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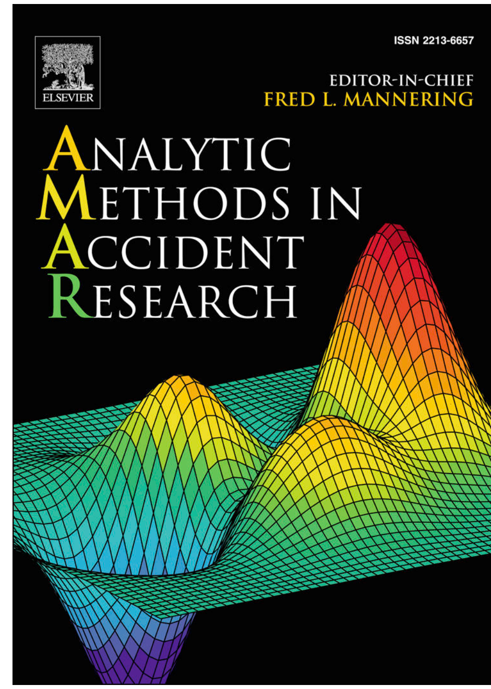

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The impact of public-private partnerships for roadway projects on traffic safety: An exploratory empirical analysis of crash frequencies

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ABSTRACT

Since the mid-2000s, Public-Private Partnerships (PPP) have been established in transportation infrastructure projects as an effective alternative to the traditional procurement process, such as design-bid-build where the design and construction are awarded separately and sequentially to private firms. PPP contracts ensure both greater participation of the private sector, as well as shared responsibility in project delivery. However, the interrelationship between various PPP approaches and the status of traffic safety during the project implementation has not been thoroughly explored to date. This paper seeks to provide new insights into the performance of different PPP contracting approaches by investigating them from the perspective of transportation safety. To that end, a statistical analysis is conducted in order to distinguish differences with respect to the characteristics of crashes that occurred during the contractual period of roadway projects. Using data from 645 PPP contracts that were executed across multiple States of the US between 1996 and 2011, count data models of crash frequencies are developed. To take into account the effect of unobserved factors on crash frequencies, correlated random parameter models with heterogeneity in the means are estimated. The results of the statistical analysis overall show that the determinants of crash frequencies and the magnitude of their impacts vary across PPP types. Contracts with higher cost, shorter duration, fewer lane-miles to be covered, more asset work activities, as well as contracts for roadways featuring better pavement and drainage conditions, low to medium AADT, and higher width of shoulder are more likely to observe fewer crashes. Additionally, several variables resulted in correlated random parameters (such as, contract size in lane-miles and truck percentage), with their distributional characteristics being affected by other exogenous factors (such as pavement characteristics), thus unveiling the heterogeneous patterns underpinning the safety performance of different PPP approaches.

Keywords: Public-Private Partnerships; Crash Frequency; Negative Binomial; Poisson; Correlated Random Parameters; Unobserved Heterogeneity.

INTRODUCTION

A substantial portion of research on traffic safety has focused on identifying factors that adversely impact safety, and on modifying or eliminating these factors either through corrective measures or preventive actions. Among the various factors that have been investigated, the impact of roadway characteristics, vehicle features and human factor elements on various crash dimensions has attracted the interest of most empirical studies (to name a few exmaples, Shankar et al., 1995; Abdel-Aty et al., 2006; Lord and Mannering, 2010; Anastasopoulos, 2016; Sarwar et al., 2017a; Park et al., 2018; Fountas and Rye, 2019). However, a relatively limited body of studies have aimed to identify and analyze the interrelationship between traffic safety, and policy, process and operational issues pertaining to the roadway networks. From the policy and process perspective, the impacts of speed limits and police enforcement on safety (Kweon and Kockelman, 2004; Anastasopoulos and Mannering, 2016; Elvik, 2018; Pantangi et al., 2019, 2020) have been predominantly investigated. Another factor that has been extensively studied from a policy perspective is work zone safety (Debnath et al., 2014; Yang et al., 2015). The objective of these studies has been to analyze crash rate and/or frequency when construction or maintenance projects are being carried out. However, limited research (for example, Rangel and Vassalo, 2015; Albalate and Bel- Piñana, 2019) has been devoted to understanding which factors influence the safety performance of a roadway project that is implemented through a public-private partnership (PPP) scheme. The most commonly employed PPP schemes for roadway construction and maintenance activities alongside their main characteristics are provided in Table 1 (Anastasopoulos et al., 2010a, 2010c).

In this study, the intent is to add new empirical evidence to the existing knowledge on the determinants of traffic safety, taking into account the inherent cost-, duration-, size-, asset-, and activity-related characteristics of conventional or emerging delivery methods for roadway projects. To accomplish this, the safety performance of traditional and various PPP types[1] is investigated, by focusing on crashes that occurred in the period during which the project tasks (i.e., construction, maintenance, rehabilitation, preservation) were carried out (this will be referred to hereafter as project implementation period). The recent study of Albalate and Bel- Piñana (2019) provides empirical insights with regard to the aggregate effect of PPPs on safety performance of highways through the estimation of fixed and random effects count data models. However, this study did not account for possible variations in the safety performance of projects across different types of PPPs, whereas the employed approaches did not explicitly control for the multilayered impact of unobserved factors on crash predictors (Mannering et al., 2016). Given that different PPP approaches reflect quite disparate project delivery mechanisms, the relationship between the PPP type of the roadway project and its safety performance may bear significant heterogeneity, which has not been taken into account by previous research to date.

To fill in this gap, the present study aims at identifying the influential factors of crashes occurred during the implementation period of roadway projects per each specific PPP type. This disaggregate analysis will also shed more light on the potential variations for several groups of factors, which may be associated with the safety performance of projects under each PPP type. For this purpose, count data econometric models that capture various nuances of unobserved heterogeneity (i.e., the impact of unobserved factors) are developed for each PPP type. Specifically, the number of crashes occurred during the project period is statistically modeled using a correlated random parameters estimation framework with heterogeneity in means. This approach can control for multi-level unobserved effects varying systematically across the roadway

[1] Table 1 present the different types of PPP contracts studied in this paper and their definition.

projects, as well as for the interaction of these unobserved effects on crash frequencies. This study is among the first-of-its-kind employing a count data approach with correlated random parameters and heterogeneity in means to model crash frequencies. For model estimation, an extensive dataset with rich PPP- and accident-related information is leveraged. Thereby, contract work activities, contract cost, duration and size are coupled with the traditional, influential factors of crash frequencies (e.g., traffic characteristics, road geometrics, pavement condition, weather conditions, etc.) in order to account for all possible dimensions of safety performance in statistical estimation.

LITERATURE REVIEW

In modern safety research, a growing body of studies seek to determine the influential factors of crash frequencies using historical data. The steps involved in any such study revolve around: (a) selecting an appropriate modeling approach; and (b) identifying the contributing factors that are likely to contribute to or mitigate the potential for crashes. Predicting crash frequencies or rates and identifying high-crash locations can result in improvements in the transportation system, and eventually can reduce crash occurrences and injury-severities.

The selection of the econometric model(s) that can be used to study the safety-related dependent variables (crash occurrence, crash frequency, crash rate, crash risk, etc.) depends on the type of available data, for both dependent and independent variables. Crash frequencies fall into the category of count data; therefore, approaches that can address the non-negative, integer nature of these data should be used for modeling purposes. The Poisson and the negative binomial models constitute the most widely used count-data approaches (Miaou, 1994; El-Basyouny and Sayed, 2009). The selection of the most appropriate approach between these two depends on the dispersion of the crash frequency data (Shankar et al., 1995; Hong and Prozzi, 2015). In cases of preponderance of spatial locations (e.g., roadway segments, intersections, and so on) where crashes did not occur over a defined period of time, zero-inflated Poisson or negative binomial models have been also extensively used (Aguero-Valverde, 2013; Dong et al., 2014; Anastasopoulos, 2016).

Another indicator of safety performance is the crash rate, which combines crash frequency and traffic exposure in a single metric. Due to the possibility of crash rate data to be left-censored, the tobit model has been established as a robust modeling approach for analyzing crash rate data (Anastasopoulos et al., 2012b, 2012c; Debnath et al., 2014; Anastasopoulos, 2016).

For the analysis of crash injury-severities, discrete outcome models have been widely employed in accident research, such as multinomial logit/probit models (Ulfarsson and Mannering, 2004; Behnood and Mannering, 2017a; Behnood and Mannering, 2019), ordered logit/probit models (Eluru et al., 2008; Russo et al., 2014; Fountas and Anastasopoulos, 2017; Fountas and Anastasopoulos, 2018; Fountas and Rye, 2019), and nested logit/probit models (Chang and Mannering, 1998). Some of the aforementioned modeling approaches can be combined using a multivariate modeling approach (Ma and Kockelman, 2006; Park and Lord, 2007; Aguero-Valverde and Jovanis, 2008; Anastasopoulos et al., 2012c; Sarwar et al., 2017b; Fountas et al., 2019; Eker et al., 2020a; Eker et al., 2020b; Fountas et al., 2020).

The absence of information related to human factors' contribution to the accident occurrence – which may potentially determine the likelihood of a crash or its resulting injury-severity – may induce misspecification issues in the modeling process arising from the impact of unobserved heterogeneity (Mannering and Bhat, 2014; Zhang and Durango-Cohen, 2014; Mannering et al., 2016). Over the last few years, random parameters modeling has been established as a universally acceptable methodological framework that accounts for unobserved heterogeneity in statistical modeling. This approach has been shown to provide superior statistical fit and forecasting accuracy relative to fixed parameter models (El-Basyouny and Sayed, 2009; Anastasopoulos and Mannering, 2011, 2014, 2016; Anastasopoulos et al., 2011; Venkataraman et al., 2013; Anastasopoulos, 2016; Ahmed et al., 2017; Zamenian et al., 2017; Semple et al., 2021). An important feature of random parameters modeling is that it allows for the effect of the estimated parameters to vary across observations, thus improving the model's explanatory power.

The factors that have been found to be related to the different safety indicators can be broadly divided into five major groups, namely roadway geometry (e.g., median width, number of curves), traffic characteristics (e.g., average annual daily traffic, truck percentage), pavement condition (e.g., international roughness index, pavement condition rating), weather conditions (e.g., temperature, precipitation), and human factors (e.g., drinking, driving experience). The effects of these factors have been extensively studied in accident research. However, because the effects of various PPP contracting approaches on crashes that occurred during the project implementation period have not been thoroughly investigated, the relevant empirical evidence is currently limited.

DATA

For the analysis of the safety performance of various PPP types, data have been drawn from 645 PPP contracts of highway projects implemented in the US, over a fifteen years' time period, from 1996 to 2011. The data were collected and collated from a diverse set of sources including the Federal Highway Administration (FHWA), and an array of State transportation Agencies: Indiana, Minnesota, Florida, Virginia, Texas, Washington DC, and Alaska. These data have been also used in previous studies (Anastasopoulos et al., 2012; Nahidi et al., 2017).

Table 1 provides the seven different PPP types of the 645 contracts that were analyzed along with a brief description of their implementation process. Out of the 645 US-based contracts, 104 were from Texas, 138 from Virginia, 195 from Indiana, 45 from Minnesota, 91 from Florida, 33 from Washington D.C., and 39 from Alaska. In Florida, Texas, Alaska, Washington D.C., and Virginia, the Design-Build (DB) and its derivatives (Design-Build-Operate-Maintain, or DBOM), and Performance Based Contracting (PBC) approaches were prevalent. Warranty, DBOM and cost-plus-time (A+B) contracts were prevalent in Minnesota, whereas in Indiana, Warranty, DBOM and traditional contracting approaches were most frequently used.

The available data also included information about the fundamental contract characteristics, i.e., duration, size in lane-miles, work activities contained in the project scope (construction, maintenance, rehabilitation, preservation, and assets that were worked on), and cost-related features (final cost, in-house cost, number of bids, highest bid). The dataset also contained information about the weather conditions (proportion of rainy and snowy days); roadway geometry (inside and outside shoulder width, presence of median, median width, drainage system, number of horizontal and vertical curves and number of lanes); pavement condition (mean and standard deviation of International Roughness Index - IRI, Pavement Condition Rating - PCR, and rutting depth)[2]; and traffic characteristics (average annual daily traffic, and truck percentage). It should be noted that all these data items were collected during the period when the project was being implemented without counting the duration of bidding and contracting.

For each of the 645 roadway projects, the number of crashes that occurred during the project implementation period at the highway location where the project work was carried out was recorded. Overall, 140 contracts were found to have no crashes, 130 contracts had one crash, 120 contracts had 2 to 10 crashes, and 250 contracts had more than 10 crashes throughout the project implementation period. Table 2 provides a summative overview of the key variables that were considered for the statistical modeling of the number of crashes per each PPP type.

Separate models were estimated for each PPP project type, except from the cost-plus-time (A+B) and incentives/disincentives (I/D) types, which were merged and analyzed through a single, aggregate model. These two types were combined due to their contractual similarities (i.e., both types encourage timely completion of contract), and due to scarcity of observations for each individual project type. Upon further investigation of the lane rentals contract type, the number of

[2] The mean and the standard deviation of the pavement condition metrics were calculated using multiple measurements per year of the project duration (Anastasopoulos, 2009).

observations related to this type was too scarce to estimate a separate model that could offer robust inferences; hence, the safety performance of lane rental projects was not analyzed in this study.

Table 1. Public-private partnership contract types and their description

Contract Type	**Description**
Traditional	• Contractor provides specific services to complete one or more tasks, on a fee-for-service basis.
Performance Based Contracting (PBC)	• Private sector operations and maintenance on a performance basis. • Final products and results important, procedure not so much. • Contractor should meet minimum physical conditions defined in agreement, that are typically measured in terms of condition measures such as: pavement surface roughness, skid resistance/friction, rutting depth, deflection, texture, etc.
Warranties	• The contractor is liable for product defects or failure, and is responsible that the product meets certain pre-agreed performance standards. • Product's quality and performance is guaranteed by the contractor throughout the course of the predetermined warranty period. • Contractor is required to provide regular maintenance for the product after project delivery.
Incentives / Disincentives (I/D)	• Structured to encourage the contractor to finish the project earlier than the time indicated in the original bid document. • Contractor awarded if project finishes early, and penalized if work is delayed. • Contractors try to use new innovative techniques, technologies to finish the contract early. • Larger companies that have more resources and financial risk drive are more likely to get selected.
Cost-Plus-Time (A+B)	• Contractor is selected based on a bi-criteria optimization on cost (contractor's bid amount - A) and time (road-user cost multiplied by project duration - B). • Contractor should meet both cost and time criteria agreed to in the bid. • Contractors use new techniques and technologies to finish the contract early.
Design-Build and its Derivatives (DBOM)	• Contractors use this method to minimize the possible risks related to the project, and also reduce the delivery schedule by overlapping the construction and design phases of the project.
Lane Rentals	• Used to accelerate the completion of a preservation project by charging the contractor with a fee for occupying lanes or shoulders throughout the project duration. • Contractor rents a lane, in order to close it and work on it. The sooner the contractor can finish work, the lower is the rental cost. • Contractor can rent either the entire site, or lane-by-lane.

Table 2. Means and standard deviations of the independent variables likely to affect the safety performance of PPP projects (standard deviations in parentheses) (continued)

Variables	All contracts	A+B	DBOM	I/D	Lane rentals	PBC	Traditional	Warranties
Contract duration (years)	4.528 (2.203)	4.151 (1.531)	5.667 (0.852)	4.273 (1.547)	2.614 (0.529)	5.532 (1.573)	3.478 (2.500)	4.761 (2.816)
Project size (lane-miles)	76.746 (142.530)	33.948 (40.335)	30.053 (31.679)	57.004 (58.848)	38.516 (33.160)	258.808 (270.234)	86.485 (123.411)	24.549 (80.171)
Number of assets	2.025 (1.999)	2.581 (2.335)	1.627 (1.672)	1.73 (1.387)	2.382 (2.387)	1.544 (1.526)	2.278 (2.221)	2.402 (2.144)
Contract cost (in \$1M)	21.858 (36.552)	9.587 (9.669)	27.715 (28.926)	19.332 (20.994)	11.255 (9.167)	60.103 (63.314)	7.008 (19.287)	19.419 (37.930)
Final cost of contract award (in \$1M)	20.731 (35.009)	10.766 (13.316)	25.143 (25.243)	19.465 (19.171)	10.338 (9.224)	63.307 (65.834)	6.346 (16.223)	15.041 (27.684)
Truck percentage (Commercial Trucks as percentage of AADT)	15% (11.3%)	15.7% (11.7%)	14.9% (10.8%)	16.9% (14.3%)	14.8% (7.4%)	13.6% (9.6%)	14.7% (11.4%)	16.2% (12.6%)
Mean of AADT (in 1000s of vehicles/day)	12.909 (16.778)	12.754 (20.281)	12.581 (16.066)	21.664 (28.960)	7.497 (5.254)	18.206 (18.496)	12.181 (15.564)	9.260 (11.790)
Average of international roughness index (in inches)	108.633 (41.278)	114.856 (35.428)	114.859 (45.852)	95.016 (28.960)	103.363 (35.607)	106.411 (30.552)	106.860 (39.148)	108.266 (50.320)

Table 2. Means and standard deviations of the independent variables likely to affect the safety performance of PPP projects (standard deviations in parentheses) (continued)

Variables	All contracts	A+B	DBOM	I/D	Lane rentals	PBC	Traditional	Warranties
Standard deviation of international roughness index (in inches)	25.716 (23.331)	28.345 (19.479)	28.052 (35.559)	21.977 (28.428)	25.636 (17.336)	24.103 (14.130)	24.379 (16.238)	26.302 (20.846)
Average of pavement condition rating (on a 0-100 scale)	88.293 (4.598)	87.313 (3.987)	87.653 (4.270)	89.689 (4.079)	88.412 (4.743)	88.149 (4.113)	88.609 (4.449)	88.621 (5.877)
Standard deviation of pavement condition rating (on a 0-100 scale)	7.652 (3.039)	9.111 (3.053)	7.707 (3.078)	7.040 (2.088)	8.0186 (3.287)	8.068 (2.918)	7.528 (3.017)	7.11 (2.947)
Average of rutting depth (in inches/mile)	0.160 (0.073)	0.169 (0.062)	0.172 (0.076)	0.138 (0.060)	0.154 (0.062)	0.155 (0.059)	0.154 (0.068)	0.161 (0.094)
Standard deviation of rutting depth (in inches/mile)	0.0565 (0.046)	0.042 (0.027)	0.059 (0.041)	0.051 (0.033)	0.051 (0.029)	0.056 (0.043)	0.059 (0.054)	0.056 (0.049)
Number of lanes	2.098 (0.614)	2.161 (0.374)	2.207 (0.544)	1.919 (0.547)	2.147 (0.500)	2.228 (0.451)	1.995 (0.771)	2.041 (0.557)
Median width (in feet)	23.76279 (40.468)	20.452 (26.867)	31.787 (46.354)	13.892 (23.310)	31.529 (45.791)	24.228 (41.761)	21.283 (38.359)	16.567 (34.626)

Table 2. Means and standard deviations of the independent variables likely to affect the safety performance of PPP projects (standard deviations in parentheses) (continued)

Variables	All contracts	A+B	DBOM	I/D	Lane rentals	PBC	Traditional	Warranties
Interior shoulder width (in feet)	6.676 (4.543)	6.839 (3.975)	7.003 (4.771)	5.986 (4.481)	6.618 (4.987)	6.101 (4.282)	6.810 (4.512)	6.532 (4.494)
Outside shoulder width (in feet)	9.437 (4.588)	9.300 (5.068)	9.286 (4.958)	9.308 (4.470)	8.241 (4.610)	9.222 (4.332)	9.776 (4.439)	9.695 (4.334)
Assets								
Bridge-Tunnel Repair/Maintenance/Management	0.175 (0.380)	0.032 (0.180)	0.053 (0.225)	0.135 (0.347)	0.088 (0.288)	0.304 (0.463)	0.222 (0.417)	0.278 (0.451)
Crack/Pothole Sealing/Repair	0.076 (0.265)	0.226 (0.425)	0.030) (0.170)	0.270 (0.450)	0 (0)	0.114 (0.320)	0.045 (0.209)	0.092 (0.292)
Culvert/Ditches/Gutters/Drainage Repair/Maintenance/Replacement	0.127 (0.333)	0.129 (0.341)	0.124 (0.331)	0.162 (0.374)	0.118 (0.327)	0.063 (0.245)	0.146 (0.354)	0.134 (0.343)
Emergency Facilities Maintenance/Response	0.016 (0.124)	0 (0)	0 (0)	0 (0)	0 (0)	0.063 (0.245)	0.020 (0.141)	0.010 (0.102)
Management	0.022 (0.146)	0 (0)	0 (0)	0.054 (0.229)	0 (0)	0.101 (0.304)	0.015 (0.122)	0.010 (0.102)

Table 2. Means and standard deviations of the independent variables likely to affect the safety performance of PPP projects (standard deviations in parentheses) (continued)

Variables	All contracts	A+B	DBOM	I/D	Lane rentals	PBC	Traditional	Warranties
General Maintenance/Repair/Rehabilitation/Treatment	0.276 (0.447)	0.355 (0.486)	0.201 (0.402)	0.081 (0.277)	0.618 (0.493)	0.101 (0.304)	0.323 (0.469)	0.381 (0.488)
Guardrail Repair/Maintenance	0.161 (0.368)	0.258 (0.445)	0.225 (0.419)	0.216 (0.417)	0.029 (0.171)	0.165 (0.373)	0.126 (0.333)	0.113 (0.319)
Illumination Repair/Maintenance	0.076 (0.265)	0.194 (0.402)	0.059 (0.237)	0.027 (0.164)	0.118 (0.327)	0.063 (0.245)	0.081 (0.273)	0.072 (0.260)
Landscape Repair/Maintenance	0.065 (0.247)	0.194 (0.402)	0.059 (0.237)	0.027 (0.164)	0.118 (0.327)	0.038 (0.192)	0.056 (0.230)	0.072 (0.260)
Litter Removal	0.079 (0.270)	0.161 (0.374)	0.154 (0.312)	0.027 (0.164)	0.118 (0.327)	0.025 (0.158)	0.040 (0.197)	0.051 (0.222)
Electrical/Cable system Repair/Maintenance	0.205 (0.404)	0.161 (0.374)	0.167 (0.373)	0.108 (0.315)	0.441 (0.504)	0.063 (0.245)	0.237 (0.427)	0.288 (0.455)
Mowing	0.040 (0.197)	0.032 (0.177)	0 (0)	0.027 (0.164)	0 (0)	0.025 (0.0158)	0.086 (0.281)	0.051 (0.222)
Pavement Repair/Maintenance/Treatment	0.158 (0.365)	0.161 (0.374)	0.136 (0.344)	0.324 (0.475)	0.088 (0.288)	0.139 (0.348)	0.101 (0.302)	0.289 (0.455)

Table 2. Means and standard deviations of the independent variables likely to affect the safety performance of PPP projects (standard deviations in parentheses) (continued)

Variables	All contracts	A+B	DBOM	I/D	Lane rentals	PBC	Traditional	Warranties
Rest Areas	0.130 (0.337)	0.129 (0.341)	0.095 (0.234)	0.027 (0.164)	0.235 (0.431)	0.051 (0.221)	0.167 (0.373)	0.186 (0.391)
Shoulder Repair/Maintenance	0.051 (0.221)	0.032 (0.180)	0.006 (0.077)	0.054 (0.229)	0.029 (0.171)	0.025 (0.158)	0.106 (0.309)	0.052 (0.222)
Traffic Signs and Signals	0.147 (0.355)	0.226 (0.425)	0.160 (0.367)	0.108 (0.315)	0.088 (0.288)	0.101 (0.304)	0.202 (0.403)	0.062 (0.242)
Vegetation/Tree Control/Maintenance/Removal	0.051 (0.221)	0.161 (0.374)	0.036 (0.186)	0.027 (0.164)	0.118 (0.327)	0.051 (0.221)	0.040 (0.197)	0.052 (0.222)
Other	0.169 (0.375)	0.129 (0.341)	0.124 (0.331)	0.054 (0.229)	0.176 (0.387)	0.051 (0.221)	0.263 (0.441)	0.206 (0.407)
All services	0.079 (0.270)	0 (0)	0.142 (0.350)	0.189 (0.397)	0.059 (0.239)	0.203 (0.404)	0.005 (0.071)	0.010 (0.102)
Number of accidents	12.915	14.323	13.899	8.432	9.000	15.139	14.258	9.278
Number of observations	645	31	169	37	34	79	198	97

A+B: Cost-plus-time contracts; I/D: Incentives/Disincentives contracts; DBOM: Design-build-operate-maintain contracts and their derivatives; PBC: Performance-based contracts.

METHODS

The number of crashes that occurred during the project implementation period falls into the category of count data (non-negative integers). Such data can be primarily modeled using Poisson or Negative Binomial models (Washington et al., 2020).

The probability that a specific number of crashes occurs at the project work site during the contract duration, can be expressed using the Poisson model as shown in Equation 1. This model can be used to study the number of crashes that occur in a given interval of time because each crash that occurs during the fixed time interval (i.e., the project duration), occurs independently of the previous crash. In the basic Poisson model, the probability, $P(n_i)$, of a contract i being associated with n crashes is (Washington et al., 2020),

$$P(n_i) = \frac{\exp(-\lambda_i)\lambda_i^{n_i}}{n_i!}, \tag{1}$$

where, λ_i is the Poisson parameter for contract i, which is the contract i's expected number of crashes in a given time interval. The Poisson model specifies the Poisson parameter λ_i as a function of explanatory variables by typically using a log-linear function, $\lambda_i = exp(\boldsymbol{\beta X_i})$, where $\boldsymbol{X_i}$ is a vector of explanatory variables, and $\boldsymbol{\beta}$ is a vector of estimable parameters. Depending on the data, a Poisson model may not always be appropriate, because the Poisson distribution restricts the mean and variance to be equal ($E[n_i] = VAR[n_i]$).

If the equality of the mean and variance does not hold, over- or under-dispersion of the crash data is expected, and the estimated parameter vector will be biased. To account for this possibility, a negative binomial model can be derived by rewriting Equation 1 as,

$$\lambda_i = EXP(\boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i), \tag{2}$$

where, $EXP(\varepsilon_i)$ is a Gamma-distributed error term with mean 1 and variance α. The Negative Binomial model has a probability function,

$$P(y_i) = \frac{\Gamma(\frac{1}{\alpha}+y_i)}{\Gamma(\frac{1}{\alpha})y_i!}\left(\frac{\frac{1}{\alpha}}{(\frac{1}{\alpha})+\lambda_i}\right)^{1/\alpha}\left(\frac{\lambda_i}{(\frac{1}{\alpha})+\lambda_i}\right)^{y_i}, \tag{3}$$

where, $\Gamma(.)$ is a gamma function, and α is the over-dispersion parameter.

For each of these count data models, the effect of unobserved heterogeneity (i.e., unobserved factors exhibiting systematic variations across the observations, or across groups of observations) needs to be considered in model estimation to avoid biased predictors and invalid inferences (Anastasopoulos and Mannering, 2011, 2016; Anastasopoulos et al., 2012a, 2017; Greene, 2016; Mannering and Bhat, 2014; Russo et al., 2014; Aguiar-Moya and Prozzi, 2015; Kang and Fricker, 2016; Mannering et al., 2016; Sarwar et al., 2016, 2017a; Fountas et al., 2018b, 2018c; Guo et al., 2018, 2020; Corrales-Azofeifa and Archilla, 2018; Jordan et al., 2019; Barbour et al., 2019; Ahmed et al., 2020; Washington et al., 2020; Ahmed et al., 2021). To that end, the random parameters modeling approach is employed, which has been widely implemented in safety research over recent years (Sarwar et al., 2017a, 2016; Anastasopoulos and Mannering, 2014, 2016; Russo et al., 2014; Yu and Abdel-Aty, 2014; Intini et al., 2020). Within this modeling context, to capture underlying variations in the effect of observable characteristics, the parameters of the explanatory variables are freely allowed to vary across the data units (i.e., roadway projects) as (Mannering et al., 2016; Greene, 2016; Behnood and Mannering, 2017a, 2017b),

$$\boldsymbol{\beta}_{in} = \beta + \mathbf{M}u_{in} + \boldsymbol{\delta}_{in}\mathbf{z}_{in}, \tag{4}$$

where, $\boldsymbol{\beta}_{in}$ is a vector of random parameters, and u_i a normally distributed term with mean zero and variance σ^2, $\mathbf{M}$ is a Cholesky matrix, which subsequently provides the covariance matrix of the random parameters, $\mathbf{z}_{\text{in}}$ is vector of explanatory variables that influence the fixed mean β of the $\boldsymbol{\beta}_{in}$, and $\boldsymbol{\delta}_{in}$ is a vector of estimable parameters for the $\boldsymbol{\beta}_{in}$ (Mannering et al., 2016; Greene, 2016; Behnood and Mannering, 2017a, 2017b). The last term of Equation 4 relaxes the assumption of a fixed mean for the random parameters, thus enabling possible latent effects due to heterogeneity in the means of random parameters to be accommodated in model estimation.

Unlike the uncorrelated random parameters approach, where the off-diagonal elements of the covariance matrix are restricted to zero, the generalized form of the **M** matrix in Equation 4 does not impose this limitation, as the below diagonal elements can take non-zero values. Hence, correlated random parameters can be estimated. It should be also noted that a possible shift in the mean of random parameters due to heterogeneity does not affect the portion of the general unobserved heterogeneity effects that are captured by the second term of the right-hand side part of Equation 4 (Mannering et al., 2016).

For estimating the model parameters, a simulation-based maximum likelihood approach is used with 1,200 Halton draws (Halton, 1960), which has been found to provide stable parameters. To ensure the stability of parameters, the final models were run multiple times with the same sequence of draws, as suggested by Venkataraman et al. (2011; 2013a; 2013b). However, 1,200 Halton draws were adequate enough to provide stable and accurate parameters in this study, thus demonstrating consistency with previous studies that featured similar statistical approaches and sample sizes (Anastasopoulos et al., 2016, Fountas et al., 2021; Ahmed et al., 2021).

For the various count data models developed in this study, the dependent variable was defined as the sum of crashes of all injury severities occurred throughout the project implementation period. Aggregating the number of crashes across the contract period allows independence of the identified effects from site-specific parameters that could have changed over the years. It also allows for the identification and comparison of the impact of different contract types on safety performance, with such a comparison not being affected by factors that vary from one year to another throughout the contractual period. In this context, attributes that define the size of the contract, such as duration and roadway lane-miles covered by the contract, were considered as potential independent variables in the statistical analysis.

MODEL ESTIMATION RESULTS

Tables 3 through 6 present the results of the count data models that were developed for each of the PPP contract types to analyze the impact of contracts' characteristics (i.e., cost, duration, size in lane-miles, work activities) and site conditions (i.e., pavement condition, weather condition, road geometry, and traffic) on the safety performance of roadways throughout the project implementation period. Apart from the parameter estimates, Tables 3 and 5 provide the marginal effects of the explanatory variables included in the estimated models. The marginal effect of an independent variable shows the effect of a one-unit change in the value of this variable on the number of crashes (Washington et al., 2020).[3]

[3] Given the diverse nature of the independent variables included in the models, the marginal effects should be interpreted with caution. In the case of binary independent variables, the marginal effect reflects the change in the dependent variable due to a shift from "0" to "1" in the independent variable. In the case of continuous independent variables, the marginal effect indicates the change in the dependent variable due to a one-unit increase in the value of the independent variable (e.g., an increase in the median width from 20 to 21 feet). Further details can be also found at Washington et al. (2020).

In total, six models were estimated. A model was developed using data from all contracts of the dataset (the all projects model), while separate models were estimated for the following PPP contracts: A+B and I/D, DBOM, PBC, Traditional, and Warranties. The estimation of separate models can provide deeper insights with regard to the determinants of safety performance for each individual contract type, as well as with regard to possible variations in the effect of such determinants across different contract types. The development of PPP-specific models is also consistent with the current state-of-the-art in accident research (Behnood and Mannering, 2017a; Mannering, 2018; Fountas et al., 2020), as it is rapidly acknowledged that such approach can offer more granular results as compared to the simple inclusion of a relevant variable in a single, comprehensive model.

For all the model specifications, both Poisson and negative binomial modeling approaches were investigated. The Poisson model was found to be appropriate for the A+B and I/D, DBOM and Warranty models, whereas the negative binomial approach was found to be appropriate for the all projects model, and for the PBC and Traditional models. The results of the estimated models helped identify factors that may be associated with the number of crashes throughout the project period in a positive or negative way. Due to the number of estimated models, the findings of the statistical analysis are comprehensively discussed by mainly focusing on the effect of different categories of contract and site characteristics on crash frequencies.

Table 3. Correlated random parameters Poisson model estimation results for crash frequency for different contract types (continued)

	A+B and I/D		DBOM		Warranty	
Variable	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**
Constant	3.769 (16.710)		1.417 (7.790)		4.162 (10.450)	
Contract Cost, Duration and Lane-miles						
Inverse of the size (lane-miles) of the contract	-11.511 (-8.780)	-17.074 (-2.32)	-3.404 (-30.760)	-0.725 (-19.280)	-5.540 (-8.950)	-8.369 (-6.100)
Square root of cost of the contract over 1,000			-0.0004 (-8.85)	-0.251 (-10.390)		
10,000 times inverse of cost of the contract			-33.583 (-3.960)	-0.038 (-4.030)		
Inverse of the duration of a contract					-0.674 (-5.350)	-0.312 (-4.450)
Square of the extension to contract (in years)					0.014 (2.050)	0.071 (1.99)
Pavement Characteristics						
10000th of square of standard deviation of IRI (inches per mile) [A+B]	5.461 (11.510)	0.478 (2.30)	1.480 (33.930)	0.302 (17.010)		
Drainage indicator (1 if poorly drained, 0 otherwise)			4.784 (22.190)	0.849 (3.290)		
Standard Deviation of parameter density function			*4.551 (13.821)*			
Average IRI (1 if between 100 and 170 inches per mile, 0 otherwise)[a]			-0.103 (-3.870)	-0.046 (-3.910)		

[a] Between the mean minus 0.25 standard deviations, and the mean plus 1.75 standard deviations.

Table 3. Correlated random parameters Poisson model estimation results for crash frequency for different contract types (continued)

	A+B and I/D		DBOM		Warranty	
Variable	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**
Standard deviation of PCR (1 if greater than 12.5, 0 otherwise)[b]			-1.763 (-15.490)	-0.125 (-12.330)		
Average PCR (1 if between 85 and 92, 0 otherwise)[c]					-1.116 (-6.360)	-0.403 (-4.440)
Standard deviation of rutting depth (1 if between 0.05 and 0.12 inches, 0 otherwise)[d]					-0.435 (-4.560)	-0.157 (-4.040)
Average rutting depth (1 if greater than 0.25, 0 otherwise)[e]					1.107 (8.770)	0.217 (5.740)
Standard Deviation of parameter density function					*0.185 (4.800)*	
Average IRI (1 if between 64 and 100 inches per mile, 0 otherwise)[f]					-1.341 (-4.290)	-0.539 (-9.300)
Standard Deviation of parameter density function					*0.957 (48.226)*	
Road Geometry and Traffic Characteristics						
Average AADT indicator (1 if between 3,900 and 52,800 vehicles per day, 0 otherwise)[g]	0.204 (1.920)	0.111 (1.41)	-6.815 (-29.280)	-4.396 (-15.870)		
Standard Deviation of parameter density function			*0.985 (26.110)*			

[b] Greater than the mean plus 1.5 standard deviations.
[c] Greater than the mean plus one standard deviation.
[d] Between the mean and the mean plus one standard deviation.
[e] Greater than the mean plus 2 standard deviations.
[f] Between the mean minus 1.25 standard deviations, and the mean minus 0.25 standard deviations.
[g] Between the mean minus 2/3 standard deviations, and the mean plus 2 standard deviations.

Table 3. Correlated random parameters Poisson model estimation results for crash frequency for different contract types (continued)

	A+B and I/D		DBOM		Warranty	
Variable	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**
Square of combination trucks percentage	-210.248 (-19.300)	-9.183 (-2.360)				
Standard Deviation of parameter density function	*65.226 (18.940)*					
Junction/Number of lanes indicator (1 if multiple lane roadway without any junction, 0 otherwise)			1.098 (6.640)	1.085 (6.240)		
Horizontal and vertical curve indicator (1 if both are present, 0 otherwise)					0.382 (2.460)	0.240 (2.35)
Inside shoulder width (in feet)	-0.452 (-10.440)	-2.880 (-2.28)				
Square of inside shoulder width	0.035 (9.420)	2.060 (2.32)				
Square root of outside shoulder width	-0.266 (-5.890)	-0.762 (-2.000)				
Contract Work Activities						
Asset type indicator (1 if management or litter Removal, 0 otherwise)	0.733 (5.900)	0.086 (2.020)				
Asset type indicator (1 if Management or illumination repair / maintenance, 0 otherwise)			1.080 (10.600)	0.064 (9.390)		
Asset type indicator (1 if guardrail repair / maintenance or illumination repair / maintenance, 0 otherwise)	-0.215 (-2.180)	-0.073 (-1.60)	-0.403 (-9.980)	-0.115 (-9.05)		
Asset type indicator (1 if Crack/Pothole Sealing/Repair, 0 otherwise)					0.332 (3.040)	0.092 (2.91)

Table 3. Correlated random parameters Poisson model estimation results for crash frequency for different contract types (continued)

	A+B and I/D		DBOM		Warranty	
Variable	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**
Weather Condition						
Square of proportion of snowy days to total days of contract			-99.062 (-21.360)	-0.321 (-15.39(		
Inverse of proportion of rainy days to total days of contract			0.264 (17.710)	1.104 (13.41)		
Log of proportion of number of rainy days to total days of contract					0.690 (2.970)	-0.977 (2.72)
Heterogeneity in means of random parameters						
Square of combination trucks indicator (in percentage) :Average IRI	1.741 (19.830)					
Average AADT indicator (1 if between 3,900 and 52,800 vehicles per day, 0 otherwise) :Average IRI			0.054 (30.660)			
Drainage indicator (1 if poorly drained, 0 otherwise) :Average IRI			-0.051 (-31.100)			
Number of observations	68		169		97	
Log likelihood at zero	-2282.118		-2034.250		-1183.754	
Log likelihood at convergence	-215.801		-799.139		-150.491	
Distributional effect of random parameters across the observations						
	A+B and I/D		DBOM		Warranty	
	Below zero	Above zero	Below zero	Above zero	Below zero	Above zero
Square of combination trucks indicator (in percentage)	99.94%	0.04%				
Average AADT indicator (1 if between 3,900 and 52,800 vehicles per day, 0 otherwise)			100%	0%		

Table 3. Correlated random parameters Poisson model estimation results for crash frequency for different contract types (continued)

	A+B and I/D		DBOM		Warranty	
Variable	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**
Drainage indicator (1 if poorly drained, 0 otherwise)			14.66%	85.34%		
Average rutting depth (1 if greater than 0.25, 0 otherwise)					100%	0%
Average IRI (1 if between 64 and 100 inches per mile, 0 otherwise)					91.94%	8.06%

A+B: Cost-plus-time contracts; I/D: Incentives/Disincentives contracts.

Table 4. Diagonal and off-diagonal elements of the Γ matrix [t-stats in brackets], and correlation coefficients (in parentheses) for the correlated random parameters included in the Poisson models

	DBOM		Warranty	
	Average AADT indicator (1 if between 3,900 and 52,800 vehicles per day, 0 otherwise)	Drainage indicator (1 if poorly drained, 0 otherwise)	Average rutting depth (1 if greater than 0.25, 0 otherwise)	Average IRI (1 if between 64 and 100 inches per mile, 0 otherwise)
Average AADT indicator (1 if between 3,900 and 52,800 vehicles per day, 0 otherwise)	0.985 [26.110] (1.00)			
Drainage indicator (1 if poorly drained, 0 otherwise)	4.541 [30.970] (0.998)	0.305 [5.570] (1.00)		
Average rutting depth (1 if greater than 0.25, 0 otherwise)			0.185[4.800] (1.00)	
Average IRI (1 if between 64 and 100 inches per mile, 0 otherwise)			0.863[-4.320] (-0.902)	0.414 [2.320] (1.00)

A+B: Cost-plus-time contracts; I/D: Incentives/Disincentives contracts; DBOM: Design-build-operate-maintain contracts and their derivatives.

Table 5. Correlated random parameters negative binomial model estimation results for crash frequency for different contract types

Variable	All Projects		PBC		Traditional	
	Parameter (*t*-stat)	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**
Constant	104.380 (26.000)		1.684 (8.650)		2.030 (9.930)	
State indicator (1 if the project was implemented in Minnesota, 0 otherwise)	-0.573 (-5.430)	-0.040 (-5.290)				
Contract Cost, Duration and Lane-miles						
Cost of the contract indicator (1 if greater than \$ 69M, 0 otherwise)[a]	-0.860 (-10.730)	-0.061 (-9.300)				
Inverse of the duration of a contract (year^{-1})	-0.720 (-13.010)	-0.328 (-10.670)			-0.424 (-4.700)	-0.365 (-3.06)
Duration of a contract indicator (1 if greater than 6 years, 0 otherwise)[b]			-3.816 (-3.880)	-0.821 (-3.24)		
Standard Deviation of parameter density function			0.953 (4.940)			
Inverse of the size (lane-miles) of the contract	-8.131 (-24.460)	-7.336 (-13.530)	-5.938 (-4.710)	-1.849 (-4.57)	-10.356 (-12.630)	-13.909 (-3.78)
Pavement Characteristics						
Average IRI (1 if greater than 170 inches per mile, 0 otherwise)[c]	-0.457 (-4.890)	-0.033 (-4.780)				
Average IRI (1 if greater than 100 inches per mile, 0 otherwise)[d]			1.695 (9.500)	0.901 (5.46)		
Average IRI (1 if between 100 and 170 inches per mile, 0 otherwise)[e]					0.791 (6.470)	0.332 (3.30)

[a] Greater than the mean plus 0.5 standard deviations.
[b] Greater than the mean plus 1 standard deviation.
[c] Greater than the mean plus 1.75 standard deviations.
[d] Greater than the mean minus 0.5 standard deviations.
[e] Between the mean plus 1.75 standard deviations, and the mean minus 1.5 standard deviations.

Table 5. Correlated random parameters negative binomial model estimation results for crash frequency for different contract types (continued)

	All Projects		PBC		Traditional	
Variable	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**
Average PCR (1 if between 80 and 90, 0 otherwise)[f]					0.806 (5.050)	0.464
Log of the average PCR	-23.061 (-26.210)	-103.296 (-13.87)				
Standard Deviation of parameter density function	0.156 (26.150)					
Average rutting depth (1 if between 0.12 and 0.25 inches, 0 otherwise)[g]	0.367 (6.110)	0.211 (5.800)				
Standard deviation of IRI (1 if between 11 and 30 inches per mile, 0 otherwise)[h]	-0.117 (-2.890)	-0.067 (-2.820)				
Drainage indicator (1 if the roadway is moderately well drained, 0 otherwise)			-0.361 (-1.900)	-0.082 (-1.83)		
Road Geometry and Traffic Characteristics						
Combination truck traffic indicator (1 if percentage of combination trucks is greater than 0.16, 0 otherwise)[i]					0.380 (3.870)	0.138 (2.83)
Number of lane indicator (1 if greater than 2 lanes, 0 otherwise)					0.303 (2.430)	0.041 (1.86)
Horizontal and vertical curve indicator (1 if both are present, 0 otherwise)	0.366 (3.350)	0.305 (3.310)				
Square of median width			0.0004 (2.780)	0.111 (2.600)		

[f] Between the mean minus 1 standard deviation, and the mean plus 1 standard deviation.
[g] Between the mean, and the Mean plus 2 standard deviations.
[h] Between the mean minus 2/3 standard deviations, and the mean plus 0.5 standard deviations.
[i] Greater than the mean.

Table 5. Correlated random parameters negative binomial model estimation results for crash frequency for different contract types (continued)

	All Projects		PBC		Traditional	
Variable	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**
Inside shoulder width indicator (1 if inside shoulder width is greater than 3.7 m, 0 otherwise)[j]					-2.207 (-7.850)	-1.572 (-2.82)
Standard Deviation of parameter density function					0.467 (5.480)	
Outside shoulder width indicator (1 if outside shoulder width is greater than 4.2 m, 0 otherwise)[k]			-0.467 (-2.950)	-0.402 (-0.900)	-1.588 (-5.260)	-1.387 (-2.71)
Standard Deviation of parameter density function			0.257 (4.767)		0.799 (16.419)	
Contract Work Activities						
Number of assets indicator (1 if greater than 2, 0 otherwise)	-0.278 (-4.830)	-0.065 (-4.700)				
Asset type indicator (1 if Crack/Pothole Sealing/Repair, 0 otherwise)	0.539 (8.200)	0.094 (7.140)				
Asset type indicator (1 if management or litter Removal, 0 otherwise)	-0.262 (-3.870)	-0.026 (-3.730)	-0.588 (-2.310)	-0.074 (-2.26)		
Weather Condition						
Proportion of snow days indicator (1 if proportion of snow days over total days is between 0.04 and 0.15, 0 otherwise)[l]	-0.812 (-5.740)	-0.351 (-1.030)				
Standard Deviation of parameter density function	0.420 (25.952)					
Heterogeneity in means of random parameters						

[j] Greater than the mean minus 2/3 standard deviations.
[k] Greater than the mean minus 1 standard deviation.
[l] Between the mean, and the mean plus 2 standard deviations.

Table 5. Correlated random parameters negative binomial model estimation results for crash frequency for different contract types (continued)

	All Projects		PBC		Traditional	
Variable	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**
Log of the average PCR: Average IRI	0.002 (8.200)					
Proportion of snow days indicator (1 if proportion of snow days over total days is between 0.04 and 0.15, 0 otherwise): Average IRI	0.005 (5.770)					
Duration of a contract indicator (1 if greater than 6 years, 0 otherwise): Average IRI			0.020 (2.700)			
Outside shoulder width indicator (1 if inside shoulder width is greater than 4.2 m, 0 otherwise):Average IRI			0.012 (4.070)			
Inside shoulder width indicator (1 if inside shoulder width is greater than 3.7 m, 0 otherwise):Average IRI					0.017 (8.610)	
Outside shoulder width indicator (1 if inside shoulder width is greater than 4.2 m, 0 otherwise):Average IRI					0.012 (6.010)	
Dispersion parameter (α)	2.565 (14.000)		1.905 (4.450)		2.565 (14.000)	
Number of observations	645		79		198	
Log likelihood at zero	-8048.196		-1016.350		-2623.430	
Log likelihood at convergence	-1654.782		-231.862		-507.542	
Distributional effect of random parameters across the observations						
	All Projects		PBC		Traditional	
	Below zero	Above zero	Below zero	Above zero	Below zero	Above zero
Log of the average PCR	100%	0%				

Table 5. Correlated random parameters negative binomial model estimation results for crash frequency for different contract types (continued)

	All Projects		PBC		Traditional	
Variable	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**	**Parameter (*t*-stat)**	**Marginal Effect**
Proportion of snow days indicator (1 if proportion of snow days over total days is between 0.04 and 0.15, 0 otherwise)	97.34%	2.66%				
Duration of a contract indicator (1 if greater than 6 years, 0 otherwise)			100%	0%		
Outside shoulder width indicator (1 if inside shoulder width is greater than 4.2 m, 0 otherwise)			96.54%	3.46%		
Inside shoulder width indicator (1 if inside shoulder width is greater than 3.7 m, 0 otherwise)					100%	0%
Outside shoulder width indicator (1 if inside shoulder width is greater than 4.2 m, 0 otherwise)					97.66%	2.34%

PBC: Performance-based contracts.

Table 6. Diagonal and off-diagonal elements of the Γ matrix [t-stats in brackets], and correlation coefficients (in parentheses) for the correlated random parameters included in the negative binomial models

	All Projects		PBC		Traditional	
	Log of the average PCR	Proportion of snow days indicator (1 if proportion of snow days is between 0.04 and 0.15, 0 otherwise)	Duration of a contract indicator (1 if greater than 6 years, 0 otherwise)	Outside shoulder width indicator(1 if inside shoulder width is greater than 4.2 m, 0 otherwise)	Inside shoulder width indicator(1 if inside shoulder width is greater than 3.7 m, 0 otherwise)	Outside shoulder width indicator(1 if inside shoulder width is greater than 4.2 m, 0 otherwise)
Log of the average PCR	0.156 [26.150](1.00)					
Proportion of snow days indicator (1 if proportion of snow days over total days is between 0.04 and 0.15, 0 otherwise)	-0.076[-1.770](-0.181)	0.413 [12.120] (1.00)				
Duration of a contract indicator (1 if greater than 6 years, 0 otherwise)			0.953 [4.940] (1.00)			
Outside shoulder width indicator (1 if inside shoulder width is greater than 4.2 m, 0 otherwise)			0.424 [4.720] (0.672)	0.467 [2.950] (1.00)		
Inside shoulder width indicator (1 if inside shoulder width is greater than 3.7 m, 0 otherwise)					0.467 [5.480] (1.00)	
Outside shoulder width indicator (1 if inside shoulder width is greater than 4.2 m, 0 otherwise)					0.660 [7.800] (0.826)	0.450 [8.080] (1.00)

PBC: Performance-based contracts.

Contract Duration

Contract duration was found to affect safety performance in the All projects, PBC, Traditional, and Warranty models. Specifically, the inverse of contract duration was observed to have an inverse effect on the number of crashes in the all projects, Warranty, and Traditional models. In other words, contracts of longer duration were found to have higher number of crashes. In the PBC model, longer contracts (with duration greater than 6 years) were found to result in lower number of crashes in almost all contracts. However, the specific variable resulted in a random parameter revealing the mixed effect of longer durations, which varies across the contracts. Given that in the all projects model (which includes PBC contracts), as contract duration increases the number of crashes increases (Table 5), and given the fact that average duration of contracts varied between 3 and 6 years (Table 2), we concluded that PBC contracts that are less than 6 years in duration may still be experiencing an increase in number of crashes as contract duration increases from 0 to 6 years.

Another duration-related factor that was observed to be associated with safety was the extension awarded to a contract (in years), beyond the original contract duration. The model for warranty contracts (Table 3) shows that longer extensions of contracts are associated with a higher number of crashes (at a 95% confidence level). Extensions awarded to contracts ranged between 0 to 11.66 years with a mean equal to 1.71 years and a standard deviation equal to 2.344 years. Taking into account the high confidence level and the likely impact of contract duration on safety, it can be concluded that contract extensions are likely to result in more crashes for the Warranty contracts, whereas all the other contract types are not likely to show a similar trend in case of contract extension.

Contract Size (Lane-Miles)

PBC contracts were typically the largest (in terms of lane-miles) amongst all the contract types. A typical PBC contract spanned approximately 260 lane-miles, which was significantly higher than a typical traditional (87 lane-miles), incentive/disincentive (57 lane-miles), cost-plus-time (33 lane-miles), A+B (34 lane-miles), DBOM (30 lane-miles), and warranty (24 lane-miles) contract. Models for each of the contract types suggested that smaller roadway projects are more likely to result in fewer number of crashes. In fact, in the A+B and I/D model, a variant of the contract size (inverse of the contract size in lane-miles) was found to have the most pronounced impact among all independent variables, as it resulted in the largest marginal effect (-17.074, as shown in Table 3).

Contract Cost

The cost of a contract was found to have a statistically significant impact on the number of crashes. For any PPP contact implemented in the US (all projects model) with contract cost greater than 69 million dollars (i.e., the mean of contract costs plus half a standard deviation of the contract cost), the number of crashes was found to decrease. This impact was observed for any contract, irrespective of its type and did not change with the cost once the cost was greater than 69 million dollars. When separate models were developed for each of the contract types, the impact of contract cost on safety was found statistically significant for the DBOM contract only. For this type of contract, a higher contract cost was found to increase the number of crashes. High cost is typically associated with high-profile contracts. These contracts either involve a significant amount of work, or work that is more complex. As such, they are expected to include more safety measures. The DBOM contracts reflect a different relationship between cost and number of crashes. This can be attributed to the general focus of the DBOM contracts, which is designing and constructing the facility as quickly as possible to make it available for operation, so the public can reap the benefits of the facility. Furthermore, for DBOM contracts, a large portion of the cost is associated with post-completion operation and maintenance of the roadway facility. The cost of DBOM contracts includes more components/line-items compared to other contract types, especially those associated with annual operations and maintenance after the facility is built (Kumar et al., 2018). Hence, the costs of DBOM and other contracts cannot be considered the same, and therefore, their relationship with the number of crashes cannot be expected to be the same. In DBOM contracts, the work-intensive operation and maintenance components combined with the need to put the facility in operation quickly may increase the exposure of roadway users to traffic accidents. This may be the cause for the occurrence of relatively more crashes in DBOM contracts with large cost.

Contract Work Activities

The activities that were found likely to have an impact on safety can be divided into two broad categories. The first category comprises the activities that are associated with repairs to the pavement surface, such as pothole repairs, crack sealing, and so on. The second category includes the activities associated with repair and maintenance of traffic devices of the roadways, such as guardrail, illumination sources, and so on.

Focusing on the first category, pavement repair and maintenance activities, such as crack or pothole sealing or repair were found to be statistically significant in determining the number of crashes (compared to other activities), in the all projects, PBC, and Warranty models. Crack or pothole repair was observed to result in an increase of crashes in the Warranty (by 0.092, as shown in Table 3) and all projects models (by 0.094, as shown in Table 5). When pavement surface repair activities are performed in two or more lanes, often one lane is closed to traffic while the other lane is being repaired. This involves subsequent lane changes, traffic in one lane, and a driving environment where the lane-width and the shoulder or median presence is often compromised. It should be noted that previous studies that reported positive impacts of pavement condition improvements on safety (Li and Huang, 2014; Sarwar, 2016), typically consider the safety improvement to be effective upon the completion of the pavement repairs as opposed to during the project implementation (as with the crashes considered in this study).

For the traffic asset-related repair activities, the DBOM, and A+B and I/D contracts were overall found more likely to observe more crashes compared to the cases when these types of contracts are used to deliver other activities. Litter removal and maintenance activities were observed to decrease the number of crashes in the all projects model (by 0.026, as shown in Table 5) and PBC model (by 0.074, as shown in Table 5), but they were associated with an increase in number of crashes in the A+B and I/D model (by 0.086. as shown in Table 3). Guardrail repair/maintenance activities, if contracted through DBOM, were also found to decrease the number of crashes compared to other activities. The litter removal and guardrail repair activities are typically performed on the shoulder, on the median, or even further away from the travel lanes. Hence, they are less likely to involve safety issues compared to other maintenance activities, such as pavement repair or illumination repair. In this context, the correlation of these activities with lower number of crashes is intuitive.

The effect of the number of activities that are typically part of a contract was also analyzed. It was found that for contracts with more than two assets, the number of crashes decreases in the all projects model. This is again intuitive considering that more assets being repaired within the right-of-way typically involve more work zone demarcations and higher visibility of work activities.

Weather Conditions

The impact of weather was analyzed by tracking the number of snowy and rainy days during the project implementation period. It was found that as the proportion of snowy days to total days of contract increases, the likely number of crashes reduces in the all projects and DBOM models. The presence of rainy days during the project implementation period was observed to increase the number of crashes in the DBOM model, but with a declining trend for larger proportions of rainy days. However, the presence of rainy days was found to decrease the number of crashes for Warranty contracts. Even though the specific coefficient is positive (see Table 3), the specific variable is formulated as a logarithm of the proportion of rainy days over the total days of the contract duration. Given that the proportion of rainy days can take values between zero and one, the logarithm can take only negative values, and subsequently the overall effect of this variable on the number of crashes is negative.

The impact of snowy days on the number of crashes is intuitive, as the response of the maintenance services is much more effective and rapid, as compared to rainy days. Also, when there is heavy snow to the extent that snow cannot be plowed adequately and winter emergency has been declared, fewer people are anticipated to drive on these roads. On the other hand, rain neither deters people from driving, nor is it being tracked and responded to proactively through snowplows and maintenance decision support systems (MDSS), which are leveraged in real-time. In general, rain has been found to be influential in increasing crash frequencies, as identified in the DBOM model. For the Warranty contracts, the accountability of the contractor for possible deficiencies of the roadway project may result in adequate safety provisions, which in conjunction with anticipated drivers' alertness under inclement weather conditions (as, for example, in rainy days) lead to the decrease of the number of crashes.

Pavement Characteristics

Three popular pavement condition indicators were used in the analysis. The international roughness index, measured in inches/mile, the pavement condition rating measured on a scale of 0 to 100, with 100 signifying perfect pavement condition, and the rutting depth, measured in inches (Warith et al., 2014, 2015; Sarwar and Anastasopoulos, 2016). Good pavement condition (low IRI, high PCR, and low rutting depth values) generally decreases crash frequencies (Anastasopoulos et al., 2012b, 2012c; Sarwar, 2016). The findings of the current study are in line with the literature. However, different PPP contracts are associated with diverse effects of the pavement conditions on the number of crashes. For example, lower IRI values (between 64 and 100 inches/mile) were found to have mixed effect on the Warranty model (with a crash reduction being observed in approximately 92% of the contracts), as the specific variable was found to vary across the contracts as a random parameter. Average PCR values (between 85 and 92) were observed to reduce the number of crashes for the Warranty contract type (by 0.403. as shown in Table 3). PCR values were also found to be non-linearly related to reduction in crashes for all PPP contract types, as shown in the all projects model. Average rutting depth (between 0.12 and 0.25 inches) was found to increase the number of crashes for all PPP contract types. Inadequate drainage was also found to increase the number of crashes in the DBOM contract type. This is also expected, as poor drainage conditions can entail the occurrence of aquaplaning incidents resulting in loss of tire traction, and subsequently in loss of vehicle control. Note that the ranges used for the IRI values, the average PCR values, and the average rutting depth, indicate the values of these pavement characteristics that are within one standard deviation of the mean values of all observations considered.

Roadway Geometry and Traffic Characteristics

The presence of horizontal and vertical curves was found to increase the number of crashes in the all projects model (by 0.305, as shown in Table 5), as well as in the model for the Warranty contract type (by 0.240, as shown in Table 3). This finding is intuitive and in line with previous research studies on crash frequencies (Shankar et al., 1995; Venkataraman et al., 2013). When 2 or more lanes are present on a roadway, the number of crashes in the work zone was found to increase when consideration is given to the Traditional model. The number of crashes was also found to increase for multi-lane roadways without any junction, in cases when DBOM contracts were used to deliver the construction or maintenance work on these sites. This is again likely due to the priority of DBOM contracts to open the roadway for traffic and start the operation and maintenance phase as quickly as possible, as compared to other contract types (see also the discussion provided in the "Contract Cost" section).

Another geometric characteristic of roadways that was found to be a statistically significant determinant of safety performance is the median width. Specifically, the variable representing the square of the median width was identified to non-linearly increase the number of crashes for the PBC contract type. Shoulder width was another characteristic that was observed to affect the number of crashes in A+B and I/D, PBC, and Traditional models. While the width of the inside shoulder was found to be non-linearly associated with the number of crashes, the width of the outside shoulder was observed to be associated with a reduction in the number of crashes during the implementation period of A+B and I/D contracts. Notably, the inside shoulder width (when greater than 3.7 feet) had a varying effect on the number of accidents in the Traditional model, as the specific variable resulted in a random parameter. Outside shoulder width (when greater than 4.2 feet) had also a mixed effect on the number of crashes in both PBC and Traditional models. In the former model, the specific variable is found to decrease the number of crashes for almost 96.5% of contracts; whereas in the latter model, the same variable is found to decrease the number of crashes for almost 97.7% of contracts.

Among the traffic characteristics, low to medium AADT (from 3,900 to 52,800 vehicles per day – these AADT values include the interval of values that are one standard deviation of the mean of the observations) is found to reduce crashes for DBOM contracts in over 99% of the cases. The same variable was found to increase the crashes for A+B and I/D, and Traditional contracts. Low traffic volume may offer drivers a feeling of safety, for which they can compensate by driving faster and possibly more aggressively, making them more crash prone. This is a direct implication of risk-compensating behavior, which may be evident when the drivers feel confident for a risk-free driving task (Winston et al., 2006). On the other hand, high AADT may inevitably result in driving conflicts and consequently increase crash frequency, and particularly the frequency of low-severity crashes, as also indicated by Fountas and Anastasopoulos (2018).

For the Traditional contract type, high traffic of combination trucks (more than 16% of the total traffic volume) was found to be associated with a greater number of crashes. For about 97% of A+B and I/D contracts, the percentage of combination trucks was associated with a reduction in the number of crashes. This finding is in line with previous research (Anastasopoulos et al. 2012b, 2012c) and it may be capturing driver-specific behavioral patterns related to more cautious driving typically evidenced throughout the period when the contractual work takes place.

Discussion on Heterogeneity in Means of Random Parameters

In all models, the average IRI was observed to affect the means of the random parameters, thus capturing heterogeneity-in-the-mean effects. The variable had a positive effect on the mean of the random parameters related to the natural logarithm of the average PCR and to the proportion of snow days in the all projects model. In both cases, a greater value of the mean entails a subsequent increase of the portion of contracts where the random parameter favors an increase of crashes. Similar effect can be observed in the A+B and I/D model, as well as in the DBOM model. For the A+B and I/D model, Table 3 shows that higher average IRI increases the means of the random parameter related to the square of combination trucks proportion. An increase in the mean signifies a successive increase of the proportion of contracts where the specific random parameter leads to a higher number of crashes. In contrast, for DBOM contracts, Table 5 shows that the average IRI variable is found to decrease the mean of the random parameter related to the drainage indicator. In other words, higher IRI values decrease the portion of contracts where poorly drained roadways are positively correlated with a higher number of crashes. This is an interesting finding, since it may be capturing the behavioral adjustments of drivers when they need to drive in poorly drained and rough-surfaced roadways. Given that the operation of the roadway is a part of the contractual object in DBOM contracts, additional safety countermeasures may be also implemented in such problematic cases of roadways resulting subsequently in lower crash risk.

Overall, the identification of the underlying effect of the average IRI on the distributional effect of the random parameters further underscores the capability of the heterogeneity-in-means approach to unravel disparate layers of unobserved heterogeneity, which could not be addressed through the conventional random parameters approach.

Interpretation of Correlation of Random Parameters

Tables 4 and 6 provide the Cholesky matrices corresponding to the random parameters identified in the estimated models. In line with previous studies (Fountas et al., 2018a; Fountas et al., 2018b; Fountas et al., 2019; Eker et al., 2019), negative correlation of the random parameters suggests that the joint effect of the unobserved factors captured by the random parameters on the number of crashes is mixed; while a positive correlation indicates a homogeneous effect of the unobserved factors on the number of crashes. It should be noted that the correlation of random parameters reflects the correlation of the latent effects captured by the random parameters and is different from the coefficients of linear correlation among the corresponding explanatory variables. For example, the positive correlation (0.998) between the random parameters related to the average AADT indicator and the drainage condition of the pavements in the DBOM model implies that both sets of unobserved characteristics captured by these two variables have either positive or negative effect on the number of crashes. In contrast, the negative correlation (-0.902) between the random parameters produced by the average IRI and the rutting depth indicators in the Warranty model indicates the counter-balancing effect of the unobserved interactions on the number of crashes. For example, the unobserved characteristics associated with the IRI indicator may have a positive effect on the number of crashes, whereas the similar effect arising from the rutting depth indicator may be negative, and vice-versa.

SUMMARY AND CONCLUSION

This study provides an empirical analysis of the safety performance (in terms of crash frequency) of various public-private partnerships (PPP) contract types, which have been used for the delivery of roadway construction, maintenance or rehabilitation projects in the USA. For this purpose, various contract types were considered: performance-based contracting (PBC), incentives/disincentives (I/D), lane rentals, warranties, design-build and its derivatives (DBOM), cost-plus-time (A+B), and traditional contracting.

Compared to previous studies (Macario et al., 2015; Nahidi et al., 2017, Wang and Zhao, 2018) that have examined the degree of effectiveness of PPP contract types in terms of project discrepancies, such as change orders, time delays, and cost overruns (Anastasopoulos et al., 2010b; Bhargava et al., 2010), the current study focuses on the safety perspective throughout the project implementation period, and identifies several factors that are associated with the number of crashes for each of the PPP contract types. To that end, correlated random parameter Poisson and negative binomial models with heterogeneity in the means were estimated. The employed methodological approaches allowed capturing disparate layers of unobserved heterogeneity using an integrated estimation framework. The results of the analysis show that the number of crashes for each of the contract types can be explained using a unique set of explanatory variables, which may vary from type to type. The determinants of safety performance of highway projects were found to consist of contract characteristics (cost, size, duration), pavement condition (IRI, PCR, rutting depth, drainage condition), road geometry and traffic characteristics (AADT, truck traffic, shoulder characteristics, median characteristics, roadway curvature), and contracted asset work activities.

Overall, contracts of shorter durations and smaller sizes were found to be safer across different contract types. Roadway geometry (such as presence of curves) and number of assets being serviced as part of the contract were found to influence the number of crashes during the project period. Presence of shoulders (inside and outside) were found to reduce the number of crashes for A+B and I/D, PBC, and traditional contracts. Contracts that were contracted for more than two assets were found to have a lower number of crashes in the all projects model. A+B and

I/D contracts were found to be safer in cases with greater percentage of trucks. The presence of days with inclement weather (such as snow) during the DBOM contract period was also found to reduce the number of crashes. On the opposite end, Traditional and DBOM contracts for multi-lane highways were found more likely to result in more crashes. In addition, for almost all contract types, poor pavement performance (as indicated by the IRI, the PCR, and the rutting depth) was associated with higher number of crashes, but the impact of the pavement conditions was found to vary across the contract types. The varying impact of the pavement performance warrants further investigation in the future, especially through more granular approaches that account for the full variation of the pavement performance metrics across the entire project duration.

Despite the use of an advanced econometric framework that allowed the detection of underlying relationships between crash frequency and contract characteristics, the identification of the explicit sources of unobserved heterogeneity was not a straightforward task. In this context, future research can focus on the impact of specific components of unobserved heterogeneity on the safety performance of highway projects, such as temporal or spatial variations (Mannering et al., 2016; Mannering, 2018). Therefore, extension of this work might include the inclusion of contract location information, which could enable the investigation of observable spatial patterns of PPP contract characteristics and their impact on crash frequency, using spatial modeling techniques, such as the Geographically Weighted Poisson Regression (GPWR). In addition, randomized control experimental approaches can be also employed in future studies to tackle potential self-selection bias that may be present in the sample of projects drawn by each PPP type. Acknowledging that the outcomes of the specific study may capture some temporal instability effects, the identification of temporal variations in the effect of safety determinants could further help public agencies select the most effective PPP type in terms of safety performance throughout the contract period.

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HIGHLIGHTS

- The safety performance of Public-Private Partnerships (PPP) in roadway projects is examined.
- Crash frequencies are modeled with correlated random parameter count data approaches.
- Heterogeneity in the means of random parameters is also considered.
- Factors affecting crash frequencies are found to vary across PPP contract types.
- Higher cost, shorter duration, and smaller size of the contract are found to reduce crashes.