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Traffic volume and crashes and how crash and road characteristics affect their relationship – A meta-analysis

Alena Katharina Høye*, Ingeborg Storesund Hesjevoll

Institute of Transport Economics, Gaustadalleen 21, 0349 Oslo, Norway

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ABSTRACT

The present study has investigated the relationship between traffic volume and crash numbers by means of meta-analysis, based on 521 crash prediction models from 118 studies. The weighted pooled volume coefficient for all crashes and all levels of crash severity (excluding fatal crashes) is 0.875. The most important moderator variable is crash type. Pooled volume coefficients are systematically greater for multi vehicle crashes (1.210) than for single vehicle crashes (0.552). Regarding crash severity, the results indicate that volume coefficients are smaller for more fatal crashes (0.777 for all fatal crashes) than for injury crashes but no systematic differences were found between volume coefficients for injury and property-damage-only crashes. At higher levels of volume and on divided roads, volume coefficients tend to be greater than at lower levels of volume and on undivided roads. This is consistent with the finding that freeways on average have greater volume coefficients than other types of road and that two-lane roads are the road type with the smallest average volume coefficients. The results indicate that results from crash prediction models are likely to be more precise when crashes are disaggregated by crash type, crash severity, and road type. Disaggregating models by volume level and distinguishing between divided and undivided roads may also improve the precision of the results. The results indicate further that crash prediction models may be misleading if they are used to predict crash numbers on roads that differ from those that were used for model development with respect to composition of crash types, share of fatal or serious injury crashes, road types, and volume levels.

1. Introduction

Crash prediction models are an important tool in many different contexts, such as evaluations of road safety measures, black spot analysis, and safety management of road networks. Traffic volume is one of the most important predictor variables in such models (besides section length and time). The volume predictor used in most published crash prediction models is the annual average daily traffic (AADT), and most models have been developed for all types of crashes taken together.

However, the relationship between volume and crash numbers may depend on several factors, such as crash type and severity (or distribution thereof), road type, volume level and changes of volume over time. Thus, averaging volumes over a whole year and summarizing different types of crashes and levels of severity may lead to imprecise or biased predictions of crash numbers (Mensah and Hauer, 1998).

Among the potential moderator variables for the relationship between volume and crash numbers that have been investigated in empirical studies, are crash type (Geedipally and Lord, 2010; Mensah and Hauer, 1998), high vs. low volume (Martz, 2017), and fatal vs. injury crashes (Gates et al., 2015). However, the results from individual studies may not always be generalizable. Other factors, such as the type of road, have to our knowledge not yet been investigated systematically.

Knowledge about potential moderator variables for the relationship between volume and crashes is essential because it can guide modelling decisions and provide information about possible sources of bias and uncertainty. Relevant modelling decisions include whether or not models should be disaggregated by, for example, crash type, type of road, or volume level.

Knowledge about typical relationships between volume and crashes can also be useful when it is not possible to calculate crash prediction models, but when one wants to predict effects of changing volumes on crash numbers or compare crash numbers between roads with different volumes. In such situations, using typical relationships may be more adequate than simply assuming a linear relationship, as is often done in the absence of more precise information (Qin et al., 2004).

Therefore, the aim of the present study is to investigate the relationship between traffic volume and crash numbers and factors that affect this relationship, by means of meta-analysis. The main research

* Corresponding author.
E-mail address: alh@toi.no (A.K. Høye).

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questions to be addressed are:

- Is it possible and meaningful to summarize volume coefficients from existing studies to an overall average volume coefficient?
- What are relevant moderator variables for the relationship between volume and crashes?

Background information about the relationship between volume and crashes and potential moderator variables to be investigated, are addressed in the following section.

2. Crash prediction models and potential moderator variables

Crash prediction models are often based on Poisson, Negative binomial, or similar regression models. The present study focuses on this type of models because they are the most common types of models and considered adequate with respect to the statistical properties of crash numbers (Lord and Mannering, 2010; Poch and Mannering, 1996; Lord et al., 2005a, 2005b; Noland and Karlaftis, 2005). Such crash prediction models have the general form:

$$\text{N of crashes} = \exp[\Sigma_i\ (b_i * X_i)]$$

where X_i are the predictor variables and b_i the regression coefficients (Elvik, 2007). Volume is included in the models as one of the coefficients X. In most crash prediction models, a logarithmic transformation of AADT is used (Ln(AADT)) to take into account the nonlinear relationship between volume and crashes (Wang et al., 2013). The percentage increase of predicted crash numbers as volume increases by a certain percentage, is then the same at all traffic volumes. When the coefficient for volume is equal to one, the predicted number of crashes is proportional to volume, i.e. an increase of volume by X percent is associated with an increase of the predicted number of crashes by X percent. A coefficient between zero and one implies that crashes increase less than proportional with volume, and a coefficient greater than one implies that crashes increase more than proportional with volume.

Potential moderator variables for the relationship between volume and crashes are described in the following. Since the study is based on meta-analysis, only potential moderator variables are described that can be defined on study level (more precisely: for each crash prediction model) and for which sufficient information is available from the studies included in meta-analysis for conducting moderator analyses.

Crash type. As volume increases, the number of opportunities for multi vehicle (MV) crashes increases, theoretically at a higher rate than the traffic volume (Elvik et al., 2009). Single vehicle (SV) crashes on the other hand occur often at low volumes. Amongst other things, monotony and boredom which often occur on low volumes roads, are typical contributing factors to SV crashes (Armstrong et al., 2008; Candappa et al., 2013). Some studies show that estimating separate models for SV and MV crashes provides more precise estimates than combining all crash types (Geedipally and Lord, 2010). On this background, volume is expected to be more strongly related to MV crashes than to SV crashes.

Crash severity. Increasing volumes may have different effects on crashes, depending on the level of severity. Results from studies that have investigated crash effects of congestion are inconsistent with respect to crash severity. Some studies found that crash severity decreases in congestion (Lord et al., 2005a, 2005b) and that crashes with property damage only (PDO) increase more with increasing volumes at high volumes than fatal and injury crashes (Harwood et al., 2013). A likely explanation for such results is reduced speed in congestion and the relationship between speed and crash severity (Elvik et al., 2019). Other studies did not find any relationship between congestion and crashes (Quddus et al., 2009). Harwood et al. (2013) found about the same effects of reducing traffic density (passenger cars per lane mile) for crashes of different severities. In contrast to these results, Wang et al. (2013) found increased crash severity at increasing congestion and only little impact of congestion on slight injury crashes.

A likely explanation for inconsistent results is that different volumes are related to numerous other factors that are associated with crash severity. Such factors may partly offset each other's effects (Noland and Quddus, 2005). For example, there are on average fewer severe crashes on divided roads (where volumes often are high) than on undivided roads with lower volumes (Stigson, 2009). At high speed, crashes are on average more severe than at lower speed (Elvik et al., 2019), but high-speed roads are often high-volume roads with a high level of safety. On this background, it is difficult to make general predictions about the effect of crash severity on the relationship between volume and crashes.

Type of road: The relationship between volume and crashes may differ between different types of road. Amongst other things, the distribution of SV and MV crashes is different between different types of road (Martensen and Dupont, 2013). SV crashes occur more often on low volume rural roads, while MV crashes more often occur on high volume, multilane roads. Moreover, the same traffic volume may be associated with different traffic densities on different roads, and traffic density has been found to be associated with crash numbers (Lord et al., 2005a, 2005b). Therefore, it is investigated in the present study if volume coefficients differ systematically between different types of road.

Area type (rural vs. urban). On urban roads, the share of MV crashes is usually larger than on rural roads (Høye, 2016). In urban areas, there are usually more intersections, lower speed limits, more potential conflict points, and more pedestrians and cyclists than in rural areas. How all these factors taken together may affect volume coefficients, is uncertain. It is therefore investigated in the present study if there are systematic differences between volume coefficients for urban and rural areas.

Volume level. Volume coefficients are usually calculated for the whole range of volume that is available in a data set. However, the relationship between volume and crashes may change at increasing volumes, especially as volumes approach capacity, i.e. in congestion.

At low volumes, there are usually more SV crashes than at higher volumes (Marchesini and Weijermars, 2010) and volume coefficients for SV crashes are expected to be smaller for SV crashes than for MV crashes (see above). As volume increases, the number of potential conflicts and the share of MV crashes increase (Elvik et al., 2009). One may therefore expect greater volume coefficients at higher volumes if all else is equal. However, all else is not always equal; for example, higher volume roads have on average higher capacity (for example more lanes) than lower volume roads. Moreover, as volume approaches capacity, speed and crash severity decrease, while the effect on crash rate varies between traffic conditions (Golob et al., 2008). In congestion at speeds approaching zero there will hardly be any more crashes (Elvik et al., 2009).

In addition to the effects of crash type, several road characteristics are related to volume and crash rate. For example, lower volume roads are on average narrower and they have sharper curves and steeper grades, all of which may be associated with higher crash rates (Ewan et al., 2016).

In summary, it is difficult to make general predictions about how the relationship between volume and crashes may change at different levels of volume. Only at the highest volumes with high levels of congestion, one may expect the relationship to be weaker than at lower levels of volume.

3. Method

A systematic review has been conducted of published crash prediction models in which traffic volume is one of the predictors. Meta-analytical methods have been used to calculate pooled volume coefficients and to investigate the effects of potential moderator variables.

The unit of analysis in the present study is a regression coefficient for traffic volume from a multivariate crash prediction model that has the general form of a Poisson or Negative binomial regression model. All volume coefficients refer to the natural logarithm of the annual average daily traffic (Ln(AADT)). A standard approach to combining the results from different regression models is a meta-analysis of the estimated regression coefficients (e.g. Becker and Wu, 2007; Cappuccio et al., 1995; Hunter and Schmidt, 2015).

3.1. Literature search

The aim of the literature search was to find at least 100 studies that can be included in meta-analysis. This limit has been set as a compromise between finding as many studies as possible and limited resources. Finding more studies would have been highly resource demanding but would not have been likely to significantly affect the results.

In order to be eligible for meta-analysis, studies had to have investigated the relationship between volume and crash numbers in Poisson or Negative binomial model and to have included Ln(AADT) as the only volume predictor. Only studies that are based on real-world crash data with road sections (not geographical areas) as the unit of analysis were included. Studies that have included additional AADT-based predictors (such as $AADT^2$ or dummy variables for high and low volume) were not included because the coefficients for Ln(AADT) are not directly comparable to those from models with Ln(AADT) as the only volume predictor. Studies based only on crashes at intersections/roundabouts or on ramps were not included either.

The literature search was conducted according to the PRISMA checklist, that was slightly modified for the purposes of this study. The steps in the literature search are schematically shown in Fig. 1 and described in the following.

Step (1)-(2) Literature search: Two searches were conducted on Google Scholar in April 2019 for the following search terms: (1) “Negative binomial” AND crash AND model and (2) "Safety performance function". Since practically all crash prediction models include a volume predictor, volume (or AADT) was not included as a search term. Both searches were limited by publication year (2005 or later). Citations and patens were excluded. The first search yielded more results than can be shown in Google Scholar (10,000). Therefore, additional searches were conducted that were limited to the latest years only (2016 and later). The total number of records screened is estimated at about 12,000 (step (3)).

Step (3)-(4) Screening of titles and abstracts: For most of the screened records, only the contents shown on Google Scholars hit list were screened. In many cases, abstracts were screened as well, but these were not systematically documented if they were dismissed immediately. Studies were immediately dismissed when they were obviously irrelevant, for example studies that are not related to road safety, real-time crash prediction models, studies based on specific crash types (such as truck crashes, pedestrian crashes, or intersection crashes), and simulation studies.

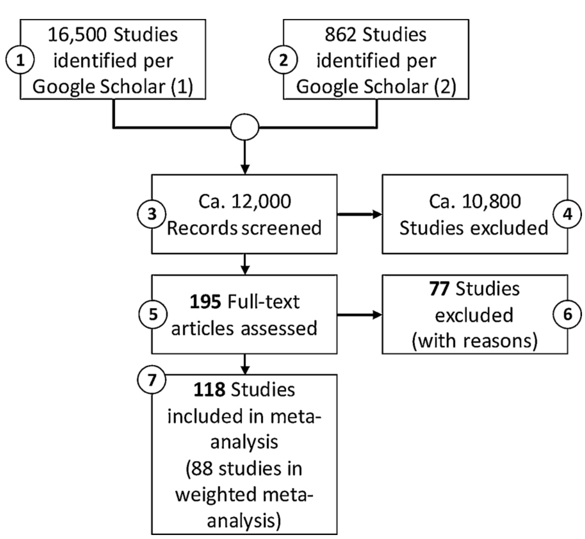

Fig. 1. Literature search and study selection.

Table 1
Reasons for exclusion of 77 studies from meta-analysis (non-overlapping categories).

Reason for exclusion	Number
Untransformed AADT	18
Same data as other study	12
Other type of model	11
Model not reported	10
Not provided by library	7
Other volume predictor	6
Intersections/ramps only	6
Crash rate dependent	3
No AADT predictor	3
Simulated data	1
Total	**77**

Step (5)-(6) Full text assessment: 195 studies were selected for full-text assessment. Among these, 77 could not be included in meta-analysis. Table 1 shows an overview of the reasons in non-overlapping categories (for some of the excluded studies several reasons apply; for these studies only the most serious or the most obvious reason is included in the overview).

Step (7) Meta-analysis: In total, 118 studies were eligible for meta-analysis. Of these, 89 studies provided enough information for calculating weights for meta-analysis, such as standard deviations for coefficients, p-values, or t-values. Studies that provided information such as “$p < 0.001$” were not included in weighted meta-analysis. The studies included in meta-analysis are listed alphabetically in the appendix.

3.2. Calculating pooled regression coefficients

Pooled regression coefficients were calculated as weighted and unweighted averages of regression coefficients. Weighted averages were calculated according to the inverse variance method of meta-analysis as follows (Elvik, 2018):

$$\textit{Pooled regression coefficient} = \frac{\sum_i Coeff._i {*} W_i}{\sum_i W_i} \tag{2}$$

Coeff.$_i$ denotes the volume coefficient from model i and W the corresponding weight which is proportional to the inverse of the coefficients’ variance.

For all pooled regression coefficients, 95 % confidence intervals are reported. They are calculated according to a random effects model which allows the individual volume coefficients to vary between crash prediction models, as described by Christensen (2003).

In the weighted analyses, I^2 is reported as a measure of heterogeneity (Borenstein et al., 2017). I^2 denotes the proportion of the total variance in the observed effect estimates (here: volume coefficients) that is due to variation in the underlying true effects in each study (here: crash prediction model). I^2 values are independent of the number of effect estimates included in meta-analysis. I^2 values below 25 % and above 75 % are traditionally interpreted as low and high heterogeneity, respectively.

Since information for calculating variances is not available for all volume coefficients, additional analyses were made of unweighted averages of regression coefficients. The confidence intervals for these are based on the variance between the individual volume coefficient. The unweighted analyses allow the inclusion of more results in the analyses and they provide a sensitivity analysis for the degree to which the results are affected by statistical weighing and study selection

Table 2
Definition of study-level moderator variables.

	Description	N of vol. coeff.
Crash type		
All crashes	All types of crashes (only results that refer to all crashes combined).	369
MV crashes	Multi vehicle crashes, including results for all MV crashes and results for specific types of MV crashes.	68
SV crashes	Single vehicle crashes, including results for run-off-road crashes.	68
Crash severity		
Fatal	Fatal crashes.	8
Injury	Injury crashes; most results refer to all severity levels, a few refer to specific levels of severity (slight, serious or KSI).	139
Unspecified severity	Unspecified crash severity; most likely including all degrees of severity including injury and property damage only crashes.	351
Injury/unspecified[1]	Unspecified and injury crashes without double-counting (injury crashes for which corresponding results for unspecified injury are available, are not included).	380
Subcategories of injury	Serious and slight injuries for which corresponding results for all injury are available (included in moderator analysis, but not in analyses for "Injury").	4
PDO	Property damage only crashes.	19
Road category		
Freeways	Grade-separated, divided multi-lane roads.	200
Multilane non-Freeways	Multilane roads with at-grade junctions; including divided and undivided roads.	109
Two-lane	Two-lane roads, undivided and not grade separated.	156
Unspecified/all roads	Unspecified road type or all types of road.	56
Area type		
Rural	Roads in rural areas.	279
Urban	Roads in urban areas.	144
Rural/urban	Roads in rural and urban areas, unspecified or other area type.	98
Volume range		
Very low	Mean AADT < 1000 and max. AADT < 5000	12
Low	Mean AADT < 10,000 and not 'Very low'	126
Medium	10,000 < Mean AADT < 30,000	124
High	30,000 < Mean AADT and not 'Very high'	58
Very high	50,000 < Mean AADT and min. AADT > 10,000	56
Mean volume	Mean AADT	375

[1] For 29 of the volume coefficients for injury crashes, corresponding volume coefficients for unspecified severity crashes are available. These 29 vol coefficients for injury crashes are not included in "injury/unspecified severity" crashes to avoid double-counting.

(Elvik, 2005). All weighted analyses were made in R, version 3.6.1, with the metafor package (Viechtbauer, 2010). All unweighted analyses were made in MS Excel.

3.3. Moderator analysis

The effects of potential moderator variables are investigated with meta-regression and subgroup comparisons. The types of analyses vary between the potential moderator variables, depending on the availability of information. An overview of the investigated moderator variables is given in Table 2.

3.3.1. Meta-regression

Meta-regression implies the development of regression models with the estimated volume predictors from crash prediction models as the dependent variable and potential study-level moderator variables as predictor variables (Shadish and Sweeney, 1991). Two sets of meta-regression models were developed:

- Meta-regression models that are based on all available studies (mostly weighted meta-regression) and all potential moderator variables, except for volume range/level in some of the models.
- Subgroup comparison meta-regression models that were developed specifically for some of the subgroup comparisons, based on limited data sets. These models are described in more detail in the respective sections. All of them apply weighted meta-regression.

All meta-regression analyses have been calculated with the metafor package in R.

3.3.2. Subgroup analyses

In subgroup analyses, pooled volume coefficients are compared between subgroups of results (Hedges and Olkin, 1985). In contrast to meta-regression, the subgroup analyses focus on only one potential moderator variable at a time and they only include directly comparable results (for example volume coefficients for crashes of the same type and severity). For some of the subgroup analyses, meta-regression models have been developed additionally.

Two types of subgroups analyses were conducted, depending on the availability of data:

- ***Matched pairs comparisons:*** Subgroups are based on studies that have reported models for different levels of a potential moderator variable (for example for fatal and injury crashes), based on otherwise identical data (for example, the same type of crashes on the same roads). Matched pairs subgroup analyses are conducted for crash type, crash severity, and volume level.
- ***Other subgroup analyses:*** These analyses are based on coefficients from otherwise similar models from different studies. Such subgroup analyses are made for road type, area type, and volume level.

4. Exploratory analysis

In the exploratory analysis, preliminary results from meta-regression are presented and the distribution of volume coefficients from all studies is investigated. Additionally, it is investigated if there are systematic differences between volume coefficients depending on other predictor variables in the crash prediction models.

4.1. Preliminary results from meta-analysis and distribution of results

Table 3 shows unweighted and weighted pooled volume coefficients, based on all available studies, by crash type and level of severity, except for crash prediction models that are based on subsets of data (such as peak volume crashes). The latter are excluded to avoid double-counting. Volume coefficients for injury and PDO crashes are included in "all severities" only if the crashes they are based on, are not included in any of the coefficients for unspecified severity; none of the volume

Table 3
Unweighted and weighted (RE) pooled volume coefficients by crash type and injury severity (based on all studies, without double-counting; see text) with 95 % confidence intervals (CI) and I^2.

	Unweighted			Weighted			
	N	Vol coeff.	*CI*	N	Vol coeff.	*CI*	I^2
All crashes							
Fatal	7	0.697	*(0.121; 1.272)*	6	0.777	*(0.572; 0.982)*	*90.7*
Injury	123	1.061	*(0.225; 1.897)*	74	1.001	*(0.919; 1.084)*	*99.4*
Unspecified severity	232	0.919	*(0.051; 1.787)*	143	0.862	*(0.810; 0.914)*	*99.4*
PDO	19	0.886	*(0.358; 1.413)*	18	0.869	*(0.751; 0.986)*	*95.7*
All severities	242	0.953	*(0.075; 1.831)*	166	0.875	*(0.826; 0.923)*	*99.4*
MV crashes							
Injury	5	1.033	*(-0.139; 2.206)*	3	0.960	*(0.463; 1.456)*	*91.7*
Unspecified severity	63	1.331	*(0.400; 2.262)*	36	1.228	*(1.083; 1.373)*	*99.0*
All severities	64	1.319	*(0.375; 2.262)*	37	1.210	*(1.064; 1.355)*	*99.0*
SV crashes							
Fatal	1	0.700	*(-0.149; 1.449)*				
Injury	11	0.650	*(0.039; 1.172)*	6	0.569	*(0.336; 0.801)*	*93.2*
Unspecified severity	56	0.606	*(-0.149; 1.449)*	43	0.557	*(0.481; 0.632)*	*99.5*
All severities	58	0.607	*(0.036; 1.178)*	44	0.552	*(0.477; 0.627)*	*99.5*

coefficients for fatal crashes are included. The weighted and unweighted pooled volume coefficients are for the most part similar in size, especially those with large N (see also section 4.2).

To visualize the distributions of those volume coefficients for which weights are available, two types of funnel plots are shown in Fig. 2 (all crashes) and Fig. 3 (MV/SV crashes). Each of the funnel plots corresponds to one of the weighted results for a specific level of severity in Table 3. The vertical lines in the funnel plots represent the respective summary effects. In both figures, the funnel plots display the volume coefficients of individual studies on the X-axis. The funnel plots on the ***left*** side show the weights on the Y-axis. These funnel plots are recommended by Elvik et al. (2009) and Sterne and Egger (2001) for meta-analysis in which there is large variation in the size of the individual studies. These funnel plots show most clearly differences between volume coefficients with large weights, while those with the lowest weights are close to the bottom line. In the funnel plots on the ***right*** side in the two figures, the standard errors of the volume coefficients are displayed on the Y-axis. This type of funnel plot is recommended by Sterne et al. (2011). These plots show most clearly differences between volume coefficients with small weights (large standard errors) while those with the largest weights are close to the top.

If there is little or no heterogeneity in the results, i.e. if all volume coefficients are from the same underlying distribution, representing the same "true" effect, one would expect the funnel plots to be symmetrical, with most of those volume coefficients with the largest weights / smallest standard errors in the middle of the distribution (Christensen, 2003). One would also expect all or most of the results to lie within the funnel shapes (dotted lines).

Fig. 2 shows very similar distributions of volume coefficients for injury and unspecified severity crashes. In both distributions large volume coefficients with small weights and small volume coefficients with large weights are overrepresented. For unspecified severity crashes, there are additionally a few very small volume coefficients with very large standard errors. The distributions for PDO crashes look relatively symmetrical.

Unsymmetrical distributions with an overrepresentation of large effect sizes with small weights would in most other meta-analyses be interpreted as a possible sign of publication bias. However, the regression coefficients in the present meta-analysis are not the main outcome of evaluation studies and they do not show the effect of any road safety measure. None of the studies had the explicit goal to investigate the relationship between volume and crashes or had a specific hypothesis for the outcome. Thus, publication bias is highly unlikely and the asymmetry in the distributions is more likely to be due to other factors.

None of the distributions follows the funnel shapes that are indicated by the dotted lines, indicating the presence of heterogeneity. Possible sources of heterogeneity are discussed in the sections about meta-regression and subgroup comparisons.

In Fig. 3, all diagrams show that volume coefficients on average are larger for MV crashes than for SV crashes. The distributions look relatively symmetrical, but many volume coefficients are outside the funnel lines which indicates heterogeneity and the likely presence of relevant moderator variables.

4.2. Meta-regression analysis

Meta-regression models were developed to investigate the effects of potential moderator variables on the relationship between volume and crashes. One set of meta-regression models is based on all available studies and includes all potential moderator variables. These meta-regression models are shown in Table 4.

A second set of meta-regression models was developed to investigate the effects of individual potential moderator variables (one per model) as a part of the subgroup comparisons. These models are shown in Table 5 and described in the next chapter.

The meta-regression models that are based on all studies in Table 4 were calculated with different sets of study-level predictor variables:

- ***Crash types:*** MV and SV crashes are not evenly distributed over the levels of the other predictor variables, and there may be interaction effects between crash type and other variables. Therefore, meta-regression models were developed (1) based on volume coefficients for all crash types (including results for all crashes, MV crashes, and SV crashes; models 1–3) and (2) based only on volume coefficients for all crashes, not including results referring specifically to MV or SV crashes (models 4–6).
- ***Volume predictor:*** Information about volume levels is not available from all studies. Therefore, for each of the above models, three meta-regression models were calculated: (1) without any volume predictor (models 1 and 4), (2) with five levels of volume as dummy variable predictors (models 2 and 5), and (3) with mean volume as a predictor (models 3 and 6).
- ***Weights:*** Most meta-regression models are weighted, only model 1c is unweighted; it is based on all studies including those without weights. It includes the availability of weights as an additional predictor variable.

To avoid double counting of data, the following types of volume

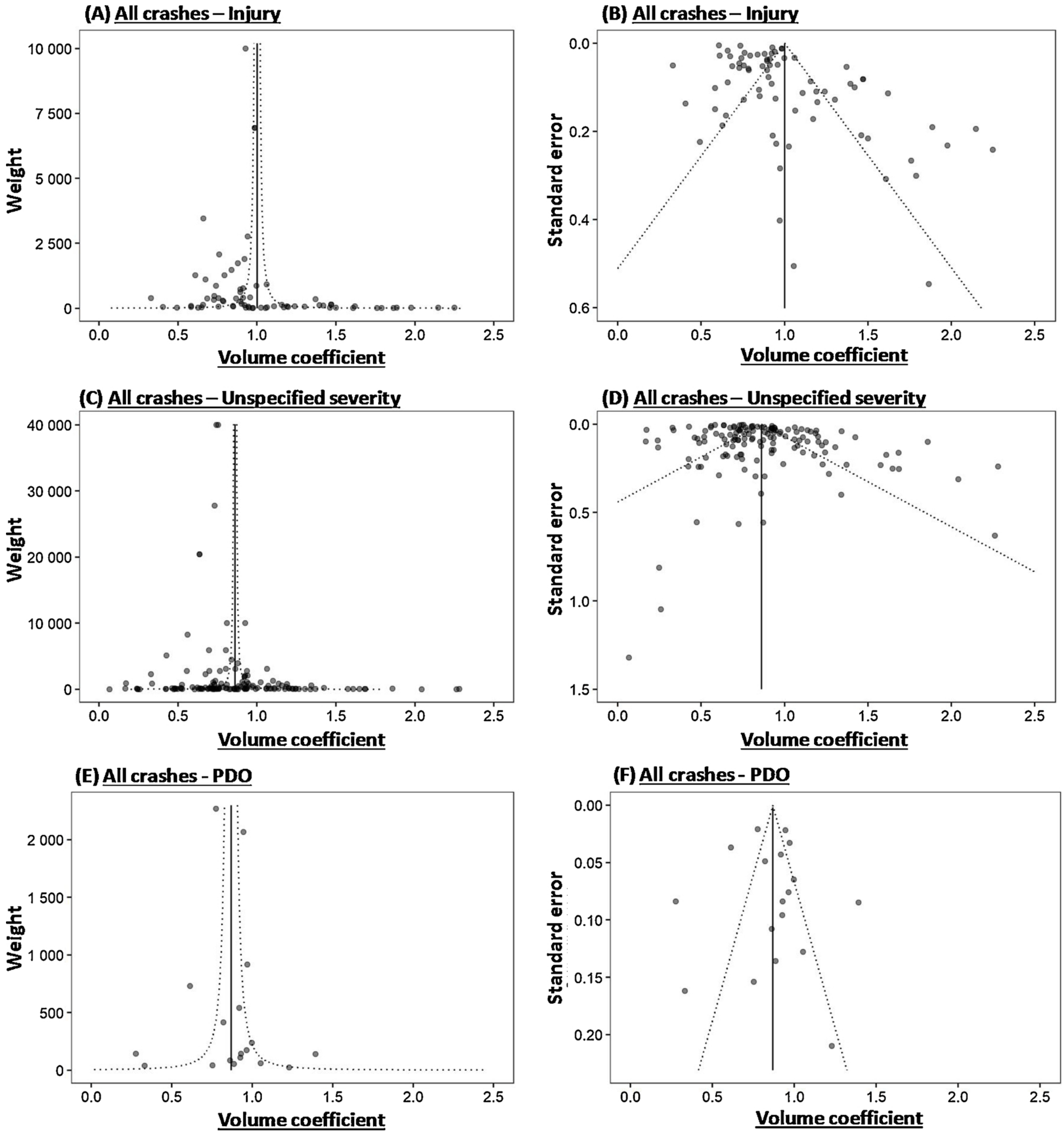

Fig. 2. Funnel plots, regression coefficients for all crashes (injury, unspecified severity, and PDO); semitransparent data points; some outlying volume coefficients are outside the diagram areas[2] .

coefficients are excluded from all meta-regression analyses: (1) ***Subgroups of data:*** Some studies have reported models for a whole data set and for parts of this data set (such as peak hour and off-peak crashes or day- and night-time crashes). In such cases, only those volume coefficients that are based on the most comprehensive set of data are included in the analysis. The subgroup results may still be included in supplementary analyses. (2) ***Injury/unspecified severity:*** From studies that have reported results for injury and unspecified severity crashes, only those for unspecified injury are included (unless explicitly mentioned otherwise). Excluding injury crashes implies that information that is specific to injury crashes is getting lost. However, including injury crashes would have implied that many injury crashes would have been counted twice (as injury and unspecified severity crash). (3) ***Volume only models:*** Volume coefficients from volume-only models are not included when a model with additional predictor variables is available, that is based on the same set of data.

The results from all meta-regression models are discussed in the next section for each of the moderator variables that have been investigated.

Availability of weights. In model 1c (Table 4) which is based on all studies including those without weights, most coefficients are very similar results to those in model 1b (Table 4) which is identical to 1c, except that it is a weighted model and does not include the weight availability predictor. Only for fatal crashes, the coefficient in model 1c is greater than in model 1b. P-values are considerably greater for all predictor variables in model 1c than in model 1b. The predictor for weight availability has a negative coefficient which is short of being statistically significant. This indicates that volume coefficients for which weights are available, on average are smaller than those for which no weights are available.

[2] (A) does not show two volume coefficients with very large weights (coeff. / weight are 0.735 / 27,778 and 0.607 / 34,294); (C) does not show one volume coefficient with a very large weight (0.583 / 77160) and one very large coefficient (2.924 / 0.013); (D) does not show one coefficient with a very large standard error (coeff. / standard error are 2.924 / 8.717).

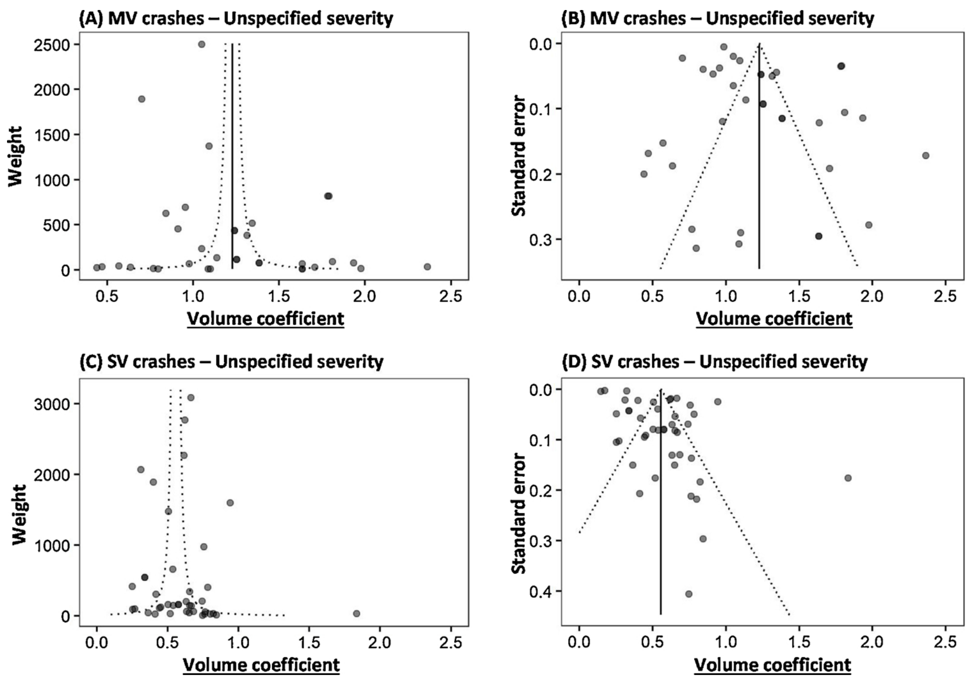

Fig. 3. Funnel plots, regression coefficients for all MV and SV crashes (injury and unspecified severity); semitransparent data points.

5. Subgroup comparisons

This section presents the results from subgroup comparisons. In each analysis, pooled volume coefficients are compared between the levels of one of the potential moderator variables (Table 6).

5.1. Crash type

To investigate differences between volume coefficients for all, MV, and SV crashes, matched pairs comparisons were made. They are based on studies that have reported results for both MV, SV, and all crashes from the same set of data (i.e. the SV and MV crashes sum up to all crashes in each study). The results are shown in Table 7.

The results in Table 7 show that volume coefficients are consistently larger for MV crashes and smaller for SV crashes than for all crashes. The same pattern was found for all available types of road and levels of severity and in each of the individual studies that are included in the matched pairs comparison. Two studies that have reported results for MV and SV but not for all crashes (which is why they are not included in the matched pairs comparison) also found far larger volume coefficients for MV crashes (all above one) than for SV crashes (between 0.25 and 0.57; Islam et al., 2014; Kim et al., 2015).

5.2. Crash severity

5.2.1. Fatal vs. injury crashes

To compare volume coefficients between fatal and injury crashes, matched pairs comparisons were made, based on studies that have reported results for both fatal and injury crashes from the same set of data. The results are shown in Table 8.

The results in Table 8 show that all pooled volume coefficients for fatal crashes are clearly smaller than those for injury crashes. Also within each of the four studies included in the analyses, volume coefficients are smaller for fatal than for injury crashes (Chimba et al., 2017; Gates et al., 2015; Jones et al., 2011; Kay et al., 2017).

5.2.2. Serious vs. slight injury

To compare volume coefficients between serious and slight injury crashes, matched pairs comparisons were made, based on studies that have reported results for both serious and slight injury crashes from the same set of data. The results are shown in Table 9.

The results in Table 9 show that all pooled volume coefficients for serious injury crashes are smaller than those for slight injury crashes. Smaller coefficients for serious than for slight injury were also found in each of the three studies that has reported such results (Høye, 2016; Jones et al., 2011; Montella and Imbriani, 2015). The studies by Høye (2016) and Jones et al. (2011) have also reported results for fatal crashes and in both studies the volume coefficients for fatal crashes are smaller than those for serious injury crashes.

The study by Lee et al. (2015; not included in this matched-pairs comparison) has reported three models, based on the same data set: One for unspecified severity (injury and PDO), one for all injuries, and one for serious injury. The volume coefficients are consistently smaller for more serious crashes (SD in parentheses): Unspecified severity: 1.023 (0.031); injury: 0.998 (0.034); serious injury: 0.899 (0.037).

5.2.3. Injury vs. unspecified severity

To compare volume coefficients for injury and unspecified severity crashes, matched pairs comparisons were made. They are based on studies that have reported results for both injury and unspecified severity crashes from the same set of data. The results are shown in Table 10. The two bottom rows in the table show results from the weighted analyses with all results from studies by Montella and colleagues omitted.

The results from the matched-pairs subgroup analysis indicate that volume coefficients for injury crashes on average are larger than those for unspecified injury crashes for all crashes on freeways and on unspecified roads, as well as for MV crashes on all roads. The remaining comparisons (all crashes on two-lane and unspecified roads, as well as for SV crashes, the differences between volume coefficients for injury and unspecified severity are only small and partly in the opposite direction.

When one looks at each of the studies that are included in the analysis for all crashes, those by ***Montella*** and colleagues are clearly different from all other studies in that they found exceptionally large volume coefficients for injury crashes. One of the Montella-studies (Montella et al., 2012) has reported results for PDO, slight, and severe injury crashes. In this study, volume coefficients are larger for slight

Table 4
Results from meta-regression analysis based on all studies, all models except for (1b) are based on injury or unspecified severity crashes (without double-counting) and all models except for (1c) are weighted analyses (statistically significant regression coefficients in bold letters).

	All, MV and SV crashes										All crashes					
	(1) No vol. predictor		(1b) No vol. predictor; injury *and* unspecified		(1c) No vol. predictor; unweighted		(2) Volume level predictors		(3) Mean volume predictor		(4) No vol. predictor		(5) Volume level predictors		(6) Mean volume predictor	
	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*
Crash type																
All crashes	(ref.)		(ref.)		(ref.)		(ref.)		(ref.)							
MV crashes	**0.314**	*< .001*	**0.299**	*< .001*	**0.304**	*0.038*	**0.371**	*< .001*	**0.360**	*< .001*						
SV crashes	**−0.332**	*< .001*	**−0.347**	*< .001*	**−0.342**	*0.021*	**−0.305**	*< .001*	**−0.318**	*< .001*						
Crash severity																
Fatal	−0.044	*0.762*	−0.066	*0.634*	−0.158	*0.676*	−0.072	*0.615*	−0.058	*0.690*	−0.084	*0.554*	−0.097	*0.457*	−0.087	*0.508*
Injury	0.044	*0.593*	**0.115**	*0.007*	0.142	*0.520*	−0.137	*0.229*	−0.167	*0.139*	0.098	*0.232*	−0.095	*0.396*	−0.064	*0.565*
Unspecified severity	(ref.)		(ref.)		(ref.)		(ref.)		(ref.)		(ref.)		(ref.)		(ref.)	
PDO	0.002	*0.982*	0.004	*0.959*	−0.003	*0.990*	−0.027	*0.777*	−0.001	*0.995*	0.022	*0.773*	0.011	*0.894*	0.039	*0.653*
Road category																
Freeways	**0.161**	*0.002*	**0.226**	*0.000*	0.260	*0.059*	0.116	*0.200*	0.050	*0.446*	**0.167**	*0.005*	−0.031	*0.741*	−0.023	*0.760*
Multilane non-freeways	0.049	*0.421*	0.050	*0.347*	0.100	*0.527*	−0.064	*0.470*	−0.081	*0.280*	0.113	*0.106*	−0.009	*0.921*	0.018	*0.830*
Two-lane roads	(ref.)		(ref.)		(ref.)		(ref.)		(ref.)		(ref.)		(ref.)		(ref.)	
Unspecified roads	0.108	*0.173*	**0.152**	*0.030*	0.099	*0.645*	0.117	*0.188*	0.087	*0.301*	0.152	*0.077*	0.113	*0.199*	0.120	*0.165*
Area type																
Rural	(ref.)		(ref.)		(ref.)		(ref.)		(ref.)		(ref.)		(ref.)		(ref.)	
Urban	0.028	*0.580*	0.012	*0.787*	0.038	*0.768*	−0.013	*0.850*	−0.012	*0.861*	0.084	*0.146*	0.000	*0.998*	0.005	*0.949*
Unspecified area	−0.090	*0.155*	−0.083	*0.132*	−0.043	*0.787*	−0.086	*0.190*	−0.074	*0.264*	−0.047	*0.533*	−0.045	*0.531*	−0.051	*0.483*
Volume																
Very low volume							−0.073	*0.619*					−0.233	*0.151*		
Low volume							0.015	*0.843*					−0.007	*0.928*		
Medium volume							(ref.)						(ref.)			
High volume							−0.099	*0.185*					0.027	*0.768*		
Very high volume							**0.221**	*0.012*					**0.408**	*0.000*		
Mean volume (cont.)									**0.0000019**	*0.050*					**0.0000032**	*0.001*
Weight availability					−0.212	*0.076*										
Intercept	**0. 801**	*< .001*	**0.779**	*< .001*	**0.969**	*< .001*	**0.823**	*< .001*	**0.822**	*< .001*	**0.752**	*< .001*	**0.825**	*< .001*	**0.782**	*< .001*

Table 5
Results from meta-regression analysis for subgroup comparisons, models explained in text (statistically significant regression coefficients in bold letters).

	(7) Crash type matched pairs		(8) Fatal vs. injury matched pairs[1]		(9) Serious vs. slight injury matched pairs[1]		(10) Injury vs. unspecified severity matched pairs		(10b) Injury vs. unspecified severity matched pairs (ex. Montella)		(11) Injury vs. PDO matched pairs[1]		(11b) Injury vs. PDO matched pairs (ex. Montella)[1]	
	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*	Coef.	*p*
Crash type														
All crashes	(ref.)						(ref.)		(ref.)					
MV crashes	**0.307**	*0.001*					−0.027	*0.871*	−0.018	*0.902*				
SV crashes	**−0.402**	*0.000*					−0.352	*0.000*	−0.333	*0.000*				
Crash severity														
Fatal			−0.158	*0.053*										
Injury	−0.150	*0.466*	(ref.)				0.082	*0.100*	0.025	*0.573*	**0.283**	0.007	0.014	*0.812*
Unspecified severity	(ref.)						(ref.)		(ref.)					
PDO											(ref.)		(ref.)	
Serious injury					**−0.246**	*0.000*								
Slight injury					(ref.)									
Road category														
Freeways	**0.261**	*0.028*			**0.913**	*0.000*	**0.298**	*0.000*	**0.257**	*0.000*	**0.330**	0.005	**0.303**	*0.001*
Multilane non-freeways	−0.026	*0.833*	−0.194	*0.096*	–		0.062	*0.408*	0.043	*0.514*	0.106	0.483	0.088	*0.235*
Two-lane roads	(ref.)		(ref.)		–		(ref.)		(ref.)		(ref.)		(ref.)	
Unspecified roads	−0.163	*0.568*			(ref.)		0.174	*0.188*	0.134	*0.242*				
Area type														
Rural	(ref.)						(ref.)		(ref.)					
Urban	0.162	*0.061*					0.066	*0.346*	0.083	*0.204*				
Unspecified area	0.267	*0.109*					0.053	*0.591*	0.077	*0.377*				
Intercept	**0.654**	*0.000*	**0.992**	*0.000*	**1.082**	*0.000*	**0.758**	*0.000*	**0.784**	*0.000*	**0.737**	*0.000*	**0.866**	*0.000*

[1] Meta-regression models are based on volume coefficients for all crashes (no specific results for MV/SV are included).

injury than for both severe injury and PDO. Thus, there is no general trend of greater volume coefficients for more serious crashes. The results in Table 10 show that when the studies by Montella and colleagues are omitted from the matched pairs comparison, there is practically no difference between volume coefficients for all crashes on freeways (all results from Montella and colleagues refer to freeways). Only for all crashes on unspecified roads and for MV crashes, the pooled volume coefficients for injury crashes are still larger than those for unspecified severity crashes. However, for both comparisons the volume coefficients for injury and unspecified severity are well within each other's confidence intervals.

5.2.4. *Injury vs. PDO crashes*

To compare volume coefficients for PDO and injury crashes, matched pairs comparisons were made. They are based on studies that have reported results for both PDO and injury crashes from the same set of data. The results are shown in Table 11. All results are based on models for all crashes. The two bottom rows in the table show results from the weighted analyses where all results from studies by Montella and colleagues are omitted.

On freeways, volume coefficients are greater for injury than for PDO crashes. However, most comparisons for freeways are based on studies by Montella and colleagues. These studies have found exceptionally large volume coefficients for injury crashes (see section above about injury vs. unspecified severity crashes).

When the results from Montella and colleagues are omitted, there are practically no differences between the volume coefficients for injury and PDO crashes. For multilane non-freeways and two-lane roads, the

Table 6
Meta-regression model statistics.

	Tau^2	SE(Tau^2)	N of studies	Tests of heterogeneity		
				Cochran's Q	*p*	I^2
Meta-regression based on all studies						
(1) No vol. predictor	0.089	0.009	264	11,818	*0.000*	99.2
(1b) No vol. predictor; injury and unspecified (double counting)	0.085	0.008	333	15,398	*0.000*	99.2
(1c) No vol. predictor (unweighted meta-regression)	0.000	0.075	370			
(2) Volume level predictors	0.081	0.010	197	8953	*0.000*	99.1
(3) Mean volume predictor	0.083	0.010	196	930	*0.000*	99.3
(4) No vol. predictor	0.080	0.010	183	6945	*0.000*	99.2
(5) Volume level predictors	0.062	0.009	128	4588	*0.000*	99.1
(6) Mean volume predictor	0.065	0.010	128	4567	*0.000*	99.2
Subgroup comparison meta-regression						
(7) Crash type matched pairs	0.060	0.016	45	2317	*0.000*	99.1
(8) Fatal vs. injury matched pairs	0.015	0.009	13	51	*0.000*	96.3
(9) Serious vs. slight injury matched pairs	0.016	0.020	8	11	*0.100*	53.3
(10) Injury vs. unspecified severity matched pairs	0.064	0.010	124	4190	*0.000*	99.2
(10b) Injury vs. unspecified severity matched pairs (ex. Montella)	0.046	0.008	114	4057	*0.000*	98.9
(11) Injury vs. PDO matched pairs	0.087	0.025	36	352	*0.000*	96.8
(11b) Injury vs. PDO matched pairs (ex. Montella)	0.015	0.006	26	149	*0.000*	88.1

Table 7
Matched pairs comparison for crash type; unweighted and weighted (RE) pooled volume coefficients for all, MV, and SV crashes by severity and road type with 95 % confidence intervals (CI) and I^2.

	All crashes				MV crashes				SV crashes			
	N	Vol coeff.	*CI*	I^2	N	Vol coeff.	*CI*	I^2	N	Vol coeff.	*CI*	I^2
Unweighted												
Injury												
All roads	3	**0.991**	*(-0.155; 2.136)*		3	**1.098**	*(-0.201; 2.396)*		3	**0.559**	*(-0.012; 1.131)*	
Unspec. sev.												
Freeways	6	**0.987**	*(0.295; 1.679)*		6	**1.517**	*(0.483; 2.55)*		6	**0.485**	*(-0.098; 1.069)*	
Multilane non-freeways	9	**0.999**	*(0.322; 1.139)*		9	**1.164**	*(0.928; 1.109)*		9	**0.594**	*(0.099; 1.089)*	
Two-lane roads	2	**0.730**	*(0.324; 1.675)*		2	**1.019**	*(0.427; 1.902)*		2	**0.360**	*(-0.298; 1.686)*	
All roads	17	**0.963**	*(0.317; 1.610)*		*17*	**1.272**	*(0.407; 2.137)*		17	**0.528**	*(0.023; 1.033)*	
Weighted												
Injury												
All roads	2	**0.711**	*(0.608; 0.814)*	*0.0*	2	**0.749**	*(0.376; 1.123)*	*83.0*	2	**0.459**	*(0.330; 0.588)*	*1.7*
Unspec. sev.												
Freeways	6	**0.959**	*(0.724; 1.195)*	*93.1*	6	**1.514**	*(1.105; 1.922)*	*96.1*	6	**0.408**	*(0.201; 0.614)*	*99.8*
Multilane non-freeways	5	**0.767**	*(0.700; 0.834)*	*85.3*	5	**0.917**	*(0.775; 1.059)*	*95.2*	5	**0.448**	*(0.300; 0.595)*	*93.6*
Two-lane roads	2	**0.730**	*(0.441; 1.019)*	*99.7*	2	**1.016**	*(0.952; 1.079)*	*89.7*	2	**0.357**	*(0.282; 0.431)*	*90.6*
All roads	13	**0.831**	*(0.729; 0.932)*	*.98.3*	13	**1.194**	*(0.957; 1.431)*	*99.5*	13	**0.404**	*(0.306; 0.502)*	*99.7*

volume coefficients are also similar between injury and PDO crashes.

5.3. Type of road

5.3.1. Four types of road

Pooled volume coefficients are compared between different types of road in Table 12. Comparisons are shown separately for different crash types and severity levels. They are based on all results, except for subgroups of models or crashes.

The results in Table 12 show a clear pattern for all crashes (injury and unspecified severity): Volume coefficients are greatest on freeways, followed by multilane non-freeways, and they are smallest on two-lane roads. For MV crashes, a similar pattern was found (greater coefficients for freeways than for multilane non-freeways). For SV crashes there are no systematic differences between different types of road.

These results might indicate that the distribution of crash type is the main explanatory factor for the differences between road types that were found for all crashes. This might be the case if the share of MV crashes were larger on freeways, followed by multilane non-freeways, and smallest on two-lane roads. However, studies that are included in the analyses and that have provided information about SV and MV crash numbers, have not found systematic differences between the proportions of MV crashes on different types of road that would be consistent with the interpretation of the findings for road type in terms of different proportions of MV crashes (Table 13).

In ***meta-regression*** (Table 4), positive and statistically significant regression coefficients were found for ***freeways*** (vs. two-lane roads) in the models without AADT as an additional predictor variable. When a volume predictor is included in the models (five volume level dummy variables or mean AADT), the regression coefficients for freeways are still positive, but smaller and no longer statistically significant. For ***multilane non-freeways***, the meta-regression coefficients are positive as well in the models without additional volume predictors, but they are smaller than those for freeways and they fall short of being statistically significant. With additional volume predictors included in the meta-regression models, they are close to zero and nonsignificant.

In the meta-regression model 1b which includes all available volume coefficients for injury crashes (including double counting), the coefficients for freeways is even greater, but this is mainly due to the results from the studies by Montella and colleagues. These studies found large volume coefficients for injury crashes, all of which refer to freeways (these volume coefficients are not included in the other meta-regression models).

Freeways have on average far higher volumes than other roads, and multilane non-freeways have higher volumes than two-lane roads (Table 13). Thus, differences in volume may be at least a part of the

Table 8
Matched pairs comparison for fatal vs. injury crashes; unweighted and weighted (RE, unless denoted otherwise) pooled volume coefficients for fatal and injury crashes by crash type and road type with 95 % confidence intervals (CI) and I^2.

	Fatal				Injury			
	N	Vol coeff.	*CI*	I^2	N	Vol coeff.	*CI*	I^2
Unweighted analysis								
All crashes								
Multilane non-freeways	1	**0.384**			1	**0.895**		
Unspecified roads**	5	**0.819**	*(0.324; 1.314)*		6	**0.991**	*(0.675; 1.307)*	
All roads**	6	**0.746**	*(0.183; 1.310)*		7	**0.977**	*(0.680; 1.275)*	
SV crashes								
Multilane non-freeways	1	**0.700**			1	**1.005**		
Weighted analysis								
All roads								
Multilane non-freeways	1	**0.384**	*(0.059; 0.709)*	*0.0**	1	**0.895**	*(0.822; 0.968)*	*0.0**
Unspecified roads**	5	**0.851**	*(0.688; 1.013)*	*84.7*	6	**0.961**	*(0.920; 1.001)*	*83.0*
All roads**	6	**0.777**	*(0.572; 0.982)*	*90.7*	7	**0.952**	*(0.913; 0.991)*	*82.6*

* Fixed effects model.
** The number of available volume coefficients is not equal for all crashes on unspecified roads because of one study that has reported two models for injury crashes (one for slight and the other for serious injury crashes) but only one for fatal crashes.

Table 9
Matched pairs comparison for serious vs. slight injury crashes; unweighted and weighted (RE) pooled volume coefficients for serious and slight injury crashes by road type with 95 % confidence intervals (CI) and I^2; all results refer to all crashes.

	Serious injury				Slight injury			
	N	Vol coeff.	*CI*	I^2	N	Vol coeff.	*CI*	I^2
Unweighted analysis								
Freeways	2	1.739	(1.077; 2.400)		2	2.017	(1.652; 2.381)	
Unspecified roads	2	0.846	(0.833; 0.860)		2	1.132	(0.659; 1.605)	
All roads	4	1.292	(0.213; 2.372)		4	1.574	(0.516; 2.633)	
Weighted analysis								
Freeways	2	1.731	(1.264; 2.198)	*55.8*	2	2.014	(1.746; 2.281)	*0.0*
Unspecified roads	2	0.842	(0.788; 0.895)	*0.0*	2	1.109	(0.778; 1.440)	*85.8*
All roads	4	1.259	(0.728; 1.789)	*94.8*	4	1.550	(1.016; 2.084)	*95.4*

explanation for the differences in volume coefficients between the different types of road.

5.3.2. *Divided vs. undivided multilane roads (non-freeways)*

For multilane non-freeways, comparisons have been made between divided and undivided roads (Table 14). The results are based on all combinations of crash type and severity for which at least one volume coefficient is available for divided and undivided multilane non-freeways.

In the weighted analysis, the pooled volume coefficients are consistently greater for divided roads than for undivided multilane non-freeways. In the unweighted analysis, MV and SV crashes with unspecified severity have greater volume coefficients on undivided than on divided roads. Otherwise, the results are similar to those from the weighted analysis.

To test the difference between divided and undivided multilane non-freeways, three meta-regression models were developed (not shown in Table 5) with the following predictor variables in all three models: Divided (vs. undivided), crash severity (injury vs. unspecified), crash type (MV / SV vs. all crashes). In the second model, volume range dummy variables are included as well and in the third model, mean AADT is included. In the model without volume predictor, the regression coefficient for divided (vs. undivided) roads is positive (0.073) but non-significant (p = .306). In the models with additional AADT-predictors, the regression coefficients for divided roads are closer to zero (0.021 and -0.044, respectively) and non-significant (p = 0.752 and p = .505, respectively). Despite the relatively large differences between volume coefficients for divided vs. undivided roads, the results from meta-regression do not indicate that there are significant differences.

5.3.3. *Number of lanes on freeways*

Five studies have reported separate models for roads with different numbers of lanes on freeways (Gan et al., 2012; Kiattikomol et al., 2008; Srinivasan and Carter, 2011; Srinivasan et al., 2016; Zheng et al., 2018). The results are highly inconsistent. Unweighted pooled volume coefficients are as follows: 1.166 on four-lane roads, 1.127 on roads with six or more lanes, and 0.998 on roads with eight or more lanes. Thus, it cannot be concluded that volume coefficients are systematically

Table 10
Matched pairs comparison for injury vs. unspecified severity crashes; unweighted and weighted (RE) pooled volume coefficients for injury and unspecified severity crashes (based only on studies that have reported results for both injury and unspecified severity crashes) by road and crash type with 95 % confidence intervals (CI) and I^2.

	Injury				Unspecified			
	N	Coeff.	*CI*	I^2	N	Coeff.	*CI*	I^2
Unweighted analysis								
All crashes								
Freeways[1]	35	**1.253**	*(0.464; 2.043)*		35	**1.183**	*(0.133; 2.233)*	
Multilane non-freeways	18	**1.010**	*(0.021; 2.000)*		18	**1.032**	*(0.041; 2.024)*	
Two-lane	29	**0.831**	*(0.460; 1.203)*		29	**0.796**	*(0.395; 1.197)*	
Unspecified roads	8	**1.065**	*(0.058; 2.072)*		8	**0.983**	*(-0.151; 2.117)*	
All roads[1]	90	**1.052**	*(0.232; 1.872)*		90	**1.010**	*(0.081; 1.94)*	
MV crashes								
All roads	3	**1.400**	*(0.508; 2.293)*		3	**0.943**	*(0.290; 1.597)*	
SV crashes								
All roads	8	**0.703**	*(-0.110; 1.516)*		8	**0.705**	*(-0.057; 1.466)*	
Weighted analysis								
All crashes								
Freeways[1]	17	**1.306**	*(1.117; 1.495)*	*92.2*	17	**1.039**	*(0.871; 1.207)*	*94.4*
Multilane non-freeways	11	**0.812**	*(0.713; 0.912)*	*97.8*	11	**0.872**	*(0.750; 0.994)*	*96.1*
Two-lane	21	**0.807**	*(0.744; 0.870)*	*97.8*	21	**0.792**	*(0.730; 0.854)*	*98.7*
Unspecified roads	6	**1.129**	*(0.777; 1.482)*	*99.7*	6	**1.039**	*(0.597; 1.480)*	*99.9*
All roads[1]	55	**0.989**	*(0.897; 1.081)*	*99.4*	55	**0.897**	*(0.823; 0.971)*	*99.5*
MV crashes								
All roads	2	**1.161**	*(0.649; 1.673)*	*86.6*	2	**0.829**	*(0.360; 1.299)*	*88.1*
SV crashes								
All roads	5	**0.611**	*(0.354; 0.867)*	*94.4*	5	**0.605**	*(0.462; 0.748)*	*88.9*
Weighted analysis (without Montella) (random effects models)								
All crashes								
Freeways	12	**1.165**	*(0.995; 1.334)*	*88.5*	12	**1.146**	*(0.962; 1.331)*	*94.2*
All roads	50	**0.922**	*(0.849; 0.994)*	*98.9*	50	**0.911**	*(0.833; 0.988)*	*99.5*

[1] Includes results from Montella-studies.

Table 11
Matched pairs comparison for injury vs. PDO crashes; unweighted and weighted (RE) pooled volume coefficients by road type (RE meta-analysis for weighted analysis); all results refer to all crashes.

	Injury				PDO			
	N	Coeff.	*CI*	I^2	N	Coeff.	*CI*	I^2
Unweighted analysis								
Freeways	9	**1.574**	(0.831; 2.317)		7	**0.835**	(0.018; 1.652)	
Multilane non-freeways	8	**0.877**	(0.739; 1.015)		8	**0.879**	(0.631; 1.128)	
Two-lane	3	**0.985**	(0.688; 1.283)		3	**1.006**	(0.600; 1.411)	
All roads	20	**1.207**	(0.370; 2.044)		18	**0.866**	(0.350; 1.382)	
Weighted analysis								
Freeways	8	**1.596**	(1.326; 1.865)	*84.0*	6	**0.784**	(0.436; 1.132)	*93.3*
Multilane non-freeways	3	**0.988**	(0.780; 1.197)	*72.0*	3	**0.930**	(0.763; 1.097)	*64.0*
Two-lane	8	**0.870**	(0.816; 0.924)	*65.1*	8	**0.874**	(0.777; 0.971)	*92.5*
All roads	19	**1.178**	(0.991; 1.365)	*97.7*	17	**0.865**	(0.740; 0.989)	*96.1*
Weighted analysis (without Montella)								
Freeways	2	**1.179**	(0.739; 1.620)	*88.0*	2	**1.132**	(0.611; 1.652)	*93.3*
All roads	13	**0.938**	(0.846; 1.030)	*89.5*	13	**0.929**	(0.827; 1.031)	*93.8*

Table 12
Subgroup comparison analysis for type of road; unweighted and weighted (RE) pooled volume coefficients for each type of road by crash type and severity.

	All crashes			MV crashes			SV crashes		
	N	Coeff.	*CI*	N	Coeff.	*CI*	N	Coeff.	*CI*
Unweighted									
Fatal									
Freeways	1	**0.398**							
Multilane non-freeways	1	**0.384**							
Unspecified/all roads	5	**0.819**	*(0.324; 1.314)*				1	**0.700**	
Injury									
Freeways	46	**1.292**	*(0.434; 2.150)*	1	**1.448**		2	**0.682**	*(-0.469; 1.833)*
Multilane non-freeways	22	**1.052**	*(0.119; 1.985)*	2	**1.377**	*(0.120; 2.633)*	5	**0.888**	*(0.147; 1.629)*
Two-lane roads	33	**0.818**	*(0.458; 1.177)*				2	**0.412**	*(0.029; 0.795)*
Unspecified/all roads	12	**1.016**	*(0.145; 1.886)*	1	**0.540**		1	**0.310**	
Unspecified severity									
Freeways	76	**1.110**	*(0.107; 2.112)*	29	**1.453**	*(0.505; 2.402)*	23	**0.591**	*(-0.099; 1.281)*
Multilane non-freeways	39	**0.945**	*(-0.031; 1.920)*	22	**1.195**	*(0.254; 2.136)*	14	**0.670**	*(0.015; 1.324)*
Two-lane roads	63	**0.754**	*(0.312; 1.195)*	10	**1.381**	*(0.671; 2.091)*	17	**0.575**	*(0.291; 0.860)*
Unspecified/all roads	27	**0.927**	*(0.084; 1.771)*	2	**0.815**	*(0.684; 0.947)*	2	**0.580**	*(0.464; 0.696)*
PDO									
Freeways	7	**0.835**	*(0.018; 1.652)*						
Multilane non-freeways	3	**1.006**	*(0.600; 1.411)*						
Two-lane roads	8	**0.879**	*(0.631; 1.128)*						
Unspecified/all roads	1	**0.930**							
Weighted analysis									
Fatal									
Multilane non-freeways	1	**0.384**							
Unspecified/all roads	5	**0.851**	*(0.688; 1.013)*						
Injury									
Freeways	24	**1.280**	*(1.100; 1.460)*	1	**1.448**		2	**0.691**	*(-0.123; 1.505)*
Multilane non-freeways	15	**0.956**	*(0.798; 1.115)*	1	**0.923**		2	**0.544**	*(0.423; 0.666)*
Two-lane roads	25	**0.795**	*(0.741; 0.850)*				1	**0.550**	
Unspecified/all roads	10	**1.035**	*(0.821; 1.249)*	1	**0.540**		1	**0.310**	
Unspecified severity									
Freeways	50	**0.964**	*(0.862; 1.065)*	18	**1.371**	*(1.143; 1.600)*	22	**0.564**	*(0.424; 0.703)*
Multilane non-freeways	28	**0.842**	*(0.761; 0.924)*	11	**0.948**	*(0.786; 1.110)*	7	**0.537**	*(0.384; 0.690)*
Two-lane roads	46	**0.770**	*(0.713; 0.828)*	7	**1.228**	*(0.996; 1.460)*	12	**0.556**	*(0.456; 0.655)*
Unspecified/all roads	23	**0.902**	*(0.735; 1.069)*				2	**0.618**	*(0.581; 0.654)*
PDO									
Freeways	6	**0.784**	*(0.436; 1.132)*						
Multilane non-freeways	3	**0.930**	*(0.763; 1.097)*						
Two-lane roads	8	**0.874**	*(0.777; 0.971)*						

different depending on the number of lanes on freeways. For other roads than freeways, no such comparisons are available.

5.4. Area type

Table 15 compares pooled volume coefficients between rural and urban areas. For all crashes, most results indicate that volume coefficients are greater in urban than in rural areas. The unweighted results indicate also that volume coefficients for MV crashes are greater in urban than in rural areas, while volume coefficients for SV crashes are greater in rural than in urban areas. However, the results for all crashes are not consistent between crash types. The results for MV and SV crashes are not consistent between unweighted and weighted results.

In meta-regression (Table 4), all regression coefficients for urban (vs. rural) roads are small (below 0.03) and far from being statistically significant. When volume is statistically controlled for, the regression

Table 13
Average mean volumes and distribution of volume levels for the four types of road.

	MV crashes (%)[1]	Mean AADT		AADT range					
		N	Mean	N	Very low vol. (%)	Low vol. (%)	Medium vol. (%)	High vol. (%)	Very high vol. (%)
Freeways	54 %	58	52,533	58		9%	29 %	31 %	31 %
Multilane non-Freeways	68 %	23	25,982	24		21 %	42 %	21 %	17 %
Two-lane	60 %	49	4266	49	10 %	78 %	12 %		
Unspecified road	46 %	22	12907	22		55%	27 %	18 %	
All roads		152	27,220	153	3%	39 %	25 %	18 %	14 %

[1] proportions of MV crashes are based on 15 different data sets in the studies by Geedipally and Lord, 2010; Kaaf and Abdel-Aty, 2015; Montella, 2009; Srinivasan et al., 2011.

coefficients are even closer to zero.

5.5. Volume levels and ranges

5.5.1. Volume levels (categorical variable)

In meta-regression (Table 4), statistically significant positive effects were found for very high (vs. medium) volume, indicating that volume coefficients are greater at very high volumes than at medium volumes. The regression coefficients for the other volume levels also indicate a trend towards greater volume coefficients at higher volumes. However, none of these regression coefficients is statistically significant and in the model that also includes results for MV and SV crashes, the relationship is not monotonic.

5.5.2. Mean AADT and volume coefficients

In meta-regression (Table 4), mean AADT has statistically significant positive meta-regression coefficients in both models, with and without results for MV and SV crashes. In the following, the relationship between mean volume and volume coefficients is investigated more closely by inspecting scatterplots.

All crashes on all roads, by severity: Fig. 4 shows the relationships between mean volume and volume coefficients for all crashes (not including specific results for MV and SV crashes) by severity.

The diagrams in Fig. 4 show for the most part positive relationships between mean volume and volume coefficient, except for the volume coefficients for fatal crashes which are only few. This is in accordance with the findings from meta-regression. However, there is large variation of volume coefficients around the trend lines. The logarithmic trend lines fit better than the linear trend lines for injury and unspecified severity. However, the trend lines differ mainly at the highest volumes (mean AADT above 150,000) and both change substantially (get steeper) when the highest volumes are omitted (not shown in Fig. 4).

MV and SV crashes: Fig. 5 shows the relationships between mean volume and volume coefficients for MV and SV crashes. The results refer to unspecified severity crashes. They include all types of road.

The trend lines in Fig. 5 show only weak relationships between mean volume and volume coefficients for MV and SV crashes. Logarithmic and other trend lines do not give higher values of R^2 and all are close to the linear trend lines (not shown in Fig. 5).

5.5.3. Within study comparisons of volume levels

Several studies have developed separate models for otherwise comparable roads with volumes above and below a certain threshold. Table 16 summarizes results from such studies. All results refer to rural two-lane roads.

The results in Table 16 show that the volume coefficients for the higher volume roads in most cases are greater than those for the lower volume roads. Exceptions are the results from Cook (2010) for injury crashes (where the coefficient for the lower volume roads is highly uncertain) and from Garach et al. (2016). On average, the volume coefficients are 0.148 greater for the higher volume roads.

6. Summary and discussion

The present study has investigated the relationship between volume and crash numbers by means of meta-analysis, based on 521 crash prediction models from 118 studies. Pooled volume coefficients by crash type are 0.875 for all crashes, 1.210 for MV crashes, and 0.552 for SV crashes. These coefficients refer to all levels of severity (mostly unspecified severity).

There is large heterogeneity in the results, indicated by I^2 values above 90 %. Heterogeneity can also be seen in the distributions of the results (weights or standard errors against the individual volume coefficients). Heterogeneity indicates different underlying distributions and thus the likely presence of relevant moderator variables (Viechtbauer, 2007). Several relevant moderator variables could be identified by means of meta-regression and by comparing pooled

Table 14
Subgroup comparison analysis for divided vs. undivided multilane non-freeways; unweighted and weighted (RE) pooled volume coefficients for each type of road by crash type and severity.

	Divided roads				Undivided roads			
	N	Vol. coeff.	*CI*	*I^2*	N	Vol. coeff.	*CI*	*I^2*
<u>**Unweighted**</u>								
All crashes - Injury	10	**0.963**	*(0.193; 1.734)*		7	**0.930**	*(0.217; 1.643)*	
All crashes - Unspecified severity	19	**0.966**	*(0.034; 1.898)*		13	**0.785**	*(-0.050; 1.621)*	
All crashes - PDO	1	**1.230**			2	**0.893**	*(0.696; 1.091)*	
MV crashes - Unspecified severity	11	**1.131**	*(0.573; 1.688)*		10	**1.221**	*(-0.050; 2.493)*	
SV crashes - Injury	1	**1.005**	*(1.005; 1.005)*		2	**0.684**	*(0.140; 1.227)*	
SV crashes - Unspecified severity	6	**0.551**	*(0.187; 0.915)*		6	**0.628**	*(0.083; 1.172)*	
<u>**Weighted analysis**</u>								
All crashes - Injury	7	**0.969**	*(0.661; 1.278)*	*98.4*	5	**0.831**	*(0.676; 0.985)*	*89.4*
All crashes - PDO	1	**1.230**			2	**0.882**	*(0.743; 1.02)*	*60.0*
MV crashes - Unspecified severity	6	**0.977**	*(0.721; 1.233)*	*95.3*	4	**0.875**	*(0.712; 1.038)*	*85.5*
SV crashes - Unspecified severity	3	**0.541**	*(0.274; 0.807)*	*97.7*	3	**0.468**	*(0.231; 0.705)*	*91.9*

Table 15
Subgroup comparison analysis for rural vs. urban roads; unweighted and weighted (RE) pooled volume coefficients by crash type, crash severity, and road type (bold letters for the larger volume coefficient in each rural-urban comparison).

	Unweighted analysis						Weighted analysis							
	Rural roads			Urban roads			Rural roads				Urban roads			
Crash type – Severity – Road type	**N**	**Vol. coeff.**	***CI***	**N**	**Vol. coeff.**	***CI***	**N**	**Vol. coeff.**	***CI***	***I2***	**N**	**Vol. coeff.**	***CI***	***I2***
All - Injury – Two-lane	30	0.791	*(0.791; 0.173)*	5	**0.918**	*(0.918; 0.213)*	22	0.789	*(0.727; 0.851)*	*97.7*	3	**0.835**	*(0.734; 0.937)*	*77.8*
All - Injury - Multilane non-freeways	8	**1.170**	*(1.17; 0.611)*	12	1.014	*(1.014; 0.414)*	6	**1.014**	*(0.785; 1.242)*	*95.9*	7	0.960	*(0.647; 1.273)*	*97.2*
All - Injury – Freeways	20	**1.385**	*(1.385; 0.464)*	14	1.183	*(1.183; 0.317)*	12	**1.391**	*(1.135; 1.647)*	*93.5*	8	1.215	*(1.004; 1.425)*	*71.3*
All - PDO – Two-lane	7	**0.917**	*(0.917; 0.072)*	1	0.613									
All - PDO - Multilane non-freeways	1	0.965		2	**1.026**	*(1.026; 0.288)*	1	0.965	*(0.816; 1.114)*	*0.0*	2	**0.975**	*(0.588; 1.362)*	*72.1*
All - PDO – Freeways	5	0.656	*(0.656; 0.338)*	1	**1.393**									
All - Unspec. – Two-lane	55	**0.758**	*(0.758; 0.201)*	10	0.719	*(0.719; 0.327)*	38	**0.788**	*(0.731; 0.845)*	*99.3*	8	0.664	*(0.456; 0.872)*	*99.0*
All - Unspec. - Multilane non-freeways	17	0.883	*(0.883; 0.53)*	19	**1.006**	*(1.006; 0.516)*	13	0.833	*(0.712; 0.953)*	*95.8*	12	**0.880**	*(0.650; 1.110)*	*94.1*
All - Unspec. - Freeways	41	1.008	*(1.008; 0.629)*	23	**1.180**	*(1.18; 0.318)*	22	0.894	*(0.750; 1.037)*	*93.9*	17	**1.173**	*(1.02; 1.326)*	*85.5*
All - Unspec. - Unspecified road	7	0.857	*(0.857; 0.337)*	5	**1.021**	*(1.021; 0.572)*	6	0.846	*(0.539; 1.153)*	*88.2*	4	**0.964**	*(0.268; 1.660)*	*90.4*
MV - Unspec. – Two-lane	5	1.278	*(1.278; 0.338)*	4	**1.580**	*(1.58; 0.38)*								
MV - Unspec. - Multilane non-freeways	3	1.213	*(1.213; 0.376)*	17	**1.244**	*(1.244; 0.495)*	3	**1.103**	*(0.815; 1.391)*	*94.6*	6	0.886	*(0.670; 1.102)*	*88.5*
MV - Unspec. - Freeways	17	1.446	*(1.446; 0.486)*	6	**1.711**	*(1.711; 0.211)*	13	1.395	*(1.173; 1.617)*	*96.2*	3	**1.816**	*(1.582; 2.050)*	*46.4*
SV - Injury - Multilane non-freeways	3	**1.024**	*(1.024; 0.422)*	1	0.880									
SV - Unspec. – Two-lane	14	**0.596**	*(0.596; 0.15)*	3	0.482	*(0.482; 0.081)*								
SV - Unspec. - Multilane non-freeways	5	**0.729**	*(0.729; 0.523)*	8	0.634	*(0.634; 0.216)*	4	0.519	*(0.245; 0.793)*	*97.5*	2	**0.530**	*(0.461; 0.599)*	*0.0*
SV - Unspec. - Freeways	15	**0.605**	*(0.605; 0.389)*	3	0.478	*(0.478; 0.35)*	15	**0.584**	*(0.403; 0.765)*	*98.3*	3	0.391	*(0.053; 0.730)*	*89.4*

volume coefficients between levels of each of the moderator variables for otherwise comparable results.

Crash type: The results show consistently that volume coefficients are larger for MV crashes and smaller for SV crashes than for all crashes. Meta-regression analyses (models based on all studies and matched pairs comparisons) show statistically significant effects of crash type.

In all subgroup comparisons, the pooled volume coefficients are greatest for MV crashes and most of them are close to or above one. This means that MV crashes increase at a higher rate as volume. The largest pooled volume coefficient was found on freeways for unspecified severity MV crashes (1.514 in the weighted analysis). This implies that an increase of volume by 10 % is associated with an increase of MV crashes by 15.5 %. Pooled volume coefficients for SV crashes are around 0.5 in the weighted analyses. A coefficient of 0.5 implies that crashes increase by 4.9 % as volume increases by 10 %.

The same pattern of differences between crash types was found for all available types of road and crash severity. Lord et al. (2005a, 2005b; not included in meta-analysis) show that even models that include the volume-capacity ratio predict increasing crash rates for MV crashes at increasing volumes but decreasing crash rates for SV crashes.

Crash severity: Volume coefficients are consistently smaller for fatal crashes than for injury crashes and they are smaller for serious than for slight injury crashes. These results are consistent in all subgroup comparison and meta-regression analyses. In meta-regression (Table 4), the coefficients for fatal crashes (vs. unspecified severity) are negative in all models but far from being statistically significant.

The comparisons between volume coefficients for injury vs. unspecified severity and for injury vs. PDO crashes are inconsistent. At first glance, the results seem to indicate that volume coefficients are greater for injury crashes than for unspecified severity and PDO crashes on freeways. However, these comparisons are strongly influenced by four studies by Montella and colleagues on Italian motorways. When the results from these studies are omitted, differences between volume coefficients for injury vs. unspecified severity and for injury vs. PDO crashes are inconsistent, small, and non-significant. Only for MV crashes, volume coefficients for injury crashes are larger than those for unspecified severity crashes (even when the Montella-studies are omitted), but the results are based on only three studies and the volume coefficients have large confidence intervals, indicating high uncertainty.

Type of road: Subgroup comparisons and meta-regression models without additional volume predictors indicate that volume coefficients are larger on freeways than on multilane non-freeways and larger on multilane non-freeways than on two-lane roads, at least for injury and unspecified severity crashes when all types of crashes are regarded together.

In meta-regression, the effects of road type get smaller or vanish altogether when volume is statistically controlled for. Thus, difference in volume are a likely explanation for the differences in volume coefficients between different types of road. Another possible explanation might have been differences in the share of MV crashes. However, this is not supported by the available data.

The fact that freeways are (per definition) divided while all two-lane roads in the present study are undivided, may also contribute to the differences in volume coefficients between different types of road. Subgroup comparisons for multilane non-freeways show that volume coefficients for the most part are larger for divided than for undivided roads. However, only small and non-significant effects of divided vs. undivided roads were found in meta-regression

Area type: Subgroup comparisons show for the most part that volume coefficients are greater in urban than in rural areas for all and MV crashes, and that they are greater in rural than in urban areas for SV crashes. However, the results are inconsistent between road types and between weighted and unweighted analyses. Meta-regression (Table 4) does not indicate that there are systematic differences between volume coefficients for roads in urban vs. rural areas.

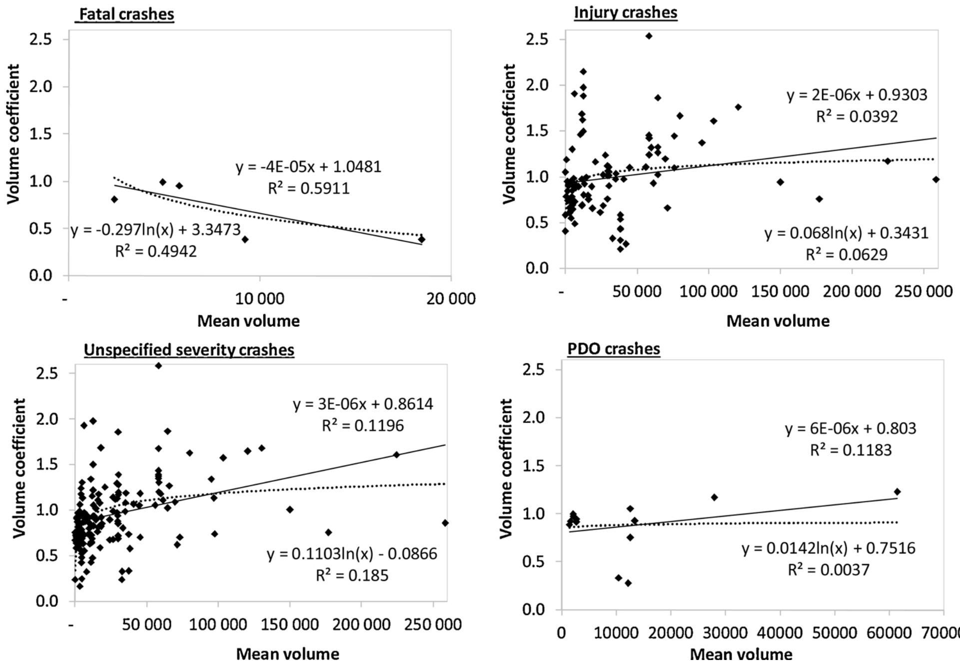

Fig. 4. Scatterplots of original volume coefficients and mean volume; results for all crashes at different levels of severity with linear (unbroken) and logarithmic (dotted) trend lines.

Volume levels and ranges: Positive relationships between volume levels and volume coefficients were found in different types of analysis. Increasing mean volumes are for the most part associated with larger volume coefficients. However, mean volumes only explain small proportions of variation. For fatal crashes and SV crashes, the relationships may be negative, but these results are based on few studies and none of the results for fatal crashes refers to volumes above 20,000.

Meta-regression analyses show that volume coefficients on average are greater at higher volumes. Models with dummy predictors that represent different ranges of volume, indicate that it is mainly roads with very high volumes that differ from roads with medium volumes and that the relationship is not necessarily monotonic. Also, within study comparisons show that volume coefficients for higher volumes for the most part are greater than volume coefficients for lower volumes.

7. Limitations

Model form and volume predictor: The present meta-analysis includes only crash prediction models that have the general form of Poisson or Negative binomial models and that have Ln(AADT) as the only volume predictor. Volume coefficients from other types of models (such as Poisson lognormal models or zero inflated Poisson or Negative binomial model) are not directly comparable to those from Poisson / Negative binomial models and could therefore not be included in the meta-analysis. The same is true for volume coefficients from models that include additional other volume predictors. For example, Caliendo et al. (2013; Caliendo and Guida, 2014; Caliendo et al., 2016) have used two additional dummy variables for volumes below 5000 and above 13000. Høye (2015 A,B) has included Ln($AADT^2$) as a volume predictor in addition to Ln(AADT). In both studies, the additional volume predictors have improved model fit compared to models with Ln(AADT) as the only volume predictor.

Instead of AADT, some crash prediction models have used disaggregated volume, for example hourly volumes (Martin, 2002). Use of average volume may attenuate the relationship between volume and crashes (Qin et al., 2004), but this is not necessarily the case. On the contrary, Wang et al. (2018) found that model results for AADT yield good estimates for hourly crash numbers, when the predictions are weighted with the actual hourly volumes. Based on the results from the present meta-analysis, one might expect stronger relationships between crashes and disaggregated volume than between crashes and AADT.

Weight availability: Volume coefficients for which weights are available, are on average smaller than those for which no weights are available. The difference is short of being statistically significant and

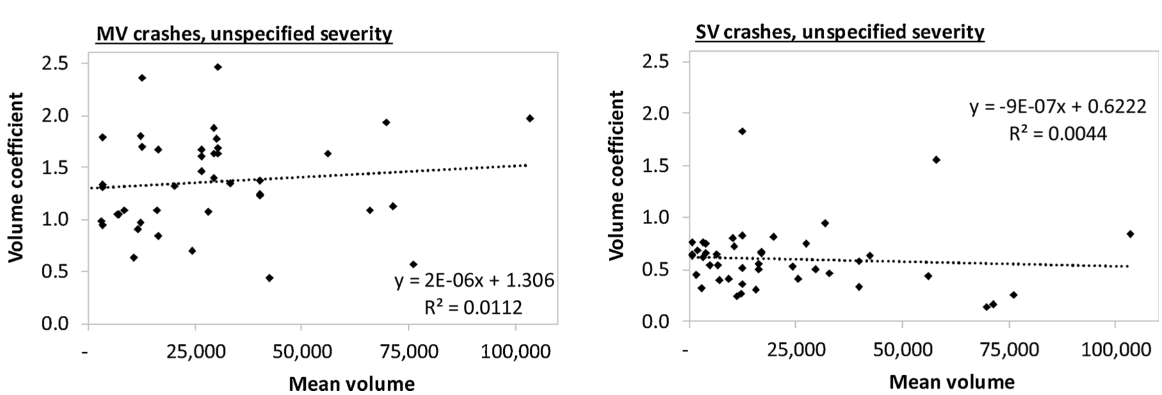

Fig. 5. Scatterplot of original volume coefficients and mean volume; results for MV and SV crashes with unspecified severity.

Table 16
Volume coefficients for roads with "high" vs. "low" volumes (above vs. below split volume) from five studies.

		Volume			Volume coefficients				Δ vol coeff. for high - low vol.
					Low volumes		High volumes		
Study	Crashes	Min.	Split	Max.	Coeff.	CI	Coeff.	CI	
Cook (2010)[1]	All, injury	1	100	400	**1.055**	*(0.063;2.047)*	**0.406**	*(0.137;0.675)*	**−0.649**
Cook (2010)	All, unspec.	1	100	400	**0.242**	*(-0.016;0.501)*	**0.760**	*(0.759;0.760)*	**0.518**
Garach et al. (2016)	All, unspec.	500	4000	21,600	**0.836**		**0.377**		**−0.459**
Martz (2017)	All, injury	90	7500	21,800	**0.865**	*(0.818;0.912)*	**1.238**	*(0.973;1.503)*	**0.373**
	All, unspec.	90	7500	21,800	**0.797**	*(0.764;0.83)*	**1.290**	*(1.045;1.535)*	**0.493**
Mayora et al. (2006)	All, unspec.	0	8000	20000	**0.761**		**1.491**		**0.730**
Stapleton et al. (2018)[2]	All, injury	0	400	13000	**0.584**	*(0.384;0.784)*	**0.741**	*(0.674;0.808)*	**0.157**
	All, unspec.	0	400	13000	**0.674**	*(0.556;0.792)*	**0.698**	*(0.660;0.736)*	**0.024**
Average					**0.727**		**0.875**		**0.148**

[1] Discontinuous paved roads (result for unspecified severity crashes refers to paved roads).
[2] Some of the low volume roads are unpaved.

there is no reason to believe that specific properties of crash prediction models are related to whether or not the authors report standard errors or confidence intervals. Meta-regression indicates that weighting results has practically no effect on the effects that are found for potential moderator variables. This means that the pooled volume coefficients from the weighted analyses may underestimate the "true" volume coefficients somewhat, but the results from the moderator analyses are unlikely to be affected by weighting of results.

Is meta-analysis of regression coefficients adequate? The present meta-analysis is based on volume coefficients from crash prediction models with different model specifications. According to a very strict view on meta-analysis, it is not defensible to meta-analyze coefficients from regression models, unless all models contain the same covariates (Card, 2015). Amongst other things, omitted variable bias and collinearity may contribute to difference between volume coefficients depending on model specifications (Elvik and Goel, 2019; Koetse et al., 2005). However, others regard a requirement of identical model specifications as overly restrictive, unless there is evidence for the regression coefficients being strongly affected by the sets of additional predictor variables (Becker and Wu, 2007; Elvik and Bjørnskau, 2017; Elvik and Goel, 2019; Hauer, 2010).

As an informal test of the appropriateness of meta-analyzing regression coefficients from models with different sets of predictor variables in the present meta-analysis, the relationship between volume coefficients in volume only models and in full models as been investigated. The comparison is based on studies that have reported both types of models for the same set of data. In "volume only models" volume is the only predictor variable (possibly in addition to section length and time). "Full models" include additional road-related predictor variables (such as number of lanes, speed limit, etc.). Ten such comparisons are available, based on the results from seven studies (Cafiso et al., 2010; Ackaah and Ackaah and Salifu, 2011; Abdel-Aty et al., 2014; Garach et al., 2016; Kaaf and Abuzwidah and Abdel-Aty, 2015; Mehta and Lou, 2013; Shankar et al., 2016). There is a strong relationship between the volume coefficients from volume only and full models ($r = .7715$; $p = .009$). The unweighted averages are similar in the full models (0.736; 95 % CI [0.215; 1.257]) and in the volume only models (0.705; 95 % CI [0.246; 1.164]). These results do not indicate that there are large or systematic differences between volume coefficients, depending on model specifications.

8. Conclusions and practical implications

The results from the present study indicate that volume coefficients in crash prediction models that have the general form of Poisson or Negative binomial models, may be affected by the composition of crash types, crash severity, volume, and type of road:

- ***Crash type:*** Volume coefficients are on average larger for MV and smaller for SV crashes than for all crashes.
- ***Crash severity:*** The relationship between volume and crash numbers is weaker for more serious crashes when only fatal and injury crashes are regarded. No systematic differences were found between crashes involving and not involving personal injury.
- ***Volume:*** The results indicate that the relationship between volume and crash numbers is stronger at higher volumes than at lower volumes. However, for fatal crashes and for SV crashes, the relationship between volume and volume coefficients may be weaker at higher volumes.
- ***Type of road:*** The relationship between volume and crash numbers is strongest on freeways, followed by multilane non-freeways, and weakest on two-lane roads. On multilane non-freeways it is stronger when the road is divided than when it is undivided. These differences may be due to differences in mean volume (highest volumes on freeways, lowest volumes on two-lane roads). They are unlikely to be due to differences in the share of MV crashes.

These results indicate that crash prediction models are likely to be more precise when crashes are disaggregated by crash type, crash severity, and road type. Disaggregating models by volume level and distinguishing between divided and undivided roads may also improve the models.

The results indicate further that crash prediction models may be misleading if they are used to predict crash numbers on roads that differ from those that were used for model development with respect to composition of crash types, share of fatal or serious injury crashes, road types, and volume levels.

CRediT authorship contribution statement

Alena Katharina Høye: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Visualization, Writing - original draft, Writing - review & editing. **Ingeborg Storesund Hesjevoll:** Software, Formal analysis, Resources, Data curation, Writing - review & editing, Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Studies included in meta-analysis

	N of vol. coeff.	Sum of weights
Abdel-Aty et al., 2014 (USA)	34	240.0
Abdel-Aty et al., 2009 (USA)	27	–
Abdel-Rahim and Khan, 2012 (USA)	3	28.0
Abuzwidah and Abdel-Aty, 2015 (USA)	4	–
Ackaah and Salifu, 2011 (Ghana)	2	12.3
Alhasan et al., 2018 (USA)	1	52.6
Avelar and Dixon, 2011 (USA)	1	9.3
Awad and Parry, 2018 (Great Britain)	4	24.2
Bektas et al., 2016 (USA)	3	–
Bornheimer et al., 2012 (USA)	1	–
Brimley et al., 2012 (USA)	1	–
Cafiso et al., 2010 (Italy)	3	43.7
Camacho-Torregrosa et al., 2013 (Spain)	1	–
Chen et al., 2011 (USA)	1	5.8
Chimba et al., 2017 (USA)	2	–
Chiou and Fu, 2015 (Taiwan)	1	11.6
Cook, 2010 (USA)	4	20.8
Dixon and Avelar, 2015 (USA)	1	3.4
Dixon et al., 2012 (USA)	1	4.0
Donnell and Mason, 2006 (USA)	2	49.4
Donnell et al., 2009 (USA)	2	8.4
Donnell et al., 2014 (USA)	2	366.7
El-Basyouny and Sayed, 2006 (Canada)	1	18.5
El-Basyouny and Sayed, 2010 (Canada)	2	23.2
Fitzpatrick et al., 2005 (USA)	2	54.9
Gan et al., 2012 (USA)	20	–
Garach et al., 2016 (Spain)	4	–
Garber et al., 2006 (USA)	3	–
Gates et al., 2015 (USA)	6	323.2
Gaweesh et al., 2019 (USA)	2	–
Geedipally and Lord, 2010 (USA)	6	101.0
Geedipally et al., 2010 (USA)	6	201.4
Geedipally et al., 2012 (US)	1	11.0
Gianfranco et al., 2018 (Italy)	1	30.2
Gooch et al., 2016 (USA)	2	135.7
Haas et al., 2010 (USA)	4	525.7
Haleem et al., 2013 (USA)	2	42.9
Hosseinpour et al., 2016 (Malaysia)	1	4.8
Hou, Meng et al., 2019 (China)	1	5.8
Hou, Meng et al., 2018 (China)	1	47.6
Hou et al., 2018a, 2018b (China)	1	5.3
Høye, 2016 (Norway)	5	271.1
Iliadi et al., 2016 (Netherlands)	1	–
Islam et al., 2014 (USA)	4	32.5
Jones et al., 2011 (UK)	3	22.6
Kaaf and Abdel-Aty, 2015 (Saudi-Arabia)	6	42.7
Kay et al., 2017 (USA)	6	325.0
Khan et al., 2015 (USA)	1	7.7
Khan, Bill et al., 2012 (US)	1	52.6
Kiattikomol et al., 2008 (USA)	4	–
Kim et al., 2015 (USA)	6	–
Kim et al., 2013 (South Korea)	1	19.6
Kweon et al., 2015 (USA)	1	–
Labi, 2006 (USA)	6	–
Lee et al., 2015 (USA)	3	88.6
Liu et al., 2008 (USA)	2	6.8
Liu et al., 2017 (USA)	1	27.8
Lord and Bonneson, 2007 (USA)	1	11.7
Lord et al., 2007 (USA)	1	45.5
Lu et al., 2013 (USA)	1	5.9
Manuel et al., 2014 (Canada)	2	14.4
Martz, 2017 (USA)	6	235.2
Martz et al., 2017 (USA)	2	101.9
Mayora et al., 2006 (Spain)	4	–
McArthur et al., 2013 (USA)	3	26.4
Mehta and Lou, 2013 (USA)	4	96.8
Mohammadi et al., 2014 (USA)	2	20.0
Monsere and Fischer, 2008 (USA)	4	36.8
Montella, 2009 (Italy)	7	36.3
Montella and Imbriani, 2015 (Italy)	18	108.5
Montella et al., 2008 (Italy)	2	–
Montella, 2010 (Italy)	2	12.3
Montella et al., 2012 (Italy)	10	99.7
Mothafer et al., 2017 (USA)	1	8.2
Naznin et al., 2016 (Australia)	1	2.5

Park and Abdel-Aty, 2015 (USA)	4	–
Park and Abdel-Aty, 2017 (USA)	2	34.8
Park et al., 2014 (USA)	4	–
Park et al., 2016 (USA)	6	–
Park et al., 2015a (USA)	2	–
Park et al., 2015b (USA)	2	–
Park et al., 2012a (USA)	2	–
Park et al., 2012b (USA)	2	57.6
Park et al., 2010 (USA)	4	41.9
Patel et al., 2007 (USA)	2	96.5
Peel et al., 2017 (USA)	2	–
Peng et al., 2012 (USA)	3	19.0
Persaud et al., 2013 (USA)	6	34.3
Potts et al., 2007 (USA)	20	–
Rengarasu et al., 2009A (Japan)	1	–
Rengarasu et al., 2009B (Japan)	1	23.8
Robicheaux and Wolshon, 2015 (USA)	8	–
Roque and Cardoso, 2014 (Portugal)	2	–
Rusli et al., 2017 (Malaysia)	1	11.0
Russo and Savolainen, 2018 (USA)	1	40.0
Saleem and Persaud, 2017 (Canada)	18	401.2
Shankar et al., 2016 (USA)	8	717.6
Shaon and Qin, 2016 (USA)	1	32.3
Singh et al., 2016 (India)	1	10.8
Srinivasan and Carter, 2011 (USA)	44	2,372.3
Srinivasan et al., 2016 (USA)	8	40.9
Stapleton et al., 2018 (USA)	6	151.8
Tarko et al., 2008a (USA)	12	239.0
Tarko et al., 2008b (USA)	5	76.0
Taylor et al., 2018 (USA)	2	32.9
Tegge et al., 2010 (USA)	23	158.1
Uhm et al., 2012 (USA)	1	19.9
Vangala et al., 2014 (USA)	2	82.4
Venkataraman, Ulfarsson et al., 2011 (USA)	1	13.5
Villwock et al., 2010 (USA)	5	76.1
Wang et al., 2009 (UK)	4	10.2
Wood and Porter, 2013 (USA)	3	35.4
Wood et al., 2015 (USA)	2	22.9
Ye et al., 2013 (USA)	1	36.0
Zeng and Schrock, 2012 (USA)	2	29.1
Zheng et al., 2018 (China)	3	51.5
Zhou et al., 2013 (USA)	3	15.8
Zou et al., 2018 (USA)	2	30.6

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.aap.2020.105668.

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