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A spatial generalized ordered response model to examine highway crash injury severity

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ABSTRACT

This paper proposes a flexible econometric structure for injury severity analysis at the level of individual crashes that recognizes the ordinal nature of injury severity categories, allows unobserved heterogeneity in the effects of contributing factors, as well as accommodates spatial dependencies in the injury severity levels experienced in crashes that occur close to one another in space. The modeling framework is applied to analyze the injury severity sustained in crashes occurring on highway road segments in Austin, Texas. The sample is drawn from the Texas Department of Transportation (TxDOT) crash incident files from 2009 and includes a variety of crash characteristics, highway design attributes, driver and vehicle characteristics, and environmental factors. The results from our analysis underscore the value of our proposed model for data fit purposes as well as to accurately estimate variable effects. The most important determinants of injury severity on highways, according to our results, are (1) whether any vehicle occupant is ejected, (2) whether collision type is head-on, (3) whether any vehicle involved in the crash overturned, (4) whether any vehicle occupant is unrestrained by a seat-belt, and (5) whether a commercial truck is involved.

1. Introduction

1.1. Background

Roadway crashes are the leading cause of death in the U.S. among individuals 5–24 years of age (Murphy et al., 2012), and impose a tremendous emotional and economic burden on society. This has led to substantial research investments to identify the risk factors associated with the occurrence of, and severity of injuries sustained in, crashes, so that appropriate improvements in vehicle and roadway design may be implemented to reduce the number of crashes as well as the injury severity of those involved in crashes. These efforts, supplemented by reinforcing safety policies and information campaigns, may have contributed (along with economic conditions) to the steady drop since 2005 in the number of roadway crashes and fatalities (see NHTSA, 2012). However, police-reported crashes in 2010 still numbered 5.4 million and resulted in 32,885 fatalities (NHTSA, 2012), underscoring the continued need to better understand the determinants of crash frequency and injury severity.

Transportation and safety researchers have adopted a wide variety of methodological approaches to model crash occurrence and injury severity. In this regard, crash frequency data are in the form of counts, while injury severity is typically reported and collected on an ordinal scale. Also, the factors associated with crash frequency and injury severity suffered in a crash can be quite different. As a result, different modeling mechanisms and different variable specifications are considered for crash frequency and injury severity conditional on crash characteristics. Lord and Mannering (2010) provide a review of methods for crash frequency analysis, while Savolainen et al. (2011) present a corresponding review of methods for injury severity analysis. In this paper, the objective is to contribute to the methods for injury severity analysis by proposing an approach to accommodate the dependence in injury severity levels sustained in proximally occurring crashes, and to apply our proposed method to the analysis of highway injury severity data obtained from the crash incident files maintained by the Texas Department of Transportation.

1.2. Injury severity analysis: an overview

There are several methodological issues that need to be considered in injury severity analysis. For example, Ye and Lord (2011) examine the effects of different under-reporting rates of crashes by injury severity level, and Bhat and colleagues (see Eluru and Bhat, 2007 and Paleti et al., 2010) develop methods to recognize the

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potential endogeneity of "explanatory" variables.[2] In this paper, our emphasis will be on recognizing three other specific econometric issues in injury severity analysis: (1) the nature of the dependent variable (and model flexibility vis-à-vis the nature of the dependent variable), (2) unobserved heterogeneity in the effects of variables, and (3) spatial dependency effects (this last issue also leads to the recognition of heteroscedasticity in the error terms in the underlying latent variable determining injury severity levels).

1.2.1. The nature of the dependent variable

The injury severity level of a traffic crash is in the form of a series of ordinal levels such as no injury, possible injury, non-incapacitating injury, incapacitating injury, and fatal injury. Thus, many injury severity studies in the past have used a standard ordered-response (SOR) model structure (including the ordered logit or the ordered probit) (see, for example, Dissanayake and Ratnayake, 2006; Xie et al., 2009; Christoforou et al., 2010; Haleem and Abdel-Aty, 2010; Quddus et al., 2010; Jung et al., 2010; Paleti et al., 2010; Liu and Donmez, 2011; Zhu and Srinivasan, 2011). However, the SOR model structure is quite susceptible to parameter inconsistency problems caused by varying under-reporting rates (across injury severity levels) in the data (see Ye and Lord, 2011). It is also saddled with a restrictive monotonic form for the effect of variables on injury severity levels. Specifically, as discussed in Eluru et al. (2008), the SOR structure holds the threshold values to be fixed across crashes, which will, in general, lead to inconsistent injury risk propensity and threshold values, and inconsistent effects of variables on the probability of different categories of injury severity. Savolainen et al. (2011) also point out this limitation of the SOR structure, with the following example. Assume the presence of three ordinal injury severity levels: no injury, some injury, and fatality, and let the deployment (or not) of an airbag be a key attribute influencing the latent injury severity propensity variable in the SOR structure. Then, the SOR structure will require that crashes in which an airbag deployed will entail a higher probability of no injury and a lower probability of fatal injury relative to otherwise observationally identical crashes where an airbag did not deploy. On the other hand, it is quite possible that the deployment of an airbag will decrease both the probability of no injury (because airbag deployment by itself can cause minor injuries) as well as fatal injury. This kind of an influence pattern cannot be captured by the SOR structure.

Another structure that has seen substantial use in injury severity analysis is the unordered-response (UR) model structure, including the multinomial logit model or the sequential binary choice model (see Shankar and Mannering, 1996; Ulfarsson and Mannering, 2004; Khorashadi et al., 2005; Rifaat et al., 2011; Yan et al., 2011), the Markov switching multinomial logit model (Malyshkina and Mannering, 2009), and the nested logit model (Savolainen and Mannering, 2007; Huang et al., 2008; Hu and Donnell, 2010; Patil et al., 2012). The UR model structure is more robust to varying under-reporting rates across injury severity levels, and is also flexible enough to accommodate unrestricted forms for the effects of variables (such as the airbag-related effects discussed earlier). However, it fundamentally does not recognize the ordinal nature of injury severity data, is somewhat more difficult to interpret than the SOR structure, and leads to a proliferation of parameters to be estimated.

A third structure that has been used more recently for injury severity modeling, and the one used in the current paper, is the generalized ordered-response (GOR) structure that essentially combines the strengths of the SOR and the UR approaches (see Eluru et al., 2008). Specifically, it strictly recognizes the ordinal nature of injury severity, while also allowing more flexibility than the SOR structure with much fewer parameters than the UR structure. The flexibility is achieved by relaxing the constant threshold assumption (across crashes) of the SOR structure through the parameterization of the thresholds themselves as a function of explanatory variables. One interpretation of the GOR structure is that, given a set of variables that characterize a certain crash context, the underlying latent continuous variable in the ordered-response structure represents the general injury risk propensity from the crash. However, there may be some specific driver and other contextual characteristics that dictate the translation of the general risk propensity into the manifested injury severity level. In the airbag example, the deployment of the airbag may reduce the risk propensity from the primary crash (which gets incorporated through the reduction of the general risk propensity), but there could also be a remnant effect not related to the primary crash that increases the probability of minor injury relative to no injury (which gets incorporated in the thresholds that map the general risk propensity into the manifested injury levels).[3]

1.2.2. Unobserved heterogeneity in the effects of variables

A majority of injury severity studies to date have assumed that there are no variations in the effects of explanatory variables in the underlying structures for the SOR or UR models. However, it is very likely that there are unobserved crash-specific factors that may moderate the impact of explanatory variables. For example, some angle crashes may lead to injury severities of those involved that may be far more severe than head-on crashes, even if the majority of angle crashes lead to a lesser degree of injury severity. This may be because some angle crashes may lead to a spinning or even an overturning of one or more vehicles involved in the crash, leading to severe injuries. Such possibilities may be reflected by accommodating a random coefficient on the "angle crash" dummy variable (with "rear-end" crashes being the base category) in the underlying risk propensity specification in the SOR and GOR model structures, or multiple random coefficients on the "angle crash" dummy variable in the injury-specific propensity specifications of the UR model structure. While the presence of unobserved heterogeneity effects will be context-dependent, the analyst should consider these effects rather than dismissing them without testing for their presence. In particular, when present, these unobserved heterogeneity effects can have very real implications for the accurate assessment of the effects of variables and for the design of countermeasures to reduce injury severity. This realization has

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[2] Endogeneity refers to the situation where explanatory variables may be correlated with the unobserved error term in the dependent variable model. For instance, there is evidence that seat belt non-users tend to be intrinsically unsafe drivers (see Janssen, 1994; Petridou and Moustaki, 2000). That is, there are personality characteristics of non-seat belt users (such as aggressive driving behavior and risk attitudes) that may not be available in the data being analyzed, and these unobserved factors that affect seat belt non-use also tend to increase injury severity propensity. If this sample selection is ignored, the result is, in general, an artificially inflated estimate of the effectiveness of seat belt use. This has been found by Eluru and Bhat (2007), while Winston et al. (2006) demonstrate similar results in the context of air bag effectiveness.

[3] The GOR structure discussed here is quite different from other generalizations of the ordered structure used in Quddus et al. (2010) and Wang et al. (2011). Specifically, the generalization in these other papers, which is based on Fu (1998) and Williams (2006), cannot be cast in the form of a continuous underlying process (risk propensity) that gets mapped to the observed outcomes (injury levels) in the way the SOR model or our GOR structure can be. More generally, the connection between the underlying injury risk propensity scale and the observed injury outcomes becomes ambiguous and unclear in this alternative form of generalization (see Greene and Hensher, 2009, p. 198). Further, this alternative generalization has the problem that the probabilities need not be positive for some combinations of explanatory variables, and it is impossible to resolve this problem unless one imposes restrictions on the generalization that brings it back to the simple SOR structure.