-conservation-code>.
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An Introduction to Statistical Learning with Applications in R*. New York: Springer.
- Kesiraju, A. (2017). "Assessing Impact of Climate Change on Oklahoma Bridge Deck and Superstructure Deterioration Using National Bridge Inventory Data." University of Oklahoma.
- Lawler, J. S., Krauss, P. D., Kurth, J., and McDonald, D. (2011). "Condition Survey of Older West Virginia Bridge Decks Constructed with Epoxy-Coated Reinforcing Bars." *Transportation Research Record: Journal of the Transportation Research Board*, 2220, 57–65.
- Li, V.C., and Zhang, L. (2001). Approaches to Enhancing Concrete Bridge Deck Durability. Long Term Durability of Structural Materials, P. J. M. Monteiro, K. P. Chong, J. Larsen-Basse, K. Komvopoulos, Eds., Elsevier, Berkeley, CA, 11-22.
- Lowe, D. J., & Parvar, J. (2004). A logistic regression approach to modelling the contractor's decision to bid. *Construction Management & Economics*, 22, 6, 643-653.
- Madanat, S., Mishalani, R., Wan Hashim Wan, I. (1995). Estimation of Infrastructure Transition Probabilities from Condition Rating Data. *ASCE Journal of Infrastructure Systems*, 1(2), 120-125.

734 Mai, T., Fosgerau, M., Frejinger, E., 2015. A Nested Recursive Logit Model for Route Choice
735 Analysis. *Transportation Research Part B: Methodological* 75, 100–112.

736 Mannering, F.L., Bhat, C.R., 2014. Analytic Methods in Accident Research: Methodological
737 Frontier and Future Directions. *Analytic Methods in Accident Research* 1, 1–22.

738 Mannering, F.L., Shankar, V., and Bhat, C.R., 2016. Unobserved Heterogeneity and the
739 Statistical Analysis of Highway Accident Data. *Analytic Methods in Accident Research* 11,
740 1–16.

741 Mateos, A., Gómez, J.A., Hernández, R., Tan, Y., Loría Salazar, L.G., Vargas-Nordcbeck, A.,
742 2015. Application of the Logit Model for the Analysis of Asphalt Fatigue Tests Results.
743 *Construction and Building Materials* 82, 53–60.

744 Mateos, A., Wu, R., Harvey, J., Denneman, E., Fan, A., 2017. The Logit Model and the Need to
745 Reproduce the Stiffness Degradation Curve of Asphalt Specimens During Fatigue Testing.
746 *Transportation Research Record* 2631.

747 Mauch, M. and Madanat, S. (2001). Semiparametric Hazard Rate Models of Reinforced
748 Concrete Bridge Deck Deterioration. *ASCE Journal of Infrastructure Systems*, 7(2), 49-57.

749 McFadden, D., 1973. Conditional Logit Analysis of Qualitative Choice Behavior. In: *Frontiers in*
750 *Econometrics*. 105–142.

751 McFadden, D., 1977. Quantitative Methods for Analyzing Travel Behaviour of Individuals:
752 Some Recent Developments. Institute of Transportation Studies. University of California.

753 McFadden, D., 1981. Econometric Models of Probabilistic Choice. In: C.F. Manski and D.
754 McFadden, eds. *Structural Analysis of Discrete Data with Econometric Applications*.
755 Cambridge, MA: MIT Press, 198–269.

- McFadden, D. and Train, K., 2000. Mixed MNL Models for Discrete Response. *Journal of Applied Econometrics*, 15(5), 447–470.
- Mishalani, R G., and Madanat, S. (2002) Computation of Infrastructure Transition Probabilities Using Stochastic Duration Models. *ASCE Journal of Infrastructure Systems*, 8(4), 139-148.
- Mishra, S., Zhu, X., Ducca, F., 2013. An Integrated Framework for Modeling Freight Mode and Route Choice [online]. Available from: http://www.roads.maryland.gov/OPR_Research/MD-13-SP209B4F_An-Integrated-Framework-for-Modeling-Freight-Mode-and-Route-Choice_Report.pdf.
- Mitra, N., Mitra, S., and Lowes, L. N. (2011). Probabilistic model for failure initiation of reinforced concrete interior beam-column connections subjected to seismic loading. *Engineering Structures*, 33, 1, 154-162.
- Morcous, G. and Hatami, A. (2011). Developing deterioration models for Nebraska bridges. Final Report. Lincoln, Neb: University of Nebraska-Lincoln.
- Morcous, G. (2006). Performance Prediction of Bridge Deck Systems Using Markov Chains. *Journal of Performance of Constructed Facilities*, 20, 2, 146-155.
- Mitra, N., Mitra, S., & Lowes, L. N. (2011). Probabilistic model for failure initiation of reinforced concrete interior beam-column connections subjected to seismic loading. *Engineering Structures*, 33, 1, 154-162.
- Mwesige, G., Farah, H., & Koutsopoulos, H. N. (2016). Risk appraisal of passing zones on two-lane rural highways and policy applications. *Accident Analysis and Prevention*, 90, 1-12.
- National Academies of Sciences, Engineering, and Medicine. (2013). *Design Guide for Bridges for Service Life*. The National Academies Press, Washington, DC.

779 Njardardottir, H., McCabe, B., and Thomas, M. D. A. (2005). "Concrete Bridge Deck
780 Deterioration Model Using Belief Networks." *Computers and Concrete*, 2(6), 439–454.

781 Ozdemir, A. (2016). Sinkhole susceptibility mapping using logistic regression in Karapınar
782 (Konya, Turkey). *Bulletin of Engineering Geology and the Environment*, 75, 2, 681–707.

783 Poston, R. W., Breen, J. E., and Carrasquillo, R. L. (1989). "Design of Transversely Prestressed
784 Concrete Bridge Decks." *PCI Journal*, 34(5), 68–109.

785 Ramsey, F.L. and Schafer, D.W., 2012. *The Statistical Sleuth: A Course in Methods of Data*
786 *Analysis*. 3rd ed. Boston, MA: Brooks Cole.

787 Reardon, M. F. (2015). *Deterioration Modeling of Subordinate Elements and Element Interaction*
788 *for Bridge Management Systems*. M.S. Thesis. University of Virginia.

789 Russell, H. G. (2004). *NCHRP Synthesis 333: Concrete Bridge Deck Performance*. Washington,
790 DC. Transportation Research Board of the National Academies.

791 Rys, D., Judycki, J., Pszczola, M., Jaczewski, M., Mejlun, L., 2017. Comparison of Low-
792 Temperature Cracks Intensity on Pavements With high Modulus Asphalt Concrete and
793 Conventional Asphalt Concrete Bases. *Construction and Building Materials* 147, 478–487.

794 Schmitt, T. R., and Darwin, D. (1995). *Cracking in Concrete Bridge Decks*. Topeka, KS. Kansas
795 Department of Transportation. Report No. KU-94-1.

796 Shan, Y., Cristian Contreras-Nieto, & Lewis, P. (2016). Using data analytics to characterize steel
797 bridge deterioration. *Construction Research Congress*. San Juan, Puerto Rico. May 31–June
798 2, 2016.

799 Smith, S. K., & McCarty, C. (2009). Fleeing the storm(s): an examination of evacuation behavior
800 during Florida's 2004 hurricane season. *Demography*, 46, 1, 127–145.

801 Strategic Highway Research Program, Federal Highway Administration, and AASHTO. (2018).
802 *America's Bridges Need Repair or Replacement: SHRP2 is On the Job*. Washington, DC.

803 Tabatabai, H., Tabatabai, M., and Lee, C.-W. (2011). Reliability of Bridge Decks in Wisconsin.
804 *Journal of Bridge Engineering*, 16(1), 53-62.

805 Tabatabai, H., and Lee, C.-W. (2006). "Simulation of Bridge Deck Deterioration Caused by
806 Corrosion." *CORROSION 2006*, San Diego, CA.

807 Tae-Hoon, H., Seung-Hyun, C., Seung-Woo, H., & Sang-Youb, L. (2006). Service Life
808 Estimation of Concrete Bridge Decks. *KSCE Journal of Civil Engineering*, 10,4, 233-241.

809 Tan, R., Adnan, M., Lee, D., 2015. A New Path Size Formulation in Path Size Logit for Route
810 Choice Modeling in Public Transport Networks. *Transportation Research Record: Journal of*
811 *the Transportation Research Board* 2538, 11–18.

812 Train, K., 2000. Halton Sequences for Mixed Logit. *Department of Economics* 1–18.

813 Train, K., 2003. *Discrete Choice Methods with Simulation*. Cambridge, MA: Cambridge
814 University Press.

815 Train, K.E., 2009. *Discrete Choice Methods with Simulation*. 2nd ed. New York, NY:
816 Cambridge University Press.

817 Ulfarsson, G. F., & Mannering, F. L. (2004). Differences in
818 male and female injury severities in sport-utility vehicle, minivan, pickup and passenger car
819 accidents. *Accident Analysis and Prevention*, 36, 2, 135-147.

820 Vandana, R.K., Bindhu, K.R., 2017. A New Model for Failure Mode of Reinforced Concrete
821 Interior Beam Column Joints Under Seismic Loading. *Asian Journal of Civil Engineering* 18
(2), 235–253.

822 Vidana-Bencomo, J.O., Balal, E., Anderson, J.C., Hernandez, S., 2018. Modeling Route Choice
823 Criteria From Home to Major Streets: A Discrete Choice Approach. *International Journal of*
824 *Transportation Science and Technology* 7 (1), 74–88.

825 Vu, K. A. T., and Stewart, M. G. (2000). “Structural Reliability of Concrete Bridges Including
826 Improved Chloride-Induced Corrosion Models.” *Structural Safety*, 22(4), 313–333.

827 Washington, S., Congdon, P., Karlaftis, M.G., Mannering, F.L., 2009. Bayesian Multinomial
828 Logit: Theory and Route Choice Example. *Transportation Research Record: Journal of the*
829 *Transportation Research Board* 2136, 28–36.

830 Washington, S.P., Karlaftis, M.G., Mannering, F.L. (2011). *Statistical and Econometric Methods*
831 *for Transportation Data Analysis*. 2nd ed. Chapman and Hall/CRC. Boca Raton, FL:
832 Chapman and Hall/CRC.

833 Wedding, P. A., Cady, P. D., & Weyers, R. E. (1983). Chloride Penetration and the Deterioration
834 of Concrete Bridge Decks. *Cement, Concrete and Aggregates*, 5, 2, 81.

835 Williamson, G. S. (2007). *Service life modeling of Virginia bridge decks*. Blacksburg, Va.:
836 University Libraries, Virginia Polytechnic Institute and State University.

837 Wong, C. H. (2004). Contractor Performance Prediction Model for the United Kingdom
838 Construction Contractor: Study of Logistic Regression Approach. *Journal of Construction*
839 *Engineering and Management*, 130, 5, 691-698.

840 Wooldridge, J.M. (2010). *Econometric Analysis of Cross Section and Panel Data*. 2nd ed.
841 Cambridge, MA: MIT Press.

842 Wu, N.-C. (2010). *An Exploratory Data Analysis of National Bridge Inventory*. MS Thesis.
843 University of Virginia.

844 Xie, N., and Shi, X. (2015). "Life-Cycle Performance of Concrete Bridge Decks Exposed to
845 Deicer Environments: A New Risk Rating Method." *Symposium on Systematic Approaches*
846 *to Environmental Sustainability in Transportation*, American Society of Civil Engineers,
847 Fairbanks, AK, 213–226.

848 Yannis, G., Laiou, A., Vardaki, S., Papadimitriou, E., Dragomanovits, A., & Kanellaidis, G.
849 (2011). Parameters affecting seat belt use in Greece. *International Journal of Injury Control*
850 *and Safety Promotion*, 18, 3, 189-97.

851