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On the causes of car accidents on German Autobahn connectors

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DISKUSSIONSBEITRÄGE ZUR STATISTIK UND ÖKONOMETRIE

SEMINAR FÜR WIRTSCHAFTS- UND SOZIALSTATISTIK
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Abstract

The work at hand tries to identify factors that explain accidents on German Autobahn connectors. To find these factors the empirical study makes use of count data models. The findings are based on a set of 197 ramps, which we classified into three distinct types of ramps. For these ramps accident data was available for a period of 3 years (January 2003 until December 2005). The Negative Binomial model proved to be an appropriate model for our cross-sectional setting in detecting factors that cause accidents. The heterogeneity in our dataset forced us to investigate the three different types of ramps separately. By comparing results of the aggregated model and results of the ramp-specific models ramp-type-independent as well as ramp-type-specific factors were identified. The most significant variable in all models was a measure of the average daily traffic. For geometric variables not only continuous effects were found to be significant but also threshold effects.

Keywords: Highway connectors, German Autobahn, accident causes, Poisson regression, Negative Binomial regression.

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1 Introduction

The traffic on German highways, the so called "Autobahn", has been increasing drastically over the past years and is expected to grow further in the future due to the geographical location of Germany in the center of Europe. The increase in traffic surpasses not only the economic growth, but also the speed of construction of roads. If the road network is not significantly expanded the increasing number of vehicles on German Autobahns will certainly lead to an increasing number of accidents. Due to the limitations in the possible expansions of the Autobahn, in particular in the short run, an important task is to discover specific accident factors and their influence on accident probabilities. Having this information may allow to implement low-cost, short-term improvements in the prevention of accidents on existing Autobahn-segments. One of the most dangerous situations for car drivers on Autobahns is the weaving out of the flow of traffic via a road connector. In the years 2003-2005 nearly 8000 accidents happened on road connectors on Autobahns in the administrative district Düsseldorf, which is the region we focus on in this study. Due to the safety-standards on Autobahns "only" 10 of these accidents ended deadly, but the economic damage was remarkable.

Several studies found that about 90% of all accidents are at least partly caused by human failure, see e.g. Treat et al. [1977]. As driver behavior is influenced by the whole environment the goal of road construction should be to construct road sites that forgive human errors. However, road connectors are constructed differently subject to distinct traffic volumes or geographical constraints. The question at hand is which factors cause the errors of the drivers. Our study contributes to the existing research by trying to find some answers to this question for the case of road connectors. The aim is to find a model that explains the number or the probability of accidents at various types of Autobahn connectors, which is a statistical problem. However, due to the nature of the problem at hand the use of standard linear regression models is inappropriate, as argued by Jovanis and Chang [1986] and Miaou and Lum [1993]. The variable of interest, namely the number of accidents during a given time interval, suggests the use of count data models in our situation.

Miaou and Lum [1993], who investigate the relationship between truck accidents and roadway geometries, and Pickering et al. [1986] used the Poisson regression model to study accident data. Hauer et al. [1988], on the other hand, introduced the more appropriate Negative Binomial model to find that traffic flow and various road characteristics have a significant effect on the number of accidents on 145 signalized intersections in Toronto. Another study applying the Negative Binomial model to determine the causes of car accidents is Shankar et al. [1995], who analyze accidents on a 61km portion of the Interstate 90 near Seattle. Both Poisson and Negative Binomial models require a cross sectional setting. Chin and Quddus [2003] found that panel count data models have the advantage that they are able to deal with spatial or temporal effects in contrast to cross sectional count data models. They analyzed different types of accidents on 52 signalized intersections in Singapore using a set of 32 variables containing geometric variables, traffic volume variables and regulatory controls. Another paper applying panel data techniques to study accident data is Shankar et al. [1998]. As accident data have the trend to have more zero-observations than are predicted by standard count data models, so-called zero-inflated models have been introduced into traffic accident research and applied by e.g. Shankar et al. [1997] who investigated accidents on arterials in Washington with two years of accident data and concluded that zero-inflated models have a great flexibility in uncovering processes affecting accident frequencies on roadway sections. Lee and Mannering [2002] got promising results in applying zero-inflated models in contrast to not-zero-inflated models in the context of run-off-roadway accidents by using a 96.6km section of highway in Washington State. However, Washington et al. [2003] and Lord et al. [2005] provide arguments against the use of zero-inflated models in the analysis of accident data.

None of the above-mentioned studies analyzes data on highway connectors, but the statistical techniques and explanatory variables they use are similar to the ones used here. We make an attempt to find an appropriate model for our dataset of 3 years of accidents at connectors on Autobahns in the administrative district Düsseldorf (approximately a fifth of the area of North Rhine-Westphalia). In our analysis we consider more than 60 Autobahn connectors with 197 ramps in an area of approximately 2300km^2 using traffic data and geometric variables both in continuous form and allowing for threshold effects.

The rest of the paper is organized as follows. In the next section we describe our methodology. Section 3 introduces and explains our dataset, whereas the empirical results can be found in Section 4. Section 5 concludes and the Appendix contains some additional information on the data.

2 Methodology

As our variable of interest, the number of accidents on highway connectors, is a so called *count variable* linear regression models are not the appropriate tool for our analysis. Instead we make use of count data regression models that have been designed for the specific purpose of modeling discrete count variables. In this section we give an overview of existing models, their estimation and techniques to compare competing specifications.

2.1 Count data models

The benchmark model for count data is the Poisson regression model, which is derived from the Poisson distribution. A random variable Y is said to follow a Poisson distribution if

$$P[Y = y] = \frac{e^{-\mu}(\mu)^y}{y!}, \qquad y = 0, 1, 2, ... \tag{2.1}$$

where $\mu > 0$ is the intensity or rate parameter that is also the mean and variance of Y. Equation (2.1) measures the probability of y occurrences of an event during a unit of time. The equality of the mean and the variance is called the *equidispersion*-property of the Poisson distribution. The Poisson regression model is obtained by allowing the intensity parameter μ to depend on a set of regressors. We assume a cross sectional setting with n independent observations, the i^{th} of which being $(y_i, \mathbf{x}_i)$, where y_i is the number of occurrences of the event of interest and $\mathbf{x}_i$ is the vector of linearly independent regressors that determine the intensity of y_i. Further, it is assumed that the dependence is parametrically exact and involves no other source of stochastic variation. Then the Poisson regression model is defined by

$$f(y_i|\mathbf{x}_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, \qquad y_i = 0, 1, 2, ... \tag{2.2}$$

with

$$\mu(\mathbf{x}_i) = \exp(\mathbf{x}_i'\boldsymbol{\beta}), \tag{2.3}$$

where the log-linear dependence of μ_i on $\mathbf{x}_i$ assures that the intensity parameter is always positive. The assumption that next to the covariates there is no other source of stochastic variation implies that the equality of the mean and variance carries over to the Poisson regression model. However, as equidispersion is unlikely to hold in reality a natural extension of the model is to allow for unobserved heterogeneity. Unobserved heterogeneity arises when the covariates do not account for the full amount of individual heterogeneity. One can think of unobserved heterogeneity as a problem of omitted variables. Assume the true conditional mean equation instead of 2.3 is

$$\theta_i = \exp(\mathbf{x}_i'\boldsymbol{\beta} + \mathrm{z}_i'\gamma), \tag{2.4}$$

where z_i are unobserved by the econometrician. Let $\exp(\mathbf{x}_i'\boldsymbol{\beta}) = \mu_i$ and $\exp(\mathrm{z}_i'\gamma) = \nu_i$. In a linear regression model the omitted variable bias arises whenever $\mathbf{x}_i$ and z_i are correlated. Next to measurement errors, omitted variables are a standard argument for introducing a stochastic relation with additive error term. However, the stochastic nature of the Poisson Regression Model is different. Y_i is a random variable because the count process is intrinsically stochastic, given an intensity μ that is measured without error. This means that a model with unobserved heterogeneity cannot be Poisson distributed. If we let $\varepsilon_i = \ln \nu_i$ then we see that the error is additive on a logarithmic scale, $\theta_i = \exp(\mathbf{x}_i'\boldsymbol{\beta} + \varepsilon_i)$ and we can write (2.4) as

$$\theta_i = \mu_i \nu_i, \qquad \nu_i > 0. \tag{2.5}$$

Note that it is assumed that μ_i and ν_i are independent. The marginal distribution Y_i can be obtained by integrating the joint distribution over ν_i:

$$h(y_i|\mu_i) = \int f(y_i|\mu_i, \nu_i) g(\nu_i) d\nu_i, \tag{2.6}$$

where $g(\nu_i)$ is the density of ν_i. If for $g(\nu_i)$ you choose the gamma distribution given by

$$g(\nu_i|\delta, \phi) = \frac{\delta^\phi}{\Gamma(\delta)} \nu_i^{\delta-1} e^{-\nu_i \phi} \tag{2.7}$$

with parameters δ and ϕ and make the restriction $\delta = \phi$, the integral in 2.6 can be solved analytically. Setting $\delta \equiv \alpha^{-1}$ gives us the Negative Binomial distribution

$$h(y_i|\mu_i, \alpha) = \frac{\Gamma(\alpha^{-1} + y_i)}{\Gamma(\alpha^{-1})\Gamma(y_i + 1)} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}} \left(\frac{\mu_i}{\alpha^{-1} + \mu_i}\right)^{y_i}. \tag{2.8}$$

The mean and variance of this distribution are:

$$\begin{aligned} \mathsf{E}[Y_i|\mu_i, \alpha] &= \mu_i && \text{and} \\ \mathsf{V}[Y_i|\mu_i, \alpha] &= \mu_i(1 + \alpha\mu_i) > \mu. \end{aligned}$$

Thus for $\alpha > 0$ this model allows for overdispersion. Cameron and Trivedi [1986] generalized this result to be more flexible in specifying the variance function by replacing α^{-1} by $\alpha^{-1}\mu_i^{2-p}$. The density then generalizes to

$$h(y_i|\mu_i,\alpha) = \frac{\Gamma(\alpha^{-1}\mu_i^{2-p}+y_i)}{\Gamma(\alpha^{-1}\mu_i^{2-p})\Gamma(y_i+1)}\left(\frac{\alpha^{-1}\mu_i^{2-p}}{\alpha^{-1}\mu_i^{2-p}+\mu_i}\right)^{\alpha^{-1}\mu_i^{2-p}}\left(\frac{\mu_i}{\alpha^{-1}\mu_i^{2-p}+\mu_i}\right)^{y_i}, \tag{2.9}$$

with the first two moments

$$\begin{aligned} \mathsf{E}[Y_i] &= \mu_i \qquad \text{and} \\ \mathsf{V}[Y_i] &= \mu_i + \alpha\mu_i^p. \end{aligned} \tag{2.10}$$

Depending on the choice of p one is able to get e.g. a conditional variance function that is a linear or a quadratic function of the mean. Using the same exponential mean function as in the Poisson regression the two most common forms of the Negative Binomial model are the $\mathsf{NB1}$ regression ($p = 1$) model and the $\mathsf{NB2}$ regression ($p = 2$) model.

2.2 Estimation and inference

Both Poisson and Negative Binomial models are estimated by maximum likelihood estimation (MLE). The log-likelihood function of the Poisson regression is

$$\ln\mathsf{L}(\boldsymbol{\beta}) = \sum_{i=1}^{n}\{y_i\mathbf{x}_i'\boldsymbol{\beta} - \exp(\mathbf{x}_i'\boldsymbol{\beta}) - \ln y_i!\}. \tag{2.11}$$

The first order conditions that yield the Poisson Maximum Likelihood Estimator (Poisson MLE), $\boldsymbol{\beta}_{\mathsf{P}}$, are given by

$$\sum_{i=1}^{n}(y_i - \exp(\mathbf{x}_i'\boldsymbol{\beta}))\mathbf{x}_i' = \mathbf{0}, \tag{2.12}$$

which must be solved numerically. Under a correct model specification MLE is consistent, asymptotically normal and efficient. Note that it is crucial that the conditional mean equation is correctly specified and that the assumption of equidispersion is satisfied. In the case of overdispersion MLE t-statistics are inflated, which can lead to too optimistic conclusions about the statistical significance of regressors.

The assumption that Y_i is Poisson distributed can be relaxed considerably as studied in Gourieroux et al. [1984b,a]. Given a correctly specified mean, the pseudo MLE based on a density from the linear exponential family (LEF) is consistent. This allows the assumption of equidispersion to be relaxed. In particular, specific function forms for the variance function like those for the NB1 and NB2 model can be assumed to estimate the covariance matrix of $\boldsymbol{\beta}_{\mathsf{P}}$ or the form of the variance can be unspecified and either a robust sandwich (RS) estimator or bootstrap (B) standard errors can be used.

For the Negative Binomial model we only present the log-likelihood function for the NB2 model to save space. It is given by

$$\begin{aligned} \ln \mathsf{L}(\alpha, \beta) &= \sum_{i=1}^{n} \left\{ \left(\sum_{j=0}^{y_i - 1} \ln(j + \alpha^{-1}) \right) - \ln y_i! \right. \\ &\left. - (y_i + \alpha^{-1}) \ln(1 + \alpha \exp(\mathbf{x}_i' \boldsymbol{\beta})) + y_i \ln \alpha + y_i \mathbf{x}_i' \boldsymbol{\beta} \right\}. \end{aligned} \quad (2.13)$$

The NB2 MLE, $(\hat{\boldsymbol{\beta}}_{\mathsf{NB2}}, \hat{\alpha}_{\mathsf{NB2}})$, is the solution to the first-order conditions:

$$\sum_{i=1}^{n} \frac{y_i - \mu_i}{1 + \alpha \mu_i} \mathbf{x}_i = \mathbf{0},$$

$$\sum_{i=1}^{n} \left\{ \frac{1}{\alpha^2} \left(\ln(1 + \alpha \mu_i) - \sum_{j=1}^{y_i - 1} \frac{1}{(j + \alpha^{-1})} \right) + \frac{y_i - \mu_i}{\alpha(1 + \alpha \mu_i)} \right\} = 0. \quad (2.14)$$

Given a correct specification of the distribution

$$\begin{bmatrix} \hat{\boldsymbol{\beta}}_{\mathsf{NB2}} \\ \hat{\alpha}_{\mathsf{NB2}} \end{bmatrix} \overset{a}{\sim} \mathsf{N} \left(\begin{bmatrix} \boldsymbol{\beta} \\ \alpha \end{bmatrix}, \begin{bmatrix} \mathsf{V}_{\mathsf{ML}}[\hat{\boldsymbol{\beta}}_{\mathsf{NB2}}] & \mathsf{Cov}_{\mathsf{ML}}[\hat{\boldsymbol{\beta}}_{\mathsf{NB2}}, \hat{\alpha}_{\mathsf{NB2}}] \\ \mathsf{Cov}_{\mathsf{ML}}[\hat{\boldsymbol{\beta}}_{\mathsf{NB2}}, \hat{\alpha}_{\mathsf{NB2}}] & \mathsf{V}_{\mathsf{ML}}[\hat{\alpha}_{\mathsf{NB2}}] \end{bmatrix} \right), \quad (2.15)$$

where

$$\mathsf{V}_{\mathsf{ML}}[\hat{\boldsymbol{\beta}}_{\mathsf{NB2}}] = \left(\sum_{i=1}^{n} \frac{\mu_i}{1+\alpha\mu_i}\mathbf{x}_i'\mathbf{x}_i\right)^{-1}, \tag{2.16}$$

$$\mathsf{V}_{\mathsf{ML}}[\hat{\alpha}_{\mathsf{NB2}}] = \left(\sum_{i=1}^{n} \frac{1}{\alpha^4}\left(\ln(1+\alpha\mu_i) - \sum_{j=0}^{y_i-1}\frac{1}{j+\alpha^{-1}}\right)^2 + \frac{\mu_i}{\alpha^2(1+\alpha\mu_i)^{-1}}\right)^{-1}, \tag{2.17}$$

$$\mathsf{Cov}_{\mathsf{ML}}[\hat{\boldsymbol{\beta}}_{\mathsf{NB2}}, \hat{\alpha}_{\mathsf{NB2}}] = \mathbf{0}. \tag{2.18}$$

The NB2 MLE is robust to distributional misspecifications for specified α (as it is a member of LEF). So provided the conditional mean is correctly specified, the NB2 MLE is consistent for β. If there is any distributional misspecification, the maximum likelihood standard errors are in general inconsistent. They are also inconsistent if the conditional variance function is not correctly specified. Furthermore, even if the variance function is correctly specified, failure of the Negative Binomial assumption leads to evaluation of (2.16) at an inconsistent estimate of α. Consistent standard error can be obtained using a robust sandwich estimator or by using an i.i.d. bootstrap. Note that Negative Binomial models other than NB2 are not robust to distributional misspecifications.

2.3 Diagnostics and model comparison

2.3.1 Testing for overdispersion

In order to decide between the competing models it is important to test for overdispersion in the data. Besides comparing the sample mean and variance, a simple formal test can be performed by noting that the Negative Binomial model reduces to the Poisson model when $\alpha = 0$. Thus the null hypothesis of equidispersion can be tested by estimating the Negative Binomial and Poisson models and performing a likelihood ratio (LR) test for $H_0 : \alpha = 0$. Since α is restricted to be positive the LR statistic asymptotically has probability mass of a half at zero and a half $\chi^2(1)$ distribution above 0. The critical value is then $\chi^2_{1-2\delta}(1)$ rather than $\chi^2_{1-\delta}(1)$ if testing at level δ.

2.3.2 Residuals and goodness-of-fit measures

For count data models residuals cannot be defined as easily as for linear regression models and for count data there is no residual-type that has zero mean, constant variance and a symmetric distribution. This also means that R^2 measures can be defined in more than one way. If we assume that Y_i is generated by a LEF density we can use the *deviance residual*, which is defined by

$$d_i = \text{sign}(y_i - \hat{\mu}_i)\sqrt{2\{l(y_i) - l(\hat{\mu}_i)\}}, \tag{2.19}$$

where $l(\hat{\mu}_i)$ is the log density of Y evaluated at $\mu = \hat{\mu}_i$ and $l(y)$ is the log density evaluated at $\mu = y$. It can be shown that for the normal distribution with σ^2 known, $d_i = (y_i - \mu_i)/\sigma$, which is the usual standardized residual.

For the Poisson Model this residual is

$$d_i = \text{sign}(y_i - \hat{\mu}_i)\sqrt{2\left\{y_i \ln\frac{y_i}{\hat{\mu}_i} - (y_i - \hat{\mu}_i)\right\}}, \tag{2.20}$$

with $y \ln y \equiv 0$ if $y = 0$.

For the $\mathsf{NB2}$ Model with α known this residual is

$$d_i = \text{sign}(y_i - \hat{\mu}_i)\sqrt{2\left\{y_i \ln\frac{y_i}{\hat{\mu}_i} - (y_i + \alpha^{-1})\ln\frac{y_i + \alpha^{-1}}{\hat{\mu}_i + \alpha^{-1}}\right\}}, \tag{2.21}$$

with $y \ln y \equiv 0$ if $y = 0$.

As the deviance defined in (2.19) is the generalization of the sum-of-squares-concept for non-linear models, an R^2-measure based on the decomposition of the deviance was proposed by Cameron and Windmeijer [1996]:

$$D(\boldsymbol{y}, \bar{\boldsymbol{y}}) = D(\boldsymbol{y}, \hat{\boldsymbol{\mu}}) + D(\hat{\boldsymbol{\mu}}, \bar{\boldsymbol{y}}), \tag{2.22}$$

where $D(\boldsymbol{y}, \bar{\boldsymbol{y}})$ is the deviance in the intercept only model, $D(\boldsymbol{y}, \hat{\boldsymbol{\mu}})$ is the deviance in the fitted model, i.e. the analogue to the residual variance, and $D(\hat{\boldsymbol{\mu}}, \bar{\boldsymbol{y}})$ is the explained deviance. Then

$$R^2_{\mathsf{DEV}} = 1 - \frac{D(\boldsymbol{y}, \hat{\boldsymbol{\mu}})}{D(\boldsymbol{y}, \bar{\boldsymbol{y}})}, \tag{2.23}$$

which measures the reduction in deviance due to inclusion of regressors. R^2_{DEV} lies between 0 and 1 and increases when regressors are added.

For the Poisson Regression Model it can be shown that

$$R^2_{\mathsf{DEV,\ P}} = \frac{\sum_{i=1}^n y_i \ln\left(\frac{\hat{\mu}_i}{\bar{y}}\right) - (y_i - \hat{\mu}_i)}{\sum_{i=1}^n y_i \ln\left(\frac{y_i}{\bar{y}}\right)} \tag{2.24}$$

and for NB2 Model

$$R^2_{\mathsf{DEV,\ NB2}} = \frac{\sum_{i=1}^n y_i \ln\left(\frac{y_i}{\hat{\mu}_i}\right) - (y_i + \hat{\alpha}^{-1}) \ln\left(\frac{y_i + \hat{\alpha}^{-1}}{\hat{\mu}_i + \hat{\alpha}^{-1}}\right)}{\sum_{i=1}^n y_i \ln\left(\frac{y_i}{\bar{y}}\right) - (y_i + \hat{\alpha}^{-1}) \ln\left(\frac{y_i + \hat{\alpha}^{-1}}{\bar{y} + \hat{\alpha}^{-1}}\right)}, \tag{2.25}$$

where $\hat{\alpha}$ is the estimate of α in the fitted model. However $R^2_{\mathsf{DEV,\ P}}$ and $R^2_{\mathsf{DEV,\ NB2}}$ have different denominators and are thus not directly comparable. For data that are considerably overdispersed it is likely that $R^2_{\mathsf{DEV,\ P}} > R^2_{\mathsf{DEV,\ NB2}}$.

Additionally, competing and potentially non-nested models can be compared by looking at information criteria, where the model that minimizes the information criterion is selected to have the better fit. The two information criteria that are usually considered are the *Akaike Information criterion* (AIC) proposed by Akaike [1973] and defined as

$$\mathsf{AIC} = -2 \ln \mathsf{L} + 2k, \tag{2.26}$$

and the Bayesian Information criterion (BIC) proposed by Schwarz [1978] and given by

$$\mathsf{BIC} = -2 \ln \mathsf{L} + (\ln n)k, \tag{2.27}$$

where k is the number of parameters in the model. Note that the BIC places a larger penalty on additional regressors and thus lead to the selection of more parsimonious models.

3 Data

In this section we describe important terms and introduce the dataset we use in this study. Further details about the data can be found in the Appendix.

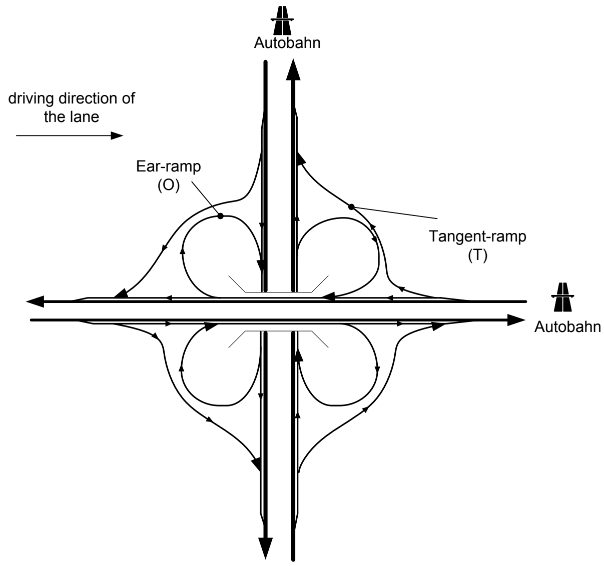

Figure 1: Autobahn-Autobahn - Connector

3.1 Clarification of Terms

In order to understand the meaning of the data and the variables presented in this chapter some terms have to be clarified first. It will be distinguished between the terms connector, ramp and curve. Figures 1 shows a schematic picture of a connector for two Autobahns. This connector consists of 8 ramps and each ramp consists of at least one curve. One has to distinguish between different types of connectors, namely connectors connecting two Autobahns as in Figure 1 and connectors connecting an Autobahn with an inferior road as in Figure 2. The schematic pictures present only two shapes of connectors as the form varies due to construction constraints. For the ramps one can distinguish between tangents, ears, egress-ramps and drive-up ramps. After a preliminary analysis drive-up-ramps are not considered here. This decision is based on two arguments. First, many variables that can be gathered for the other types of ramps, like the length of a declaration lane, cannot be found for this type of ramps and hence the heterogeneity in the dataset would be increase. Second, on these ramps significantly fewer accidents happen than on the other ramps. One could argue that the fact that less accidents happen at these ramps might be an interesting fact that should not be neglected in a

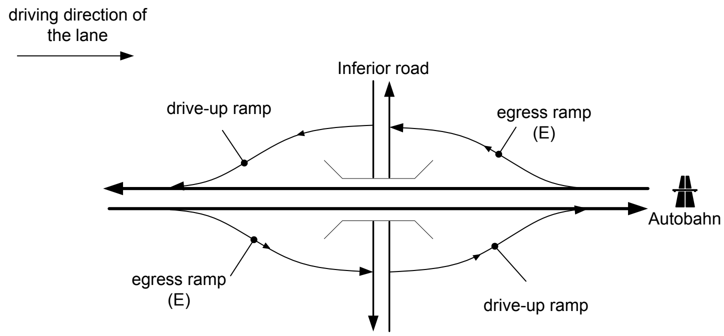

Figure 2: Autobahn-Inferior Road - Connector

statistical analysis. However, we are certain that the low number of accidents is due to the fact that the speed at which cars drive up on such a ramp is significantly lower than on the other ramps, as the speed limit on inferior roads is lower than on the Autobahn. Thus we only consider ramps in the analysis on which cars leave one specific Autobahn and change onto another Autobahn or an inferior road. For the sake of simplicity tangent ramps, ear-ramps and egress-ramps will be called T-ramps, O-ramps and E-ramps respectively.

3.2 Data description

Our data provides the following information: details on individual accidents, traffic flow data and geometrical properties of the ramps. We describe each type in turn.

Accident data The raw data on accidents we study in this paper was offered by the "Autobahnpolizei Düsseldorf", the highway police for the district Düsseldorf. The dataset contains detailed information for all reported accidents on Autobahns in the administrative district in the time period January 2003 until December 2005. This amounts to a total of 39032 accidents (12887 in 2003, 13433 in 2004 and 12712 in 2005). The detailed information includes the exact point in time of the accident, the location of the accident, the type and number of vehicles involved, severity and type of the accident, information on the driver, sight conditions, and road sleekness. Out of the

Table 1: Descriptive Statistics, Accidents, whole sample period

	all ramps	*E-ramps*	*O-ramps*	*T-ramps*
Min number of accidents on a ramp	0	0	0	0
Max number of accidents on a ramp	103	76	99	103
Mean number of accidents per ramp	15.32	10.97	15.86	21.03
Mode	4	4	2	4
Median	9	7	11	12
Standard deviation	18.53	12.01	18.56	23.84
Variance	343.33	144.20	344.48	568.44
Inter Quartile Range	15	12	18	25
Total number of accidents	3048	1042	555	1451
Number of ramps	197	95	33	69
Number of zero-accident ramps	10	5	1	4

nearly 40000 accidents reported we filtered out the accidents that happened on ramps of the various connectors. Given the constraints imposed by the datasets we had a total of 197 ramps under investigation of which 95 were E-ramps, 33 were O-ramps and 69 were T-ramps. Additionally we have to stress that as we are using Count models we have to disregard the detailed information of the accidents. After the filtering process a total of 3048 accidents was to be analyzed. This is due to the fact that count models are based on aggregated counts over a certain time period at a particular location. Table 1 shows some descriptive statistics for accidents on the different types of ramps. The significant differences in the mean accident numbers for the different types of ramps is eye-catching. Therefore it might be interesting to investigate the accidents for the different types separately and not only for all ramps together, which has the additional advantage of reducing the heterogeneity in the data at the price of having fewer observations.

A phenomenon that is often present in accident data analysis is the predominance of zero-observations, which calls for the use of zero inflated models, i.e. count data models that explicitly account for the presence of a large number of zero-observations. Lord et al. [2005] concluded that excess zeros indicate an inappropriate choice of time scale. Referring to Table 1, for neither ramp-type the mode is zero. We have only 10 zero-observations out of the 197 ramps (5 E-ramps, 1 O-ramp and 4 T-ramps). On the other hand on 35 ramps 25 or more accidents happened in our sample period of three years. Furthermore, Cheng and Washington [2005] found that three years of crash-history data provides an appropriate crash history duration, which initially motivated our choice of the data period. Therefore we decided against the use of zero inflated models in our analysis.

Traffic flow data The traffic flow data was offered by the Landesbetrieb Straßenbau Nordrhein-Westfalen (abbreviated: Straßen.NRW). This institution is responsible for the planning, the construction and the maintenance of the Autobahn in the area of North Rhine-Westphalia.

The traffic volume is counted automatically by so-called induction loops. The loops additionally recognize the length of the car that passed the loop and categorizes it into the group of cars smaller than 7.50 meters and the group of cars larger than 7.50 meters. For ease of writing we will use the term passenger cars for the prior and trucks for the latter group of cars.

The raw dataset contained daily data for all induction loops on Autobahns in the administrative district Düsseldorf for the period 4^{th} of March 2005 until 7^{th} of March 2006. Note that the sample period is not exactly the same as for the accident data. However, we believe that the available data captures the essential information on the amount of traffic and can be used without any reservations. For each day the dataset contains information on the number of passenger cars and the number of trucks that passed this loop. Additionally there are observations for six sub periods of each day, namely the periods between 0am and 6am, 7am and 9am, 6am and 10am, 3pm and 7pm, 6am and 10pm and 10pm and 12pm. From this data we filtered out the data of loops that lie on the ramps of interest. Finally we had daily observations for 218 loops, of which 197 could be used in the empirical part due to missing observation caused, e.g., by defect induction loops.

For a cross sectional analysis we calculated the average daily traffic (abbreviated ADT) for each ramp. The ADT for ramp i is defined as:

$$\mathrm{ADT}_i = \frac{1}{T_i} \sum_{t=1}^{T_i} \mathrm{TV}_{i,t}, \tag{3.1}$$

where $\mathrm{TV}_{i,t}$ is the traffic volume on ramp i on day t and T_i is the number of daily observations we had for ramp i. We also calculated the truck percentage on each ramp:

$$\text{Truck Percentage} = \frac{\mathrm{ADT}_{\text{Trucks}}}{\mathrm{ADT}_{\text{Trucks}} + \mathrm{ADT}_{\text{PC}}}. \tag{3.2}$$

Table 2 shows some statistics for the variable ADT. It is imminent that there is a large spread in the distribution of traffic volume on the various ramps.

Table 2: Descriptive Statistics ADT, whole sample period

Average Daily Traffic (ADT)	
All Vehicles ($\mathbf{ADT_{Total}}$)	
Mean	6630.8
Maximum	28178.47
Minimum	579.26
Standard Deviation	4579.36
Passenger Cars ($\mathbf{ADT_{PC}}$)	
Mean	5173.95
Maximum	25094.72
Minimum	472.57
Standard Deviation	3582.56
Trucks ($\mathbf{ADT_{Trucks}}$)	
Mean	1456.85
Maximum	15844.4
Minimum	51.94
Standard Deviation	2051.49

Geometry data The geometry data was collected manually by using satellite images of the ramps of interest. Some details on how the variables were constructed can be found in the Appendix. Table 3 presents a list of the geometry variables along with their descriptive statistics for all ramps jointly.[1] Next, a number of dummy variables were constructed that are shown in Table 4. Finally, we have information on the type of surface lying on the ramps. Three different types of surface have to be distinguished, melted or mastic asphalt (MA), mastic asphalt using chipping MAC and asphaltic concrete (AC). Table 5 shows the frequency distribution of the different surface types on the investigated ramps. The main advantages of the different surface types, without going into deeper details (taken from Richter and Heindel [2004]), are: MA is known to have a good grip with the trade-off of being a quite loud surface type. AC has the worst grip however it is the cheapest of the three surface types. Roads build out of MAC are very durable and thus

[1]Descriptive statistics for the individual ramp types are available upon request.

Table 3: Descriptive Statistics of Geometry Variables (all ramps)

Variable	*Minimum*	*Maximum*	*Mean*	*Stand.Dev.*
Length of the ramp (in meters)	49.56	1868.15	335.12	243.95
Length of the declaration lane (in meters)	0.00	902.24	258.00	158.08
Total Width of the lanes on the ramp (in meters)	3.30	8.19	4.93	1.13
Width per Lane (in meters)	3.02	7.16	4.33	0.73
Width of the shoulder lane (in meters)	0.00	4.81	2.14	1.40
Radius steepest curve (in meters)	28.43	1428.47	164.78	195.56
Total Angle passed (in degrees)	0.00	305.15	115.78	92.75
Absolute Total Angle passed (in degrees)	4.32	305.15	148.29	83.97
Angle of the steepest curve (in degrees)	3.76	302.00	119.86	86.47
Length of the steepest curve (in meters)	30.05	1259.25	205.49	155.90
Number of Lanes on the Ramp	1	2	1.17	0.38
Number of Inflection Points on the Ramp	0	4	0.59	0.86
Position of the steepest curve on the Ramp	1	4	1.45	0.72
Number of Curves on the Ramp	1	6	1.72	0.93
Number of Lanes on the Autobahn leaving	1	3	2.48	0.51

Table 4: Descriptive Statistics Dummy Variables (all ramps)

Variable	*Mean*	*Stand.Dev.*
Decl. lane comes from Autobahn lane	0.06	0.24
A curve gets steeper	0.24	0.43
A curve gets less steep	0.13	0.34
Incline on the ramp	0.50	0.50
Decline on the ramp	0.54	0.50
Trees inside	0.87	0.33
Trees outside	0.78	0.42
Crossing lane at the access of the ramp	0.22	0.42
Crossing lane at the exit of the ramp	0.22	0.41
Median between Autobahn and decl. lane	0.38	0.49

Table 5: Frequency Distribution of Surface Types

Surface	*Frequency*
AC	57
MA	136
MAC	4

MAC is perfect for roads with high traffic exposure.

3.3 Missing information

In this section we shortly discuss which information might have been worth to be collected, but could not be obtained.

First of all we did not have any information on traffic signs on the connectors. As on German Autobahns there is no general speed limit, this is also the case on the ramps. However, on several ramps there are speed limit signs. "Slippery road"-signs can also be found on several ramps. In our point of view, knowing the existence of signs would have enriched our analysis.

The satellite images we used for the collection of our geometry variables did not give us any information on standing guardrails on the ramps. An interesting hypothesis that might have been investigated would have been if guardrails make the driver feel confident and thus leading to higher accident rates.

One shortcoming of our dataset was the short period of our traffic flow variable, not allowing us for a substantiated panel data approach and hence making us ignoring information on seasonality. As a panel approach was not conducted no weather variables have been used in our research. As the area of the connectors investigated is quite small (around 2300km^2) we think there are no significant differences in weather-conditions for aggregated data. Nevertheless, in a panel approach it might have been interesting to take weather into consideration, not only to explain cross-sectional differences, but also to explain seasonality.

The information we had on the surface of the road was also quite rudimentary. Without doubt, not only the type of the surface, but also the age of the surface has an impact on the grip of the road and thus an influence on the accident frequency.

4 Empirical findings

In this section we apply the count data models introduced in Section 2 to the accident data on German Autobahn connectors we introduced in Section 3. We start with a preliminary analysis studying the time series properties of our data to motivate the use of cross sectional models only. Next we present some evidence of overdispersion in our data that justifies the use of the Negative

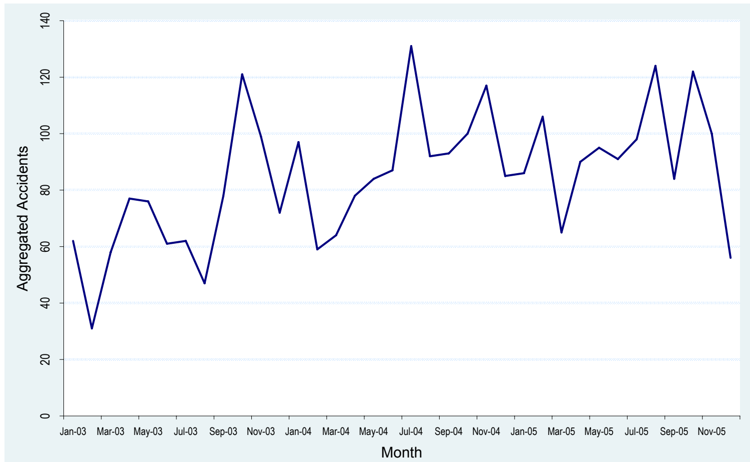

Figure 3: Monthly Time Series of aggregated accidents (all ramp-types)

Binomial model instead of the more restrictive Poisson regression. Thus we apply the Negative Binomial model to the complete dataset, as well as to each type of ramp separately. After finding appropriate models for our data we interpret the results and try to draw conclusions regarding the practical relevance of our results.

Before we start presenting our results we would like to note the following. First, Table 6 presents all variables we use along with their abbreviations. Second, for the regressions the unit of measurement of all ADT-variables was changed to thousands of cars to avoid unreadably small regression results. Finally, we note that the models are numbered by a capital letter M and a consecutive arabic number.

4.1 Preliminary analysis

Figure 3 shows a time series plot of the aggregated accidents for all types of ramps. A clear seasonal effect cannot be seen and we perform a simple OLS-regression of aggregated monthly accidents on the monthly dummies for our sample period of three years. Only the dummy for the month October is significant at a 5% significance level. Additionally we perform an OLS-regression with dummies representing the four seasons of the year. No dummy can significantly catch any seasonal effects. Given that only the October dummy is significant, which is likely the case due to chance given that we perform twelve hypothesis at a 5% significance level, we decide not to make seasonal adjustments.

Next, we estimate a Poisson regression to identify the variable that can explain the number of accidents. We start by adding the variables that seem most obvious to us in having the ability of explaining accident frequencies, such as ADT. Disregarding assumptions about equidispersion for the Poisson regression model we look at the t-statistics calculated with the hessian maximum likelihood (MLH) standard errors and Pseudo-R^2 to get the following preliminary model:

$$\begin{aligned}\overline{\text{nb\_acc}} = \exp(&\beta_0 + \beta_1 \text{ADT\_pc} + \beta_2 \text{ADT\_trucks} + \beta_3 \text{angle\_abs} \\ &+ \beta_4 \text{radius} + \beta_5 \text{length\_ramp} + \beta_6 \text{pos\_steepest} \\ &+ \beta_7 \text{D\_less\_steep} + \beta_8 \text{D\_steeper} + \beta_9 \text{D\_cross\_exit} \\ &+ \beta_{10} \text{D\_trees\_out} + \beta_{11} \text{D\_incline} + \beta_{12} \text{D\_autob\_decl}),\end{aligned} \tag{M1}$$

where $\overline{\text{nb\_acc}}$ indicates the conditional mean of the variable nb_acc. Table 7 shows the variables that are all significant at the 5% significance level (MLH-standard errors). The Pseudo-R^2 calculated with formula (2.24) is $R^2_{\mathsf{DEV}} = 0.3009$. The table also presents standard errors calculated using the alternative approaches introduced in Section 2.2, namely using the formulas for NB1 and NB2, as well as the robust sandwich (RS) method and an i.i.d. bootstrap (B) with 500 bootstrap replications. It is evident that these standard errors are much larger than the MLH-standard errors, which is strong evidence for overdispersion. A further indicator for overdispersion is the sample variance/mean ratio of around 22. This implies that many of the variables in (M1) are not significant, since overdispersion causes inflated t-statistics. Although the various standard errors we presented in this section account for overdispersion they cannot cope with the second flaw of the Poisson regression model, namely non-allowance for unobserved heterogeneity, which is probably the reason for overdispersion in our dataset. As a consequence we will exclusively use Negative Binomial regression to model our data.

4.2 Data analysis with the Negative Binomial model

Initially we considered both the NB1 and NB2 models for our analysis. However, in all cases the AIC and BIC favored the NB2 model, which means that a quadratic variance function seems to model the variation better than a linear function of the mean. Thus we restrict our attention to the NB2 specification. Furthermore, since the NB2 model nests the Poisson regression model when $\alpha = 0$ the null of a Poisson Model and hence the null of equidispersion can be tested with the LR test as described in Section 2.3.1. We report this LR statistic whenever we present the complete results for estimated models, but we already note that the test has p-values of virtually zero for all the model specifications we considered. We start by reporting the results by considering all ramp types jointly, but the descriptive statistics in our data description already suggested investigating the different ramps types separately. This procedure allows us to find out whether the heterogeneity in our data is severe. Although the investigation of the types separately sounds more fruitful we have to deal with the trade-off of having less observations.

4.2.1 Analyzing all ramps

Considering the original variables in our dataset our search for the most appropriate model gave us the following simple model with statistically significant variables at a 5% significance-level:

$$\overline{\text{nb\_acc}} = \exp(\beta_0 + \beta_1 \text{ADT\_pc} + \beta_2 \text{radius} + \beta_3 \text{truck\_perc} + \beta_4 \text{D\_steeper}). \quad \text{(M2)}$$

Note that for the sake of readability we do not report parameter estimates until we have arrived at a final form of the model.[2] It is evident that the NB2 model that accounts for overdispersion leads to a very parsimonious model compared to the (misspecified) Poisson regression. In the next step of our analysis we test for the different functional forms of the regressor ADT_pc: first we will add a quadratic term and then consider the model with the log-transformed variable. This gives us the following two new models:

$$\begin{aligned}\overline{\text{nb\_acc}} = \exp(&\beta_0 + \beta_1 \text{ADT\_pc} + \beta_2 (\text{ADT\_pc})^2 \\ &+ \beta_3 \text{radius} + \beta_4 \text{truck\_perc} + \beta_5 \text{D\_steeper})\end{aligned} \quad \text{(M3)}$$

and

$$\begin{aligned}\overline{\text{nb\_acc}} = \exp(&\beta_0 + \beta_1 \ln(\text{ADT\_pc}) + \beta_2 \text{radius} \\ &+ \beta_3 \text{truck\_perc} + \beta_4 \text{D\_steeper}).\end{aligned} \quad \text{(M4)}$$

Table 8 clearly shows that all evaluation criteria suggest a different functional

[2] Detailed estimation results for the intermediate models are available upon request.

form of ADT_pc than the level-form. However, there is no clear indication whether the squared form is to be preferred over the logarithmic form. In order to get an additional evaluation criterion we conducted the LR-test for non-nested models proposed by Vuong [1989]. The test statistic is equal to 0.2634 and given an asymptotic standard normal distribution of the Vuong test the null hypothesis of equivalence of the models cannot be rejected in favor of any of the models.

Although we do not have any clear indication in favor of any functional form of ADT_pc at this stage of the analysis, we continue presenting only the squared form from Model (M3) in this section as it gave more promising results in the upcoming analysis. As none of the remaining variables was found to have additional significant effects in explaining accident frequencies we investigate whether there are possible threshold effects. We shortly describe the procedure we use to identify the thresholds: We create dummy variables that are one for values exceeding the supposed threshold value and zero otherwise. By varying the threshold-value and comparing the information criteria and the pseudo R^2 we try to determine the actual threshold-value. After we find the threshold we calculate the RS-standard errors and the bootstrapped standard errors to assure that our inference is valid. The notation of the threshold variables is as follows: A "T" in front of the variable will indicate that this is a dummy measuring the threshold and the index-number shows the value of the threshold. This means the variable is 1 for values larger than this threshold and zero otherwise.

Three variables seem to have a threshold effect, namely the length of the declaration lane (length_decl), the total width of the lane(s) (width_lanes) and the position of the steepest curve (pos_steepest). After our threshold-analysis we find the following model that extends model (M3):

$$\begin{aligned}\overline{\text{nb\_acc}} = \exp(&\beta_0 + \beta_1 \text{ADT\_pc} + \beta_2 (\text{ADT\_pc})^2 + \beta_3 \text{radius} \\ &+ \beta_4 \text{truck\_perc} + \beta_5 \text{D\_steeper} + \beta_6 \text{T\_length\_decl}_{180} \\ &+ \beta_7 \text{T\_width\_lanes}_{3.90} + \beta_8 \text{T\_pos\_steepest}_1). \end{aligned} \tag{M5}$$

We would like to note two things for model (M5): 1) the variable width_lanes measures the total width of the officially accessible lanes without accounting for the width of a possible shoulder lane. We also investigated a possible threshold effect of the total width of the official road together with the shoulder lane (so the whole possibly accessible road). However no threshold effect could be found. 2) the variable T_pos_steepest_1 takes on the value one if the first curve is not the steepest curve on the ramp. Table 9 presents the estimation results of this model with the estimated RS and bootstrapped standard errors.

4.2.2 Analyzing E-ramps

With n=95 the majority of ramps in our dataset are egress-ramps. We perform a similar model search as for all ramp types jointly. First of all, it turned out that a model with log-transformed ADT_pc is to be preferred over the specification including a quadratic term. Next we searched for threshold effects and the following two models both turned out to give a good fit for the E-ramps, with the latter being slightly preferable:

$$\begin{aligned}\overline{\text{nb\_acc}} = \exp(\beta_0 + \beta_1 \ln(\text{ADT\_pc}) + \beta_2 \text{nb\_curves} + \beta_3 \text{radius} \\ + \beta_4 \text{truck\_perc} + \beta_5 \text{T\_length\_decl}_{190}).\end{aligned} \tag{M6}$$

and

$$\begin{aligned}\overline{\text{nb\_acc}} = \exp(\beta_0 + \beta_1 \ln(\text{ADT\_pc}) + \beta_2 \text{truck\_perc} \\ + \beta_3 \text{T\_length\_decl}_{190}) + \beta_4 \text{T\_radius}_{90}).\end{aligned} \tag{M7}$$

Tables 10 and 11 presents the regression results along with the goodness-of-fit measures for these models.

4.2.3 Analyzing T-ramps

Out of the 197 ramps in our data 69 were tangent ramps. As in the case of E-ramps there are differences to the estimation results for all types of ramps. However, this time the functional form of ADT_pc with a quadratic term is the appropriate one. The best fitting model turned out to be

$$\begin{aligned}\overline{\text{nb\_acc}} = \exp(\beta_0 + \beta_1 \text{ADT\_pc} + \beta_2 (\text{ADT\_pc})^2 + \beta_3 \text{angle\_abs} \\ + \beta_4 \text{D\_decline} + \beta_5 \text{T\_length\_decl}_{150} + \beta_6 \text{T\_width\_lanes}_{3.90}).\end{aligned} \tag{M8}$$

The regression results can be found in Table 12.

4.2.4 Analyzing O-ramps

For the last type of ramps we have only 33 observations. Probably due to this small sample relatively few variables were found to be statistically significant and we came up with the model

$$\overline{\text{nb\_acc}} = \exp(\beta_0+\beta_1\ln(\text{ADT\_pc})+\beta_2\text{T\_radius}_{48}+\beta_3\text{T\_width\_lanes}_{4.40}) \quad \text{(M9)}$$

with its estimation results given in Table 13.

4.3 Interpretation of the results

Table 14 summarizes the estimated coefficients of the five models. Due to the non-linear nature of the NB-models we also present other measures that may help us in getting a feeling for the magnitude of response of the number of accidents to changes in regressors. In contrast to OLS-regression coefficients the response does not stay constant with varying regressors. The estimated coefficients of the NB2 model can be interpreted as semi-elasticities. The mean-effect-measures "Avg" and "At Avg" give a change in the number of accidents on a ramp due to a one-unit change of regressors. "Avg" is calculated as

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial \mathsf{E}[Y_i|\mathbf{x}_i]}{\partial x_{ij}} = \frac{1}{n}\sum_{i=1}^{n}\beta_j\exp(\mathbf{x}_i'\boldsymbol{\beta}). \tag{4.1}$$

whereas "At Avg" is given by

$$\left.\frac{\partial \mathsf{E}[Y|\mathbf{x}]}{\partial x_j}\right|_{\bar{\mathbf{x}}} = \beta_j\exp(\bar{\mathbf{x}}'\boldsymbol{\beta}), \tag{4.2}$$

The column "Elast" gives $\hat{\beta}_j\bar{\mathrm{x}}_j$, where $\bar{\mathrm{x}}_j$ is the mean of the regressor, which measures the elasticity of $\mathsf{E}[\mathrm{Y}]$ with respect to changes in regressors. Finally, for dummy variables the conditional mean of the dependant variable is $\exp(\hat{\beta}_j)$ times larger if the dummy variable is one rather than zero. The exponential of the estimated coefficients can be found in the last column of the table labeled "Exp".

4.3.1 Interpreting Model (M5), all ramps

The effect of ADT_pc on accidents is the most significant variable in Model (M5). As the variable enters the equation also in a squared form even a constant semi-elasticity is not given. Assume an average ADT_pc of 5000 passenger cars per day, hence ADT_pc=5 and $(\text{ADT\_pc})^2$=25. An increase of 100 cars per day leads to a $0.1 \times (0.2681 - 2 \times 0.0072 \times 5) = 0.01961$

proportionate change or 1.9% change in the expected number of accidents. An increase of truck_perc by 0.1 units, hence an increase of the truck ratio by 10 percentage points leads to an increase in the expected number of accidents by 8.21%. The mean effects Avg suggests that the average effect of a 10 percentage point increase in the ratio of trucks yields to 1.8 more expected accidents per ramp in a time period of three years. The "Avg" estimates for this model are about 27% higher than those of the "representative" ramp given in "At Avg", which is due to the convex exponential mean function. The same phenomenon can therefore be observed for the other models.

The other variables are more interesting from an engineering perspective. For the radius an MLE of -0.1035 indicates that an increase of the radius by 10 meters decreases the expected accident number by slightly more than 1%. To get a feeling for the mean effects assume an average ramp (mean of radius=164 meter). If the radius of the steepest curve of this ramp were increased to 174 meters the expected number of accidents in three years would decrease by 0.188 accidents. Next, a ramp on which a curve gets steeper has a $\exp(0.4886) = 1.63$ times higher expected number of accidents than a ramp on which no curve is getting steeper.

The estimates of the remaining two variables were rather counterintuitive. The estimate of 0.3988 for the coefficient of the variable T_length_decl$_{180}$ suggests that on ramps with declaration lane larger than 180 meters we have to expect $\exp(0.4433) = 1.557$ times more accidents than on ramps with a declaration lane that is smaller than 180 meters. Similarly, the expected number of accidents on ramps with a width of their lanes exceeding 3.9 meters is 1.49 times higher than on ramps with a width of less than 3.9 meters. The estimate of the threshold variable T_pos_steepest$_1$ suggests that we can expect the number of accidents to be 1.4 times higher if the first curve is not the steepest on the ramp. A reason for these three at first glance counterintuitive results might be that an unsafe looking ramp leads to more awareness of the driver. Another explanation is an omitted variables bias, since it is likely that there are stricter speed restrictions (or warning sings) on these unsafe ramps, which in turn would decrease the number of accidents.

4.3.2 Interpreting Model (M6), E-ramps (I)

The results for the first model of the E-ramps are in line with the results we got for all ramps together although ADT_pc enters the model in a different functional form. If the traffic volume increases by 1% the expected number of accidents will increase by 0.7%. A value of -0.33 for the estimated coefficient of nb_curves suggests that if the number of curves on the ramp could be increased by 1 the expected number of accidents would go down by 33%. The mean effect "At Avg" shows us that if we add one curve to the average ramp the expected number of accidents in three years will decrease by 0.38. The truck percentage seems to have a much higher impact on the expected number of accidents for egress-ramps than in a model with all ramps. An increase of the truck-ratio by 10 percentage points leads to an increase in the expected number of accidents by more than 20%. Finally, the threshold effect for the declaration lane seems also to be much more severe for egress ramps. If the declaration lane exceeds 190 meters the expected number of accidents has to be multiplied by the factor 3. Such a high response is surprising, but can again be attributed to the omitted variable bias.

4.3.3 Interpreting Model (M7), E-ramps (II)

The results for the alternative model for egress ramps are similar to the ones reported above. The exponential of the estimated coefficient of T_radius_{90} suggests that there are 45% less expected accidents if the radius of the steepest curve is below 90 meters. The mean effects are also quite interesting for this variable: "Avg" is -6.718. This means that in three years there are on average nearly 7 expected accidents less on ramps if the radius of the steepest curve is not below 90 meters. Together with the results of Model (M6) it cannot be dismissed that there seems to be a strong negative relationship between the radius of the steepest curve on a egress ramp and the number of accidents.

4.3.4 Interpreting Model (M8), T-ramps

Model (M8) is the only model among the five here presented that did not show a significant effect of radius, neither in the continuous form nor as a threshold variable. Nevertheless angle_abs entered the model as a kind of curvature measure. A coefficient of 0.0049 indicates that if angle_abs rises by 10 degrees the expected number of accidents rises by 4.9%. Given the average response over all ramps an increase by 10 degrees leads to 1 more expected accident in three years. A variable we were quite surprised to find in one of the models was D_decline. This variable does not only enter the model significantly, but it does improve the overall fit of the model considerably.

If there is a decline on the ramp the expected number of accidents is 35% smaller. Finally two threshold variables can be found in the model that already were in Model (M5) investigating all ramps. The threshold value of $T\_length\_decl_{150}$ is even 40 meters smaller than before. The exponential of the estimated coefficient implies that if the declaration lane exceeds 150 meter the expected number of accidents increases by a factor of 1.77. The estimates of the other threshold variable imply that if the width of a lane exceeds 3.90 meters we expect the number of accidents to be higher by a factor of 2.4

4.3.5 Interpreting Model (M9), O-ramps

For O-ramps we see that a 1% increase in passenger car flow increases the expected number of accidents by 0.94%. Compared to the estimates of ln(ADT_pc) in Models (M6) and (M7) with values of 0.70 and 0.58 respectively, a proportionate increase of traffic flow has a more severe impact on the number of accidents on O-ramps than it has on E-ramps. Next to the traffic flow only two threshold variables entered the model. The estimated coefficient are for T_radius_{48} as well as for $T\_width\_lanes_{4.40}$ positive, again a counterintuitive result. We conclude that this result is disputable due to our small sample of only 33 observations.

5 Conclusion

The aim of this paper was to find an appropriate statistical model that helps explain accident frequencies on Autobahn connectors in Germany. The nature of the data suggested the use of count data models for the analysis and a Negative Binomial regression model turned out to be the appropriate tool. The available dataset contains detailed accident data on Autobahn for the entire administrative district Düsseldorf for the years 2003 to 2005. In particular, the number of accidents on the connector ramps was extracted as the dependent variable in this study. Additionally, traffic flow data for 197 ramps was available, which can be subdivided in three different ramp-types, the so-called E-ramps (n=95), T-ramps (n=69) and O-ramps (n=33). For all ramps we collected a set of nearly 30 geometry variables. These variables already indicated that the various types of ramps have very different characteristics and the induced heterogeneity by investigating all ramps jointly appeared to be quite severe. The aggregated model contained a mixture of the variables that were also significant in the individual E-ramp and the T-ramp models. Therefore, the resulting estimates from the aggregated model should be interpreted with care, as some effects might be due to one specific type of ramps. Nevertheless if the results of the aggregated model are compared to the results of the specific models one may deduce valuable information. In particular, the dummy variable indicating a curve that gets steeper on a ramp is only significant in our aggregated model, but not in the ramp specific models. We reason that this is a ramp type independent effect that was not found in the ramp specific models due to the small number of observations. Based on our results, on average a ramp on which a curve gets steeper is expected to suffer 11 more accidents in 3 years. As the other variables in the aggregated model can also be found in one of the ramp specific models, conclusions should be based on the estimates of the latter models.

For E-ramps we found that the radius of the steepest curve plays a role in explaining accident frequencies. We could identify a continuous as well as a threshold effect. Ramps with a radius of the steepest curve exceeding 90 meters suffer on average 6.7 accidents less in 3 years. Additionally to the radius a threshold value for the length of the declaration lane could be identified. Surprisingly, less accidents happen if the declaration lane does not exceed the threshold value of 190 meters, but this is likely the results of an omitted variable bias, since no information on road signs and speed restrictions was available.

In the case of T-ramps the absolute total angle of the ramp plays a role. Additionally a decline on the ramp has a negative effect on the expected number of accidents. As in the E-ramps case a, threshold value was identified for the length of the declaration lane with the same counterintuitive sign. For the width of the lane a threshold value of 3.90 meters could be found leading to less accidents if the width of these ramps is smaller than the threshold, which again is a counterintuitive result.

For O-ramps our model could only identify two threshold variables, whose signs are again quite counterintuitive: a threshold value for radius of 48 meters and a threshold value for the width of the lanes of 4.40 meters, but due to the small number of observations we have doubts in the validity of these results.

The final question at hand it whether and how our findings can be used improve the safety of existing Autobahn connectors and to give recommendations in the construction of new ones. The accident factors identified in this study cannot be used for simple short term improvements, which is not surprising, as the easiest and cheapest solution one can think of is putting up additional warning signs and speed restrictions. Since we had no data available on these, and it is likely that these measures were already taken on relatively dangerous connectors, we have to leave the recommendation of simple solutions to future research that includes such information. However, if connectors are build from scratch our results might be helpful. The finding that curves getting steeper yield higher accident frequencies is definitely a result that future planning should not disregard. The radius effect on E-ramps might also be interesting for the design of such ramps. As we not only found a threshold value, but also a continuous effect we can say: *the steeper a curve, the more accidents can be observed* (a 10 meter increase in the radius of the steepest curve decreases the expected number of accidents on a ramp by 1%). The significant positive parameter of the variable absolute total angle in the case of T-ramps can be interpreted as: *the simpler a T-ramp is constructed, the less accidents can be expected.*

In future research, next to using the information not available here one may try to expand the dataset and consider temporal and dynamic effects. However, as our attempt to reveal seasonal effects was not successful this may not be the most promising road to take. It might be more effective to investigate a larger dataset with more ramps, as the number of observations was a limiting factor here.

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A Connectors in the analysis

Table 15 shows a list of all connectors of which ramps have been used in this study. The connectors are sorted by the number of their Autobahn. Connectors of an Autobahn and an inferior road are called *Anschlussstelle* in Germany, which is abbreviated AS in the following table. Connectors of two Autobahns are called *Autobahnkreuz* (abbreviated AK) or *Autobahndreieck* (abbreviated AD). For these types of connectors the Autobahn with the lower number is stated.

Table 15: Connectors in dataset

Autobahn-Number	*Connector-Name*
A2	AS Oberhausen-Königshardt
A2	AK Oberhausen
A3	AK Oberhausen-West
A3	AS Oberhausen-Lirich
A3	AS Dinslaken-Süd
A3	AK Duisburg-Kaiserberg
A3	AS Duisburg-Wedau
A3	AK Ratingen-Ost
A3	AS Mettmann
A40	AK Duisburg
A40	AS Duisburg-Häfen
A40	AS Duisburg-Homberg
A40	AS Duisburg-Rheinhausen
A40	AS Moers-Zentrum
A40	AS Moers
A42	AK Kamp-Lintfort
A42	AS Duisburg Beeck
A42	AK Duisburg-Nord
A42	AS Duisburg-Neumühl
A42	AS Oberhausen-Buschhausen
A42	AS Oberhausen-Zentrum
A42	AS Oberhausen-Neue Mitte
A44	AK Meerbusch
A44	AS Ratingen-Schwarzbach
A44	AS Osterath
A44	AS Düsseldorf-Stockum (W)
A44	AS Düsseldorf-Stockum (O)
A44	AS Düsseldorf Flughafen
A44	AK Düsseldorf-Nord
A46	AK Neuss-Süd

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...continued

Autobahn-Number	*Connector-Name*
A46	AS Neuss-Holzheim
A46	AS Neuss-Uedesheim
A46	AS Düsseldorf-Bilk
A46	AS Düsseldorf-Holthausen
A52	AK Kaarst
A52	AS Kaarst-Nord
A52	AS Bderich
A52	AS Düsseldorf-Rath
A52	AS Ratingen
A52	AS Tiefenbroich
A52	AD Breitscheid
A52	AS Essen-Kettwig
A52	AS Essen-Haarzopf
A52	AS Essen-Rütenscheid
A52	AS Essen-Süd
A52	AS Essen-Bergerhausen
A57	AS Krefeld-Gartenstadt
A57	AS Krefeld-Zentrum
A57	AS Krefeld-Oppum
A57	AS Bovert
A57	AS Holzbttgen
A57	AS Neuss
A57	AS Neuss-Reuschenberg
A57	AS Moers-Hülsdonk
A57	AS Moers-Kapellen
A57	AS Dormagen
A59	AS Duisburg-Fahrn
A59	AS Duisburg-Marxloh
A59	AS Duisburg-Althamborn
A59	AS Duisburg-Meiderich
A59	AS Duisburg-Wahnheimerort
A59	AS Duisburg-Buchholz

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Autobahn-Number	*Connector-Name*
A59	AS Duisburg-Groenbaum
A516	AS Oberhausen-Sterkrade Nord
A516	AS Oberhausen-Sterkrade Süd
A516	AS Oberhausen-Eisenheim
A524	AS Duisburg-Rahm
A524	AS Lintfort

B Determination of the geometry data

All variables presented in the last section were determined by using satellite images that can be found on the home page of the land surveying office of North-Rhine-Westphalia (Landesvermessungsamt NRW)[3]. On this home page one can find satellite images of whole North-Rhine-Westphalia with the accompanying Gauss-Krüger-coordinates.

By means of an example we show how we constructed the data. Figure 4 shows a satellite image of a connector (connector *Autobahnkreuz Moers*, connecting Autobahn A40 and Autobahn A57) that connects two Autobahns. For our example we chose the bottom left tangent (cars are coming from the west and change directions to the south). There are three curves on that ramp, two inflection points and there is clearly a decline. There are trees inside and outside of the ramp. The Autobahn leaving has two lanes and there is a declaration lane. There is only one lane on this ramp, but there is also a shoulder lane.

Figure 5 shows then a zoom onto this tangent-ramp, where already the angles measured are indicated. Angle α is the *total angle passed on the ramp*, the sum $\beta + \gamma + \delta$ is the *absolute total angle passed on the ramp*, where it holds that $\alpha = |\beta - \gamma + \delta|$. As can be seen in the picture, the last curve is the steepest one, which is on the 3$^{\text{rd}}$ position. Hence, angle γ is the *angle of the steepest curve.*

Figure 6 shows how the lengths were measured. The lane that leads directly to the ramp was in the previous section defined as the declaration lane. The declaration lane starts in point A and ends in point B, the first

[3]http://www.tim-online.nrw.de/tim-online/LVermA/index.html

Figure 4: Satellite Image of the Autobahnkreuz Moers

Figure 5: Determination of the angles on a ramp

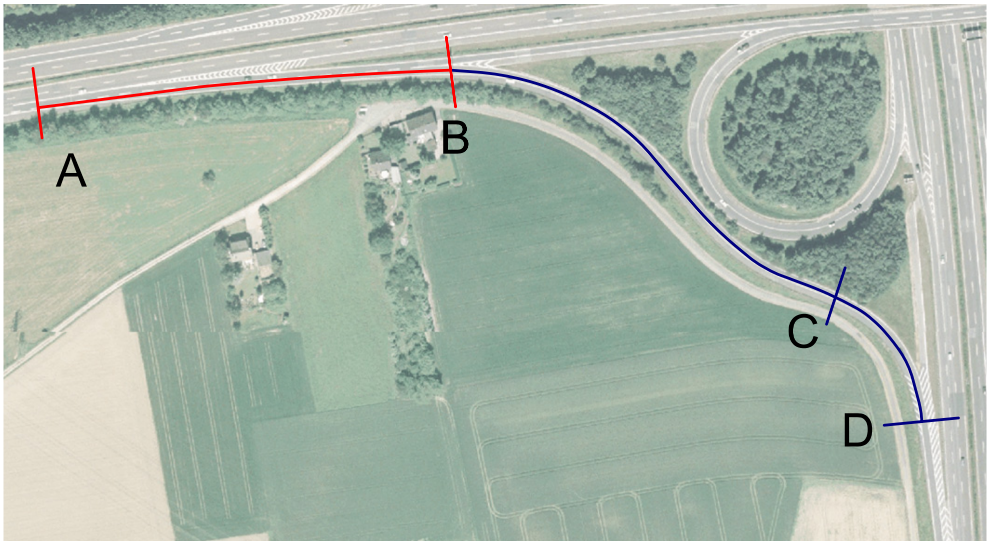

Figure 6: Determination of the lengths on a ramp

steering movement on the ramp. Thus the distance between A and B is the length of the declaration lane. From point B on the length of the ramp itself was measured. The distance between B and D is the length of the ramp. In point C the steepest curve starts, so the distance between C and D is the length of the steepest curve.

The radius r_i of the steepest curve of ramp i is calculated by the formula:

$$r_i = \frac{360 \cdot l_i}{2\pi\alpha_i}, \tag{B.1}$$

where l_i denotes the length of the curve and α_i denotes the angle of the curve (for the calculation of the radius it is assumed that the radius of the curve stays constant).

A similar procedure was conducted for all 197 ramps.

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Table 6: Abbreviations of variables in our dataset

Variable	*Abbrevation*
Number of Accidents	nb_acc
Length of the ramp	length_ramp
Length of the declaration lane	length_decl
Total Width of the lanes on the ramp	width_lanes
Width per Lane	width_per_lane
Width of the shoulder lane	width_should
Radius steepest curve	radius
Total Angle passed	angle_tot
Absolute Total Angle passed	angle_abs
Angle of the steepest curve	angle_steepest
Length of the steepest curve	length_steepest
Number of Lanes on the Ramp	nb_lanes
Number of Inflection Points on the Ramp	nb_infl
Position of the steepest curve on the Ramp	pos_steepest
Number of Curves on the Ramp	nb_curves
Number of Lanes on the Autobahn leaving	nb_autob_lanes
Dummy - Decl. Lane comes from Autobahn lane	D_autob_decl
Dummy - A Curve gets steeper	D_steeper
Dummy - A Curve gets less steep	D_less_steep
Dummy - Incline on the ramp	D_incline
Dummy - Decline on the Ramp	D_decline
Dummy - Trees Inside	D_trees_in
Dummy - Trees Outside	D_trees_out
Dummy - Crossing lane at the Access of the Ramp	D_cross_access
Dummy - Crossing lane at the Exit of the Ramp	D_cross_exit
Dummy - Median between Autobahn and Decl. Lane	D_median
ADT Passenger Cars	ADT_pc
ADT Trucks	ADT_trucks
Truck percentage	truck_perc
Threshold Dummy - Length declaration lane	$\text{T\_length\_decl}_{\text{threshold}}$
Threshold Dummy - Width of the lanes	$\text{T\_width\_lanes}_{\text{threshold}}$
Threshold Dummy - Position of the steepest curve	$\text{T\_pos\_steepest}_{\text{threshold}}$
Threshold Dummy - Radius of the steepest curve	$\text{T\_radius}_{\text{threshold}}$

Table 7: Parameter estimates and standard errors Poisson Regression, Model (M1)

Variable	Coefficient	Standard Errors				
		MLH	NB1	NB2	RS	B(500)
ADT_pc	0.11341	0.00537	0.0196	0.0284	0.0176	0.0226
ADT_trucks	0.06532	0.00681	0.0248	0.0472	0.0160	0.0261
angle_abs	0.00205	0.0003	0.0013	0.0016	0.0011	0.0013
radius	-0.00037	0.0001	0.0005	0.0005	0.0003	0.0004
length_ramp	-0.00048	0.00008	0.00030	0.00048	0.00024	0.00036
pos_steepest	0.17989	0.02714	0.09902	0.13095	0.09412	0.10947
D_less_steep	0.17433	0.05319	0.19405	0.25442	0.24148	0.27316
D_steeper	0.40499	0.0514	0.187686	0.211761	0.1786	0.2067
D_cross_exit	-0.28331	0.05058	0.18454	0.2459	0.19707	0.22971
D_trees_out	0.23733	0.05432	0.19820	0.20486	0.25290	0.25391
D_incline	0.11686	0.0399	0.145885	0.166006	0.1441	0.1574
D_autob_decl	0.33232	0.07333	0.26755	0.322815	0.25572	0.28117
Constant	1.20651	0.0919	0.33558	0.36656	0.271	0.29336

Table 8: Model evaluation criteria different functional forms of ADT

	Model (M2)	Model (M3)	Model (M4)
pseudo R^2	0.0487	0.0537	0.0529
ln L	-703.55	-699.88	-700.46
AIC	1412.10	1405.76	1405.92
BIC	1418.57	1413.52	1412.39

Table 9: Estimation Results all ramps, Model (M5)

Variable	Coefficient	standard errors RS	standard errors B(500)	t-statistic RS	(p-value)	t-statistic B(500)	(p-value)
ADT_pc	0.2681	0.0504	0.0585	5.31	(0.000)	4.58	(0.000)
$(\text{ADT\_pc})^2$	-0.0072	0.0020	0.0028	-3.57	(0.000)	-2.62	(0.009)
truck_perc	0.8212	0.3862	0.4054	2.13	(0.033)	2.03	(0.043)
radius	-0.0010	0.0003	0.0004	-3.27	(0.001)	-2.77	(0.006)
D_steeper	0.4886	0.1606	0.1671	3.04	(0.002)	2.92	(0.003)
$\text{T\_length\_decl}_{180}$	0.4433	0.1407	0.1425	3.15	(0.002)	3.11	(0.002)
$\text{T\_width\_lanes}_{3.90}$	0.3988	0.1973	0.2038	2.02	(0.043)	1.96	(0.050)
$\text{T\_pos\_steepest}_{1}$	0.3368	0.1536	0.1604	2.19	(0.028)	2.10	(0.036)
Constant	0.9190	0.2566	0.2774	2.03	(0.043)	3.31	(0.001)
$\hat{\alpha}$	0.6378						
LR	1276.63						
(p-val.)	(0.000)						
ln L	-691.14						
AIC	1391.29						
BIC	1402.94						
pseudo R^2	0.0655						
n	197						

Table 10: Estimation results E-ramps, Model (M6)

Variable	Coefficient	standard errors RS	standard errors B(500)	*t*-statistics (p-values) RS		*t*-statistics (p-values) B(500)	
ln(ADT_pc)	0.7094	0.1427	0.1608	4.97	(0.000)	4.41	(0.000)
nb_curves	-0.3225	0.1323	0.1375	-2.44	(0.015)	-2.35	(0.019)
radius	-0.0011	0.0004	0.0005	-2.67	(0.008)	-2.01	(0.047)
truck_perc	2.0780	0.4265	0.4908	4.87	(0.000)	4.23	(0.000)
$T\_length\_decl_{190}$	1.2195	0.2051	0.2266	5.95	(0.000)	5.38	(0.000)
Constant	0.5390	0.3218	0.3638	1.68	(0.094)	1.48	(0.139)
$\hat{\alpha}$	0.50954						
LR	348.7						
(p-val.)	(0.000)						
ln L	-302.343						
AIC	610.68						
BIC	618.45						
Pseudo R^2	0.0737						
n	95						

Table 11: Estimation results E-ramps, Model (M7)

Variable	Coefficient	standard errors RS	standard errors B(500)	*t*-statistics (p-values) RS		*t*-statistics (p-values) B(500)	
ln(ADT_PC)	0.5808	0.1318	0.1425	4.41	(0.000)	4.08	(0.000)
truck_perc	1.4978	0.4125	0.4323	3.63	(0.000)	3.47	(0.001)
$T\_length\_decl_{190}$	1.1316	0.1943	0.2127	5.82	(0.000)	5.32	(0.000)
T_radius_{90}	-0.6153	0.1631	0.1694	-3.77	(0.000)	-3.63	(0.000)
Constant	0.4864	0.2879	0.3105	1.69	(0.091)	1.57	(0.117)
$\hat{\alpha}$	0.5048						
LR	345.99						
(p-val.)	(0.000)						
ln L	-302.18						
AIC	609.37						
BIC	615.85						
Pseudo R^2	0.0742						
n	95						

Table 12: Estimation results T-ramps, Model (M8)

Variable	Coefficient	standard errors RS	standard errors B(500)	t-statistics (p-values) RS		t-statistics (p-values) B(500)	
ADT_pc	0.2219	0.0695	0.0835	3.20	(0.001)	2.66	(0.008)
$(\text{ADT\_pc})^2$	-0.0071	0.0025	0.0039	-2.82	(0.005)	-1.80	(0.072)
angle_abs	0.0049	0.0014	0.0015	3.60	(0.000)	3.37	(0.001)
D_decline	-0.4426	0.2084	0.2342	-2.12	(0.034)	-1.89	(0.059)
$\text{T\_length\_decl}_{150}$	0.5756	0.2476	0.2630	2.32	(0.020)	2.19	(0.029)
$\text{T\_width\_lanes}_{3.90}$	0.8875	0.3839	0.4383	2.31	(0.021)	2.03	(0.043)
Constant	0.1812	0.5322	0.5878	0.34	(0.734)	0.31	(0.758)

$\hat{\alpha}$	0.5592
LR	442.19
(p-val.)	(0.000)
ln L	-257.94
AIC	522.88
BIC	531.94
Pseudo R^2	0.0808
n	69

Table 13: Estimation results O-ramps, Model (M9)

Variable	Coefficient	standard errors RS	standard errors B(500)	t-statistics (p-values) RS		t-statistics (p-values) B(500)	
ln(ADT_pc)	0.9431	0.1678	0.1696	5.62	(0.000)	5.56	(0.000)
T_radius_{48}	0.9960	0.2685	0.3687	3.71	(0.000)	2.7	(0.007)
$\text{T\_width\_lanes}_{4.40}$	0.7593	0.3013	0.3467	2.52	(0.012)	2.19	(0.029)
Constant	-0.3171	0.3775	0.4465	-0.84	(0.399)	-0.71	(0.478)

$\hat{\alpha}$	0.4988
LR	141.44
(p-val.)	(0.000)
ln L	-108.7194
AIC	221.43
BIC	226.61
Pseudo R^2	0.1242
n	33

Table 14: Response measures for best models

Model	Variable	Coefficient	Mean Effect Avg	Mean Effect At Avg	Elast	Exp
(M5), all ramp types						
	ADT_pc	0.2681	6.1644	4.8592	1.3870	1.3074
	$(\text{ADT\_pc})^2$	-0.0072	-0.1660	-0.1309	-0.2855	0.9928
	truck_perc	0.8212	18.8836	14.8854	0.1625	2.2733
	radius†	-0.1035	-2.3809	-1.8768	-0.1717	0.9016
	D_steeper	0.4886	11.2359	8.8569	0.1215	1.6301
	$\text{T\_length\_decl}_{180}$	0.4433	10.1929	8.0348	0.3173	1.5578
	$\text{T\_width\_lanes}_{3.90}$	0.3988	9.1702	7.2286	0.3360	1.4900
	$\text{T\_pos\_steepest}_{1}$	0.3368	7.7441	6.1045	0.1111	1.4004
	Constant	0.9190				
(M6), E-ramps (I)						
	ln(ADT_pc)	0.7094	7.7531	6.3244	0.9112	2.0328
	nb_curves	-0.3225	-3.5249	-2.8754	-0.5025	0.7243
	radius†	-0.1055	-1.1534	-0.9409	-0.1988	0.8998
	truck_perc	2.0780	22.7097	18.5247	0.4247	7.9881
	$\text{T\_length\_decl}_{190}$	1.2195	13.3272	10.8712	1.0141	3.3853
	Constant	0.5390				
(M7), E-ramps (II)						
	ln(ADT_pc)	0.5808	6.3415	5.1796	0.7460	1.7875
	truck_perc	1.4978	16.3532	13.3570	0.3061	4.4717
	$\text{T\_length\_decl}_{190}$	1.1316	12.3546	10.0910	0.9410	3.1005
	T_radius_{90}	-0.6153	-6.7183	-5.4874	-0.2915	0.5405
	Constant	0.4864				
(M8), T-ramps						
	ADT_pc	0.2219	4.6548	3.5008	1.4648	1.2485
	$(\text{ADT\_pc})^2$	-0.0071	-0.1479	-0.1112	-0.4464	0.9930
	angle_abs	0.0049	0.1036	0.0779	0.6605	1.0050
	D_decline	-0.4426	-9.2834	-6.9820	-0.2694	0.6423
	$\text{T\_length\_decl}_{150}$	0.5756	12.0730	9.0800	0.4088	1.7782
	$\text{T\_width\_lanes}_{3.90}$	0.8875	18.6147	13.9999	0.7589	2.4291
	Constant	0.1812				
(M9), O-ramps						
	ln(ADT_pc)	0.9431	14.5218	10.3466	1.2850	2.5678
	T_radius_{48}	0.9960	15.3364	10.9270	0.8752	2.7073
	$\text{T\_width\_lanes}_{4.40}$	0.7593	11.6918	8.3303	0.5522	2.1367
	Constant	-0.3171				

† For a better illustration the unit of measurement has been changed to hundreds of meters