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A METHOD FOR ESTIMATING DELTA-V DISTRIBUTIONS FROM INJURY OUTCOMES IN CRASHES

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16. Abstract

Two key national crash data samples from the National Automotive Sampling System (NASS) program are the General Estimates System (GES) and the Crashworthiness Data System (CDS). The former is a larger (50,000 crashes per year) sample of police-reported crashes and contains only information coded from the police report. The latter is a smaller (~3,000 crashes per year) sample of light-vehicle towaway crashes that are investigated by trained accident investigators. One key advantage of CDS is that it includes estimated crash severity, or delta-V, assigned to each vehicle in a crash. Delta-V is the best single predictor of injury outcome and thus is a key variable in prediction models. However, because it requires special data collection, it is absent from police-report-based datasets.

In contrast to CDS, GES is a much larger sample and includes more than just light-vehicle crashes. Thus, it would be ideal to have delta-V available for GES crashes to improve models of injury outcome from those data. Some attempts to do this for individual crashes were unsuccessful (e.g., Farmer, 2003). However, in some analyses, especially statistical simulations, it is sufficient to have a distribution of delta-V for a given crash mode rather than tying a specific delta-V to a specific crash-involved vehicle.

This report presents a method of estimating a distribution of crash severity using only police-reported crash data. The approach uses an injury risk curve developed from CDS and a parametric distributional assumption for the delta-V distribution. While the distribution can take any parametric form, I use the lognormal in this report. The method uses maximum likelihood to fit parameters to the delta-V distribution based on the observed injury distribution using the police-reported KABCO scale. That is, individuals in crashes fall into one of five injury categories. Each pair of lognormal parameters produces a distribution of injury when multiplied by the injury risk curve. Thus, the parameters that produce the multinomial injury distribution that best fits the observed distribution are chosen for the estimated delta-V distribution. The report includes results from a simulation study as well as a fit to CDS data with known delta-V distribution.

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INTRODUCTION

Crash severity is a key predictor of injury outcome in crashes (e.g., Kononen et al. 2011, Klinich et al. 2010, Viano and Parenteau 2010, Ydenius 2010, Sunnevang et al. 2009, Digges and Dalmotas 2007). The best available measure of crash severity is delta-V, the nominal change in velocity experienced by a vehicle involved in a crash. Although delta-V is expressed as a velocity, it represents the energy absorbed by each vehicle and accounts for mass and stiffness differences between vehicles involved in multi-vehicle crashes.

The National Automotive Sampling System (NASS) includes three major datasets that are sampled annually from crashes in the U.S. The General Estimates System (GES) is a complex stratified sample of 50,000 police-reported crashes in the U.S. This dataset includes only information available from the police report, which does not include delta-V. The Crashworthiness Data System (CDS) is a complex stratified sample of 5,000 towaway crashes involving light vehicles. This dataset includes details of in-depth crash investigations performed on vehicles selected for inclusion. Delta-V is included in CDS. The Fatality Analysis Reporting System (FARS) is a census of all fatal crashes that occur on public roads in the U.S. Most information in FARS comes from police reports, though there is some additional phone follow-up. No delta-V information is available in FARS. When injury data are based on police reports, they are limited to the categories of killed (K), incapacitating injury (A), non-incapacitating injury (B), possible injury (C), or no injury (O).

Each dataset has a different data collection approach, and only CDS includes delta-V. Delta-V estimates are calculated by measuring vehicle crush and entering the measurements and other vehicle information into the WinSMASH (Sharma et al. 2007) program. WinSMASH uses vehicle mass and dimensions, as well as stiffness coefficients based on crash tests, to estimate the delta-V required to produce the observed level of crush.

An alternative method of measuring delta-V is to download recorded acceleration from Event Data Recorders (EDRs). At this time, only some vehicles are equipped with EDRs, and only a small portion record lateral acceleration. Most crashes (other than full-frontals) have a lateral component of delta-V. CDS includes EDR reports for any vehicles for which they have received permission. However, the EDR reports are only available for a nonrandom subset of CDS case vehicles. EDR reports are not available for GES or FARS. Although EDRs provide promise for collecting measured delta-V, they will not replace delta-V based on in-depth damage measurements in the near future.

While CDS includes delta-V, the database is limited to towaway crashes and light vehicles. It would often be useful to know delta-V distributions for GES or FARS, which include different populations of crashes, since analysis of outcomes or safety benefits must account for crash severity.

To this end, researchers have attempted to estimate crash severity for individual cases in GES using injury outcome. Farmer (2003) compared two commonly used measures of crash severity from police reports to corresponding measures from accident investigations in CDS. First, he compared posted speed limit to delta-V. Posted speed limit is often used as a proxy for crash speed (or crash severity) in analyses of GES data. Although Farmer found a relationship between posted speed and delta-V, it is too weak to reasonably use posted speed limit as a substitute for the probable delta-V in a given GES case. Farmer also investigated injury coding by police compared to outcomes recorded in medical records, but he did not explicitly explore injury outcome as an indication of crash severity.

Farmer's goal was to identify a substitute measure of crash severity for individual cases when delta-V is not available. Although it would be ideal to have an adequate delta-V surrogate for each case, an estimate of the delta-V distribution for a class of cases would be useful in several other circumstances. For example, evaluations of NHTSA's crash testing program commonly compare the test speed to field distributions of delta-V for similar crashes to understand what real-world benefit might result from crash testing (Hackney et al (1996), Newstead et al (1996), Arbalaez et al, 2005). Delta-V distributions could also prove beneficial when estimating safety benefits for any countermeasure (e.g., forward collision warning, crash-imminent braking) that might reduce delta-V without eliminating a crash altogether.

This paper presents a method that uses injury patterns in GES, combined with the relationship between delta-V and injury from CDS, to estimate the *distribution* of delta-V for a group of similar crashes. The method does not estimate delta-V for individual crashes, but instead identifies general patterns of the relationship between delta-V and injury that should hold for a larger population of similar crashes.

METHODS

The proposed approach to estimate delta-V depends on two assumptions. First, the delta-V distribution can be modeled with a parametric form that will hold for different classes of crashes, though each class of crashes will have different parameters. Second, the relationship between delta-V and injury is fixed for a given impact direction, and that relationship will hold for the general population of vehicles involved in impacts in the same direction.

The estimation process itself requires three elements:

1) Injury risk curve for a specific damage location
2) Distributional form for delta-V
3) Injury distribution for occupants in target crashes

The injury risk curve captures the relationship between delta-V and injury. Delta-V describes the severity of the crash as experienced by a given vehicle, and injury risk is related to crashworthiness. Since crashworthiness differs for different parts of the vehicle structure, this relationship must be modeled for a specific crash direction. Since CDS contains delta-V estimates as well as multiple measures of injury severity (AIS and KABCO), it can be used to develop injury risk curves.

Choosing an appropriate statistical distribution reduces the number of parameters needed to define the model. In general, a lognormal distribution describes the CDS delta-V distributions well. There should be fewer parameters in the delta-V distribution than there are levels of injury. The lognormal has two free parameters.

The distribution of injury levels is the data-based target of the fitting process. The injury distribution is the percentage of occupants who sustain injury at each level. Since there are several available injury scales (e.g., AIS, KABCO), it is important to use the same injury outcome measure for both the injury risk curves and the empirical injury distribution. When using GES or FARS, the injury coding system will be the KABCO scale. Even though AIS is a more precise injury scoring system, the injury risk curves from CDS should predict risk on the KABCO scale. If AIS scoring is available in the injury data source (e.g., a hospital database that has injury outcome but few or no crash details), CDS-based risk curves should predict risk of AIS injury levels instead. In this paper, only KABCO-based estimation is demonstrated.

Estimation

The first step in estimation is to sort crashes by damage areas in a manner that can be achieved in both CDS and GES. The second step is to generate the risk curves for the each crash type. In this paper, the risk curves are based on cumulative logistic regression using log-transformed delta-V as the predictor and KABCO injury level as the outcome variable. Cumulative logistic regression is an extension of binary logistic regression, which fits one or more predictors to a binary outcome. The logistic regression model is given by Equation 1.

$$p = {}^{1}\!/_{1 + \exp(-(\beta_0 + \sum_i \beta_i \mathrm{x}_i))} \qquad (1)$$

where, p is the estimated probability of the outcome (e.g., injury),

β_0 is the intercept, and

β_i are the estimated coefficients of each predictor, x_i, $i=1..r$ where r is the number of predictors in the equation

Cumulative logistic regression is essentially the same as logistic regression except that it allows more than two ordered categories of outcome. The model creates a series of increasing cutpoints among the ordered categories and fits a single slope parameter for each x_i and a separate intercept for each cutpoint. Thus when KABCO is the outcome variable and ln delta-V is the predictor, the model fits a single slope parameter for ln delta-V and separate intercepts for four cutpoints: K (vs. ABCO), KA (vs. BCO), KAB (vs. CO), and KABC (vs. O). The advantage of the cumulative model (rather than other possible choices such as generalized logit) is that the predicted risk of more severe injury is always lower than the predicted risk of less severe injury, which generally describes real-world injury patterns.

The joint distribution of each injury level in the database is the product of the risk of injury at each delta-V and the probability of experiencing that delta-V in a crash. As an example, Figure 1 shows a lognormal delta-V distribution with parameters μ=2.0 and σ=0.4 that might represent the probability of experiencing a frontal crash at each delta-V. Figure 2 shows the same delta-V distribution plotted with the KA injury risk curve and their joint distribution (the product at each delta-V value). Figure 3 shows the joint injury distribution for each injury level.

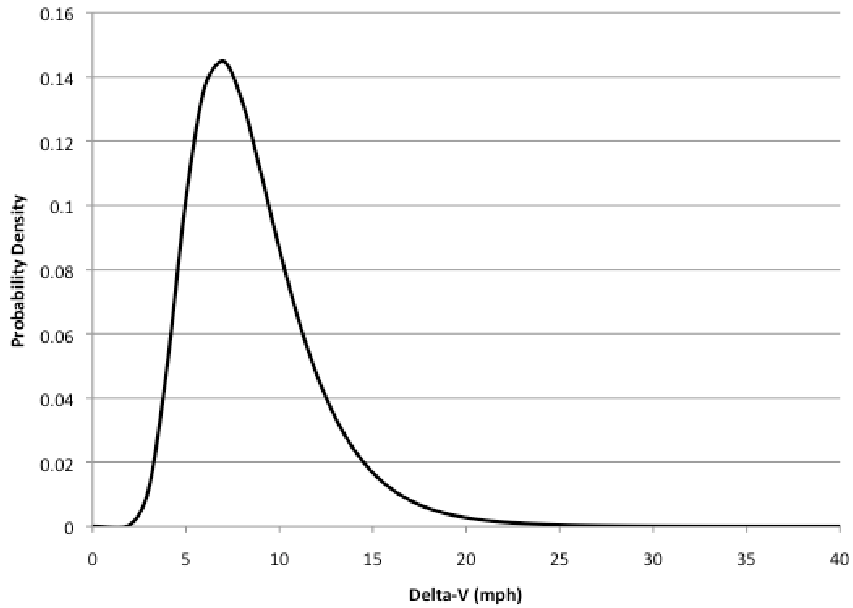

Figure 1. Example of lognormal delta-V distribution. In this graph, μ=2.0 and σ=0.4.

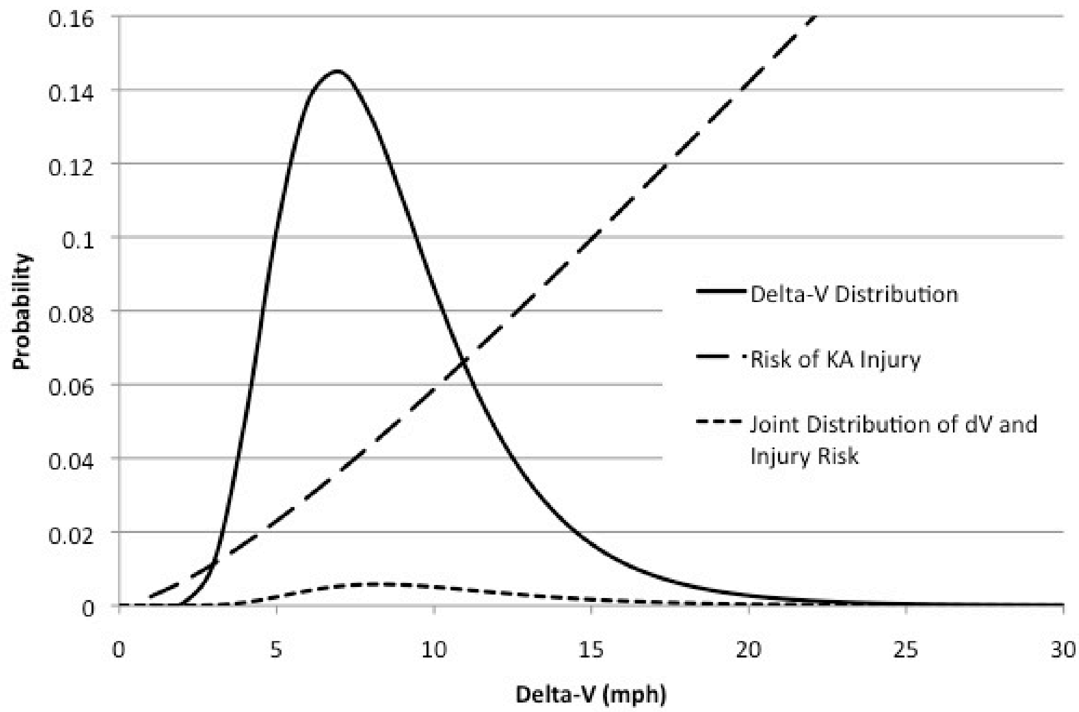

Figure 2. Injury risk curve for KA injuries, distribution of crash severity, and the distribution of injury KA injury probability (the product of injury risk and crash severity distribution.)

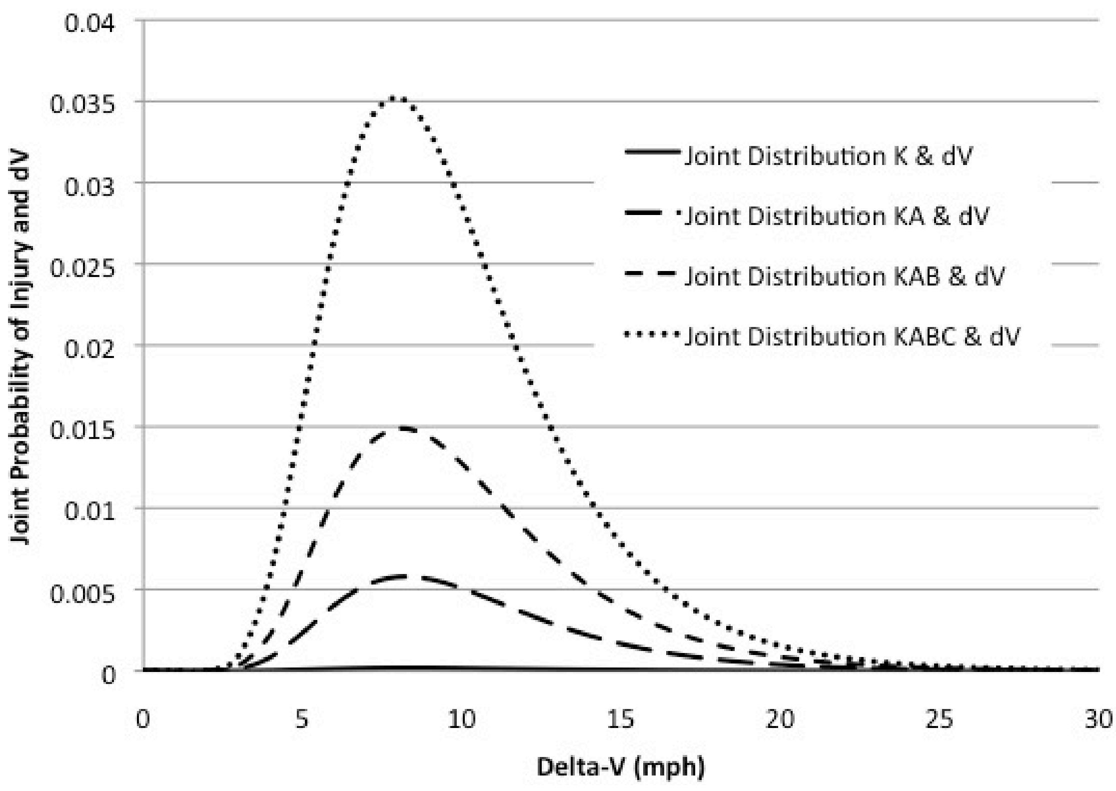

Figure 3. Joint risk of being in a crash with a given delta-V and injured (at each injury level).

For each of the joint distributions in Figure 3, the area under the curve represents the total risk of the group of injury levels (e.g., KAB). Since each outcome is cumulative, the area *between* the curves represents the total risk of a specific (non-cumulative) outcome (e.g., B injury only). The remaining probability (1 minus probability of any injury) is the probability of no injury. Thus the proportion of injuries among K, A, B, C, and O can be estimated using these products of the injury risk model and a given delta-V distribution.

If the injury-risk curves based on CDS models are considered fixed, then the only free parameters in the system illustrated in Figure 3 are those that describe the delta-V distribution. If the KABCO injury distribution is known for a dataset but the delta-V distribution is not, different values of μ and σ defining the delta-V distribution can be tested until the product of the injury risk and delta-V curves come as close as possible to the target (data-based) proportions of K, A, B, C, and O injuries.

Because the injury distribution has four degrees of freedom (the fifth injury level is constrained to sum to 1) and the delta-V distribution has two degrees of freedom, not all injury distributions can be perfectly recovered with this system. As a result, we need a loss function to score the match between the injury distributions in the target dataset and those predicted by the product of injury risk and delta-V distribution.

The chi-square test statistic is a common measure of correspondence between model and data for a contingency table and is suitable for this application. The equation for the chi-square statistic is given in Equation 2. The parameters that minimize this loss function are selected for the delta-V distribution that results from the estimation process.

$$\mathrm{X}^2 = \sum_i \frac{(o_i - e_i)^2}{e_i} \qquad (2)$$

where

o is the observed cell proportion,

e is the expected cell proportion (from lognormal model), and

i sums over the five cells in the table (one for each injury level)

Validation

In this paper, the performance of the method is tested in two ways. First, a simulation explores issues related to bias and required sample size for use of the method. Each run of the simulation involved generating a sample of simulated injury levels for 100, 1000, or 5000 cases and then using the delta-V estimation method described above to estimate the parameters of the underlying delta-V distribution.

Each case in the simulation was generated in two steps, each of which corresponds to the model assumptions underlying the method. First, a value of delta-V was selected at random from a lognormal distribution with parameters μ=3.0 and σ=0.7. Next, an injury level on the KABCO scale was selected at random based on the risk model developed from CDS and the delta-V value selected in the first step. Once a simulated sample was generated, the empirical distribution of injury levels for that sample was returned. Based only on the distribution of the five injury levels, along with the fixed injury risk curves, the method described above was used to estimate the parameters of the delta-V distribution for each simulated sample. The process was repeated 100 times for each sample size.

Second, to explore the performance of the method on real data, the model was used to estimate the parameters of the delta-V distribution for frontal cases in the CDS database (where delta-V distribution is known.) The outcome of the injury-based estimation process is compared to both a direct sample estimate of the parameters of the lognormal delta-V distribution from CDS and the purely empirical (non-parametric) distribution of delta-V from the same cases.

These validation efforts do not push the boundaries of the underlying assumptions of the model. The simulation uses the assumed model to produce test data and the CDS comparison is to the same data from which the injury risk curves are developed. However, there are infinitely many ways the model can be wrong relative to real-world data, so it is appropriate to limit the scope of this paper to testing the model under friendlier conditions. Future work should explore the robustness of the model to violations of its underlying assumptions.

RESULTS

Delta-V Distribution Form

The typical method of testing the fit of a distributional form to data is the Kolmogorov-Smirnoff test. However, this method does not work with a stratified, weighted sample. Instead, graphical methods were used to look at the relationship between the delta-V distribution for frontals (defined as general area of damage (GAD1) equal to “F”) in CDS and a variety of candidate distributions.

The lognormal distribution fits the delta-V distribution for classes of crashes fairly well. Figure 4 shows how ln delta-V for frontals in CDS is related to the normal distribution. (Comparing the log of delta-V to the normal distribution is equivalent to comparing delta-V to the lognormal distribution.) Specifically, the proportion of the delta-V distribution for frontal crashes was computed for bins in 1 mph increments. This proportion was cumulated and compared to the z-score associated with the cumulative proportion of each delta-V bin. The straight line in Figure 4 between the normal variate and ln(delta-V) indicates that the lognormal distribution is a good fit to delta-V in frontals in CDS. Additional investigation of delta-V distributions indicated that the lognormal is a good fit for other crash modes as well. The gamma distribution was also a good candidate but was not used in this paper.

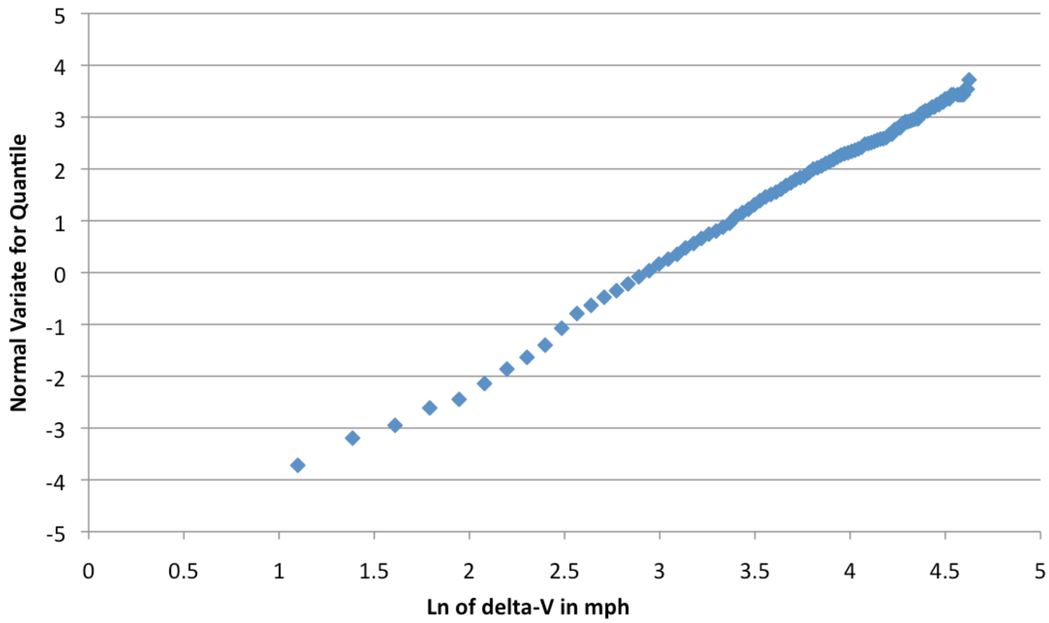

Figure 4. Plot of normal variates for each quantile vs. ln delta-V (in mph).

Injury Risk Curves

Injury risk curves using cumulative logistic regression to identify risk of KABCO injury outcome as a function of delta-V for vehicles with frontal damage in CDS are shown in Table 1 and Figure 5. There is a single coefficient for log-transformed delta-V and a separate intercept for each level of injury (cumulated). No other potential injury predictors were considered in the model, so they reflects the distribution of age, gender, and belt use found in CDS and GES. The risk curves have a common slope, and each successive intercept predicts the probability of a given level or worse injury. For example, the "B" intercept of -4.9928 determines the risk of K, A, or B injury as a function of delta-V in a frontal impact.

Table 1
Coefficients and Fit Statistics for Injury Model in Frontal Impacts

Analysis of Maximum Likelihood Estimates						
Parameter		**DF**	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	**K**	1	-9.4901	0.3145	910.4918	<.0001
Intercept	**A**	1	-6.0136	0.6559	84.0483	<.0001
Intercept	**B**	1	-4.9928	0.3382	217.9715	<.0001
Intercept	**C**	1	-3.9414	0.2559	237.2877	<.0001
Ln (delta-V mph)		1	1.4070	0.1056	177.6847	<.0001

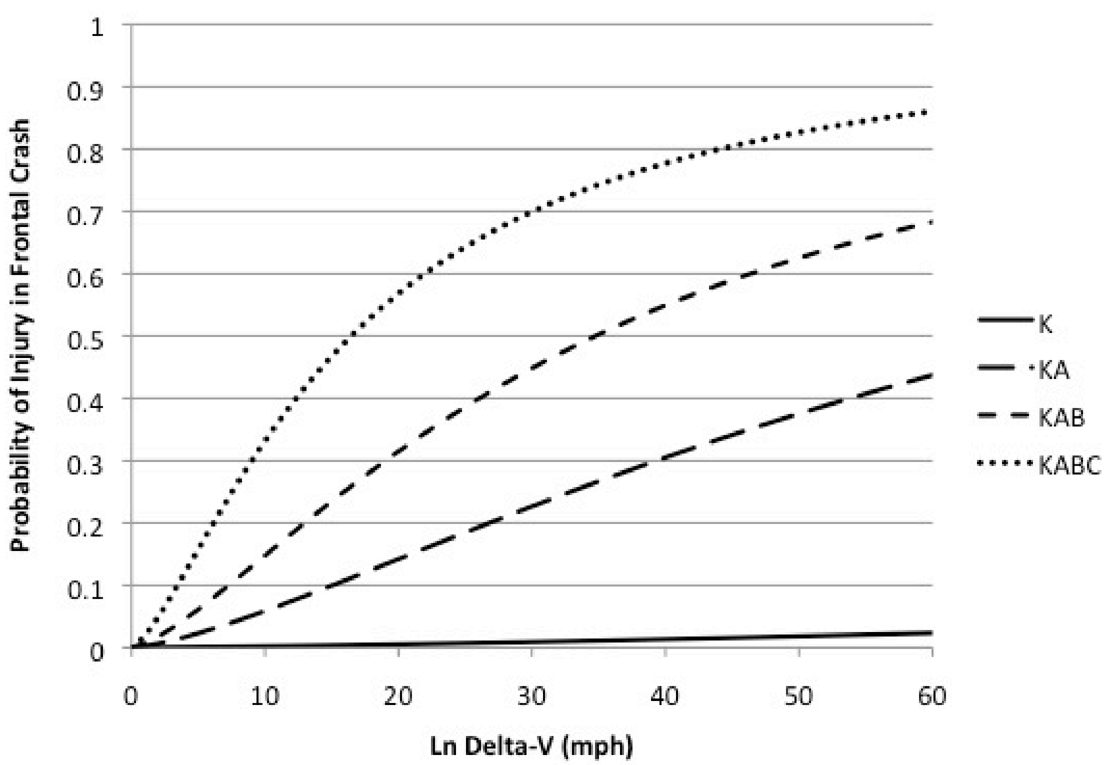

Figure 5. Cumulative logistic risk models for KABCO injuries in frontal impacts. Each line represents the risk of the group of injury levels for a given delta-V value.

Simulation

The arbitrary parameters of the simulation were μ=3.0 and σ=0.7, and three sample-size scenarios were tested for the injury data: 100, 1000, and 5000 cases. Figure 6 shows the distribution of the estimated mean of the delta-V distribution for simulated samples sizes of 100, 1000, and 5000 crashes. The estimation process becomes more precise as sample size goes up. In addition, there is no evidence of bias as the average estimate for all three sample sizes was 3.0.

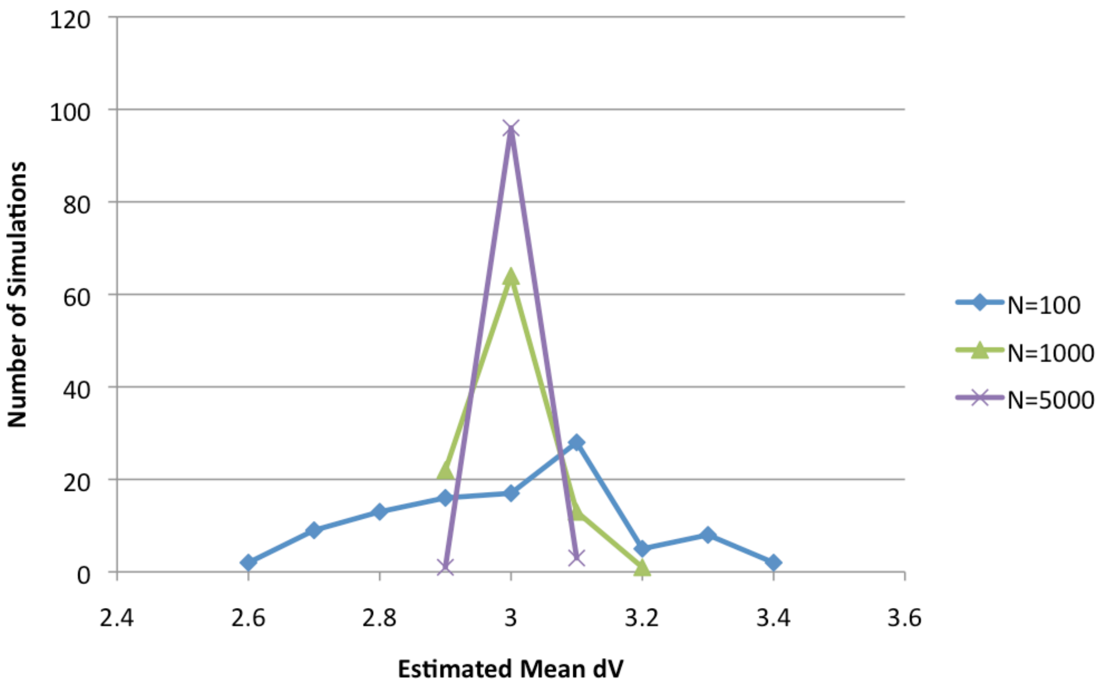

Figure 6. Simulation results for estimation of mean delta-V. The true value is 2.0.

Figure 7 shows the distribution of estimated standard deviation of the delta-V distribution for simulated samples sizes of 100, 1000, and 5000 crashes. As with estimating the mean value, the estimation process becomes more precise as sample size goes up. However, standard deviation is more difficult to estimate precisely and the results are more varied. At a sample size of 100, the estimation method frequently reaches the end of the search space, suggesting that the estimates are not stable for such a small sample size. The standard deviation estimates for sample sizes of 100, 1000, and 5000 were 0.65, 0.69, and 0.70, respectively. This suggests that the approach is unbiased for standard deviation as well, but sufficient sample size is required to have a stable estimate.

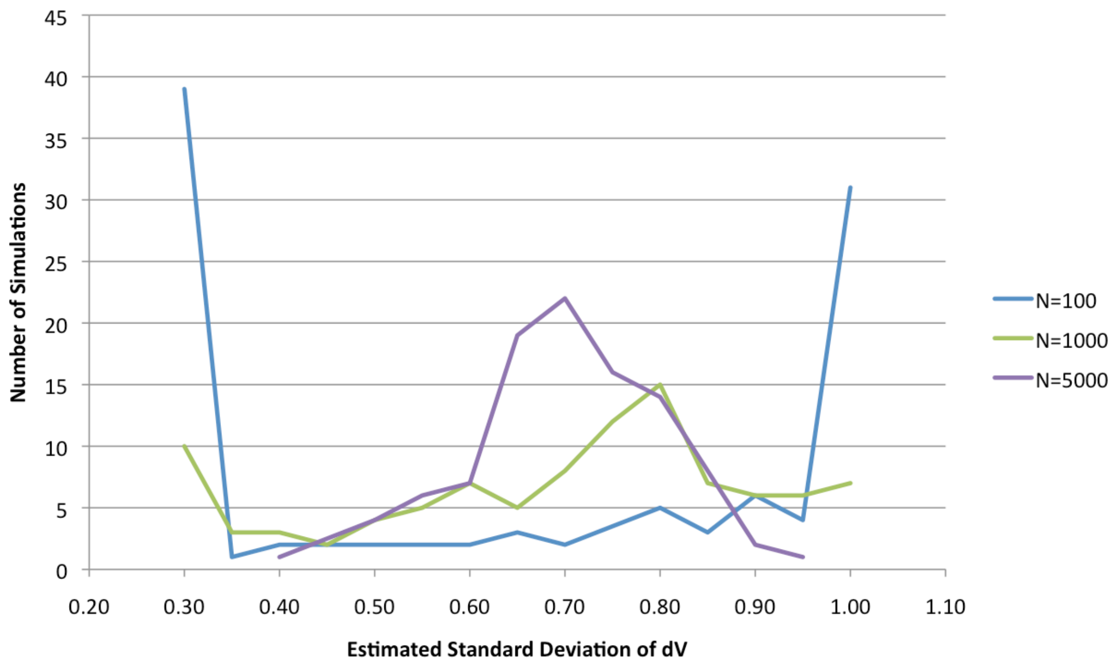

Figure 7. Simulation results for estimation of standard deviation of delta-V. The true value is 0.7.

Estimation of CDS Delta-V Distribution

When the estimation approach was applied to the injury distribution from CDS frontals, the resulting parameters to define the delta-V distribution were μ=2.47 and σ=0.43. The parameters developed from the actual data were μ=2.43 and σ=0.44. Table 3 shows the empirical (weighted) distribution of injury for CDS frontals (with non-missing delta-V). The last column shows the estimated injury distribution, based on the best-fit lognormal parameters and the embedded risk models for frontal crashes. The proportions match quite well with X^2=xxx.

Table 3
Empirical and Estimated Proportion of KABCO Injuries for Frontals in CDS

Injury Level	**Empirical Proportion of Cases**	**Estimated Proportion of Cases (μ=2.47, σ=0.43)**
K	60.59%	60.62%
A	19.82%	19.88%
B	11.20%	11.08%
C	8.10%	8.12%
O	0.29%	0.30%

Figure 8 shows three distributions for comparison. The solid black line is the weighted cumulative distribution of delta-V from frontal cases in CDS. The dashed gray line shows the lognormal distribution calculated directly from the data in CDS. The dotted gray line shows the lognormal distribution estimated using the injury-risk-curve approach. The correspondence of all three distributions is quite close, suggesting that the injury-based approach proposed in this paper works well.

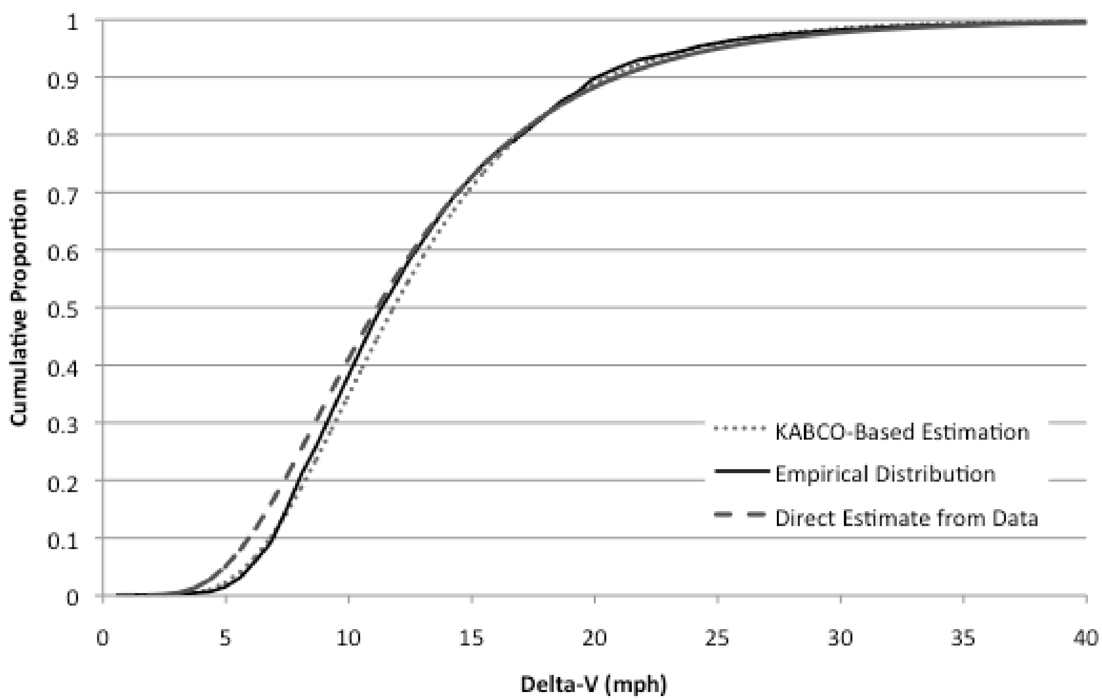

Figure 8. Three distributions of delta-V for frontals in CDS. Solid line represents empirical delta-V cumulative curve. Dashed line is the lognormal distribution estimated directly from the data, and the dotted line is the lognormal distribution estimated only from the injury distribution.

DISCUSSION

This paper presents a method of estimating the delta-V distribution for a group of cases when only injury patterns are known. The method does not estimate delta-V for a specific case. Its primary purpose is to understand the general nature of crash severity for groups of crashes.

The comparison between predicted and actual delta V distributions in CDS are very promising. Simulation shows that the method is unbiased when the underlying assumptions are not violated. When used for CDS data, the injury-based approach produced a lognormal distribution that was very close to the empirical distribution.

However, the conditions for these comparisons were ideal. In the simulation, the underlying model matched the one used in the estimation process. The goal was to identify bias and appropriate sample size, but future work might explore the robustness of the method under varying violations of the underlying assumptions. In the comparison to CDS, the risk models used for the injury-based estimation come from the same data that are being estimated, and the distributional form is known to work well for these data. Nonetheless, the match to the empirical results encouraging.

There are a variety of practical uses for this method. For example, frontal crash tests for NCAP are targeted at the 95th percentile of delta-V so that protection in such a crash should be as good or better for 95 percent of frontal crashes. However, the 95th percentile estimated from CDS data has two potential problems. On the one hand, CDS crashes are all towaways and are therefore more severe, on average, than all police-reported crashes. On the other hand, CDS cases with missing delta-V have higher injury rates, suggesting that the distribution for known-delta-V cases in CDS is biased low.

The injury-based estimation method described in this paper could address either of these issues. Used with frontals from GES, this method can identify the percentile of all police-reported crashes at which testing is conducted. This percentile is likely to be substantially higher than 95%. Alternatively, the method could be used (and possibly compared to results from multiple imputation) to estimate the delta-V distribution for all CDS frontals, including those without delta-V based on crush measurements.

A limitation of this method is that injury-risk is only considered a function of delta-V, even though additional predictors such as belt use and occupant age affect injury. Although age is available in GES, belt-use coding in GES is considered unreliable because it is based on police reports rather than evidence collected by an accident investigator. Vehicle occupants are motivated by belt-use laws to report being belted, even if they were not. Thus in this model, the intercepts reflect the general distribution of age, belt use, and other relevant variables. For example, if the overall belt-use rate is 80%, then the risk associated with each level of injury will be a mixture of the risk for belted and the risk for unbelted occupants in an 80-20 mix. If the CDS and GES populations have similar belt-use rates and similar age distributions, which should generally be the case, then the models based on CDS data will be appropriate for GES cases. In addition, although the vehicle age distribution is newer for raw counts in CDS compared to GES, the weighted distributions of vehicle age for the two datasets are similar, as would be expected.

Another limitation is that the simulation does not account for the stratified sampling used with GES. In GES, sampling is stratified in favor of cases with greater injury and then reweighted to national population proportions. Because the sampling approach was not simulated, the results of the simulation with respect to sample size will not directly apply to GES raw sample sizes. Nonetheless, the large samples available in GES for most groups of crashes should be sufficient.

As vehicles are increasingly equipped with crash avoidance technologies that may mitigate crash severity, as well as more sophisticated occupant protection countermeasures, it will be increasingly important to understand delta-V in crashes beyond those measured in CDS. The benefits of crash mitigation can only be estimated relative to existing delta-V distributions. The estimation method described here can help to better characterize crashes for benefits estimation and other purposes.

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