Probabilistic Infrastructure Deterioration Models with Panel Data

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Abstract: Statistical models of infrastructure facility deterioration are typically estimated using panel data sets of in-service facilities. For example, biannual ratings of bridges have been used to develop discrete models of component deterioration by a number of researchers. Unfortunately, these models have not accounted for the presence of heterogeneity in the panel data, which may lead to biased coefficient estimates. Furthermore, researchers have usually imposed a Markovian specification in the development of such models, implying that the probabilistic deterioration in a given period is independent of history. This assumption may be unrealistic for some types of facilities in which early stress initiation leads to accelerated deterioration in later stages of their lives. In this paper, we adopt a random-effects specification to control for heterogeneity in a probit model of bridge-deck deterioration and extend the model to investigate the presence of state dependence. The proposed model yields improved results in comparison with a simple probit model and provides evidence that is inconsistent with the Markovian assumption in bridge-deck deterioration. An implication of this study is that both heterogeneity and state dependence may need to be accounted for in developing probabilistic infrastructure deterioration models.

INTRODUCTION

Infrastructure Maintenance and Rehabilitation (M&R) decision making, either at the network level or at the project level, is based on current (measured) and future (predicted) infrastructure facility conditions. Accurate predictions of future facility conditions are essential for effective M&R decision making. An infrastructure condition is often represented by discrete ratings. The Federal Highway Administration's (FHwA's) bridge-rating system, for example, is commonly used for bridge decks (Table 1). Bridge inspectors use ratings of 0–9, with 9 representing near-perfect conditions (FHwA 1979). The use of discrete representation of facility condition has made it necessary to develop discrete models of deterioration.

In this paper, we present incremental facility deterioration models. Incremental models, which are used to compute infrastructure transition probabilities, predict changes in conditions over time as a function of a set of explanatory variables, such as traffic, age, environmental factors and design, and material characteristics. State-of-the-art discrete infrastructure deterioration models (Butt et al. 1987; Feighan et al. 1988; Jiang et al. 1988; Scherer and Glagola 1994; Madanat et al. 1995; Madanat and Wan Ibrahim 1995) have typically been developed using panel data sets of in-service facilities but have not accounted for the presence of heterogeneity, which is likely to exist in such data. Heterogeneity refers to the presence of persistent facility-specific but unobserved factors, such as construction quality. If not corrected for, heterogeneity may lead to biased model coefficient estimates (Heckman 1981a).

Another potential limitation of state-of-the-art models is that they are based on a Markovian representation of facility deterioration, which states that facility deterioration is independent of history. However, a number of researchers [see for example Ramaswamy (1989)] have questioned the realism of this assumption; it has been argued that the history of a facility's deterioration influences future deterioration, a phenomenon known as state dependence. For example, the initiation of rebar corrosion in an area of a concrete bridge deck often leads to the initiation of corrosion in the surrounding areas, thus leading to an acceleration of the deterioration process. To test empirically for the presence of state dependence in panel data of infrastructure facilities, it is essential to first account for heterogeneity—if not, it may be mistaken for state dependence.

The purpose of this paper is to present the development of a random-effects model of infrastructure deterioration using a panel data set. The random-effects specification is used to capture heterogeneity and is then extended to empirically test for the presence of true state dependence. The random-effects model is also compared to a simple model that does not account for heterogeneity.

The remainder of this paper is organized as follows. The next section critically reviews the state-of-the-art methods for estimating facility transition probabilities. The third section reviews the available data and develops the relevant statistical methodology used in this paper. In the fourth section, the model specification and estimation results for both a simple binary probit and a random-effects probit model are presented. Two sets of models are developed: the first assumes no true state dependence, and the second tests for its presence. The last section summarizes the findings of this research.

TABLE 1. Concrete Bridge Condition Ratings (FHwA 1979)

	Condition Indicator (% Deck Area)			
Rating (1)	Spall (2)	Delaminations (3)	Electrical potentials (4)	Chloride content (lb/cu yd) (5)
9	None	None	0	0
8	None	None	None > 0.35	None > 1.0
7	None	<2%	45% < 0.35	None > 2.0
6	<2% spall or sum of all deteriorated or contaminated deck concrete < 20%			
5	<5% spall or sum of all deteriorated or contaminated deck concrete 20–40%			
4	>5% spall or sum of all deteriorated or contaminated deck concrete 40–60%			
3	>5% spall or sum of all deteriorated or contaminated deck concrete > 60%			
2	Deck structural capacity grossly inadequate			
1	Deck repairable by replacement only			
0	Holes in deck—danger of other sections of deck falling			

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PREVIOUS WORK

Most of the current methods used to estimate transition probabilities are based on linear regression (Carnahan et al. 1987; Jiang et al. 1988). These models suffer from several methodological limitations and practical inconsistencies that have been pointed out by Madanat and Wan Ibrahim (1995). First, the use of linear regression is not appropriate when the dependent variable (condition rating) is a discrete variable. Second, these models, by linking causal variables to facility condition rating directly, do not recognize the latent nature of the infrastructure deterioration process. Finally, the method used to estimate the transition probabilities from the deterioration model imposes limitations on the number of parameters that can be estimated.

In contrast, some researchers have recently applied econometric methodologies, which are theoretically appropriate and practically feasible. Madanat et al. (1995) introduced the application of the ordered probit model for the estimation of transition probabilities from inspection data. The ordered probit model has come into fairly wide use as a framework for analyzing responses where the dependent variable is discrete and ordinal (McElvey and Zavoina 1975). The model assumes the existence of an underlying continuous random variable and therefore allows the latent nature of infrastructure performance to be captured. In the work of Madanat et al. (1995), ordered probit analysis was used to develop an incremental discrete deterioration model where the difference in observed ratings is an indicator of the underlying latent deterioration. The model is then used to compute the time-dependent transition probabilities.

Although the application of these modeling methods has advanced the state-of-the-art in infrastructure deterioration modeling, they have not adequately accounted for the presence of heterogeneity and have provided few insights into the validity of the Markovian assumption. The next section formulates a random-effects probit model that allows us to address these issues.

MODEL DEVELOPMENT

Issues in Model Development

In the context of deterioration modeling, the Markovian assumption states that the probability that a facility's condition drops to a lower state in a given time period is independent of its deterioration in previous time periods. It has been argued that future deterioration is not independent of history, as implied by the Markov model, because facilities that have experienced deterioration in the past are more likely to deteriorate faster in the future (Ramaswamy 1989). This means that the probability that a facility will experience a change in condition state in the future is a function of past experience. Such behavior is known as state dependence, and it may be due to either or both of the following reasons. First, due to the occurrence of deterioration in the past, the facility can become more deterioration-prone; this is the case of true state dependence, as described by Heckman (1981a, b). For example, a highway pavement section that has started to crack will deteriorate faster than one that has not because its subsurface is now more exposed to water. Second, facilities differ in certain unmeasured characteristics that influence deterioration but are not influenced by history: this is the case of heterogeneity. If not properly accounted for, heterogeneity can be mistaken for state dependence (indeed, it is often referred to as "spurious" state dependence). These two phenomena, however, have different implications on the Markovian assumption; the presence of true state dependence invalidates it, and heterogeneity, if properly accounted for in the model, does not. It is therefore important to control for possible spurious dependence before investigating the validity of the Markovian assumption for a given data set. This is the approach that we follow in the present paper.

Formulating the Random-Effects Model

Heterogeneity occurs in a structural model based on panel data if the differences among cross-sectional units are not appropriately reflected in the existing explanatory variables. If this heterogeneity is not accounted for, it is captured by the error term, leading to biased parameter estimates. To treat for heterogeneity, two modeling formulations exist: the fixed-effects and the random-effects model. The fixed-effects model is appropriate if one is interested in the magnitudes and signs of the individual effects in the observed sample. Since we are interested in making inferences about a population rather than about the specific facilities in the sample, a random-effects model is developed.

In the remainder of this section, a model of bridge-deck deterioration that captures possible heterogeneity in the data is presented. It is expected that the models estimated herein will outperform the state-of-the-art specifications by accounting for differences across infrastructure units that may not be appropriately reflected in the available explanatory variables.

Following Madanat et al. (1995), we define the change in latent deterioration y^* as a linear function of explanatory variables $\mathbf{x}_{it}$, as shown

$$\log y^*_{it} = \mathbf{b}'\mathbf{x}_{it} + u_i + v_{it}, \quad i = 1, \ldots, N, \; t = 1, \ldots, T_i \qquad (1)$$

where $\mathbf{b}$ = vector of parameters to be estimated; $\mathbf{x}_{it}$ = vector of exogenous variables for facility i in time-period t; u_i = individual facility (random) effect; v_{it} = random error term; N = number of individual facilities in the sample; and T_i = periods of observation for facility i. The use of the logarithm of y^* as the dependent variable guarantees that the latent deterioration is positive, i.e., in the absence of maintenance, no improvement in condition is possible. We define y_{it} as an indicator of change in the observed condition state

$$y_{it} = \begin{cases} 1 & \text{if } \log(y^*_{it}) > 0 \\ 0 & \text{otherwise} \end{cases} \qquad (2)$$

which implies that the value of $y_{it} = 1$ if the condition rating of facility i has dropped by at least 1 in time-period t. It can be seen that this definition of y_{it} is a censored version of the indicator variable used in Madanat et al. (1995), where it was the actual observed change in discrete condition states and took values 0, 1, 2, 3.

In general, statistical models analyzing cross-sectional data ignore individual differences and treat the aggregate of the individual effects, and the omitted-variable effects as a pure chance event (Hsiao 1993). It is possible, through the use of the panel data, to separate a model of individual facility behavior from a model of average behavior of a group. The heterogeneity across cross-sectional units can be captured in the model through a combined error term $\varepsilon_{it} = u_i + v_{it}$, where u_i is a facility-specific error term that captures the effect of unobserved and persistent effects, and v_{it} is an error term that varies by facility and time period. In a random-effects probit model, these factors are treated as random, and it is assumed that

$$E(u_i) = E(v_{it}) = 0 \qquad (3a)$$

$$\mathrm{Var}(u_i + v_{it}) = \mathrm{Var}(\varepsilon_{it}) = \sigma_u^2 + \sigma_v^2 \qquad (3b)$$

$$\mathrm{Corr}(\varepsilon_{it}, \varepsilon_{is}) = \rho = \sigma_u^2/(\sigma_v^2 + \sigma_u^2), \quad \text{if } t \neq s \qquad (3c)$$

The parameters of this model, $\mathbf{b}$ and ρ, can be estimated by the method of maximum likelihood. Following Greene (1995), the likelihood function under this random-effects specification can be written as

$$\ln L = \sum_i \ln \left[\int_{-\infty}^{\infty} \frac{1}{(2\pi)^{1/2}} e^{-\varepsilon_{it}^2/2} \prod_t \Phi(r_{it} z_{it})\, d\varepsilon_{it} \right] \quad (4a)$$

$$r_{it} = 2y_{it} - 1 \quad (4b)$$

where

$$z_{it} = \mathbf{b}'\mathbf{x}_{it} + [\rho/(1-\rho)]^{1/2}\varepsilon_{it} \quad (5)$$

The econometric software LIMDEP (Greene 1995) was used in the present paper for estimating the model parameters.

Data Set

The data set used in this paper is the Indiana Bridge Inventory database. It consists of approximately 5,700 state-owned bridges in Indiana and is a subset of the National Bridge Inventory database. The data set contains inspection records from 1978 through 1988. The condition evaluation rates and condition of the major bridge components, e.g., deck, superstructure, substructure, etc. on a scale from 0 to 9, where bridges with a 0 rating are in the poorest condition, and those with a rating of 9 are in the best condition (FHwA 1979). This rating scheme has already been presented in Table 1 of the present paper (FHwA 1979). The focus of this paper is on the bridge-deck data set.

There are three major mechanisms of deterioration for bridge decks: scaling, cracking, and spalling. Scaling is the wear of low-quality concrete as water freezes and thaws in small cracks and capillaries in the concrete (Carrier and Cady 1973). Cracking occurs primarily due to concrete volume changes. Slow placement of concrete, excessive water-cement ratio, improper curing, high temperature during hardening, and the subsidence of the concrete around the top reinforcement result in shrinkage, which is the direct cause of cracking. Spalling is the corrosion of steel reinforcement resulting from the infiltration of corrosive elements, such as salt, used in deicing the deck. The electric potential of the reinforced steel changes as a result of variation in chloride, and the anodic areas begin to rust (Newlon et al. 1973). To explicitly link the deterioration in conditions (manifested in any of the three previous ways) with a set of appropriate explanatory variables, the following list of variables was compiled:

- Type of bridge: it has been well established (Freyermuth et al. 1970) that the type of bridge affects the rate of deterioration. Simple-span bridge-deck structures generally have high deterioration rates due to the high flexibility of the simple span compared to the continuous concrete structures.
- Span length: the length of the bridge span affects deterioration of concrete bridges. The rate of deterioration increases with increasing span length (Freyermuth et al. 1970).
- Type of protective system: concrete bridges with protective systems generally have lower deterioration rates than bridge decks without a protective system.
- Skewness: it has been observed that the higher the skewness of bridge decks, the higher the deterioration rates (Busa 1985).
- Environmental factors: bridge deterioration is strongly affected by humidity and freeze-thaw cycles. The deterioration is higher on bridge decks exposed to high moisture and freeze-thaw cycles (Busa 1985).
- Traffic volume: it has been observed that deterioration is higher with higher traffic volumes (Newlon et al. 1973).
- Age: decks on older bridges deteriorate faster than those on younger bridges; this is due to longer exposure to detrimental environmental factors, such as the freeze-thaw cycles. It is important to differentiate between the effect of age on deterioration and state dependence. A bridge deck may deteriorate in a Markovian manner, with transition probabilities that change with age but are independent of the history of deterioration. Such probabilities are known as nonhomogeneous Markov chains in the stochastic process literature (Ross 1989).

The variables used in the model estimation are listed in Table 2 (Madanat et al. 1995).

MODEL ESTIMATION

Random-Effects Specification

As was mentioned previously, the available data is a cross section of time-series observations of bridge decks that did not undergo any rehabilitation during the observation period. These bridges have not all been observed an equal number of times, creating what is known as an unbalanced panel data set. From Fig. 1 it can be seen that a large number of bridges have been observed once, twice, and three times, and a much

TABLE 2. Variables Used in Analysis

Variable name (1)	Variable description (2)
Wearing-surface type 1	Concrete without protective system (dummy variable)
Wearing-surface type 2	Asphaltic concrete without protective system (dummy variable)
Wearing-surface type 6	Asphaltic concrete with known membrane (dummy variable)
Wearing-surface type 9	Concrete with coated rebar protective system (dummy variable)
Structure type 1	Simple concrete (dummy variable)
Structure type 2	Continuous concrete (dummy variable)
Structure type 5	Prestressed concrete (dummy variable)
Structure type 6	Continuous prestressed concrete (dummy variable)
Climatic region	Dummy variable: North = 1
Bridge age	Inspection year-construction year
Average daily traffic	Incremental cumulative average daily traffic per lane
Primary	Dummy variable for primary highway classification
Secondary	Dummy variable for secondary highway classification
Interstate	Dummy variable for interstate highway classification
Deck width	In meters
Span length	In meters
Number of spans	—
Skewness	Skew of main span from approach roadway (in degrees)

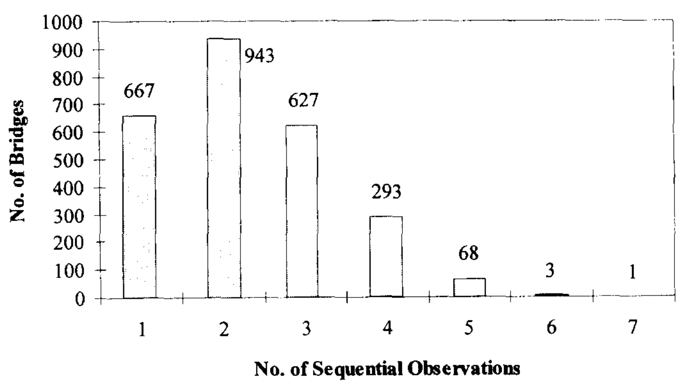

FIG. 1. Number of Sequential Bridge Observations

TABLE 3. Drops in Condition Rating (Successive Observations)

Drops (1)	Number of observations (2)	Percent of observations (3)
0	4,713	78.9
1	975	16.3
2	206	3.4
3	72	1.2
4	2	0.0
5	0	0.0
6	1	0.0

TABLE 4. Initial Deck-Condition Rating

Condition rating (1)	Number of observations (2)	Percent of observations (3)
2	4	0.0
3	71	1.2
4	165	2.7
5	508	8.5
6	1,710	28.6
7	2,473	41.4
8	908	15.2
9	132	2.2

smaller number of bridges have been observed four and five times. From this data the difference in condition rating between two successive observations of the same bridge is calculated. Table 3 reports that in approximately 80% of the observations there was no drop in the condition rating of a bridge. Further, in 16% of the cases there was a drop of one state in condition, and drops in conditions of 2 and 3 states were observed in only 3.4 and 1.2% of the cases, respectively.

In the present paper, a simple binary probit model is calibrated, the results of which are compared to a random-effects probit specification. To create the binary dependent variable, all the drops in conditions higher than zero are set equal to one so that the resulting variable is a censored form of the original drops in condition. A bridge can either stay in the same condition (the drop in condition is equal to 0), or it can drop to a lower condition rating (the drop in condition is equal to 1, regardless of the true number of drops in condition state). It is expected that this censoring of the dependent variable will not affect the model estimation significantly, since only approximately 5% of the bridges dropped more than one condition state. This was verified by excluding these observations and re-estimating the model. The coefficient estimates of the two models were identical in sign and within 5% of each other in magnitude, and the *t*-statistics for the coefficients were significant at a higher level for the censored model.

Based on previous research (Madanat et al. 1995) and a series of rigorous market segmentation tests, different deterioration models were estimated for different condition states. The market segmentation tests indicated that the same deterioration model can be developed for condition states 7, 8, and 9, and a different deterioration model should be used for lower condition states. A total of 58.8% of the observations belong to condition states 7, 8, and 9 at the time of initial inspection, with observations in condition state 7 making up 41.4% of the entire data set (Table 4).

The estimation results for the random-effects deterioration model associated with condition states 7, 8, and 9 are shown in Table 5. The estimation results for the model associated with condition states 4, 5, and 6 are quite similar and are not presented in this paper. The results are in agreement with a priori hypotheses and previous research (Busa 1985; Madanat et al. 1995). Decks on older bridges are more likely to experience a drop in condition than decks on newer bridges, as indicated by the positive sign of the coefficient of the AGE variable. An increase in incremental average daily traffic (ADT) increases the deterioration propensity of bridge decks; it should be noted that the effect of ADT on bridge decks on interstate and primary highways is of equal magnitude, and the effect of ADT on the deterioration rate of bridge decks on secondary roadways is higher (the equality of the coefficient estimates for the effects of an independent variable on the deterioration rates of different types of decks was tested using the WALD test).

The number of spans also affects the deterioration of bridge decks, with the deterioration rate increasing with an increased

TABLE 5. Estimation Results for Probit Model without State Dependence—Starting Condition States 7–9

Variable name (1)	Probit Model: Coefficient estimate (2)	Probit Model: *t*-ratio (3)	Random Effects Probit: Coefficient estimate (4)	Random Effects Probit: *t*-ratio (5)
Constant	−4.89	−1.69	−8.43	−2.01
Interstate	−0.95	−3.23	−1.05	−2.51
Primary	−0.45	−3.15	−0.53	−2.77
Age	2.000E-03	1.48	3.60E-03	1.91
Average daily traffic (specific to interstate and primary)	1.35E-05	3.44	1.69E-05	3.31
Average daily traffic (specific to local)	2.19E-05	1.93	2.47E-05	1.82
Climatic region (specific to interstate)	0.31	2.6	0.35	1.87
Climatic region (specific to primary)	0.44	5.9	0.56	4.91
Number of spans (specific to interstate)	0.240E-03	3.1	0.31	2.9
Number of spans (specific to primary and local)	0.065	3.3	0.099	3.45
Wearing-surface type 1 (specific to interstate and primary)	0.67	5.41	0.78	5.05
Wearing-surface type 2 (specific to interstate and primary)	0.85	6.19	1.03	5.89
Structure type 1	0.11	1.97	0.21	2.63
Rho	—	—	0.41	7.39
Summary statistics				
Number of observations	3,513	—	3,513	—
$L(0)$	−2,807.754	—	−2,807.754	—
$L(B)$	−1,971.783	—	−1,901.255	—
Rho-squared	0.297	—	0.323	—

number of spans. The positive sign of the dummy variable for structure type 1 (simple-span structure) indicates that this type of bridge deck has a higher probability of deterioration than bridge decks on continuous structures. Wearing-surface types 1 and 2 refer to bridge decks without any protective system. The positive coefficient for wearing-surface types 1 and 2 indicate that these bridge decks deteriorate at a faster rate than bridges with protective systems (Table 4). Furthermore, the bridges in the northern part of Indiana have a higher deterioration propensity than bridges in the southern part. This result was expected, since bridges in the northern part are subjected to a higher number of freeze-thaw cycles and deteriorating effects of the deicing salts used during winter time. Finally, the negative signs on the interstate and primary highway

TABLE 6. Actual and Predicted Bridge Condition Rating—Starting Condition States 7–9

Actual		Predicted (number of observations)					
		PROBIT MODEL			RANDOM EFFECTS PROBIT		
		Number of Drops		Percent correctly predicted (5)	Number of Drops		Percent correctly predicted (8)
Number of drops (1)	Number of observations (2)	0 (3)	1 (4)		0 (6)	1 (7)	
0	2,519	2,303	216	91.4	2,375	144	94.2
1	994	456	538	54.1	368	626	62.9

dummy variables indicate that the more stringent design requirements for bridge decks on these highways result in structures that deteriorate at a slower pace than those on secondary roadways. These explanatory variables capture group-specific heterogeneity, where the groups correspond to different design types, environmental factors, and so on.

The coefficient ρ, which captures the effect of unobserved heterogeneity, is positive and highly significant (t-statistic = 7.39). This suggests that heterogeneity is present in the sample even after accounting for the effects of structure type, environment, traffic, etc., and is successfully captured with the use of the random-effects specification. It is also important to note that the significance of the AGE variable in the random-effects specification indicates that the assumption of time homogeneity of the transition probabilities would not be appropriate for this data set.

As can be seen from Table 5, the random-effects specification coefficients do not seem significantly different from those of the simple probit model. However, the performance of a χ^2-test of the equality of the coefficients across the two models indicated that the data in the present sample is consistent with the random-effects model, i.e., there is evidence of random effects in the data. Furthermore, the random-effects estimation yields a model with a higher goodness-of-fit ρ^2 and better predictions (Table 6). The prediction results from Table 6 indicate that with the use of the random-effects estimator, the percentage of correct predictions in the case of bridge decks that did not drop in condition rating was 94.2%; for bridge decks that dropped in condition rating, the percentage was 62.9%. These prediction results are rather satisfactory, even though the model has a tendency to "underpredict" the drops in condition rating.

Investigating True State Dependence

The model formulated in the previous section attempted to account for heterogeneity with the use of the random effects, but assumed no true state dependence, i.e., the model that was formulated on the assumption that the probability of a bridge-deck condition moving from (or staying in) a state is independent of the history of deterioration. As was previously discussed, it is possible that bridge decks that have experienced deterioration in the past are likely to become more deterioration-prone in the future, a condition known as true state dependence. Since it is likely that serial correlation exists in successive observations of bridge-deck conditions due to persistent and unobserved effects (design characteristics, materials, and so on), true state dependence, as noted by Chamberlain (1978), can be captured by incorporating lagged exogenous variables in the model. In the presence of such serial correlation, the estimated coefficients of a lagged dependent variable will be biased and inconsistent. The lagged dependent variable "picks up" the serial correlation and may appear more significant than it really is. On the other hand, lagged exogenous variables or a linear function thereof such as an instrumental lagged dependent variable will not suffer from such bias.

TABLE 7. Estimation Results for Probit Model with State Dependence—Starting Condition States 7–9

	Probit Model		Random Effects Probit	
Variable name (1)	Coefficient estimate (2)	t-ratio (3)	Coefficient estimate (4)	t-ratio (5)
Constant	−3.17	0.51	5.03	0.52
Lagged predicted dependent variable	0.26	1.63	0.39	1.64
Interstate	−0.071	−0.142	−0.42	−0.41
Primary	−0.51	−2.01	−0.96	−2.07
Age	2.10E-03	0.68	3.40E-03	0.7
Average daily traffic (specific to interstate and primary)	1.20E-05	1.82	1.10E-05	1.11
Average daily traffic (specific to local)	−2.20E-05	−0.87	−3.60E-05	−0.44
Climatic region (specific to interstate)	0.26	1.17	0.27	0.73
Climatic region (specific to primary)	0.097	0.64	0.084	0.36
Number of spans (specific to interstate)	−0.062	−0.44	−0.034	−0.11
Number of spans (specific to primary and local)	0.061	1.77	0.1	1.98
Wearing-surface type 1 (specific to interstate and primary)	0.73	3.41	1.22	3.15
Wearing-surface type 2 (specific to interstate and primary)	0.97	3.84	1.56	3.54
Structure type 1	−0.15	−1.43	−0.15	−0.93
Rho	—	—	0.62	5.46
Summary statistics				
Number of observations	1,246	—	1,246	—
$L(0)$	−1,259.68	—	−1,259.68	—
$L(B)$	−761.8	—	−736.8	—
Rho-squared	0.395	—	0.415	—

Therefore, we used a random-effects model and included the fitted value of the lagged deterioration variable y^*_{t-1} as an explanatory variable for the deterioration in time-period t, to capture possible state dependence. The presence of the true state dependence was tested by examining the significance of the coefficient of the lagged instrumented dependent variable, and the presence of spurious state dependence is indicated by the "rho" coefficient (Table 7) (Chamberlain 1978). It should be noted that the original model was not altered, and new specification search was not performed since the objective of this exercise was to examine state dependence. The model developed in this section does not represent a "dynamic" model.

Indeed, as outlined by Heckman (1981b), this model assumes exogenous initial conditions for all facilities in the sample, which would only be true if our sample consisted entirely of new decks. Since this is not the case, we can only view the current model as a means to test for state dependence, not as an improved version of the previous model.

The results of the previous model with the addition of the predicted lagged dependent variable from the original model as an explanatory variable appear in Table 7. It is interesting to note that, in most cases, the signs of the coefficients remained the same compared with the original model. Nevertheless, the coefficients for ADT specific to secondary roadways, number of spans specific to interstate, and structure type have perverse signs. While this is surprising, the t-statistic for these coefficients indicates that the null hypotheses that these coefficients are independently equal to zero cannot be rejected; as a result, these coefficients would probably be excluded if a new specification search was undertaken.

The coefficient of interest in the context of this analysis is the instrumented lagged deterioration. This coefficient, both in the case of the probit and the random-effects probit model, is significant at the 90% level of significance. This result indicates that state dependence is probably present in the process of bridge-deck deterioration for the current data set. By using a random-effects specification in the second model, we have controlled heterogeneity, and the instrumentation of the lagged dependent variable should have eliminated the possible bias in parameter estimation. Therefore, it is expected that the lagged dependent variable is capturing true state dependence. This implies that the use of a simple Markovian model to represent the deterioration of these facilities would be erroneous.

It should be noted, however, that most explanatory variables in the model are now insignificant, which is due to collinearity with the instrumented lagged dependent variable. Strong collinearity is expected because most explanatory variables have constant values over time, for a given bridge deck. It is particularly troubling that the variable AGE has become insignificant, which indicates that, in this data set, it is not possible to empirically distinguish between the effects of state dependence and time nonhomogeneity. However, this also implies that the variable AGE, which seemed highly significant in Table 5, may have been actually capturing the effect of true state dependence. While the present data set did not lend itself to empirically distinguishing between these two effects, their management implications are significantly different, which warrants further investigation of this issue.

CONCLUSIONS

The goal of the present paper is to develop a probit model for bridge-deck deterioration. The probit model used a panel data set and estimated a random-effects probit model to account for heterogeneity in the sample. This paper also examined the presence of state dependence in the bridge-deck deterioration process. The results suggest that there are indeed random effects present in the bridge-deck sample and that a model that accounts for these heterogeneous effects yields improved results when compared to the simple probit model. Furthermore, the results from the estimation of a deterioration model with an instrumented lagged dependent variable indicate that state dependence is probably present in the bridge-deck deterioration process, which would invalidate the Markovian assumption. The random-effects probit model that is described in the present paper is an improvement over other state-of-the-art models, which do not attempt to account for heterogeneity. The model is realistic in that it links deterioration to a set of explanatory variables, is theoretically sound, and provides estimates that are satisfactory. One issue that was left unresolved in the current paper is the distinction between true state dependence and time nonhomogeneity; due to strong collinearity, it was not possible to confirm the presence of time nonhomogeneity when state dependence was accounted for. This issue deserves further investigation.

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