Title

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Property Damage Crash Equivalency Factors for Solving the Crash Frequency-Severity Dilemma: Case Study on South Korean Rural Roads

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Abstract

Safety interventions (e.g. median barriers, photo enforcement) and road features (e.g. median type and width) can influence crash severities, crash frequencies, or both. Both dimensions—crash frequency and crash severity—are needed to obtain a full accounting of road safety. Extensive literature and common sense both dictate that all crashes are not 'created' equal—with fatalities costing society more than 1000 times the cost of property damage only crashes. Despite this glowing disparity, the profession has not unanimously embraced or successfully defended a non-arbitrary severity weighting approach for analyzing safety data and conducting safety analyses.

This paper argues that both the crash frequency and severity dimensions are made available by intelligently and reliably weighting crash frequencies and converting all crashes to property damage only crash equivalents (PDOEs) using comprehensive societal unit crash injury costs. This approach is analogous to calculating axle load equivalents when predicting pavement damage—for instance a 40,000 lb truck causes 4025 times more stress than does a 4000 lb car and so simply counting axles is not sufficient. Calculating PDOEs using unit crash costs is the most defensible and non-arbitrary weighting scheme, allows for the simple incorporation of severity and frequency, and leads to crash models that are sensitive to factors that affect crash severity. Moreover, we show that using PDOEs diminishes the errors introduced by under-reporting of less severe crashes—an added benefit of the PDO equivalent analysis approach. The method is illustrated using rural road segment data from South Korea (which in practice should apply Korean crash cost data). Finally, the results and remaining issues with PDOEs and their adoption in safety analysis are discussed.

Background

Causal mechanisms that influence crash frequency and crash severity are different but overlapping. Fundamental knowledge and empirical evidence dictate that crash countermeasures or interventions can influence crash severity, crash frequency or both to varying degrees. Often there are trade-offs between severity and frequency as a result of safety investments. Thus both the crash frequency and severity dimensions are needed to fully assess the safety impacts of interventions. While there is a long list of examples to illustrate this two-dimensionality of safety interventions, a couple of idealized hypothetical examples are considered here for illustrative purposes.

Consider the widening of a paved shoulder. The primary motivation for widening a paved shoulder is to provide systematically a larger margin of error and recovery distance should a driver wander out of the travel lane—it provides a greater ability to recover safely and without incident should a driver depart the travel lane. There are secondary motivations ignored here for illustrative purposes. If a vehicle should exit the paved shoulder the chance for a safe recovery is severely diminished, and crash severity depends on the roadside environment and impact speed. The severity of crashes that exit the road assuming the roadside has remained unchanged and exit speeds are constant would remain unchanged due to the widening—crashes involving vehicles exiting high speed roads would be more severe than those exiting lower speed roads. However, if the intervention works as intended, fewer drivers will leave the roadway because they will recover from their lane departure more easily. As a result this countermeasure is expected to reduce the frequency of run off road crashes, as described in Souleyrette et al. (*1*) and found by Turner et al. (*2*), Rogness et al. (*3*), Crane et al. (*4*), and Zegeer et al. (*5*). Since run-off road crashes tend to be severe, reducing their occurrence will also reduce the overall severity distribution of crashes on these same roads. Thus, to understand the safety performance of paved shoulders one must examine both crash frequency and severity.

Now consider cable median barriers, which are installed within the medians of high speed mostly rural roads with intent to eliminate or significantly reduce median cross-over crashes that often result in head-on, severe collisions. This device is predominately installed to mitigate a crash severity problem, and is unlikely to have a significant effect on crash frequencies, as vehicles have already departed the travel lane when they encounter this countermeasure (*6*, *7*). It is very difficult (though not impossible) to imagine a situation where the cable barrier systematically impacts the frequency of crashes (e.g. there is a new obstacle to hit). Thus, the effects of this countermeasure will be best measured through examination of the effect of the barriers on crash severity, while a frequency based analysis will be insufficient.

There are numerous additional examples with ample empirical support that highlights the importance of considering both crash frequency and severity and their tradeoffs. Despite this fundamental two-dimensional nature of system safety, the safety profession has focused primarily on modeling crash frequencies and refining the statistical methods for doing so. A fundamental thrust of this paper rests on the assertion that ignoring either the frequency or severity aspect of crash occurrence results in an incomplete analysis of road safety (or risk), and ignores the fundamental mechanisms by which safety countermeasures actually function to improve road safety.

Numerous recent studies have explored advanced approaches for modeling crash frequencies, all of which were focused on the modeling of raw crash counts without regard to crash severities. Lord (*8*) examined the use of Poisson-Gamma models when sample sizes or sample means are low using fatal and non-fatal injury crash counts from 59 unsignalized intersections from 1990 to 1995. Anastasopoulos et al. (*9*) examined crash rates (dividing total crash counts by traffic volumes) of police reported crashes occurring on 337 roadway segments during a 5 year period. Li et al. (*10*) examined the viability of support vector machine models for predicting motor vehicle crashes using roadway segment data at 88 frontage road roads in Texas using a total of 122 crashes over a 5-year period. Li et al. (*11*) explored the nature of the modeled relationships with crashes, including Bayes' and Empirical Bayes' approaches, using the count of crashes per month at roadway segments during 1982 to 2004. Brijs et al. (*12*) examined the effects of weather on daily crash counts on major roads in three cities in the Netherlands. Is it possible that the examination of crash counts examined in these studies could be enhanced by the inclusion of crash severity? As described previously, road safety is two dimensional—and thus it is likely that additional insights could be obtained by considering both frequency and severity dimensions.

In practice some also include severity weights but the selection of weights are seldom justified and seem to be arbitrarily determined. For example, in the FHWAs Five Percent Report (*14*), Exhibit 1, presents a severity weighting scheme that applies 5 to fatalities, 4 to incapacitating injuries, 3 to non-incapacitating injuries, 2 to possible injuries, and 1 to PDOs. In failing to provide a justification for the weights, the report reads: "Each of the severity classifications are assigned weighting factors as follow: (Note it is anticipated that greater weights will be given to more severe crashes in future years)." While a greater emphasis on severe crashes is provided here; the weighting appears to be entirely arbitrary, or subjective. A similar sampling of arbitrary weights can be found in methods surveyed by Tarko et al. in a 2000 report (*15*). A weighting scheme based on crash data from Denmark (*16*) developed a weighting scheme based on socio-economic costs and factors such as accident type, accident location, and number of vehicles involved. Although the source document is written in Danish, this weighting scheme is likely to be a similar approach to the one proposed in this paper.

Perhaps the most comprehensive and current effort to explicitly model both frequency and severity is described in Ma et al. (*17*). In their quite complex (statistically speaking) approach, a multivariate Poisson-lognormal specification is used to model the simultaneous nature of severity and frequency while also accounting for correlation among severity counts and over-dispersion. While this approach is extremely capable of modeling both frequency and severity, it is cumbersome for practitioners and safety managers to apply due to its significant complexity and time commitment to estimate.

Finally, there is a large body of research that has explored the economic impacts associated with various crash severities. In these studies crash costs are typically applied post-modeling, where modeling is done by severity or crash type (e.g. rear-end, sideswipe, etc.) and is coupled with unit crash costs. For example, Shin et al. (*13*) tracked crash severity and frequency differences in a before-after evaluation of freeway photo enforcement in Scottsdale, Arizona. The study estimated the effects of photo enforcement on both crash frequencies and severities separately. This considerable research is not reviewed here, as its focus is on explicit consideration of crash costs after crash frequencies (by type or severity) have been modeled.

The objective of this research is to devise a non-arbitrary weighting scheme for use in modeling that facilitates the analysis of crash severity and frequency simultaneously while implicitly reflecting crash costs. Its origin and development is defended, and how such weights will impact the analysis and conclusions drawn from crash data are empirically demonstrated. Of course the strengths and limitations of the approach are documented.

PDOEs for Capturing Both Crash Severity and Frequency

The pavements profession explicitly recognizes that the wheel load a vehicle axle imparts on pavements is a non-linear function of the weight or load over the axle. As a result, the pavements profession developed axle load equivalency factors to aid in the assessment of pavement damage (*18*). The pavement stresses and strains in fact are so non-linear that for a flexible pavement (with terminal serviceability index , TSI = 2.5 and Structural Number, SN = 3) a 20,000 lb single axle load does 1620 times the damage to pavement as does a 2000 lb single axle load. Moreover, 80,000 and 40,000 lb axle loads do 392,000 and 20,600 times the damage to flexible pavements as does a 2000 single axle load respectively (*19*). The main point is this: simply counting traffic over a section of road is insufficient for predicting or explaining pavement damage (and their associated costs), since all axle loads are not created equal.

A corollary exists in roadway safety, one might ask: What is the prime unit of interest with respect to the impact of an intervention or countermeasure on safety? Clearly, there are parallels between pavement damage and motor vehicle crashes. Not all crashes are created equal, since fatal and severe injury crashes are far more costly to society than are property damage only (PDO) crashes. As seen in Table 1, the average fatal crash in 2000 cost nearly $3,366,388, whereas the average PDO crash cost $2,532—a ratio of about 1330 to 1. Societal crash costs include medical, emergency services, lost market productivity, lost household productivity, insurance administration, workplace costs, legal costs, travel delays, and property damage. Additional details of the societal costs can be found in Blincoe et al. (*20*). In terms of societal safety cost, or total safety impact, the average fatal crash in 2002 was 1330 times more costly than the average PDO crash. Equivalently, a PDO-equivalency factor suggests that a fatal crash is worth 1330 PDO crashes. PDO equivalency factors calculated for major and minor injury crashes (adapted from Blincoe et al., (*20*)) are 949 and 11 respectively.

Table 1: Crash Costs by Injury Severity Class (Blincoe et al. (*20*))

Since the vast majority of surface transportation systems in the United States are publicly owned and operated, the relevant costs to be considered in severity weighting are those to society. It is argued, therefore, that estimates from Blincoe et al. (*20*) represent appropriate, current, and defensible estimates of the relative safety impacts of PDO, injury, and fatal crashes. These estimates include a wide variety of costs of crashes to society, as listed previously, and represent a non-arbitrary weighting scheme for leveling the playing field with respect to crash impacts. Moreover, assuming that Blincoe et al. (*20*) represents the most current and accurate estimates of US crash costs—other weighting schemes are arbitrary. For example, subjectively weighting fatal crashes by a factor of 100 compared to PDOs is not based on any defensible or logical discourse—it merely reflects the desire to correct for perceived crash cost imbalances.

What happens when differential safety impacts are considered in a safety analysis as is done in pavement distress calculations? How will a PDO equivalency analysis compare to the modeling of crashes that are simply counted and modeled, as has been the standard practice? Answers to these questions are addressed next using hypothetical, idealized, yet somewhat realistic examples. The intent of these scenarios is to present compelling *theoretical* arguments for the use of PDOEs instead of raw crash counts in a variety of crash analysis applications. Empirical data are examined later in this paper.

Scenario 1: Suppose, for explication purposes, an analyst is interested in comparing the safety performance of two road segments, each 1 mile in length. The road segments are for all intents and purposes identical (traffic, weather, roadway design, road users, etc.) except that segment A has posted speed of 100 km/h while segment B is posted 80 km/h. Suppose that both sites record 5 crashes each in a given year. Suppose furthermore, that the ratio of reported fatal to minor injury crashes was 1:4 at site A and 0:5 at site B. *For any type of analysis of these two sections using crash counts—be it a before-after study, with and without comparison, regression, etc., one would conclude that each site revealed equivalent safety performance.* One might conclude that the differential in speed had no effect on safety. This is often not the case, however—as higher speeds often increases crash severities.

If instead PDO equivalency factors were applied, site A would have 4(11) + 1330 = 1374 PDOEs, while site B would have 5(11) = 55 PDOEs. *For any type of analysis of these two sections using PDOEs—be it a before-after study, with and without comparison, regression, etc., one would conclude that the speed limit differential is responsible for the difference in PDOEs.*

This simplistic scenario yields a general result for the use of PDOEs: analyses on raw crash counts will fail to identify (statistically) *site-related factors* that affect crash severity. In particular, site-related factors that reflect crash impact speeds (e.g. posted speeds, average speeds, speed at impact, speed controls), severity upon impact (e.g. roadside environment variables), and crash attenuation devices (e.g. median treatments can affect severities) will be minimized or not identified as contributing factors.

Scenario 2: Suppose interested is focused on comparing the safety performance of two road segments, each 1 mile in length. The road segments are practically identical (travel speeds, traffic, weather, roadway design, road users, etc.). Suppose furthermore, that the ratio of reported fatal to PDO crashes was 1:4 at site C and 0:5 at site D. It turns out that in one of the crashes at site A, a driver was not wearing her safety restraint and as a result died. All other drivers and occupants involved in crashes at site C and D were wearing safety restraints and as a result did not suffer injuries.

As in the prior scenario, an analysis using crash counts would reveal no differences in sites and no difference in crashes to explain. Conversely, the PDO equivalency analysis would reveal Site C as having recorded 1334 PDOEs compared to 5 at Site D.

Scenario 2 also yields a general result: analysis using PDOEs will enable the identification of driver-related factors that affect severity, whereas a crash count analysis will fail to identify driver-related factors that affect severity. In practice, however, many driver-related factors are often missing from a crash database. As a result the PDOE approach may introduce variation across sites that is unexplained given the set of possible covariates. This is not a limitation of the PDOE approach per se, but instead a limitation of crash datasets where many if not most driver-related factors are unavailable. The simple fact remains, however, that the PDOE data will reflect sensitivity to driver factors that given their missing status will lead to increased modeling error or the identification of measured factors that are correlated with driver-related factors.

Scenario 3: Suppose the safety performance of a roadside improvement project on a road segment 1 mile in length (assume random selection for treatment) is of interest. The road segment is ideal for a naïve before-after study, as travel speeds, traffic, weather, roadway design, road users, etc. are the same from before to after. A roadside improvement project is implemented at the site which results in a more forgiving roadside environment. Suppose furthermore, that the reported crashes before and after are as follows:

Before: 2 fatal, 3 major injury, 6 minor injury, 15 PDO = 26 total crashes,
After: 1 fatal, 2 major injury, 8 minor injury, 17 PDO = 28 total crashes.

In terms of PDOEs, these crashes yield:
Before: 2(1330) + 3(949) + 6(11) + 15 = 5588 PDO equivalent crashes,
After: 1(1330) + 2(949) + 8(11) + 17 = 3333 PDO equivalent crashes.

Using raw crash counts, a naïve before-after analysis of these sites reveals a deterioration of safety of 2 crashes whereas the same analysis using PDOEs yields a safety improvement of over 2200 PDOEs. The respective estimated accident modification factors (AMFs) for this roadside improvement project would be $\theta = 1.07$, while $\theta = 0.60$ using PDOEs. The PDO equivalency estimate reflects the estimated reduction of true crash impacts (costs), whereas the former reflects simply a percentage reduction/increase in crash frequencies irrespective of their severity.

Furthermore, consider the likely under-reporting of PDO and minor injury crashes in this above scenario—an artifact of safety analysis that is particularly problematic (*21*). According to Blincoe et al. (*20*), about 50% of all PDO and 20% of minor injury crashes are not reported to the police, while major injury and fatal crashes are close to 100% reported. Hauer and Hackert (*22*) estimated these same values to be 60% and 20% respectively. Of course under-reporting varies across time and space, and so PDOs may be under-reported by 40% in one period, 60% in another, etc.

If one were to apply national average corrections to the reported crashes in the previously described hypothetical scenario with the intent to obtain a more accurate estimate of the 'true' crash counts, a more realistic crash count at the site would be (rounded to nearest whole crash):

Before: 2 fatal, 3 major injury, 6(1.2) minor injury, 15(1.5) PDO = 35 total crashes,
After: 1 fatal, 2 major injury, 8(1.2) minor injury, 17(1.5) PDO = 38 total crashes.

In terms of PDOEs:
Before: 2(1330) + 3(949) + 6(11)(1.2) + 15(1.5) = 5609 PDO equivalent crashes,
After: 1(1330) + 2(949) + 8(11)(1.2) + 15(1.5) = 3358 PDO equivalent crashes.

Comparing the estimates corrected for un-reported crashes the following is obtained:

Crash Counts
Before: Reported—26, Corrected—35; Percent Difference—25.7%
After: Reported—28, Corrected—38; % Percent Difference—26.3%

PDOEs
Before: Reported—5588, Corrected—5609; % Percent Difference—0.4%
After: Reported—3333, Corrected—3358; % Percent Difference—0.7%

Thus, the use of PDOEs—because more completely reported crashes are weighted more heavily—results in significantly lower analysis errors due to incomplete reporting. In this example, errors are 40 to 50 times less when using PDOEs then when using raw crash counts. Also, the overall magnitude of error is negligible—less than 1% when using PDOEs (in this example), whereas the error (compared to truth) deviates as much as 25% using raw crash counts. This benefit cannot be over-emphasized and is an added advantage of using PDOEs that has heretofore not been acknowledged.

Using PDOEs in lieu of raw crashes: Modeling Implications

The impact of performing a regression analysis on both raw crash counts versus PDOEs using rural road segment data from South Korea is now examined. Standard negative binomial regression (*23*) models with structured over-dispersion (*24*) are estimated. Despite the preponderance of zeroes in the data, the use of zero inflated models is avoided for reasons iterated in Lord et al. (*25*).

Case Study: Analysis of rural road segments in South Korea

For the empirical investigation of PDOEs rural road segment data from South Korea are examined. This, of course, raises a fundamental question regarding the use of South Korean data and PDOEs developed from US crash costs. Since the intent of this paper is to illustrate a concept this inconsistency is largely ignored; however, in practice US factors should be applied to US data and vice versa. Moreover, an attempt was made to obtain these same factors from South Korean medical cost data but these data were unavailable. In fact the medical crash costs associated with motor vehicles are difficult to obtain and estimate, and as such many countries such as South Korea may opt to use US derived factors until such data are made available. It is worth noting that the PDOEs are ratios, and thus the absolute dollar values of crash costs do not influence the analysis.

Data for this study were collected under the explicit recognition that accidents at rural road segments are affected by both local and regional characteristics. Road segments in rural locations adjacent to metropolitan areas, for example, may consist of different driving populations and hence safety compared to intersections in rural locations. Roadside conditions are different depending on the location of rural segments within South Korea. Considering this expected heterogeneity across sites, road segment crash and geometric data were obtained from two sites in South Korea, as shown in Figure 1. Site A is outside of Seoul, which is the capital of South Korea and the largest city in South Korea. The population of Seoul was about 10 million in 2008. Site B represents a rural site, with no major cities nearby.

Figure 1: Sampling Locations of Sites within South Korea

The data are based on a total of 2,916 highway road segments in rural areas and were obtained from two sources. First, detailed accident records from 2005 to 2007 were obtained from the national policy agency. Roadway inventory data were secondly obtained from field surveys that were conducted from 09/01/2008 through 11/30/2008. Based on underlying theories of crash causation and with the intent to establish defensible statistical models to enable the examination of possible relationships among accident frequencies, geometric, and traffic characteristics of road segments, a total of 45 possible variables were considered in the analysis.

Table 2 shows the variables collected during the study, their mnemonics applied in the modeling and later references, and their measurement units. All of the variables that appear in the table were collected either as a result of prior studies having revealed a possible relationship to safety or due to an anticipated association. Average daily traffic volumes (ADT) and heavy truck traffic volumes (HVADT) for example have been well established to affect safety in numerous prior studies, while the number of bus stops (bustop) is a potential factor worthy of exploration.

Table 2: Road Segment Variable Names, Descriptions, and Measurement Units or Levels

The means, standard deviations, minimums, and maximums for the variables listed in Table 2 are shown in Table 3. The segment with the most fatal (fatal) crashes recorded 2, while one site recorded 8 minor injury crashes (mininj). The range of total crashes is zero to thirteen. Note that for binary and ordinal variables the means have less useful interpretations.

Table 3: Variable Samples Sizes, Means, Standard Deviations, Minimums, and Maximums (N=2916)

Negative binomial regression models are estimated using crash frequencies (crashfreq) in the first regression and PDO-equivalents (PDO-E) in the second. The results are first presented followed by a detailed discussion of the contrast.

An unusual feature of the model output is that model coefficients are provided as incident rate ratios (IRRs), that is exp(β) rather than β. Standard errors and confidence intervals are similarly transformed. The advantage is that IRRs represent the multiplicative effect of a unit change in the predictor (with other variables assigned their means).

Negative Binomial Regression Models

Negative binomial regression models were used to estimate mean crash frequencies as a function of covariates across sites using the raw crash count data (crashfreq) and then using PDOEs as described previously. Negative Binomial regression has become the standard practice for modeling crash data and references on this subject and slight variants are abundant (*8*, *11*, *17*, *21*, 22, *23*, *24*, *25*). In keeping with sound modeling practice only predictors that were both logically defensible and statistically significant at $\alpha \leq 0.05$ were retained in the regressions. Segment length (length) is applied as an exposure variable in all of the regressions (no coefficient), and dispersion is allowed to be structured if appropriate.

Table 4: Negative Binomial Regression Model I: Raw Crash Counts

Table 4 shows the generalized negative binomial regression model results based on reported raw crash count data (Model I). Crash frequencies across road segments in South Korea are a function of a variety of statistically significant factors.

The presence of a horizontal curve within a segment suggests that the frequency of predicted crashes increases by 50% on average. As the radius of a horizontal curve increases it has a decreasing average effect on crash frequencies, albeit this effect is very small in magnitude.

Traffic volumes have a large effect on crash frequencies as found in a multitude of studies. For every 10,000 vehicles (all vehicles) there is an average 1.32 factor increase in crash frequencies, while for each 1,000 heavy duty vehicles there is a 3.2 factor increase in crash frequencies. These results suggest that for predicting crash frequencies heavy duty trucks are far more important than are total volumes which include cars, trucks, vans, motorcycles, etc.

Land use seems to serve as a reliable proxy for operational differences across land uses that affect crash frequencies. Residential (landuse 1) and industrial areas (landuse 4) are associated with increases of about 5.8 and 5.2 times the crash frequencies observed in all other land use categories, including commercial areas, farmland, and their interactions. An unexpected finding is the omission of commercial areas which tend to contribute complex vehicle turning movements not explained by the other land use categories. Finally, when the terrain is flat (compared to rolling or mountainous) there is about a 30% reduction in reported crash frequencies on average.

Finally, the only speed limit category that seems to be associated with crash frequencies is the 40 km/h category, which has about double the frequency of crashes compared to all other road types. All other speed limit categories were not statistically significant.

The negative binomial model using PDOEs as the dependent variable—shown in Table 5—identifies a substantially different set of statistically significantly and logically defensible predictors. To remind the reader, the model on PDOEs is intended to reflect a more complete picture of segment safety by including both frequency and severity effects. As shown previously, an analysis based on PDOEs will not mask the safety effect of severity-related variables. Moreover, the reduced effect of under-reporting substantially reduces the error in analysis. To facilitate comparisons between the models it is important to note that raw crash counts range from 0 to 13, whereas PDOEs range from 0 to 2091. As a result, the incident rate ratios will differ significantly across the models. Also, dispersion is substantially higher in the PDO-equivalency analysis, and thus the ability to explain differences across sites more difficult.

Table 5: Negative Binomial Regression Model II: PDOEs

The effect of traffic volume in Model II (PDO-equivalents) is diminished compared to Model I (raw crash counts). All else being equal, a 10k increase in traffic volume will increase PDOEs by a factor of 1.7.

Land use category 7 replaces category 4 and acts to reduce PDOEs on average. Thus, farmland-industrial areas seem to have one-tenth the PDOEs than do other land uses (except category 1), whereas residential areas seem to increase PDOEs by a factor of slightly more than 4.

The large increases in PDOEs are associated with posted speed limits in Model II. Model 1 revealed 40 km/h segments as 'more dangerous' than other posted speeds by a factor of 2. In contrast, Model II reveals significant speed effects across 4 posted speed categories. The largest effect is on 40 km/h roads (184 segments)—these roads have 3700 times more PDOEs than did 30 km/h and 50 km/h roads (35 and 7 segments respectively). Eighty km/h roads had approximately 1060 times more PDOEs than did 30 km/h and 50 km/h roads, whereas 70 km/h roads had nearly 1750 times more PDOEs. Finally, 60 km/h roads had about 900 more PDOEs than did 30 km/h and 50 km/h roads.

No other variables were statistically significant in the Model II. Notably, truck volumes do not uniquely contribute to explaining PDOEs. Nor does the presence of a horizontal curve, its radius, or whether terrain is flat or not.

The additional dispersion introduced by the PDOEs is explained in part by both total traffic volumes and truck volumes in Model II. In other words, unexplained variation is a function of not only the mean PDO equivalent prediction but also traffic and truck volumes—with higher volumes contributing to higher unexplained variation.

The speed-related results were anticipated and are insightful. It is readily seen that the largest magnitude systematic effects on PDO-equivalents are associated with posted speed limits. The fact that speed affects severity is expected; however, that 40 km/h roads have the highest association with PDOEs is quite surprising. The impact of this speed category cannot readily be explained and points simply to a need to examine the South Korean road data and to examine further what other factors may be associated with 40k roads. Both Models I and II identify this class of road as the 'most risky'; however, Model II identifies other speed limits as having substantial effects on the predicted safety performance of facilities.

The large magnitude IRRs in Model I are associated with land use, that is, the "message" from Model I is that being in a residential or industrial area has a significant effect on safety. Model II, in contrast, suggests that whether or not a road segment is in a residential area has about 1/265 the effect on safety as does the facility being posted 80 km/h. Thus, Model II suggests that speed limit is far more important than land use in explaining both severity and frequency of crashes, as expected.

A direct quantitative comparison of these models is not possible because the dependent variables are measured on different scales. All GOF comparisons are based on statistics derived from the dependent variable (R-squared, log-likelihood, mean square error, absolute error, etc.) and thus comparisons of them are not meaningful. The results do not suggest that Model II is superior in any way to Model I; instead the results indicate simply that Model II is sensitive to total societal crash cost and Model I is not. The modeling results suggest that the set of predictors that are sensitive to both severity and frequency are revealed through the use of PDOEs as compared to raw crash counts.

Discussion and Conclusions

Crashes are not equal when it comes to their influence on safety. Substantial research reveals and common sense dictates that a fatal crash is far more costly than a PDO crash, and injury crashes also represent a greater impact on system risk than do PDOs. Much like using axle load equivalents to measure pavement damage (and associated costs), the use of PDOE factors is proposed for an enlightened analysis of crashes. PDOEs are derived from the relative costs to society of fatal, major injury, and minor injury crashes compared to PDOs. These weights are non-arbitrary—unlike past efforts that have considered weights—and can be defended based on their reflection of true crash costs to society.

Through several hypothetical, somewhat idealistic, and insightful scenarios we demonstrate several properties that result from using PDOEs. First, analyses of system locations (segments, intersections, etc.) using raw crash counts will fail to illuminate site-related factors that affect crash severity—be they before-after studies, regression analysis, etc. Statistically, these factors will not be identified as statistically significant, with likely candidates being factors such as driving speeds and factors that influence crash survivability. Conversely, using PDOEs will enable the identification of factors that are sensitive to crash severity and the true societal costs of crashes.

A second finding is that the use of PDOEs enables the identification of driver-related factors that influence crash severity. Often, however, driver-related factors are not available in the analysis of system segments. For example, we often do not have disaggregate or aggregate occupant restraint use information associated with crashes that occur at an intersection. If PDOEs are used and driver-related factors that affect severity are unavailable, then unexplained variation will exist and increase the overall model error term. The unexplained variation may be systematic if there are, say, patterns of restraint compliance rates within a region, otherwise it will be largely random.

A third scenario showed that applying a before-after analysis using crash counts can be misleading. If a countermeasure influences the severity of crashes but has a minor influence on the frequency of crashes (many countermeasures behave this way), raw crash counts are inferior. PDOEs, in contrast, do a superior job in enabling a before-after analysis to reveal the true impact of a countermeasure on safety. Moreover, PDOEs are less prone to analysis errors due to the impact of under-reporting, with a simple example revealing a 40 fold decrease in the analysis error compared to raw crash counts.

A negative binomial regression analysis using South Korean segment data (in practice US data should be coupled with US based PDOEs) revealed stark differences using raw crash counts vs. PDOEs. As theoretically argued, speed-related factors become more prevalent when both frequency and severity are considered in the analysis. Factors that typically explain crash frequency become less important when severity is considered. While the concept of weighting crashes by severity is not new, using PDOEs based on the true costs to society is non-arbitrary and, it is argued, better reflects true safety impacts. Despite the strong case made for PDOEs, important questions remain.

How would this approach influence a before-after analysis, and would the results be improved? As discussed previously, before-after results could be drastically altered if crash counts across severity classes were simply being used in the analysis. The change in both severity and frequency from before to after would provide a much more complete assessment of the safety impact of a countermeasure. The introduction of PDOEs to the largely accepted before-after methodology, and its impact on the statistical computations has yet to be explored.

Could the approach be used to improve the ability to identify 'high risk' sites? Clearly using PDOEs to rank high risk sites has strong intuitive appeal. Again, ranking would not be a function of only crash frequency—which is influenced heavily by under-reporting of PDO crashes, but by severity as well. Sites with a high proportion of severe crashes would be on average ranked much higher than those with large numbers of PDOs. The influence on safety management and high risk site identification also deserves exploration.

How does one justify the weights applied to calculate PDOs? In this analysis the most recent national study on the costs of crash severity were used along with assumptions about vehicle occupancy and number of vehicles involved in crashes. If another researcher depended upon another study or made different assumptions—the results here would then change. In addition, issues associated with methods used to value human life could contribute to this debate. A discussion on the correct relative weights and assumptions warrants attention, and might require an agreed upon standard of measure that is adopted by the profession. While this debate could be significant, we believe it pales in comparison to the need to consider severity in order to gain a complete representation of road safety, with a ratio of PDOs to Fatal costs of 1:1330 clearly their societal impacts are drastically different no matter what assumptions are agreed upon.

Isn't the approach an approximation based on severity classes? Yes, weights could be established for a number of different severity classes, such as the commonly used KABCO scale which would require five weights instead of the four applied here. Moreover, weights could be calculated 'within severity class'; for example, severe rear-end crashes may be less costly on average than severe angle crashes. As all researchers must defend all aspects of their research with sound science, the selection and calculation of how many weight classes to use and apply represents yet another of those aspects that must be defended. In the final analysis severity classes are an arbitrary discretization of a continuous cost function of crashes, which in the final analysis results in an approximation. It is argued, though, that the explicit consideration of costs—even if approximate—is better than their exclusion.

Do statistical complexities arise from the PDO equivalent approach? The usual assumptions of Poisson and Negative Binomial distributed crash counts are severely strained in this approach. The PDO equivalency calculation introduces a great deal of dispersion into the data, which theoretically makes the identification of statistically significant variables easier but places distributional assumptions on questionable ground. The impact of the method on the econometrics deserves more attention, and it is likely that more suitable statistical approaches for analyzing PDO equivalency data can be applied, such as non-parametric methods.

Aren't severe crashes influenced more by random events than less severe crashes? Severe crashes—including fatalities and severe injuries, are captured more accurately in crash databases. Some of the mechanisms differentiating severe from fatal crashes are quite simple and thought to be random, such as weather passengers are wearing safety restraints or are carrying excessive speed. However, the argument for randomness also applies to minor injury and PDO crashes as well, since past research has established that about 90% (or so) of all accidents are caused by human error (distraction, failure to perceive, etc.); thus it seem unfair to single out the most severe crashes in this regard. Small datasets, regardless of severity, will lead to greater difficulties in drawing firm conclusions regarding roadway safety.

The intent of this research was to devise, develop, and illustrate the use of a straightforward and heretofore untested analysis method for considering both severity and frequency. Based on both theoretical and empirical arguments herein we believe the PDOE approach offers considerable complement to, if not significant advantages over state of the practice methods in raw crash count modeling. The sole intent is to solve the problem posed by the two-dimensional character of motor vehicle safety that is often analyzed in only one dimension or is offered in cumbersome and complex multi-level models.

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Figure 1: Sampling Locations of Sites within South Korea

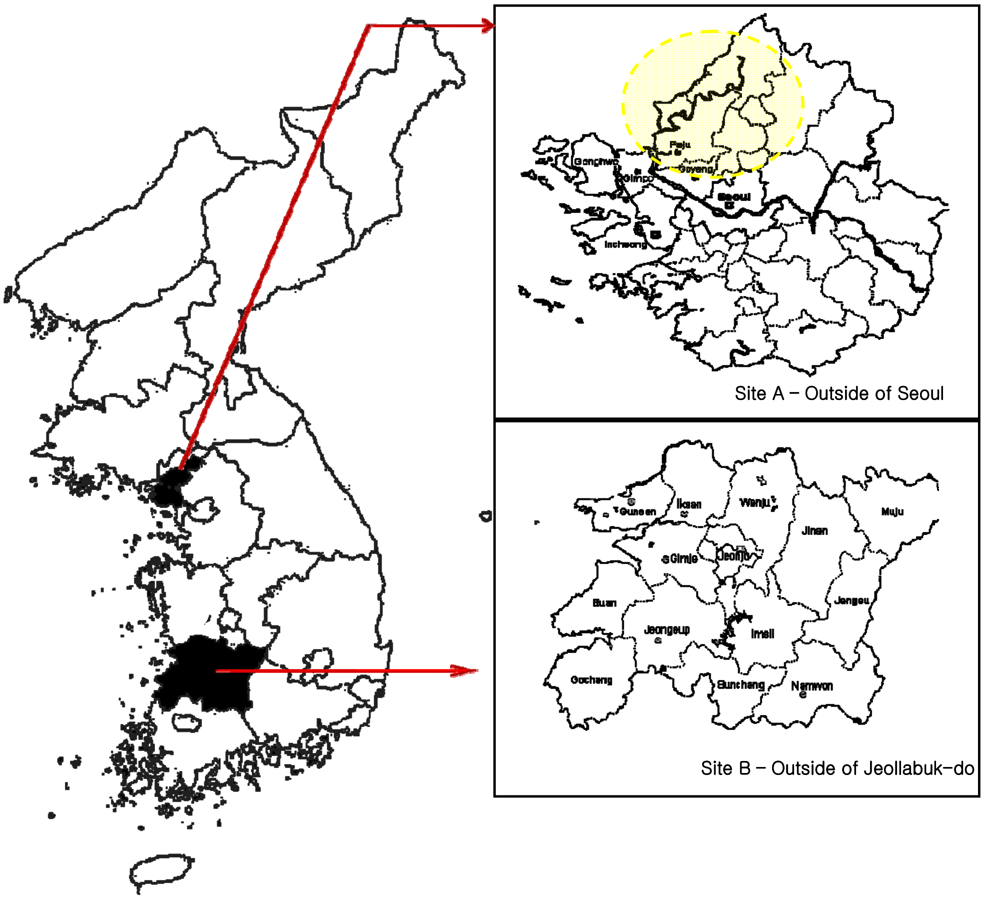

Table 1: Crash Costs by Injury Severity Class (Blincoe et al.(*20*))

2000 Dollars

	PDO	MAIS0	MAIS1	MAIS2	MAIS3	MAIS4	MAIS5	Fatal
INJURY COMPONENTS								
Medical	$0	$1	$2,380	$15,625	$46,495	$131,306	$332,457	$22,095
Emergency Services	$31	$22	$97	$212	$368	$830	$852	$833
Market Productivity	$0	$0	$1,749	$25,017	$71,454	$106,439	$438,705	$595,358
HH Productivity	$47	$33	$572	$7,322	$21,075	$28,009	$149,308	$191,541
Insurance Admin.	$116	$80	$741	$6,909	$18,893	$32,335	$68,197	$37,120
Workplace Cost	$51	$34	$252	$1,953	$4,266	$4,698	$8,191	$8,702
Legal Costs	$0	$0	$150	$4,981	$15,808	$33,685	$79,856	$102,138
Subtotal	**$245**	**$170**	**$5,941**	**$62,020**	**$178,358**	**$337,301**	**$1,077,567**	**$957,787**
NON-INJURY COMPONENTS								
Travel Delay	$803	$773	$777	$846	$940	$999	$9,148	$9,148
Property Damage	$1,484	$1,019	$3,844	$3,954	$6,799	$9,833	$9,446	$10,273
Subtotal	**$2,287**	**$1,792**	**$4,621**	**$4,800**	**$7,739**	**$10,832**	**$18,594**	**$19,421**
Total	**$2,532**	**$1,962**	**$10,562**	**$66,820**	**$186,097**	**$348,133**	**$1,096,161**	**$977,208**
QALYs	$0	$0	$4,455	$91,137	$128,107	$383,446	$1,306,836	$2,389,179
Comprehensive	**$0**	**$0**	**$15,017**	**$157,958**	**$314,204**	**$731,580**	**$2,402,997**	**$3,366,388**
Total Comprehensive ratio/Fatal		0.45%	4.69%	9.33%	21.73%	71.38%	100.00%	
Injury Component ratio/Fatal			0.31%	4.58%	9.16%	21.53%	71.24%	100.00%

Note: Unit costs are on a per-person basis for all injury levels. PDO costs are on a per damaged vehicle basis.

Table 2: Road Segment Variable Names, Descriptions, and Measurement Units or Levels

Variable Mnemonic	Description of variable
crashfreq	Total Number of traffic crashes
fatal	Number of reported fatal crashes (crash where at least 1 person is fatally injured)
majinj	Number of reported major injury crashes (crash where at least 1 person suffers non-fatal major injury)
mininj	Number of reported minor injury crashes (crash where at least 1 person suffers non-fatal minor injury)
PDO	Number of reported property damage only crashes
ADT10k	Average daily traffic volume [veh/day] in tens of thousands of vehicles
HVADT1k	Average daily heavy vehicle volume [veh/day] in thousand of vehicles
site	Rural segments outside metropolitan area=0, rural segments located in level and rolling areas =1
length	Roadway segment length [meters]
hc	The presence of horizontal curve
vc	The presence of vertical curve
hcradius	Horizontal curvature [meters]
grade	Vertical grades [%]
numdriv	The number of driveways
numlite	The number of lighting
width	Traveled width [meters]
numlan	The number of lanes
shldwdth	The shoulder width [meters]
shldtyp [1-4]	The shoulder type [Non=0, Pavement=1, Non pavement=2, Others=3]
spdcntrl	The number of speed control system/ Device
terrain [1-3]	Terrain [level=1, rolling=2, mountainous=3]
delin	The presence of delineation system [yes=1, no=2]
medtype [1-5]	The median type [None=0, Concrete=1, Guardrail=2, greenbelt=3, Others=4]
medwidth	The median width [meters]
postspeed	Posted speed in km/h [30=1, 40=2, 50=3, 60=4, 70=5, 80=6]
landuse [1-10]	Land-use around Roadway Segment [residential area=1, commercial area=2, farmland area=3, industrial area=4, residential-commercial area=5, farmland- industrial area=6, farmland –industrial area=7, residential-farmland area=8, industrial-farmland area=9, others=10]
crosswalk	The number of crosswalks
bustop	The number of bus stops

Conversion: 1km/h = 0.621mi/h ; 1m = 3.28ft

Table 3: Variable Samples Sizes, Means, Standard Deviations, Minimums, and Maximums (N=2916)

Variable	Mean	Std. Dev.	Minimum	Maximum
hc	0.5366941	0.4987372	0	1
hcradius	183.5152	381.1388	0	6800
vc	0.9358711	0.2450245	0	1
gradbeg	-0.3631687	2.745238	-10	8
gradend	-0.3727709	2.737566	-10	8
length	178.3254	136.3228	25	3000
width	9.732545	4.196879	6	45
numlan	2.684499	0.9490881	2	4
numdriv	0.5562414	0.9348919	0	10
shldtyp	0.9406722	0.2650197	0	3
shldwdth	1.123457	0.5200196	0	5
numlite	0.6412894	1.622609	0	16
medtyp	0.6683813	1.076543	0	4
medwidth	0.414952	0.9560905	0	20
postspeed	64.93827	11.87252	30	80
ADT10k	.9135172	.9938237	.0961	4.3992
HVADT10k	.110033	.1164396	.0047	.4342
spdcntrl	0.021262	0.1442812	0	1
terrain	1.752743	0.8155285	1	3
LU	3.83642	2.29123	1	10
crosswalk	0.1796982	0.4452294	0	6
bustop	0.1563786	0.4226403	0	3
delin	0.1203704	0.3254499	0	1
crashfreq	0.2040466	0.8119164	0	13
fatal	0.0130316	0.1249423	0	2
majinj	0.0836763	0.374845	0	4
mininj	0.0617284	0.3338475	0	8
PDO	0.0452675	0.3054815	0	5
PDO-E	40.81001	175.3895	0	2091

Table 4: Negative Binomial Regression Model I: Raw Crash Counts

Variable	IRR	Std. Err.	Z-value	P>|z|	95% Confidence Interval	
Crash Frequency Predictors						
hc	1.502059	.2548964	2.40	0.017	1.07706	2.09476
hcradius	.9996784	.0001791	-1.79	0.073	.9993274	1.00003
ADT10k	1.32805	.1154485	3.26	0.001	1.120002	1.574744
HVADT1k	3.210471	2.52819	4.41	<0.001	.6859028	15.0271
landuse 1	5.818681	1.827065	5.61	<0.001	3.14447	10.76717
landuse 4	5.267146	3.244749	2.70	0.007	1.574726	17.61756
terrain 1	.6900592	.1127516	-2.27	0.023	.5009622	.9505341
postspeed 2	2.045392	.8567063	1.71	0.088	.9000227	4.64836
constant (β)	-7.841476	.2004915	-39.11	<0.001	-8.234432	-7.44852
length	(exposure)					
Dispersion Function Predictors (β's)						
ADT10k	-.9394965	.1210357	-7.76	<0.001	-1.176722	-.7022708
constant	3.191968	.1724014	18.51	<0.001	2.854068	3.529869

Model Log Likelihood = -1218.9287
Pseudo R-Squared = 5.32%

Table 5: Negative Binomial Regression Model II: PDOEs

Variable	IRR	Std. Err.	Z-value	P>|z|	95% Confidence Interval	
Crash Frequency Predictors						
ADT10k	1.703442	.3938173	2.30	0.021	1.082776	2.679883
landuse 1	4.167768	3.043731	1.95	0.051	.9960221	17.43966
landuse 7	.1079958	.088743	-2.71	0.007	.0215751	.5405817
postspeed 2	3707.715	7789.995	3.91	<0.001	60.35487	227772.1
postspeed 4	906.2048	1746.919	3.53	<0.001	20.71758	39638.19
postspeed 5	1740.362	3609.499	3.60	<0.001	29.87126	101397.1
postspeed 6	1060.69	2087.303	3.54	<0.001	22.41464	50193.22
constant (β)	-9.062803	1.911832	-4.74	<0.001	-12.80993	-5.315681
length	(exposure)					
Dispersion Function Predictors (β's)						
ADT10k	-.3672362	.0824673	-4.45	<0.001	-.5288691	-.2056033
HVADT1k	-2.484343	.7570695	-3.28	0.001	-3.968172	-1.000514
constant	5.103508	.109587	46.57	<0.001	4.888721	5.318294

Model Log Likelihood = -2800.5798

Pseudo R-Squared = 0.59%