

Updating and transferring Random Effect models: The case of operating speed percentile estimation

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Updating and transferring Random Effect models: the case of operating speed percentile estimation

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Corresponding Author:	Cinzia Cirillo University of Maryland College Park, MD United States
First Author:	Jean-Michel Tremblay, PhD
Order of Authors:	Jean-Michel Tremblay, PhD Cinzia Cirillo Marco Bassani, PhD
Abstract:	<p>Random Effect (RE) models are used for analyzing data that are non-independent or when data are characterized by a hierarchical structure. In traffic and highway engineering, RE models have been successfully employed to estimate free-flow speed distributions from data containing observations that are naturally nested according to different levels (i.e. direction, sections, roads). Empirical studies conducted on both urban arterials and rural two-lane highways have shown that RE models, by properly accounting for the survey design, are superior to traditional Fixed Effect (FE) models. In this paper, the transferability of RE models to road sections that were not in the original sample used for model estimation was studied, under the assumption that for these additional sections very few observations are available or can be collected. This problem poses two challenges. First, random effects for the new road sections should be estimated in order to make out-of-sample predictions. Second, the original model formulation makes use of speed quantiles as predictors of the linear model which are not readily available for the new sections. The method proposed estimates an auxiliary model, in which the RE of the original model are correlated to the RE to be defined for the new section, with the former being used to predict the latter. The RE pairs are modeled jointly, taking advantage of their potential mutual correlation. The model coefficients obtained are also validated using a jackknife technique. Results show that the method converges quite fast and that a handful of observations for the new road section are sufficient for good RE estimates.</p>
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1 Updating and transferring Random Effect models:
2 the case of operating speed percentile estimation

3 Jean-Michel Tremblay¹, Cinzia Cirillo², and Marco Bassani³

4 ¹*Edgybees Ltd., jeanmi.tremblay@gmail.com*

5 ²*University of Maryland, Department of Civil and Environmental Engineering, ccirillo@umd.edu*

6 ³*Politecnico di Torino, Department of Environment, Land and Infrastructure Engineering,*
7 *marco.bassani@polito.it*

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9 Abstract

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30 knife resampling technique, out-of-sample prediction. .

1 Introduction

Among the parameters characterizing vehicular flows, speed is used in multiple applications including traffic analysis, speed management, road design, and road safety. Speeds are collected through spot speed observations or by recurring to permanent acquisition units in the field (Garber and Hoel 2020; Catani et al. 2017). This data may be used to calibrate models to explain how speed is related to some significant variables depicting the road scenario. As a result, analysts and road designers can select the most appropriate road features to modulate risk perception and compel drivers to adopt consistent speed decisions and behaviors. Starting from the '80s, a conspicuous quantity of papers proposed models to predict the 85th speed percentile (i.e., V85) of operating speeds (OS), and OS differential (e.g., $\Delta V85$, 85MSR) between road elements (Dimaiuta et al. 2011).

V85 is conventionally considered representative of OS distribution since it separates the speed of prudent drivers from that of more aggressive ones. V85 models may include geometric characteristics of roads (e.g., lane width, radius or curvature), environmental conditions (e.g., lighting, weather, land use), and driving regulations affecting driver behavior (Himes et al. 2013). The variation in operating speed between road elements has repeatedly been used to support design decisions (Lamm et al. 1988). Park and Saccomanno (2006) evidenced that speed variations must be evaluated for individual drivers (i.e., disaggregated data) rather than from aggregated data for the observed group, in order to prevent the so called “ecological fallacy” problem. However, this approach is challenging due to the need to monitor individual vehicles along entire road segments (McFadden and Elefteriadou 2000).

However, when attention is focused on a section, the use of V85 becomes controversial since different OS distributions may exhibit the same 85th percentile. To address this issue, Shankar and Mannering (1998) proposed the use of simultaneous equations to model the average and standard deviation of speed in each lane of multilane highways. Later on, Figueroa-Medina and Tarko 2005 introduced a model to predict any speed percentile combining the mean and the standard deviation in a linear regression equation.

Most of the available literature has proposed models of the Fixed Effect (FE) type, in which each speed observation along a road section is assumed to be dependent on the predictors included in that model only (Dimaiuta et al. 2011). This is only acceptable when speed clusters used to calibrate the model are not distinguished per direction, are from segments that do not belong to the same road, and are sufficiently distant from each other. However, when speed observations are clustered and spatially close to each other, each of them may share unobserved effects. Thus, it is not possible to assume independence of errors for individual observations without considering Random Effects (RE) for these groups.

Tarris et al. (1996) carried out a panel analysis of free-flow speed data collected from individual drivers with speed values recorded at sensor locations. In the proposed model, RE were associated with groups and speed location. Islam and El-Basyouny (2015) used RE to account for differences in hourly free-flow speed data related to site and community in

70 a pilot study aimed at reducing OS. More recently, Cheng et al. (2018) evidenced that RE
 71 are fundamental in predicting the speed and speed deviation along lanes in multilane high-
 72 ways. They used RE to account for the variation between adjoining lanes, between adjacent
 73 segments, and among segments.

74 RE models reach a higher coefficient of determination than those obtained assuming FE
 75 coefficients for groups and sensor locations (Bassani, Dalmazzo, et al. 2014). RE models for
 76 OS was proposed by the authors (Bassani, Dalmazzo, et al. 2014; Bassani, Cirillo, et al. 2016;
 77 Bassani, Catani, et al. 2016) in multiple observations for the same direction (d) of a section
 78 (s), on several sections of a road (r), and on several roads of the network. In the model:

$$V_{rsd,i} = \beta_0 + \beta_k X_{rsd,k} + \beta_j Z_p X_{rsd,j} + \alpha_r + \alpha_{s|r} + \alpha_{d|rs} + \epsilon_{rsd,i}, \quad (1)$$

79 where β_0 is the general model intercept, β_k and β_j are calibration parameters for the k and
 80 j variables affecting the estimated mean $X_{rsd,k}$, and the estimated standard deviation $X_{rsd,j}$
 81 respectively, and Z_p is the standardized normal variable. In eq. 1, α_r , $\alpha_{s|r}$ and $\alpha_{d|rs}$ are the
 82 three nested RE accounting for the variability introduced by the random selection of roads
 83 in the network, the section within a road, and the directions in the section.

84 The objective of this study is to transfer RE models calibrated on a given sample of lanes,
 85 sections and roads to road sections that were not included in the estimation sample and
 86 for which few speed observations were collected or available to the analyst. The problem
 87 has relevant practical implications, as the method proposed will facilitate the use of existing
 88 models on different sections without the need to collect a significant number of new obser-
 89 vations, which is usually a lengthy and costly process. In order for this transferability to be
 90 effective and to have realistic out-of-sample predictions, RE need to be predicted for the new
 91 road section. Also, the model specification is based on speed quantiles, which are not readily
 92 available for the new road sections.

93 REs in most situations are assumed to have zero mean and therefore the best a priori predictor
 94 for REs in a new road section is zero as well. However, it is likely that better predictors can
 95 be produced by considering a simpler, auxiliary RE model whose purpose is to overcome the
 96 unavailability of quantiles in the validation sample. Specifically, following McCulloch et al.
 97 (2008), it is possible to build an auxiliary model which, although inferior to the actual model,
 98 takes advantage of the potential correlation existing across RE pairs in order to provide good
 99 RE predictors. The method is based on the assumption that REs of the original model are
 100 correlated with the REs to be defined for the new section and that the first one can be used
 101 to predict the latter. The methodology is first developed in the case of one RE, and then
 102 extended to the case of a model including two REs. The best predictor is derived and the
 103 convergence is tested on empirical data. Finally, validation is performed on the quantiles of
 104 all the road sections considered using a jackknife technique (Efron and Tibshirani 1993).

105 The remaining of this paper is articulated as follows. Model formulation for one RE and
 106 two REs is presented in Section 2. Numerical results derived from real data collected in the
 107 North-West of Italy are reported in Section 3. The case where predictors are multiplied by

108 the normal quantiles is solved in Section 4. In Section 5, a Jackknife re-sampling technique is
 109 used to analyze the causes of poor estimation results. Conclusions and suggestions for future
 110 research are given in Section 6.

111 2 Model formulation

112 In this Section, we derive the statistical method to transfer an estimated random effect
 113 model to a new road section for which very few observations are available to the analyst.
 114 The problem is that for this new road section, only the model predictors are available, while
 115 the random effect(s) are unknown. Under the hypothesis that the random effect of the new
 116 section are correlated to those of the section for which the model has been estimated, we
 117 derive the conditional mean of the *Best Linear Unbiased Predictor* (BLUP) of the error in
 118 the new section. The method is developed first for a one random effect model (Section 2.1)
 119 and then generalized to a two random effect model (Section 2.2).

120 2.1 One random effect model

121 Following the formulation in eq.1, we first develop the proposed methodology for a simple
 122 case that contains one random effect. Let's assume that speed data is available for several
 123 sections s , and that the response variable $V_{s,i}$ is affected by a set of predictors $X_{s,k}$. The
 124 model contains one random effect α_s and an error term $\epsilon_{s,i}$:

$$V_{s,i} = \beta_0 + \beta_k X_{s,k} + \alpha_s + \epsilon_{s,i}, \quad (2)$$

125 where α_s and $\epsilon_{s,i}$ are independent and follow a normal distribution:

$$\begin{aligned} \alpha_s &\sim N(0, \sigma_s^2), \\ \epsilon_{s,i} &\sim N(0, \sigma^2). \end{aligned}$$

126 while β is defined as the the vector of fixed coefficients to be estimated and that includes
 127 both β_0 and β_k .

128 Once the model is calibrated, estimates for the model parameters (denoted as $\hat{\beta}$, $\hat{\sigma}_s^2$, and
 129 $\hat{\sigma}^2$) are available to the analyst, and predictions for the random variables α_s and $V_{s,i}$ can be
 130 obtained (McCulloch et al. 2008).

131 Assuming the analyst is interested in predicting random effects for a new section s' with
 132 unknown random effect $\alpha_{s'}$, the best *a priori* estimate of $\alpha_{s'}$ is zero since $\alpha_{s'} \sim N(0, \sigma_s^2)$.
 133 In some contexts this may be satisfying, but other methods can be explored under the
 134 assumption that it is possible to sample a few observations for the new section s' in order to

135 improve the knowledge about $\alpha_{s'}$ and build a better *a posteriori* prediction. This is precisely
 136 the ultimate objective of our method.

137 Suppose that n observations $V_{s',1}, V_{s',2}, \dots, V_{s',n}$ are collected in the new section. $\alpha_{s'}$ cannot
 138 be observed directly, because we always observe the *sum* of the errors. Hence according to
 139 eq. 2 the sum of the residuals is:

$$r_{s',i} = \alpha_{s'} + \epsilon_{s',i} = V_{s',i} - \beta X_{s',k}.$$

140 The difference $V_{s',i} - \beta X_{s',k}$ cannot be measured because the value of the parameters in β is
 141 unknown, so the estimated value $\hat{\beta}$ from model calibration is used to approximate the total
 142 residuals $r'_{s',i}$.

143 Let's define $u = (\alpha_{s'})$ and let's assume that it follows a normal distribution with mean zero
 144 and variance $D = (\sigma_s^2)$. In this case, u refers to a single random effect, but as we will see
 145 in the next Section, the methodology applies to any number of effects to be predicted. The
 146 residuals $r = (r_{s',1}, r_{s',2}, \dots, r_{s',n})$ have zero mean and variance W :

$$W = \begin{bmatrix} \sigma_s^2 + \sigma^2 & \sigma_s^2 & \dots & \sigma_s^2 \\ \sigma_s^2 & \sigma_s^2 + \sigma^2 & \dots & \sigma_s^2 \\ \dots & \dots & \dots & \dots \\ \sigma_s^2 & \sigma_s^2 & \dots & \sigma_s^2 + \sigma^2 \end{bmatrix}.$$

147 W can be written as follows:

$$W = \sigma^2 I + \sigma_s^2$$

148 where I is the identity matrix.

149 The covariance between the random effect $\alpha_{s'}$ and one given total residual is:

$$Cov(\alpha_{s'}, r_{s',i}) = \sigma_s^2.$$

150 and more generally, the covariance C between u and r is:

$$C = [\sigma_s^2 \quad \sigma_s^2 \quad \dots \quad \sigma_s^2] = \sigma_s^2 \mathbf{1}_{1 \times n}$$

151 and therefore:

$$\begin{bmatrix} u \\ r \end{bmatrix} \sim \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} D & C \\ C^T & W \end{bmatrix} \right).$$

152 At this stage, it is not necessary to formulate hypotheses on the joint distribution of (u, r) ; it
 153 is sufficient to know the first and second moments of (u, r) to derive the *best linear unbiased*
 154 *predictor* (BLUP) of u (McCulloch et al. 2008). If the joint distribution were normal, the
 155 BLUP would be the overall best predictor of u . This not the case for our real application.

156 Once r is observed, the BLUP of u is the conditional mean. The expectation of $u|r$ is given
 157 by:

$$\hat{\alpha}_{s'} = E(u|r) = CW^{-1}r.$$

158 The estimated values of the coefficients are used to produce numerical values for the BLUP.
 159 The predicted value for an observation i in section s' will be:

$$\hat{V}_{s',i} = \hat{\beta}X_{s',k} + \hat{\alpha}_{s'}.$$

160 $\hat{\beta}$ can be estimated in a relatively easy way, so the main challenge for this problem is to
 161 predict $\hat{\alpha}_{s'}$. The objective here is to investigate what is the smallest sample in section s' that
 162 we can use to predict $\alpha_{s'}$ satisfactorily. In general, it can be observed that the prediction
 163 converges faster when σ^2 is low relative to σ_s^2 ; this is because one single observation of r is
 164 expected to be less noisy and more correlated with the unknown realized value $\alpha_{s'}$.

165 2.2 Two random effects models

166 The case with two nested random effects is formulated in eq. 3:

$$V_{sd,i} = \beta_0 + \beta_k X_{sd,k} + \alpha_s + \alpha_{d|s} + \epsilon_{sd,i}, \quad (3)$$

167 where the subscript d stands for direction, so speed data can be distinguished into two
 168 different directions for the same section. The random effect $\alpha_{d|s}$ is nested within the levels
 169 of α_s .

We make the assumption that this new random effect is normally distributed:

$$\alpha_{d|s} \sim N(0, \sigma_d^2)$$

170 As a result, in this model a sample from the new section s' also includes some levels of the
 171 direction effect. For illustration purposes, one section, two directions and n observations per
 172 direction are assumed. The RE to be predicted is:

$$u = (\alpha_{s'}, \alpha_{d1}, \alpha_{d2}),$$

173 and the total residuals are given by:

$$r_{s'd,i} = V_{s'd,i} - \beta X_{s'd,k}.$$

174 where β is the vector of coefficient to be estimated.

175 Similar to the one RE model, the RE cannot be directly observed. In this case, the covariance
176 structure for the total residuals is:

$$\begin{aligned} \text{var}(r_{s'd,i}) &= \sigma_s^2 + \sigma_d^2 + \sigma^2, \\ \text{cov}(r_{s'd,i}, r_{s'd,j}) &= \sigma_s^2 + \sigma_d^2, \\ \text{cov}(r_{s'd,i}, r_{s'd',i}) &= \sigma_s^2 \end{aligned}$$

177 Two residuals in the same section but for different directions only share the α_s term so their
178 covariance is σ_s^2 . Residuals in the same direction also share $\alpha_{d|s}$ so their covariance is the
179 sum $\sigma_s^2 + \sigma_d^2$. Finally, the total variance of r is the sum of its three components $\sigma_s^2 + \sigma_d^2 + \sigma^2$.
180 These results are a consequence of the independence assumption made on the three REs.

181 As in the previous section, we want to derive the joint moments of (u, r) . The covariance
182 matrices D , C and W of (u, r) are respectively:

$$D = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_d^2 \end{bmatrix}, W = \sigma_s^2 + \begin{bmatrix} \sigma_d^2 + \sigma^2 & \sigma_d^2 & \sigma_d^2 & 0 & 0 & 0 \\ \sigma_d^2 & \sigma_d^2 + \sigma^2 & \sigma_d^2 & 0 & 0 & 0 \\ \sigma_d^2 & \sigma_d^2 & \sigma_d^2 + \sigma^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_d^2 + \sigma^2 & \sigma_d^2 & \sigma_d^2 \\ 0 & 0 & 0 & \sigma_d^2 & \sigma_d^2 + \sigma^2 & \sigma_d^2 \\ 0 & 0 & 0 & \sigma_d^2 & \sigma_d^2 & \sigma_d^2 + \sigma^2 \end{bmatrix}$$

183 with $\mathbf{0}$ being a matrix of zeros and I the identity matrix:

$$W = \sigma_s^2 + \begin{bmatrix} \sigma_d^2 + \sigma^2 I & 0_{n \times n} \\ 0_{n \times n} & \sigma_d^2 + \sigma^2 I \end{bmatrix}$$

184 C is finally given by:

$$C = \begin{bmatrix} \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 \\ \sigma_d^2 & \sigma_d^2 & \sigma_d^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_d^2 & \sigma_d^2 & \sigma_d^2 \end{bmatrix} = \begin{bmatrix} \sigma_s^2 \mathbf{1}_{1 \times n} & \sigma_s^2 \mathbf{1}_{1 \times n} \\ \sigma_d^2 \mathbf{1}_{1 \times n} & \mathbf{0}_{1 \times n} \\ \mathbf{0}_{1 \times n} & \sigma_d^2 \mathbf{1}_{1 \times n} \end{bmatrix}$$

185 The predicted random effects are given by the expected mean:

$$E(u|r) = CW^{-1}r.$$

186 The predicted value for an observation i in section s' and direction d will be:

$$\hat{V}_{s'd,i} = \hat{\beta}_{s'di} X_{s'd,k} + \hat{\alpha}_{s'} + \hat{\alpha}_{d|s}.$$

187 3 Numerical examples on OS data

188 Speed data used in this study were collected in road sections of two-lane rural highways
189 in the North-West part of Italy. Individual speeds of isolated vehicles were collected under
190 free-flow conditions in sections where vehicles travel at constant speed (i.e. in the center of
191 tangents and curves). Speeds were included in the database only when a minimum headway
192 of six seconds was observed. The data for model estimation were extracted from a larger
193 database already used by the authors in (Bassani, Cirillo, et al. 2016). The density and the
194 presence of elements along the road section was evaluated along one km across the sample
195 sections. Table 1 lists the values assumed by the variables that were found to be significant
196 in the calibration of the model reported in eq. 1. In the table, the variables are divided
197 into those affecting the average (X_k) and the dispersion (X_j) of predictors. The latter are
198 also divided into numerical and Boolean variables. Finally, the last five columns summarize
199 the minimum (V_{min}), the maximum (V_{max}), the 50th ($V50$) and the 85th ($V85$) percentile of
200 speeds included in the database, while n_{obs} indicates the number of data available for each
201 section. The notes at the end of table 1 describe the acronyms used to identify the variables.

Table 1: Summary of characteristics of the selected road sections

Sections	X_{i_1}		Significant variables in model 1												X_{i_2} (boolean)					Speed data				
	1/R $m-1$	PedD n/km	LW m	SLW m	SRW m	LG %	TRDLS n/km	TRDRS n/km	DDRS n/km	IDLS n/km	IDRS n/km	PSL km/h	Δ PSL km/h	LBLS	LRRS	SLS	SRS	SBLs	SBRs	V_{min} km/h	V_{50} km/h	V_{85} km/h	V_{max} km/h	N
1	0.00	0	3.60	0.40	0.40	1.50	0	0	1	0	0	70	0	1	1	1	0	0	0	39.0	66.0	76.0	97.0	429
3	0.00	0	3.75	0.40	0.40	0.00	0	0	2	0	0	50	0	1	1	0	0	1	1	32.0	74.0	85.0	157.0	972
5	0.00	0	3.70	0.00	0.00	1.00	0	0	1	0	0	90	0	0	1	0	0	0	0	38.0	74.0	89.0	130.0	669
7	3.29e-3	0	3.75	1.50	1.50	5.14	0	0	0	0	0	70	0	1	1	0	0	1	1	24.0	82.0	94.0	114.0	312
8	0.00	0	3.75	1.50	1.50	2.09	0	0	0	0	0	70	0	1	1	0	0	1	1	57.0	86.0	98.0	124.0	101
9	3.10e-4	0	3.75	1.50	1.50	4.69	0	0	0	1	0	70	0	1	1	0	0	1	1	52.0	80.0	91.0	114.0	101
10	6.67e-3	0	3.25	0.00	0.00	8.50	0	1	3	0	2	50	0	0	0	0	0	1	1	46.0	62.0	70.1	77.0	87
11	0.00	0	3.00	0.50	0.50	1.50	0	0	4	0	3	70	0	0	0	0	0	0	0	42.6	71.0	90.3	129.4	107
12	0.00	0	3.00	0.50	0.50	0.00	0	0	1	0	1	70	0	0	0	0	0	0	0	46.7	81.5	94.3	128.6	120
13	0.00	0	3.00	0.50	0.50	0.00	0	0	1	0	0	70	0	0	0	0	0	0	0	50.0	80.2	90.4	114.0	108
14	0.00	0	3.00	0.50	0.50	2.00	0	0	2	0	0	70	0	0	0	0	0	0	0	49.6	83.0	101.7	129.4	125
15	0.00	0	3.00	0.50	0.50	0.00	0	0	0	0	1	70	0	0	0	0	0	0	0	46.3	82.7	95.9	127.8	127
16	0.00	0	3.00	0.50	0.50	0.00	0	0	1	0	0	70	0	0	0	0	0	0	0	49.4	83.2	98.9	128.3	138
17	0.00	0	3.00	0.50	0.50	0.00	0	0	6	2	1	70	0	0	0	0	0	0	0	49.4	78.5	95.3	149.6	128
18	0.00	0	3.50	1.20	1.20	0.50	0	0	1	0	0	90	0	0	0	0	0	0	0	42.0	67.2	88.5	115.2	41
20	4.44e-4	0	3.50	1.20	1.20	0.50	0	0	0	1	1	90	0	0	0	0	0	0	0	70.0	97.0	107.0	118.0	26
21	0.00	0	3.50	1.20	1.20	0.50	1	0	0	4	4	90	0	0	0	0	0	0	0	58.0	99.5	112.9	127.0	28
22	0.00	0	3.50	1.20	1.20	0.00	0	0	5	1	1	90	0	0	0	0	0	0	0	55.0	77.0	100.3	130.0	30
23	6.66e-4	0	3.50	1.20	1.20	1.00	0	0	1	1	4	50	0	0	0	0	0	1	1	32.0	50.0	57.4	72.0	32
24	0.00	0	3.50	1.20	1.20	0.00	0	0	8	0	3	70	0	1	0	0	1	0	0	59.0	77.0	92.6	110.0	27
25	1.10e-3	0	3.50	1.20	1.20	1.00	0	0	1	0	0	70	0	0	0	0	0	1	1	44.0	69.0	78.0	96.0	37
26	1.20e-4	0	3.50	1.20	1.20	0.00	0	0	6	0	2	70	0	1	0	0	1	0	0	47.0	75.0	85.5	98.0	38
27	2.21e-3	4	3.50	1.20	1.20	0.00	0	0	4	3	3	50	0	0	1	1	1	0	0	44.0	51.0	57.5	70.0	36
28	6.65e-4	0	3.50	1.20	1.20	1.00	0	0	2	0	0	90	0	0	0	0	0	0	0	56.0	87.0	97.0	130.0	43
29	0.00	0	3.50	1.20	1.20	1.00	1	0	1	0	0	90	0	0	0	0	0	0	0	65.0	91.0	107.9	119.5	38
30	0.00	1	3.50	1.20	1.20	0.00	0	0	7	3	5	70	0	0	1	1	0	0	0	54.7	69.3	85.1	108.1	42
31	0.00	0	3.50	1.20	1.20	0.00	0	0	6	0	1	70	0	0	0	0	1	0	0	44.3	73.1	83.6	120.2	140
32	3.33e-3	2	3.20	0.80	0.80	0.00	0	0	4	4	2	70	0	0	1	0	0	0	0	27.6	66.7	75.8	93.3	116
33	0.00	0	3.80	1.26	1.26	0.00	0	0	3	1	0	90	0	0	0	0	1	0	0	42.6	67.4	75.3	106.6	67
34	0.00	3	3.50	0.40	0.40	0.00	0	0	5	1	4	50	0	0	1	1	1	0	0	34.7	55.0	68.5	105.4	154
36	0.00	1	3.50	0.70	0.70	0.00	0	0	8	1	1	50	0	1	1	0	0	0	0	36.9	69.1	82.5	134.8	161

Notes: 1/R = curvature, PedD = pedestrian density, LW = lane width, SLW = shoulder left width, SRW = shoulder right width, LG = longitudinal grade, TRDLS = total ramp density left side, TRDRS = total ramp density right side, DDRS = driveway density right side, IDLS = intersection density left side, IDRS = intersection density right side, LBLS = lay-by left side, LBRS = lay-by right side, SLS = sidewalks left side, SRS = sidewalks right side, SBLs = safety barriers left side, SBRs = safety barriers right side, PSL = posted speed limit, Vmin = minimum speed value, V50 = 50th percentile of speed, V85 = 85th percentile of speed, Vmax = maximum speed value, N = number of speed data. Binomial values = 1 when present, = 0 otherwise. LG is in absolute value and is specified per direction

3.1 Results: one RE model

The first case study models speed data with only one RE, as formulated in 2.1; specifically, it accounts for the RE related to sections but ignores the RE related to directions. A model is calibrated using thirty sections out of the thirty one available in the database and listed in Table 1. Once the model is fitted on the thirty sections, the RE effect is predicted for the section that was left out from model estimation. This is repeated for all the thirty one sections in the dataset. This procedure provides a series of predicted REs; these results are used to assess the convergence of the method proposed.

Figures 1 and 2 illustrate the results obtained for each section. Each subplot represents the predicted RE in the section used for validation. The x-axis corresponds to the number of observations that were used from the validation section in order to predict the REs. For example, an x-value of 10 for section 3 means that a model with all sections but the third one was estimated, and that ten observations in the third section were used in order to predict the (realized) effect of section 3.

Each subplot contains a solid line, a dashed line, and a dotted line. The solid line shows the predicted effects obtained with the **full** model, for which the quantile information in the validation sample is assumed to be known. This is ultimately the effect that we aim to predict. The dotted line shows the predicted effects obtained with a **simple** auxiliary model that only contains the predictors $X_{s,k}$ that affect the mean speed. The dashed line shows the predicted effects for the **conditional** model obtained using information from the auxiliary model. This is the prediction that ultimately is going to be used.

From figures 1 and 2, the following three remarks can be made: (i) a relative convergence in the predicted effects as the number of observations grows is observed; (ii) there is a substantial difference between the dotted line and the black solid line; meaning that the closer the two lines are, the more likely that the one can be predicted from the other; (iii) the dashed line does not approximate the solid line and it is mostly super-posed to the dotted line. Therefore, it can be concluded that the predicted effect of the full model using the auxiliary model are no better approximation than just the predicted effects of the auxiliary model. This results might be seen as disappointing, but later it will be proved that correctly accounting for the sample design solves the problem observed.

Figure 1: Sections 1-22

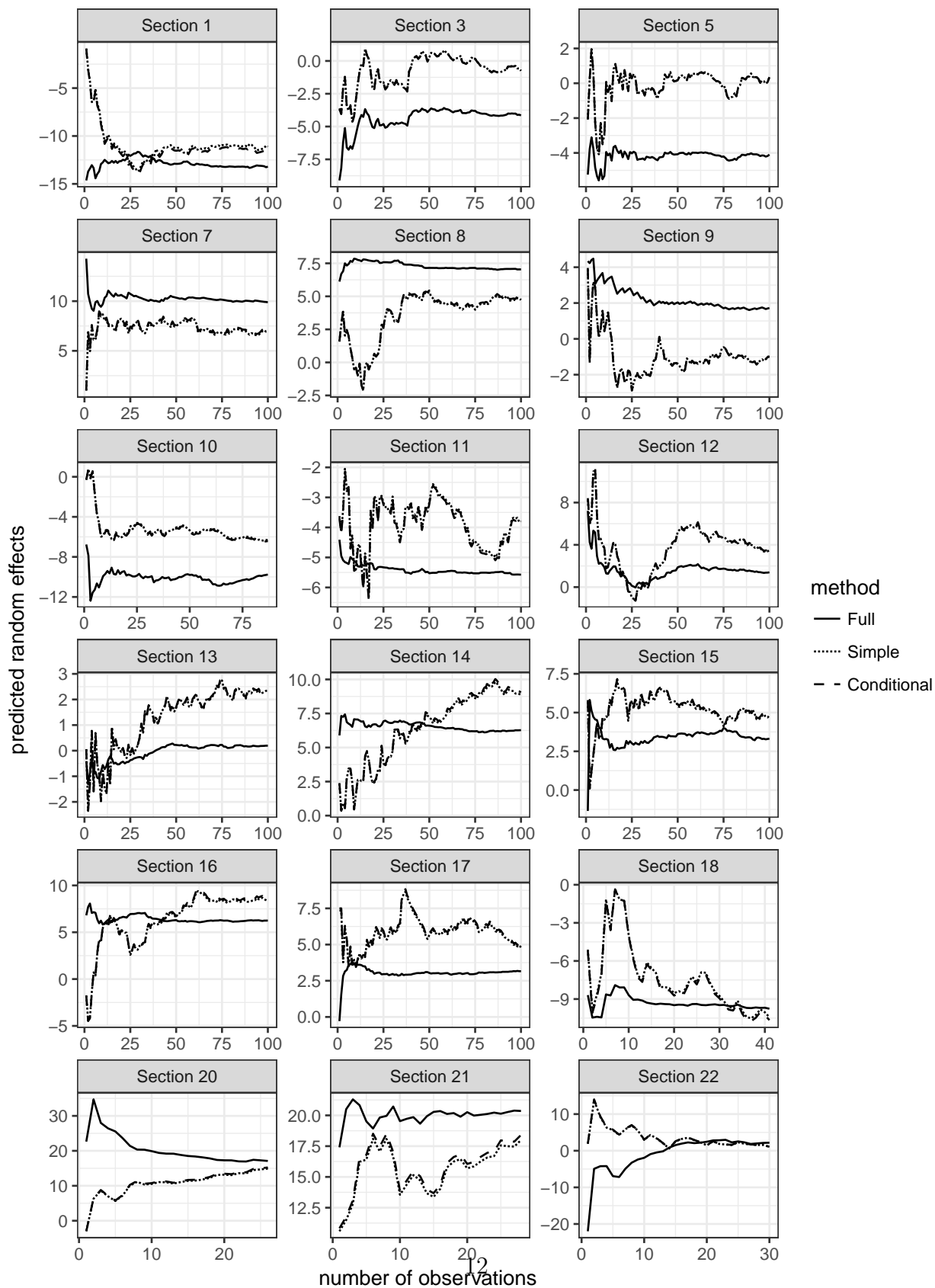
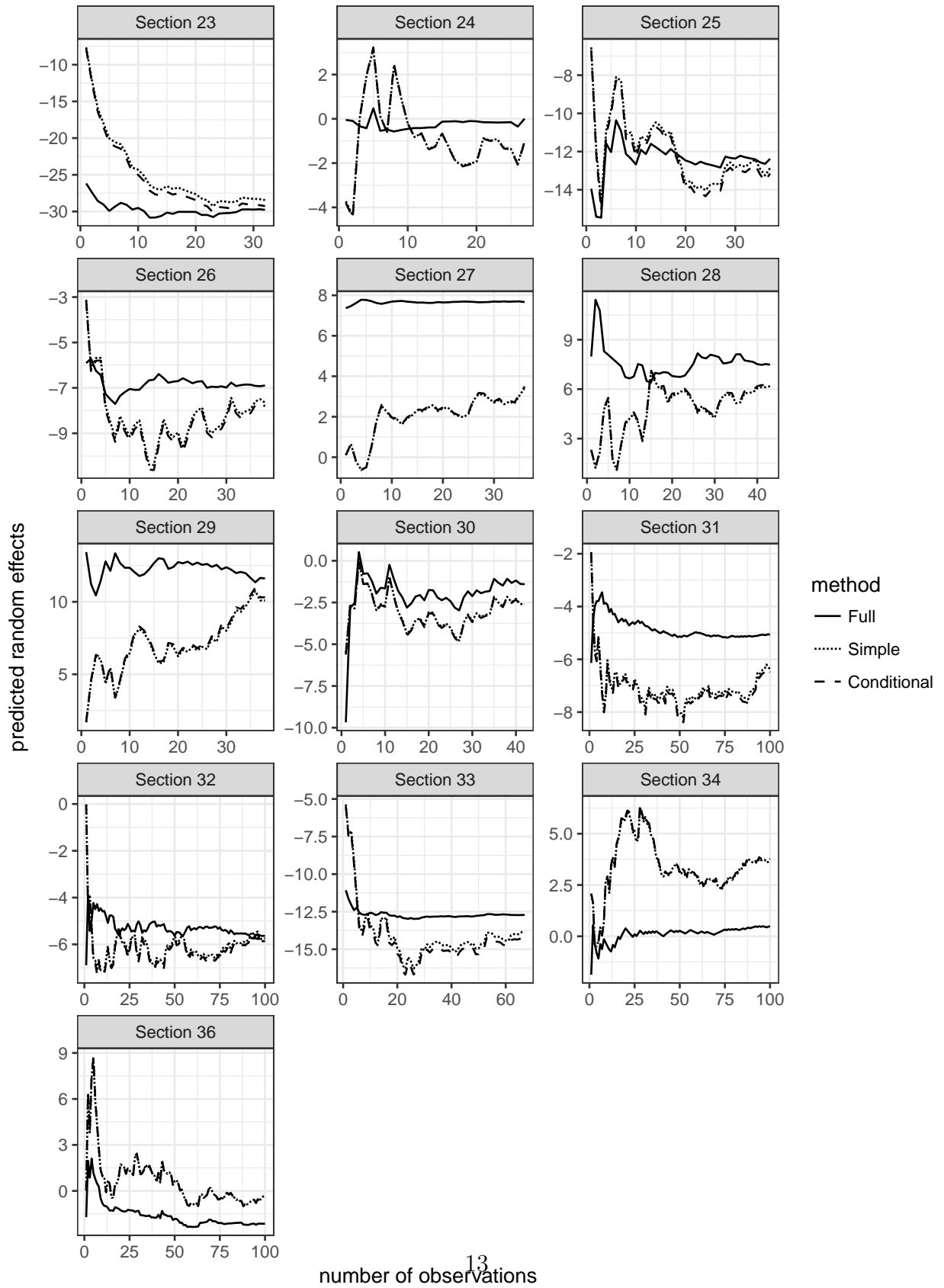


Figure 2: Sections 23-36



3.2 Results: two RE model

The second case study models two REs as formulated in 2.2; this time both section and direction effects are taken into account. The scope here is to assess the convergence of $\hat{\alpha}_{s'}$, $\hat{\alpha}_{d1}$ and $\hat{\alpha}_{d2}$ in the presence of two REs; this model formulation is fully consistent with the survey design.

Figures 3 and 4 should be read in the same way as figures 1 and 2. The thick solid line corresponds to the predicted section effect, and the two fine solid lines correspond to the predicted direction effects. The dashed lines correspond to the predicted effects using the auxiliary model and those are used to compute the REs in the validation section.

For both sections and directions, the predicted effects using the auxiliary model are very close to the ones using the full model. However, there are still noticeable differences when very few observations are used for the prediction. For example, predictions in sections 8 and 27 are not very precise for only two or three observations.

It is worth noting that striking differences exist between predictions with one and two REs. Effects with only the section component are not close to the *true* effects of the full model; incorporating the direction effects, thus accounting for the design of the sample, drastically improves the predictions.

4 Computation of the residuals

We now turn our attention to the case where the model includes variables $X_{sd,j}$ multiplied by the normal quantile Z_p in addition to the regular predictors $X_{sd,k}$, (see Bassani, Dalmazzo, et al. 2014; Bassani, Cirillo, et al. 2016; Bassani, Catani, et al. 2016). This is done to calculate any percentile speed as a linear combination of variables affecting both the central tendency and the dispersion of the collected speed data. Those quantiles are not available for the validation sample, which is too small to allow for the calculation of variance indicators. Note that $Z_{sd,j}$ is a scalar so the term $Z_p X_{sd,j}$ is simply a scalar multiplied by a vector.

$$V_{sd,i} = \beta_0 + \beta_k X_{sd,k} + \beta_j Z_p X_{sd,j} + \alpha_s + \alpha_{d|s} + \epsilon_{sd,i}$$

In this case, it is not possible to isolate the sum of REs and we must rely on alternative methods. The strategy that is proposed here makes use of the estimated total residuals from a restricted model that only contains observable variables ($X_{sd,k}$) to predict the REs of an unrestricted model (with both $X_{sd,k}$ and $X_{sd,j}$).

Figure 3: Sections 1-22

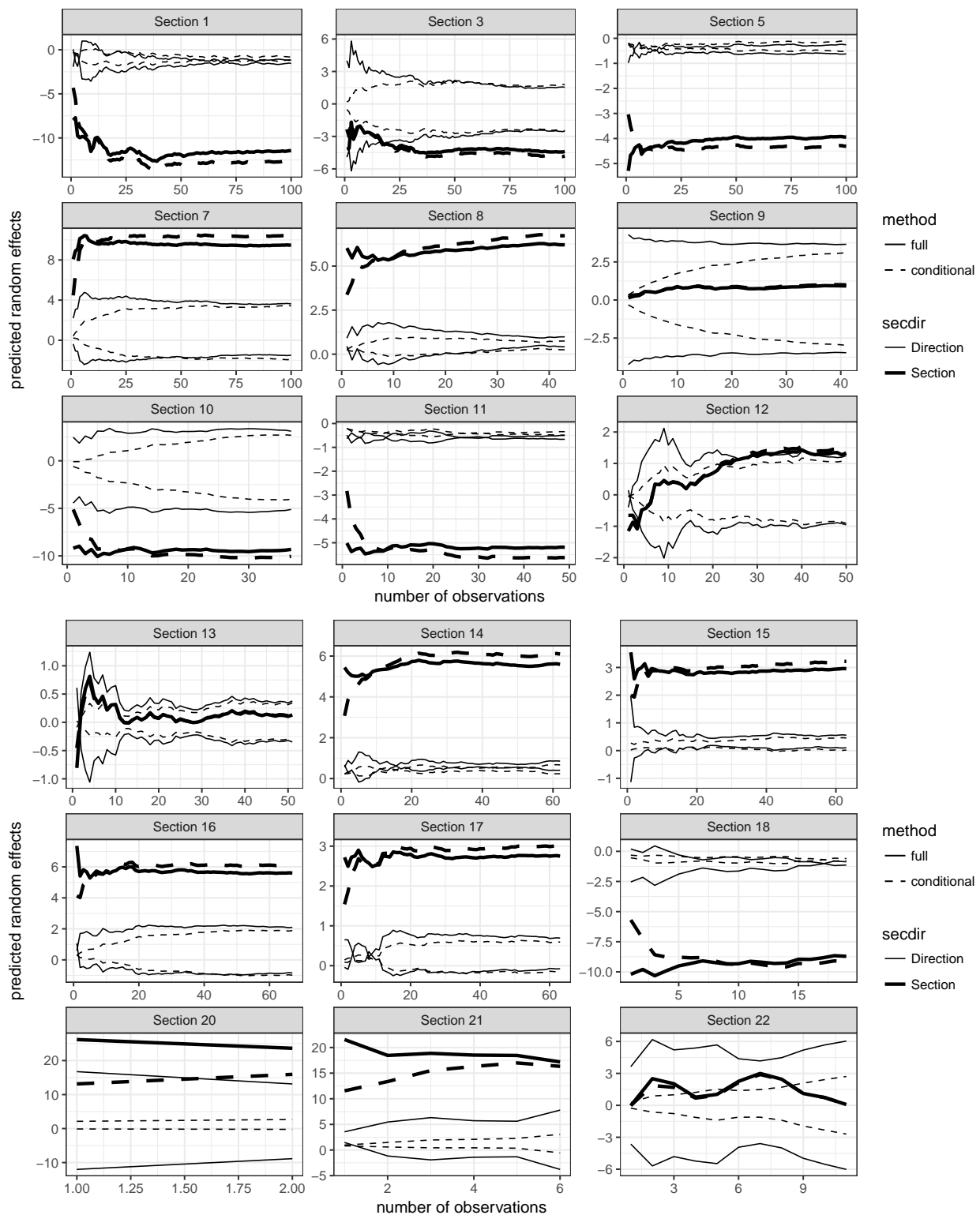
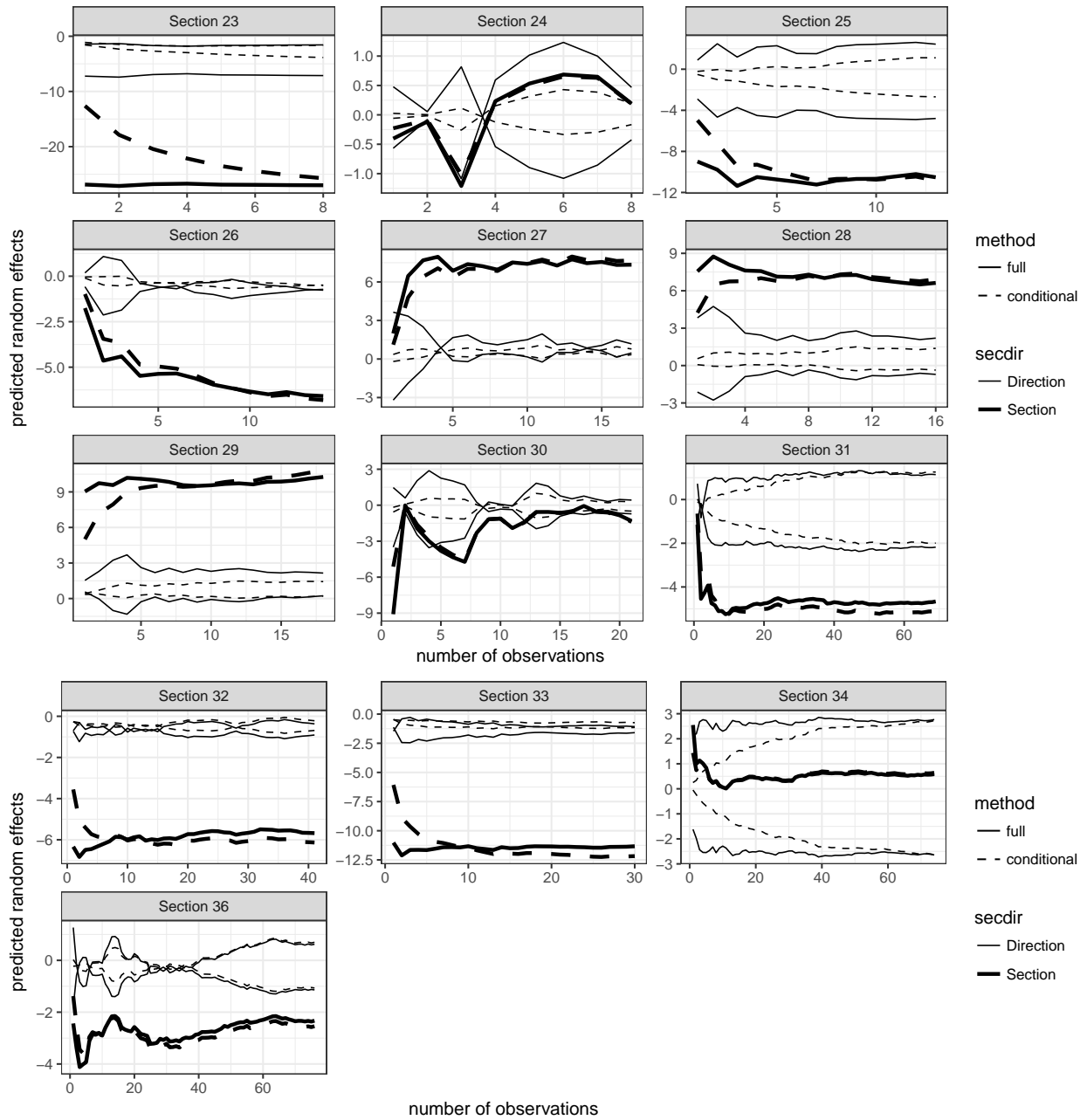


Figure 4: Sections 23-36



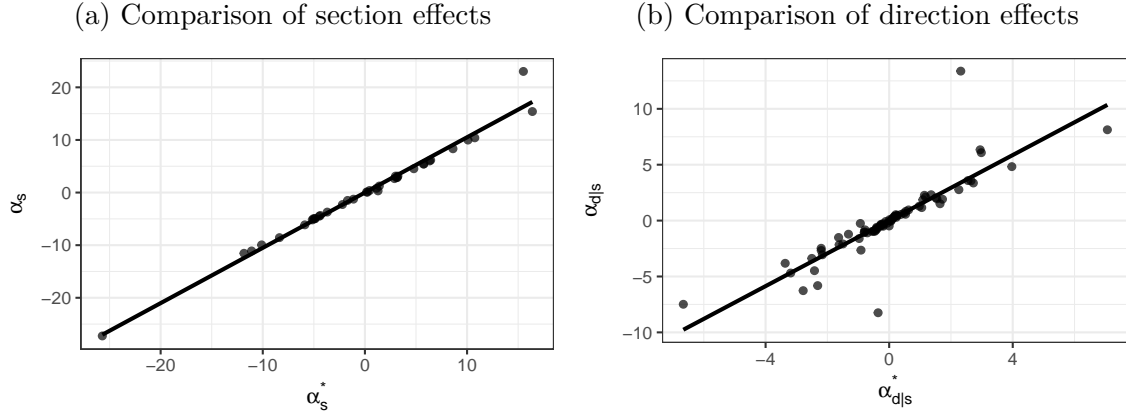
$$\begin{aligned}
V_{sd,i} &= \beta_k X_{sd,k} + \alpha_s^* + \alpha_{d|s}^* + \epsilon_{sdi}^*, \\
\alpha_s^* &\sim N(0, \sigma_s^{*2}), \\
\alpha_{d|s}^* &\sim N(0, \sigma_d^{*2}), \\
\epsilon_{sdi}^* &\sim N(0, \sigma^{*2}).
\end{aligned} \tag{4}$$

$$\begin{aligned}
r_{sd,i}^* &= V_{sd,i} - \beta_k X_{sd,k} \\
V_{sd,i} &= \beta_k X_{sd,k} + \beta_j X_{sd,j} + \alpha_s + \alpha_{d|s} + \epsilon_{sdi}, \\
\alpha_s &\sim N(0, \sigma_s^2), \\
\alpha_{d|s} &\sim N(0, \sigma_d^2), \\
\epsilon_{sdi} &\sim N(0, \sigma^2).
\end{aligned} \tag{5}$$

$$r_{sd,i} = V_{sd,i} - \beta_k X_{sd,k} - \beta_j X_{sd,j}$$

261 The restricted (eq. 4) and unrestricted models (eq. 5) are calibrated and parameters are
262 estimated, together with the empirical correlation (ρ_{α_s} and $\rho_{\alpha_{d|s}}$) across the effects of both
263 models. Figures 5a and 5b plot the predicted section and direction effects of the restricted
264 model and the unrestricted model respectively. As anticipated, the more correlated these
265 effects are, the easier will be to predict one using the other.

Figure 5: Predicted effects



266 The term r_{sdi}^* can be calculated in the validation sample, while the variance of one of those
267 residuals is given by:

$$Var(r_{sdi}^*) = \sigma_s^{*2} + \sigma_d^{*2} + \sigma^{*2}.$$

268 The covariance of two residuals is given by:

$$\begin{aligned}
Cov(r_{sdi*}, r_{sdj*}) &= \sigma_{s*}^2 + \sigma_{d*}^2 && \text{in the same direction,, and} \\
Cov(r_{sd,i*}, r_{sd',i*}) &= \sigma_{s*}^2 && \text{not in the same direction.}
\end{aligned}$$

269 The covariance between residuals and REs are given by:

$$\begin{aligned} Cov(r_{sdi}^*, \alpha_s) &= Cov(\alpha_s^* + \alpha_{d|s}^* + \epsilon_{sdi}^*, \alpha_s) = Cov(\alpha_s^*, \alpha_s) = \rho_{\alpha_s} \sigma_s \sigma_s^* = \sigma_{ss}^*, \\ Cov(r_{sdi}^*, \alpha_{d|s}) &= Cov(\alpha_s^* + \alpha_{d|s}^* + \epsilon_{sdi}^*, \alpha_{d|s}) = Cov(\alpha_{d|s}^*, \alpha_{d|s}) = \rho_{\alpha_{d|s}} \sigma_d \sigma_d^* = \sigma_{dd}^*. \end{aligned}$$

270 Therefore, the joint covariance of r_* and u is described by the following variance components:

$$D = \begin{bmatrix} \sigma_s^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_d^2 \end{bmatrix},$$

$$W = \sigma_{s^*}^2 + \begin{bmatrix} \sigma_d^{*2} + \sigma^{*2} & \sigma_d^{*2} & \sigma_d^{*2} & 0 & 0 & 0 \\ \sigma_d^{*2} & \sigma_d^{*2} + \sigma^{*2} & \sigma_d^{*2} & 0 & 0 & 0 \\ \sigma_d^{*2} & \sigma_d^{*2} & \sigma_d^{*2} + \sigma^{*2} & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_d^{*2} + \sigma^{*2} & \sigma_d^{*2} & \sigma_d^{*2} \\ 0 & 0 & 0 & \sigma_d^{*2} & \sigma_d^{*2} + \sigma^{*2} & \sigma_d^{*2} \\ 0 & 0 & 0 & \sigma_d^{*2} & \sigma_d^{*2} & \sigma_d^{*2} + \sigma^{*2} \end{bmatrix},$$

$$C = \begin{bmatrix} \sigma_{ss}^* & \sigma_{ss}^* & \sigma_{ss}^* & \sigma_{ss}^* & \sigma_{ss}^* & \sigma_{ss}^* \\ \sigma_{dd}^* & \sigma_{dd}^* & \sigma_{dd}^* & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{dd}^* & \sigma_{dd}^* & \sigma_{dd}^* \end{bmatrix}.$$

271 Note that D is the same as before, but W is different because the random effects in r are
272 from the simpler model, and C is also affected.

273 Tables 2 through 9 report predicted speed deciles (pred.) and compare them with the ob-
274 served ones (obs.).

Table 2: Predicted quantiles sections 1,3,5 and 7

quantile	Section 1				Section 3				Section 5				Section 7			
	dir 1		dir 2		dir 1		dir 2		dir 1		dir 2		dir 1		dir 2	
	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.
10	50	56	48.6	54	65.2	58	70.4	63	59.3	60	53.5	57	65.4	66	66.1	72.6
20	56.7	59	56.2	58	68.7	63	73.1	68	64.7	64	61	63	70.7	69	71.8	76
30	61.5	62	61.6	60	71.2	66	75	71	68.6	68	66.3	67	74.5	73	76	79.8
40	65.6	65.8	66.3	62	73.3	69	76.7	74	72	71	70.9	70	77.8	77	79.5	82
50	69.5	67	70.7	65	75.3	72	78.2	77	75.1	73	75.2	75	80.9	80	82.8	85
60	73.3	69	75	67	77.3	74	79.8	79	78.3	77	79.5	77	84	82	86.1	87
70	77.4	71	79.7	70	79.4	77	81.5	82	81.6	81	84.1	81.9	87.3	86.8	89.6	89
80	82.3	73	85.2	74	81.9	81	83.4	85	85.5	85	89.5	87	91.1	90	93.8	93
90	88.9	77.3	92.8	79	85.3	88	86.1	89	91	90	97	94	96.5	95	99.5	97.4

Table 3: Predicted quantiles sections 8,9,10,11

quantile	Section 8				Section 9				Section 10				Section 11			
	dir 1		dir 2		dir 1		dir 2		dir 1		dir 2		dir 1		dir 2	
	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.
10	68.2	69.4	67.9	74.2	63.2	60	65.2	70	47.4	50	54.5	56	56.4	59.3	56.4	59.3
20	73.9	75.4	73.5	77	68.4	67	70.4	72.8	51.8	51.2	57.2	60	62.5	63.2	62.5	61.7
30	78	81	77.5	77.6	72.1	68	74.1	76	54.9	54.6	59.1	63	66.9	65.1	66.8	67.1
40	81.5	84	81	81.6	75.2	73	77.3	79.6	57.6	55	60.8	64	70.6	68.1	70.6	71
50	84.8	86	84.2	85	78.2	75	80.3	82	60.1	56	62.4	65	74.2	70.6	74	72.5
60	88.1	88.2	87.4	87.2	81.1	79	83.3	86.4	62.6	57	63.9	67	77.7	71.9	77.5	74
70	91.6	90	90.9	90	84.3	86	86.5	88	65.3	59	65.6	68	81.5	75.9	81.2	76.4
80	95.7	94.2	94.9	94.8	87.9	87	90.2	91.2	68.4	60.8	67.5	71.2	85.9	81.6	85.6	81.6
90	101.4	103.5	100.5	100.6	93.1	90	95.4	94.1	72.7	64.4	70.2	73	92	95.6	91.6	93

Table 4: Predicted quantiles sections 12,13,14,15

quantile	Section 12				Section 13				Section 14				Section 15			
	dir 1		dir 2		dir 1		dir 2		dir 1		dir 2		dir 1		dir 2	
	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.
10	60.9	59.7	61.1	59	62.9	62.7	62.2	65.8	64.5	67.1	63.4	67.8	64.6	64.3	63.7	65.7
20	66.9	64.2	67.4	67.5	68.6	67.4	68.3	68.5	71.2	70.6	70.6	72.1	70.7	69.5	70.2	73.8
30	71.3	71.3	71.8	72	72.7	70.7	72.7	72	76	76.3	75.7	75.3	75	74.3	74.8	75.6
40	75	73.9	75.7	78.3	76.3	75.4	76.5	74.3	80.1	79.6	80.2	79.1	78.8	78	78.7	80.2
50	78.5	76.9	79.3	82.9	79.6	79.8	80	81.9	83.9	83.1	84.3	83	82.2	81.9	82.4	83.8
60	81.9	85.7	82.8	86	82.9	84.2	83.5	84.4	87.7	85.9	88.5	90.6	85.7	84.3	86.1	85.2
70	85.7	88.8	86.7	90	86.4	87.8	87.3	84.8	91.8	91	92.9	94.1	89.4	88.6	90.1	88.7
80	90	92.1	91.2	91	90.5	89.1	91.7	86.9	96.6	96.3	98.1	97.9	93.8	92.6	94.7	93.7
90	96.1	94.8	97.4	106.8	96.3	93.2	97.8	93.4	103.3	107.1	105.3	105.9	99.8	103.1	101.1	97.2

Table 5: Predicted quantiles sections 16,17,18,21

quantile	Section 16				Section 17				Section 18				Section 21			
	dir 1		dir 2		dir 1		dir 2		dir 1		dir 2		dir 1		dir 2	
	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.
10	65	71.7	64.4	71.3	62.4	66.2	64.2	67.8	51.4	51.9	51.2	52.6	85.8	73	86.2	81.7
20	71.8	75.2	71.1	74.6	69.1	69.2	70.3	70.9	57.8	54.2	57.8	56.6	89.3	88	90.3	89.2
30	76.6	80.2	76	76.3	74	72.9	74.8	74.4	62.4	58.4	62.6	60.9	91.9	92.5	93.2	95.3
40	80.8	82.5	80.2	79.6	78.1	74.5	78.6	77.4	66.3	65.3	66.7	62.2	94	97	95.6	98.4
50	84.7	85	84	82.2	82	76.9	82.2	80	70	67.2	70.5	68.5	96.1	98	98	104
60	88.6	88.3	87.9	84.4	85.9	85.4	85.7	83.3	73.7	69.7	74.3	71.8	98.1	99	100.3	105
70	92.7	90.5	92.1	91.5	90.1	92.3	89.6	88.7	77.6	74.9	78.4	75.4	100.3	99.5	102.8	105
80	97.6	93.5	96.9	94.3	95	96.3	94	92.4	82.2	80.3	83.1	84.9	102.8	100	105.7	111.8
90	104.3	108.6	103.7	100.2	101.7	99.3	100.2	94.1	88.6	91.2	89.7	91.7	106.3	105	109.7	114.9

Table 6: Predicted quantiles sections 22,23,24,25

quantile	Section 22				Section 23				Section 24				Section 25			
	dir 1		dir 2		dir 1		dir 2		dir 1		dir 2		dir 1		dir 2	
	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.
10	60.8	64.8	56.3	64	45.5	39.1	43.7	46	63.6	67	66.6	59.7	53.7	54	55.5	50.4
20	68	69	64	70	48.3	42.4	47.6	47	69.1	68.6	71.2	66	58.7	56.2	60.5	55.2
30	73.2	71.4	69.6	71	50.3	46.1	50.5	48	73.1	69	74.6	75.3	62.2	59.8	64.1	65.4
40	77.6	78	74.4	72	52	46.8	52.9	50	76.4	72.4	77.5	77.4	65.3	62.6	67.2	71.4
50	81.8	82	78.9	72	53.6	47.5	55.2	50.5	79.6	74	80.1	79	68.1	66	70.1	73
60	86	94	83.3	75	55.2	48.2	57.4	51.8	82.7	79.4	82.8	81.8	71	68.6	73	78.4
70	90.4	97.8	88.1	76	57	48.9	59.8	54.1	86.1	81	85.7	88.1	74	71	76	81.2
80	95.6	101	93.7	79	59	50.2	62.7	57.4	90	86	89	90.2	77.6	75	79.7	84.2
90	102.8	108.4	101.5	82	61.7	51	66.6	61.5	95.5	99	93.7	96.1	82.5	75	84.7	89

Table 7: Predicted quantiles sections 26,27,28,29

quantile	Section 26				Section 27				Section 28				Section 29			
	dir 1		dir 2		dir 1		dir 2		dir 1		dir 2		dir 1		dir 2	
	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.
10	57.8	59.4	60.8	57.2	34.8	44.6	35.4	45.8	66.5	67	68.3	76.6	68.2	72.3	67.2	78.5
20	63.5	65.6	65.4	60.6	40.4	46.2	41	47.6	73.3	75	74.7	78	75.2	77.1	74.8	80.1
30	67.5	67	68.8	65.5	44.4	47.8	45	48.4	78.1	77	79.4	83.8	80.2	84	80.3	82.6
40	71	67.6	71.6	68.8	47.9	49.4	48.4	49.2	82.3	78	83.4	86.4	84.5	89.2	85	85.1
50	74.2	73	74.3	76	51.1	51	51.6	51	86.2	87	87.1	87	88.5	93.1	89.4	85.1
60	77.5	75.8	76.9	76.8	54.3	53.6	54.8	53.6	90	87	90.8	87.6	92.6	93.1	93.8	93.7
70	81	77.1	79.8	77.3	57.7	54.2	58.2	55.6	94.2	88.5	94.8	91	96.9	93.1	98.5	101.2
80	85	80.8	83.1	80.4	61.7	55	62.2	56.8	99	89	99.4	96.8	101.9	94.9	103.9	103.9
90	90.7	86.7	87.7	86.6	67.3	60	67.8	60.2	105.8	103	105.9	100.8	108.9	109.7	111.5	108.8

Table 8: Predicted quantiles sections 30,31,32,33

quantile	Section 30				Section 31				Section 32				Section 33			
	dir 1		dir 2		dir 1		dir 2		dir 1		dir 2		dir 1		dir 2	
	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.
10	62.6	56.3	65.3	57.4	56.8	61.2	60.6	67.2	46.2	52.1	47.4	55.2	54	52.7	56.5	58.2
20	64.2	56.3	66.5	62.1	62.9	66.5	65.6	68.9	52.9	57.5	53.7	59.2	58.8	58.1	60.6	60.9
30	65.3	57.5	67.4	62.1	67.2	68	69.3	70	57.7	59.6	58.3	62.2	62.2	60	63.6	64
40	66.3	61.4	68.1	63.8	70.9	70.3	72.3	73	61.9	59.6	62.2	63.9	65.2	62.7	66.1	67.4
50	67.3	65.9	68.8	71.8	74.4	71.9	75.2	74.4	65.7	64.2	65.8	67.4	67.9	66.2	68.5	67.4
60	68.2	69.3	69.5	74.1	77.9	73.2	78.1	77.1	69.6	66.7	69.4	69.3	70.7	67.6	70.9	67.4
70	69.2	69.3	70.2	74.1	81.6	74.6	81.2	79.6	73.7	69.5	73.3	71.4	73.6	71.1	73.4	71.1
80	70.3	87.2	71.1	79.2	85.9	76.9	84.8	83.4	78.5	79.4	77.9	73.5	77.1	73.8	76.4	71.9
90	71.9	93.2	72.3	79.2	92	84.1	89.8	87.5	85.2	83.4	84.2	77.3	81.9	81.3	80.5	75.3

Table 9: Predicted quantiles sections 34,36

quantile	Section 34				Section 36			
	dir 1		dir 2		dir 1		dir 2	
	pred.	obs.	pred.	obs.	pred.	obs.	pred.	obs.
10	45.6	42.5	43.9	43.1	45.3	44.6	46.5	56.7
20	49.3	46.5	48.7	50.6	53.1	50.9	53.8	59.1
30	52	49.1	52.2	52.7	58.8	59.2	59.1	62.2
40	54.3	51.2	55.2	56.2	63.6	64.2	63.6	65.2
50	56.5	53.2	57.9	58.8	68.1	68.2	67.8	69.5
60	58.6	54.7	60.7	60.2	72.6	70.9	72	72.4
70	60.9	58	63.7	64.9	77.5	74.9	76.5	76.8
80	63.6	62.2	67.2	70.3	83.1	79.3	81.8	78.8
90	67.3	68.4	72	76	91	94.6	89.1	82.5

275 When analyzing Tables 2 to 9, a number of patterns can be observed. First, the speed
276 quantiles of most sections are predicted accurately, which attests the validity of our statistical
277 methodology. For example, most of the sections have predictions that are within an interval
278 of 2-3 kilometer per hour (km/h) and for almost all the quantiles. Most central deciles (40th
279 to 60th quantiles) have very good predictions and therefore it is possible to say that additional
280 observations collected to predict the REs can be successfully used to predict the mean speed
281 of the section with some accuracy. The worst value obtained for the predicted median (50th
282 quantile) is the one related to section 29, direction 1, with an observed median of 93.1 km/h
283 and a prediction of 88.5 km/h. This compares with the 10th quantile that predicts 68.2 km/h
284 for an observed value of 72.3 km/h.

285 Second, some sections are likely to have an error in part due to the prediction error of the
286 random effects. One way to assess this is to observe the extreme quantiles of those sections
287 for which both the 10th and the 90th quantiles are underestimated. Example of this type is
288 section 22, direction 1. Looking back at the plots of predicted REs in figure 3, it is possible
289 to observe that the direction effects are not very precise with only five observations and this
290 is likely a case where the prediction has created a small error. For section 23 (figure 4) the
291 section effect and one of the direction effect are overestimated with five observations, which
292 would explain this component of the prediction error.

293 Third, the most obvious prediction error is the overestimation of low deciles and the under-
294 estimation of high deciles, or vice-versa. This can be observed for example in section 10,
295 direction 1 for which the 10th quantile is underestimated by 2.6 km/h while the 90th quantile
296 is overestimated by 8.3 km/h. There might still be an error in the predicted RE for this
297 section but it cannot be fixed because the RE is a constant added to all predictions in the
298 same section and direction. The most likely cause for this kind of error lies in the estimated
299 coefficients. This possible source of error will be investigated in the next section using a
300 re-sampling technique that will determine if data from a particular section has a relevant
301 effects on the values of the coefficients estimated.

302 5 Jackknife coefficients

303 A jackknife re-sampling technique (Efron and Tibshirani 1993) is adopted to explore the poor
304 predictions obtained for some combinations of sections and directions; we are particularly
305 interested in predictions of high and low speed quantiles. We have already discussed in the
306 previous section how to compute out of sample predictors for REs. However, the prediction
307 of speed quantiles in a new section also requires the model's coefficients to be estimated for
308 the validation sample.

309 The use of a jackknife procedure is based on the following observations: (1) the modeling
310 approach suggested in this paper involves the fitting of a model on a set of road sections and
311 the application of it to another section for which data is not available; (2) some sections are
312 poorly predicted by the suggested model but (3) the majority of sections are predicted with

313 remarkable accuracy.

314 We are specifically interested in comparing the jackknife coefficients obtained by excluding
315 a generic section s and the quality of the forecasts for that section. We hypothesize that
316 significant discrepancies among the values predicted and observed indicate the existence of
317 one or more of the following problems: (i) inaccuracies in the data, (ii) errors in data collection
318 (perhaps these sections have been sampled by operators who did not get proper training,
319 and/or did not assess accurately if the vehicle was traveling under free flow conditions), (iii)
320 different driving conditions might alter motorists' behavior, (iv) the omission of important
321 covariates that were overlooked and that affect some sections. These scenarios would generally
322 cause some sections to be poorly modeled by the approach suggested in this paper and the
323 assessment of such conditions is expected to greatly simplify the investigation task as the
324 model's user validates his data.

325 In a model that is appropriate for its data, it is expected that the exclusion of any observation
326 does not change the estimates of the model coefficients in a relevant way. The re-sampling
327 scheme suggested discards a substantial number of observations. This way to proceed makes
328 it impossible to directly use the standard re-sampling literature to quantify the effect of a
329 specific coefficient, and ultimately to identify the specification issue. Furthermore, the use
330 of such a criteria would involve a different threshold for each section due to the variability
331 of their size. Simulations could be used to derive a more systematic identification method
332 for sections requiring attention, however this is outside the scope of our analysis and we rely
333 instead on a qualitative evaluation of the effect of each section on coefficients' estimates.

334 Tables 10, and 11 in Appendix A present the jackknife coefficients used for speed data
335 validation and should be read together. Each line corresponds to estimates obtained by
336 removing one section, except the first one that contains the estimations on the whole sample.
337 Each column provides the estimated coefficients for a specific predictor. The cells in bold
338 indicate the coefficients that are very different from the full sample equivalent (outside two
339 standard deviations). Ideally, the estimated coefficients in a given column would be stable and
340 comparable to the coefficient estimated using the entire sample. Large differences between
341 a coefficient estimated by excluding one section and those obtained with the whole sample
342 raise concerns about the specific section or the predictor.

343 When reading the results, it can be observed that the jackknife coefficients for $Z*SRW$ are
344 very similar across the thirty one jackknife samples and are very similar to the coefficients
345 estimated on the overall sample, whereas the coefficients for $Z*1/R$ appear to be off only
346 for sections 7 and 10. Sections 1, 3, 7, and 36 generate some of the extreme jackknife
347 coefficients. We can probably conclude that these sections (1,3,7, and 36) behave according
348 to a different model, or that the measurement of predictors and speed data was less reliable
349 on these sections. This is also confirmed in the comparison between prediction and observation
350 reported in the Tables 2 to 9.

6 Conclusions

In this paper we have explored methods to predict speed distributions using mixed linear models. Difficulties associated with this problem are twofold. First we rely on model with random effects to make prediction on new road sections. Second, we are using normal quantiles of the dependent variables as predictors.

We have discussed that it is necessary to observe at least some speed data in the section for which decile predictions were computed. To overcome the problem created by the use of normal quantiles in the calculation of residuals, we propose the use of an auxiliary model. It has been shown how the relationship between this auxiliary model and the full actual model can be used in prediction in order to derive the *best linear unbiased predictor* (BLUP) in this context. It was also observed that this method was not performing well when used to make random effect predictions for a model that ignored the sampling design of the data, but turned out to be very precise when the full sampling design was accounted in the model.

The approach was further tested to validate the models' coefficients associated with the variables of the model. The estimates obtained were roughly stable except for some variables that generated more extreme coefficients for some sections. The sections with extreme coefficients were consistently the same for all the affected variables.

A jackknife technique was used to understand what road sections caused poor predictions of the random effects. It was found that most road sections were predicted satisfactorily. Large errors in the prediction of random effect were mostly caused by errors in the coefficients of the model. Some sections appeared to have a disproportionate effect on the model, suggesting that they should be modeled in a different way.

Overall, this paper has contributed to the transferability of RE models, has identified the problems arising in the estimation of Operating Speeds, has developed a theory to calculate the best predictors and to validate the results obtained. Future efforts should be directed towards the use of the method proposed in practice and possibly to different model types that include REs.

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387 **Appendices**

Table 10: Jackknife coefficients - Part 1

section out	Intercept	PedID	1/R	Z*Lane	Z*1/R	Z*SLS	Z*SBLS	Z*IDRS	Z*SRS	Z*SBRS	Z*SRW	Z*SLW
none	79.33	-7.59	-1946.46	20.54	-274.07	-3.46	-1.56	-0.83	-2.88	-0.64	-13.38	13.85
1	79.8	-7.77	-2042.39	25.07	-227.05	-1.95	-2.82	-0.91	-0.79	-1.36	-13.62	13.09
3	79.51	-7.67	-1983.47	22.96	-170.71	-2.49	-1.19	-0.97	-2.03	-0.31	-12.56	14.29
5	79.48	-7.65	-1976.76	19.71	-279.35	-3.38	-2.24	-0.95	-3.1	0.12	-13.41	13.74
7	79.21	-7.55	-2277.82	21.89	-289.06	-3.45	-0.93	-0.83	-2.72	-0.47	-13.36	14.13
8	79.09	-7.5	-1896.77	20.86	-283.21	-3.44	-1.44	-0.83	-2.86	-0.57	-13.36	13.9
9	79.3	-7.58	-1943.43	20.46	-274.26	-3.48	-1.64	-0.84	-2.88	-0.59	-13.4	13.87
10	79.2	-7.54	-1208.28	21.33	-248.33	-3.31	-1.48	-0.81	-2.82	-0.54	-13.34	13.78
11	79.53	-7.67	-1987.44	19.97	-267.14	-3.45	-1.5	-0.8	-2.88	-0.71	-13.37	13.85
12	79.28	-7.57	-1936.44	18.9	-271.29	-3.47	-1.53	-0.82	-2.94	-0.66	-13.37	13.89
13	79.33	-7.59	-1946	21.35	-283.83	-3.46	-1.58	-0.84	-2.88	-0.58	-13.39	13.85
14	79.12	-7.51	-1901.82	20.27	-274.76	-3.45	-1.57	-0.83	-2.91	-0.61	-13.36	13.84
15	79.22	-7.55	-1922.98	20.74	-273.66	-3.45	-1.59	-0.86	-2.88	-0.61	-13.38	13.85
16	79.12	-7.51	-1901.59	21.76	-266.84	-3.43	-1.58	-0.87	-2.83	-0.64	-13.38	13.82
17	79.23	-7.55	-1924.69	20.26	-270.36	-3.46	-1.6	-0.86	-2.88	-0.62	-13.38	13.85
18	79.68	-7.72	-2017.04	21.32	-276.61	-3.41	-1.49	-0.82	-2.84	-0.56	-13.4	13.84
20	78.42	-7.24	-1757.97	19.7	-278.04	-3.52	-1.65	-0.83	-2.93	-0.72	-13.37	13.87
21	78.71	-7.36	-1819.11	21.88	-244.19	-3.32	-1.37	-0.9	-2.78	-0.51	-13.39	13.82
22	79.33	-7.59	-1944.68	20.45	-274.83	-3.46	-1.5	-0.81	-2.94	-0.7	-13.37	13.89
23	80.41	-8	-2168.41	20.52	-276.31	-3.46	-1.55	-0.83	-2.88	-0.64	-13.38	13.86
24	79.33	-7.59	-1945.62	20.49	-273.89	-3.55	-1.54	-0.82	-2.86	-0.66	-13.4	13.84
25	79.73	-7.74	-2028.57	20.52	-273.66	-3.47	-1.57	-0.83	-2.89	-0.66	-13.39	13.85
26	79.58	-7.69	-1997.16	20.52	-273.93	-3.59	-1.46	-0.79	-2.74	-0.71	-13.38	13.88
27	79.48	-8.74	-1976.04	20.47	-269.15	-3.5	-1.59	-0.86	-2.83	-0.59	-13.35	13.85
28	79.09	-7.5	-1895.65	19.77	-272.6	-3.5	-1.67	-0.85	-2.91	-0.7	-13.36	13.85
29	78.93	-7.44	-1863.92	20.07	-267.62	-3.49	-1.65	-0.85	-2.93	-0.73	-13.34	13.86
30	79.37	-7.56	-1954.05	19.1	-214.59	-4.27	-2.05	-0.99	-3.53	-1.15	-13.43	13.63
31	79.52	-7.66	-1983.91	20.34	-256.36	-3.1	-1.63	-0.87	-2.74	-0.71	-13.26	13.93
32	79.47	-7.43	-1973.31	21.44	-295.67	-3.71	-1.6	-0.7	-3.11	-0.74	-13.36	13.82
33	79.78	-7.76	-2037.72	21.32	-276.67	-3.33	-1.5	-0.81	-3.05	-0.6	-13.39	13.83
34	79.34	-7.66	-1947.25	19.84	-275.81	-3.59	-1.67	-0.79	-3.01	-0.76	-13.35	13.87
36	79.39	-7.52	-1958.78	17.03	-257.65	-4.26	-2.33	-0.91	-3.62	-1.11	-13.31	13.82

Table 11: Jackknife coefficients - Part 2

section out	Z*PLS	Z*DDRS	Z*TRDLS	Z*LW	Z*IDLS	Z*LG	Z*ΔPSL	Z*PedD	Z*TRDRS	Z*LBRS	Z*LBS
none	0.06	0.43	-0.29	-3.52	-0.43	0.07	0.07	1.62	0.41	1.31	1.16
1	0.04	0.26	-0.78	-4.16	-0.3	0.09	0.19	0.11	0.03	2.57	2.52
3	0.16	0.6	-0.82	-6.73	-0.52	0.06	0.03	2.13	-0.3	1.03	1.25
5	0.07	0.45	-0.27	-3.37	-0.4	0.11	0.06	1.71	0.34	1.53	0.87
7	0.07	0.44	-0.86	-4.13	-0.46	-0.08	0.05	1.66	0.04	1.67	1.09
8	0.06	0.43	-0.4	-3.67	-0.43	0.06	0.07	1.62	0.31	1.36	1.17
9	0.06	0.42	-0.31	-3.48	-0.42	0.05	0.07	1.62	0.42	1.33	1.13
10	0.06	0.44	-0.25	-3.77	-0.49	0.13	0.07	1.58	0.5	1.19	1.17
11	0.06	0.43	-0.27	-3.37	-0.49	0.08	0.07	1.63	0.4	1.32	1.12
12	0.06	0.47	-0.24	-3.17	-0.42	0.07	0.08	1.61	0.4	1.35	1.26
13	0.06	0.42	-0.3	-3.75	-0.39	0.07	0.07	1.59	0.4	1.3	1.18
14	0.06	0.44	-0.26	-3.48	-0.42	0.09	0.07	1.6	0.39	1.3	1.22
15	0.06	0.43	-0.29	-3.58	-0.41	0.07	0.07	1.62	0.41	1.29	1.18
16	0.06	0.39	-0.32	-3.78	-0.46	0.07	0.07	1.65	0.41	1.26	1.06
17	0.06	0.42	-0.28	-3.44	-0.42	0.07	0.07	1.63	0.41	1.29	1.17
18	0.06	0.44	-0.3	-3.83	-0.42	0.07	0.08	1.59	0.37	1.39	1.27
20	0.06	0.4	-0.28	-3.18	-0.43	0.07	0.07	1.63	0.44	1.24	1.03
21	0.06	0.46	-0.46	-4	-0.51	0.07	0.07	1.67	0.17	1.38	1.3
22	0.06	0.45	-0.27	-3.53	-0.45	0.06	0.07	1.6	0.41	1.41	1.08
23	0.06	0.42	-0.3	-3.5	-0.43	0.07	0.07	1.61	0.39	1.31	1.14
24	0.06	0.41	-0.3	-3.5	-0.45	0.07	0.07	1.67	0.41	1.34	1.11
25	0.06	0.43	-0.28	-3.52	-0.43	0.06	0.07	1.62	0.42	1.33	1.16
26	0.06	0.44	-0.29	-3.53	-0.48	0.06	0.07	1.59	0.39	1.38	1.08
27	0.06	0.36	-0.33	-3.5	-0.44	0.07	0.06	2.12	0.46	1.33	1.03
28	0.06	0.4	-0.28	-3.19	-0.44	0.08	0.07	1.65	0.43	1.23	1.03
29	0.06	0.43	-0.12	-3.43	-0.45	0.07	0.08	1.65	0.57	1.28	1.14
30	0.05	0.34	-0.37	-2.7	-0.53	0.06	0.1	1.99	0.43	1.44	1.18
31	0.06	0.46	-0.27	-3.39	-0.46	0.07	0.08	1.38	0.38	1.21	1.12
32	0.06	0.38	-0.33	-3.75	-0.41	0.08	0.08	1.76	0.38	1.6	1.13
33	0.06	0.43	-0.31	-3.81	-0.43	0.07	0.08	1.63	0.37	1.41	1.24
34	0.06	0.41	-0.3	-3.19	-0.44	0.07	0.08	1.25	0.39	1.28	1.1
36	0.04	0.43	-0.35	-1.76	-0.38	0.1	0.1	1.81	0.28	0.82	1.29

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