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Safety-in-numbers: An updated meta-analysis of estimates

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ABSTRACT

Safety-in-numbers denotes the tendency for the number of accidents to increase less than in proportion to traffic volume. This paper updates a meta-analysis of estimates of safety-in-numbers published in 2017 (Elvik and Bjørnskau, Safety Science, 92, 274–282). Nearly all studies find safety-in-numbers, but the numerical estimates vary considerably. As virtually all studies are cross-sectional, it is not possible to determine if safety-in-numbers represents a causal relationship. Meta-regression analysis was performed to identify factors which may explain the large heterogeneity of estimates of safety-in-numbers. It was found that safety-in-numbers tends to be stronger for pedestrians than for cyclists, and stronger at the macro-level (e.g. citywide) than at the micro-level (e.g. in junctions). Recent studies find a stronger tendency towards safety-in-numbers than older studies.

1. Introduction

It is increasingly understood that more walking and cycling is likely to bring public health benefits, and may be associated with other benefits, like reduced congestion and air pollution, if those who take up walking or cycling reduce car travel (Mueller et al., 2018). Cost-benefit analyses (Masters et al., 2017) have found that the benefits of walking or cycling exceed the costs by a wide margin.

However, one important societal cost which is likely to increase if walking or cycling increases, is traffic injury. Pedestrians and cyclists have a higher rate of injury per kilometre of travel than car occupants (Bjørnskau, 2015). Therefore, more walking or cycling will most likely be associated with an increase in the number of injury accidents. Against this, it is argued that the more pedestrians or cyclists there are, the lower becomes the risk of injury to each pedestrian or cyclist. This phenomenon is referred to as safety-in-numbers and has attracted considerable research interest in recent years.

Elvik and Bjørnskau (2017) synthesised evidence from studies estimating safety-in-numbers by means of meta-analysis. Their review included primary studies up to 2014. Although this is only five years ago, several new studies have been published. Moreover, their review missed a few relevant studies published before 2014. The objective of this paper is to update the meta-analysis of studies estimating the safety-in-numbers effect. Use of the word "effect" should not be taken to suggest causality; it is a shorthand for "coefficients whose values are consistent with a less-than-proportional to traffic volume increase in the number of accidents". The main questions this paper tries to answer are:

1 Is safety-in-numbers consistently found in studies aiming to estimate it?
2 Does the safety-in-numbers effect vary between studies? If so, what are the principal sources of variation?
3 Is there an association between characteristics of the infrastructure, in particular facilities for walking or cycling, and the safety-in-numbers effect?

2. Models estimating safety-in-numbers

All studies included in the meta-analysis reported in this paper are multivariate accident prediction models of the following basic form:

Number of accidents involving motor vehicles and cyclists or pedestrians =

$$e^{\beta_0} MV^{\beta_1} CYCL^{\beta_2} e^{\left(\sum_{n=3}^{i} \beta_n X_n\right)} \tag{1}$$

In Eq. (1), e denotes the exponential function, i.e. the base of the natural logarithms (2.71828) raised to the power of a regression coefficient β. The first term is the constant term. The next two terms refer to traffic volume. MV denotes motor vehicles, CYCL denotes cyclists (PED for pedestrians in models including pedestrian volume). Traffic volume typically enters models in the form of average daily traffic (AADT). The final term ($e^{(\Sigma \beta n X n)}$) is a set of predictor variables (X) other than traffic volume, which may influence the number of accidents.

While all models share this basic form, they are not identical in all details. Some models include traffic volume variables only (e.g.

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Nordback et al., 2014); other models include many variables describing infrastructure and traffic environment (e.g. Cai et al., 2016). Some models account for spatial correlations (e.g. Tasic et al., 2017); some have been estimated by Bayesian techniques, rather than (or in addition to) maximum likelihood estimation (e.g. Osama and Sayed, 2017a, 2017b, 2017c, 2017d). It is, as argued by Elvik and Bjørnskau (2017), overly restrictive to require the models to be identical in all respects.

Nevertheless, it is well-known that regression coefficients can vary depending on which variables are included in a model and the specification of the functional relationships between them (Hauer, 2010). Therefore, some check on the stability of regression coefficients across model specifications should be part of an exploratory analysis, to safeguard against inclusion of a coefficient whose value could have been very different if the model had been specified differently.

The coefficients of principal interest in the meta-analysis are those that refer to traffic volume. If these coefficients have a value larger than 1, that shows that the number of accidents increases more than in proportion to traffic volume, e.g. if traffic volume increases by 40%, accidents increase by 55%. If the coefficients have positive values between 0 and 1, that indicates a less than proportional increase in the number of accidents, e.g. traffic goes up by 40%, but accidents only go up by 15%. If the coefficients have negative values, that suggests that an increase in traffic volume is associated with a reduction in the number of accidents, e.g. traffic increases by 20%, but the number of accidents is reduced by 6%. The lower the value of the coefficients for traffic volume, the stronger the safety-in-numbers effect. The safety-in-numbers effect arises in the interaction between motor vehicles and non-motorised road users; hence, relevant models must include regression coefficients referring both to motor vehicles and to cyclists or pedestrians.

3. Study retrieval, coding and statistical weighting

The studies included by Elvik and Bjørnskau (2017) were also included in the present study. To identify new studies, searches were made of Scopus, MEDLINE (Ovid), Web of Science and TRID (TRIS and ITRD) databases using multiple iterations of the relevant keywords and Mesh terms. The search was not limited by time period and all search results were completed by May 2018. New studies were also identified through the weekly newsletter SafetyLit, which lists new studies published during the last week. The ancestry approach, i.e. identifying studies on the reference lists of studies already obtained, was also used.

Fig. 1 presents the screening of studies according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). Studies were included in the meta-analysis if the standard errors of the regression coefficients for the traffic volume variables were stated or could be estimated.

Table 1 lists the studies included in the meta-analysis. For each study, the table reports the year of publication, the country it was made in, the number of study units, the number of accidents in total at these study units, estimated regression coefficients for motor vehicle volume, cyclist volume and pedestrian volume, and the number of confounding factors controlled for in statistical analysis.

Based on 15 studies, Elvik and Bjørnskau (2017) included 25 regression coefficients for motor vehicle volume, 15 regression coefficients for pedestrian volume and 11 regression coefficients for cyclist volume in the meta-analysis. In this paper, 45 studies were included in the analysis contributing 75 regression coefficients for motor vehicle volume, 39 for cyclist volume and 38 for pedestrian volume. Hence, the literature available for meta-analysis has expanded considerably in recent years. The number of studies and estimates of effect included in this paper are roughly three times the number included by Elvik and Bjørnskau (2017).

A number of studies were identified that could not be included in the meta-analysis. Table 2 lists these studies and the reasons for not including them in the meta-analysis. The list does not include studies that were excluded from Elvik and Bjørnskau (2017). Moreover, it only includes studies dealing with safety-in-numbers, but not providing enough information to be included in the meta-analysis.

It is seen that there are many reasons for excluding studies from meta-analysis. A few studies could in principle have been included, had they reported the standard errors of regression coefficients or used the count of accidents, rather than accident rate, as dependent variable. For the studies that were included in the meta-analysis, the following information was coded for each study:

1 One or more estimates of a regression coefficient for motor vehicle volume, cyclist volume or pedestrian volume
2 The standard error of each regression coefficient
3 The country where the study was performed
4 Publication year
5 Estimates of motor vehicle-, cyclist- and pedestrian volume
6 Level of analysis (micro, meso or macro; see comments in text)
7 Number of covariates included (in addition to the traffic volume

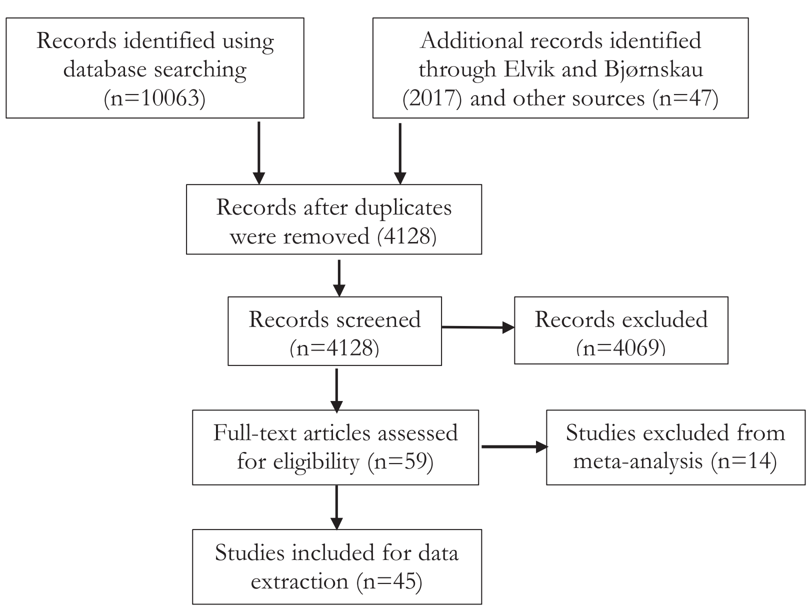

Fig. 1. Literature search and study screening.

Table 1
Data for studies included in meta-analysis.

Study	Country	Number of locations	Number of accidents	Coefficients (standard errors in parentheses)			Confounders controlled
				Motor vehicles	Cyclists	Pedestrians	
Inwood, Grayson 1979	Great Britain	140	166	0.92 (0.224)		0.27 (0.097)	3
Inwood, Grayson 1979	Great Britain	140	55	0.58 (0.260)		0.79 (0.138)	3
Hall, 1986	Great Britain	177	510	1.27 (0.080)		0.18 (0.030)	0
Summersgill, Layfield 1996	Great Britain	970	693	0.72 (0.082)		0.44 (0.035)	5
Lyon, Persaud 2002	Canada	684	5280	0.57 (0.063)		0.74 (0.027)	0
Lyon, Persaud 2002	Canada	263	1065	0.40 (0.157)		0.41 (0.049)	0
Lyon, Persaud 2002	Canada	122	159	0.53 (0.137)		0.66 (0.100)	0
Lyon, Persaud 2002	Canada	123	319	0.58 (0.164)		0.71 (0.075)	0
Jonsson, 2005	Sweden	393	143	0.76 (0.154)	0.35 (0.064)		3
Jonsson, 2005	Sweden	393	130	0.83 (0.216)		0.38 (0.091)	3
Zegeer et al., 2005	United States	1000	188	1.01 (0.184)		0.38 (0.065)	1
Zegeer et al., 2005	United States	1000	41	0.30 (0.258)		0.60 (0.134)	1
Geyer et al., 2006	United States	247	185	0.15 (0.122)		0.61 (0.115)	2
Harwood et al., 2008	United States	450	728	0.05 (#)		0.41 (0.040)	2
Harwood et al., 2008	United States	1433	4824	0.40 (0.060)		0.45 (0.020)	2
Schneider et al., 2010*	United States	81	Not stated	1.50 (0.425)		0.58 (0.162)	6
Daniels et al., 2011*	Belgium	148	410	0.91 (0.387)	0.26 (0.111)		1
Daniels et al., 2011*	Belgium	148	61	1.62 (1.080)		0.20 (0.500)	1
Miranda-Moreno et al., 2011	Canada	753	787	0.40 (0.117)	0.44 (0.117)		4
Schepers et al., 2011	Netherlands	490	183	0.73 (0.112)	0.48 (0.125)		8
Schepers et al., 2011	Netherlands	524	156	0.50 (0.151)	0.56 (0.102)		3
Tin Tin et al., 2011*	New Zealand	8	Not stated	0.78 (0.190)	−0.14 (0.260)		0
Tin Tin et al., 2011*	New Zealand	8	Not stated	0.76 (0.180)	0.25 (0.290)		0
Buch, Jensen 2013	Denmark	332	191	0.27 (0.115)	0.34 (0.099)		4
Buch, Jensen 2013	Denmark	709	305	0.32 (0.110)	0.39 (0.115)		4
Elvik et al., 2013	Norway	159	316	0.59 (0.132)		0.31 (0.077)	6
Schepers, Heinen 2013	Netherlands	387	412	0.62 (0.107)	0.26 (0.097)		2
Schepers, Heinen 2013	Netherlands	387	7411	0.55 (0.059)	0.44 (0.051)		2
Nordback et al., 2014	United States	105	198	0.64 (0.170)	0.53 (0.140)		0
Nordback et al., 2014	United States	106	285	0.58 (0.130)	0.65 (0.110)		0
Prato et al., 2014	Denmark	289	5349	0.35 (0.088)	0.67 (0.036)		16
Strauss et al., 2014* $	Canada	647	408	0.22 (0.043)	0.87 (0.071)		3
Strauss et al., 2014*	Canada	647	744	0.56 (0.045)		0.57 (0.022)	3
Strauss et al., 2014*	Canada	435	57	0.26 (0.098)	0.75 (0.149)		1
Strauss et al., 2014*	Canada	435	29	0.42 (0.204)		0.70 (0.204)	0
Kaplan, Prato 2015* $	Denmark	383479	1155	0.60 (0.110)	0.23 (0.047)		16
Kaplan, Prato 2015* $	Denmark	383479	4194	0.73 (0.110)	0.44 (0.027)		16
Kröyer, 2015*	Sweden	113	89	0.71 (0.370)	0.36 (0.180)		4
Kröyer, 2015*	Sweden	113	22	0.64 (0.770)		0.30 (0.360)	3
Strauss et al., 2015* $	Canada	635	Not stated	0.31 (0.061)	0.51 (0.054)		3
Tulu et al., 2015*	Ethiopia	22	256	0.82 (0.390)		0.65 (0.320)	4
Abou-Senna et al., 2016* &	United States	50	210	0.36 (0.260)	0.30 (0.069)		1
Cai et al., 2016*	United States	8518	15307	0.16 (0.010)	0.07 (0.012)		14
Cai et al., 2016*	United States	8518	16240	0.14 (0.009)		0.07 (0.011)	14
Elvik, 2016*	Norway	239	310	0.05 (0.101)	0.12 (0.055)	0.07 (0.058)	8
Gates et al., 2016*	United States	26	54	0.48 (0.226)		0.48 (0.226)	8
Nabavi Niaki et al., 2016*	Canada	1442	4447	−0.35 (0.071)		0.28 (0.071)	2
Nashad et al., 2016*	United States	8518	16240	0.12 (0.006)		0.07 (0.010)	15
Nashad et al., 2016*	United States	8518	15307	0.13 (0.006)	0.14 (0.009)		15
Osama, Sayed 2016*	Canada	134	1703	0.39 (0.086)	0.46 (0.054)		3
Yao, Loo 2016*	China	282	3198	2.55 (0.690)	0.24 (0.030)		4
Yao, Loo 2016*	China	289	4144	2.33 (0.590)	0.19 (0.030)		4
Yasmin and Eluru, 2016*	United States	837	4185	0.65 (0.075)	0.12 (0.042)	0.14 (0.062)	22
Aldred et al., 2018*	Great Britain	12290	6244	1.31 (0.054)	0.82 (0.013)		6
Aldred et al., 2017*	Great Britain	202	12781	−0.13 (0.071)	0.42 (0.033)		1
Aldred et al., 2017*	Great Britain	202	7898	−0.32 (0.069)	0.52 (0.038)		1
Aldred et al., 2017*	Great Britain	202	9303	−0.10 (0.061)	0.62 (0.041)		1
Aldred et al., 2017*	Great Britain	202	20679	−1.16 (0.628)	0.34 (0.117)		1
Aldred et al., 2017*	Great Britain	202	17201	2.19 (0.663)	0.75 (0.168)		1
Guo et al., 2017*	China	786	2168	0.17 (0.035)		0.24 (0.033)	13
Heydari et al., 2017*	Canada	647	406	0.24 (0.070)	0.41 (0.065)		3
Heydari et al., 2017*	Canada	647	745	0.30 (0.046)	0.30 (0.036)		4
Omer et al., 2017*	Israel	535	273	1.13 (0.221)		0.52 (0.157)	3
Omer et al., 2017*	Israel	444	311	−0.01 (0.308)		1.40 (0.342)	4
Osama and Sayed, 2017a, 2017b, 2017c, 2017d*	Canada	134	2070	0.56 (0.100)		0.87 (0.110)	3
Osama and Sayed, 2017a, 2017b, 2017c, 2017d*	Canada	134	1703	0.32 (0.087)	0.49 (0.057)		4
Osama and Sayed, 2017a, 2017b, 2017c, 2017d*	Canada	134	1703	0.36 (0.080)		0.76 (0.110)	3

(*continued on next page*)

Table 1 (*continued*)

Study	Country	Number of locations	Number of accidents	Coefficients (standard errors in parentheses)			Confounders controlled
				Motor vehicles	Cyclists	Pedestrians	
Osama and Sayed, 2017a, 2017b, 2017c, 2017d*	Canada	134	1703	0.26 (0.100)	0.46 (0.066)		6
Osama and Sayed, 2017a, 2017b, 2017c, 2017d*	Canada	134	2070	0.57 (0.090)		0.68 (0.090)	3
Tasic et al., 2017*	United States	801	7632	0.22 (0.028)	0.49 (0.045)		5
Tasic et al., 2017*	United States	801	14218	0.05 (0.028)		0.30 (0.036)	8
Xu et al., 2017*	China	288	1003	0.27 (0.078)		0.21 (0.051)	4
Guo et al., 2018*	Canada	134	1703	0.27 (0.092)	0.46 (0.058)		6
Saha et al., 2018*	United States	11355	27820	0.32 (0.011)	0.02 (0.009)		23
Lee et al., 2019*	United States	219	63	0.31 (0.130)		1.01 (0.221)	4

*This study was not included in Elvik and Bjørnskau (2017).
(#) This coefficient was not included in meta-analysis; the coefficient for pedestrian volume was included.
$ A weighted mean coefficient for motor vehicle volume was estimated by means of the inverse variance method.
& This study was re-analysed by means of negative binomial regression. Coefficients based on the re-analysis were used in meta-analysis.

variables)

A distinction was made between three levels of analysis. The micro level typically consists of a sample of junctions, using a junction as unit of analysis. The meso level typically consists of parts of a city, like traffic analysis zones. Each zone may consist of several links and junctions. The macro level typically consists of larger jurisdictions, like an entire city or a state or region. Estimates of traffic volume were not available in all studies.

Each regression coefficient was assigned a statistical weight inversely proportional to its sampling variance:

$$\text{Fixed− effects statistical weight} = W(fe) = \frac{1}{SE^2} \quad (2)$$

SE is the standard error of a coefficient. A weighted mean value of a set of regression coefficients was estimated as follows:

$$\text{Summary estimate} = \bar{Y} = \frac{\sum_{i=1}^{n} Y_i \bullet W_i}{\sum_{i=1}^{n} W_i} \quad (3)$$

Y_i denotes the coefficient estimate in study i, W_i is the statistical weight assigned to coefficient i and $\bar{Y}$ is the summary estimate, i.e. weighted mean estimate of a coefficient.

Statistical weights as defined above account for random sampling variation only. However, as noted, regression coefficients may vary substantially and systematically between studies. To determine whether there is systematic between-study variation in estimated regression coefficients, the following test statistic is computed:

$$Q = \sum_{i=1}^{g} W_i \bullet Y_i^2 - \frac{\left(\sum_{i=1}^{g} W_i \bullet Y_i\right)^2}{\sum_{i=1}^{g} W_i} \quad (4)$$

This test statistic has a Chi-square distribution with g − 1 degrees of freedom, where g is the number of regression coefficients. If there is between-study variation in estimates of regression coefficients, an adjusted statistical weight is estimated:

$$\text{Random− effects statistical weight} = W(re) = \frac{1}{SE_i^2 + \tau^2} \quad (5)$$

The variance component (τ^2) is estimated as follows:

$$\text{Variance component } (\tau 2) = \frac{Q - (g - 1)}{C} \quad (6)$$

Q and g are defined above and C is estimated as follows (w in Eq. 7 is the fixed-effects weight):

$$C = \sum_{g=1}^{n} w_i - \left(\frac{\sum_{g=1}^{n} w_i^2}{\sum_{g=1}^{n} w_i}\right) \quad (7)$$

4. Exploratory analysis

An exploratory analysis was performed to help decide whether proceeding to a main analysis makes sense. The exploratory analysis addressed the following topics:

1 The possible presence of publication bias
2 The existence of outlying data points

Table 2
Studies not included in meta-analysis and reasons for exclusion.

Study	Reason for exclusion from meta-analysis
Strauss et al., 2013	The same data were analysed in a 2015-paper; the most recent paper was preferred
Wei and Lovegrove, 2013	Standard errors of regression coefficients not reported and not possible to estimate
Aldred and Crosweller, 2015	Does not use accidents as dependent variable
Teshke et al., 2015	Defines exposure and risk so that a negative relationship will arise by necessity; spurious estimate of safety-in-numbers
Aldred 2016	Does not use accidents as dependent variable
Amoh-Gyimah et al., 2016	Standard errors of regression coefficients not reported and not possible to estimate
Eluru et al., 2016	Coefficients not comparable to other studies because different functional form was assumed
Ursachi and Owen, 2016	Does not include data on motor vehicle volume
Murphy et al., 2017	Defines depend variables as risk, not as count of accidents; not possible to convert regression coefficients
Poulos et al., 2017	Does not use accidents as dependent variable
Strauss et al., 2017	Does not use accidents as dependent variable
Thomas et al., 2017	Does not include data on motor vehicle volume
Hampshire et al., 2018	Does not identify the variables regression coefficient refer to (X_1 and X_2 are not explained)
Carlson et al., 2018	Defines depend variables as risk, not as count of accidents; not possible to convert regression coefficients
Smith et al., 2019	Studies safety-in-distance, not safety-in-numbers

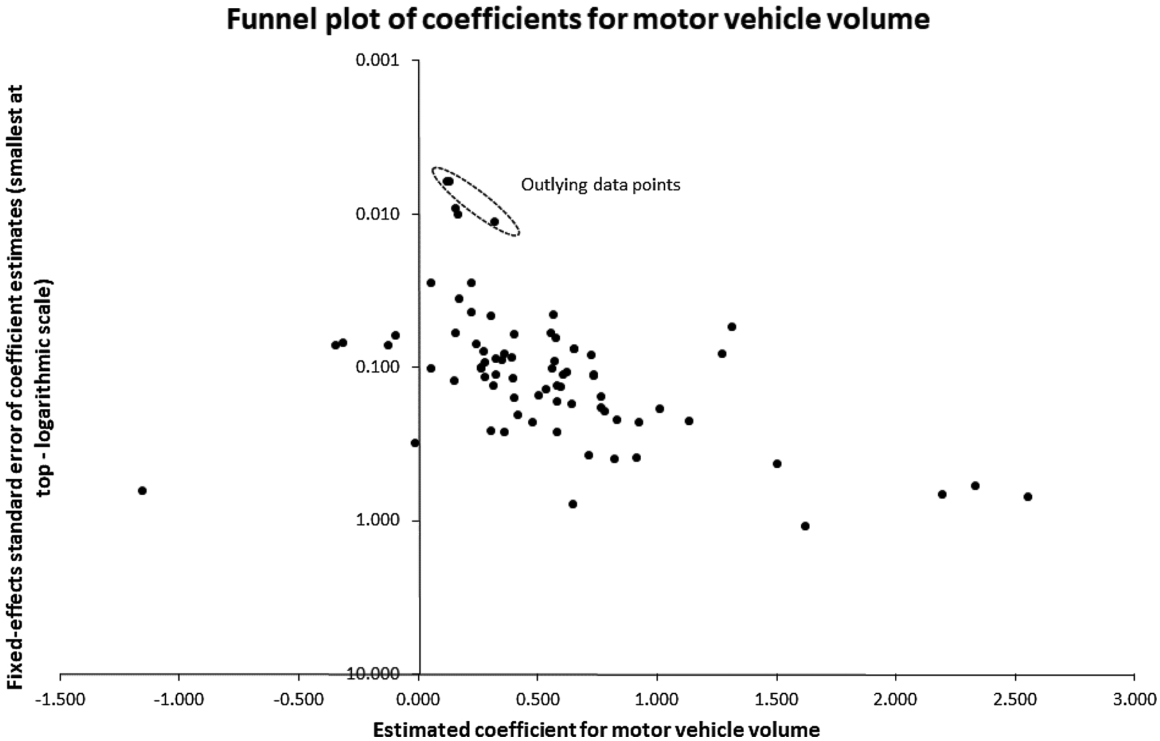

Fig. 2. Funnel plot of coefficient estimates for motor vehicle volume.

3 The extent of heterogeneity in coefficient estimates
4 The stability of regression coefficients across model specifications

4.1. Publication bias

Elvik and Bjørnskau (2017) applied the trim-and-fill technique (Duval and Tweedie, 2000A, 2000B, Duval, 2005) to assess the possible presence of publication bias. The natural logarithm of each coefficient was taken and multiplied by minus one. These transformed coefficient values were ordered from the lowest to the highest, assuming that publication bias would take the form of suppressing the left tail of the distribution (i.e. a funnel plot indicating publication bias would be asymmetric with a tail to the right, consisting of low coefficient estimates indicating a strong safety-in-numbers effect). In general, Elvik and Bjørnskau found little evidence of publication bias.

Funnel plots of coefficient estimates for motor vehicle volume, cyclist volume and pedestrian volume are shown in Figs. 2–4. No log-transformation of the coefficients was applied, as there are negative coefficients both for motor vehicle volume and cyclist volume, for which the natural logarithm is undefined. Coefficients are therefore shown in the original metric.

All funnel plots show a wide dispersion of estimates. There is, except perhaps for the coefficients for motor vehicle volume, no tendency for the dispersion to be smaller for coefficients with small standard errors than for coefficients with large standard errors. The diagrams do not reveal a clear funnel shape. The trim-and-fill method was applied to the coefficients without transforming them to natural logarithms. For the sake of completeness, the essential elements of the trim-and-fill technique are summarised below.

The trim-and-fill method is based on the assumption that the data points in the funnel plot should have a symmetric distribution around the summary mean if there is no publication bias. Asymmetry indicates publication bias and the trimmed mean, estimated after data points have been trimmed away, indicates what the summary estimate of the regression coefficients would have been if there was no publication bias. Two estimators are commonly used: L and R.

To estimate these and test for publication bias, estimates of the regression coefficients are sorted from the lowest to the highest. A summary estimate of the regression coefficient is obtained and the differences between the individual estimates and the summary estimate are computed. The absolute values of these differences are ranked from the smallest to the largest and the ranks are signed. The ranks of the coefficients with a lower value than the weighted mean get a negative sign and those of the coefficients with a higher value get a positive sign. The estimator R is based on the length of the rightmost number of ranks associated with positive effects, i.e. the number of positive ranks larger than the absolute value of any of the negative ranks. Denoting this length with γ, the estimator is defined by $R_0 = \gamma - 1$. The second estimator is based on the sum of ranks for the positive effects. Denoting the ranks by r_i, the sum of positive ranks is defined by $T_n = \sum_{r_i>0} r_i$, an estimator of the number of missing studies is defined by:

$$L_0 = \frac{4T_n - n(n+1)}{2n-1} \tag{8}$$

For motor vehicles, using coefficients in the original metric, R was estimated to 4 and L to 30. The indicators are thus highly inconsistent, with one of them suggesting a minor publication bias the other suggesting a substantial publication bias. The L-estimator implies trimming away the 30 highest coefficient estimates, some of which are larger than 1 and do therefore not indicate safety-in-numbers. Were these coefficients to be trimmed away, the summary estimate would indicate a stronger safety-in-numbers effect than if they are retained. This result is highly implausible.

The analysis was repeated, multiplying all coefficient estimates by minus one. The value of R was then 0 and L had a negative value, thus giving no indication of publication bias. The data points in Fig. 2 are slightly asymmetric to the right. Three data points have been classified as outlying (see the next section for a discussion of these data points). When the summary coefficient was re-estimated, omitting the outlying data points, R became 4 and L 29 based on positive coefficient values. When coefficients are multiplied by minus one, R became 0 and L negative. Researchers looking for safety-in-numbers might be tempted to reject regression coefficients with values larger than 1, as these are not

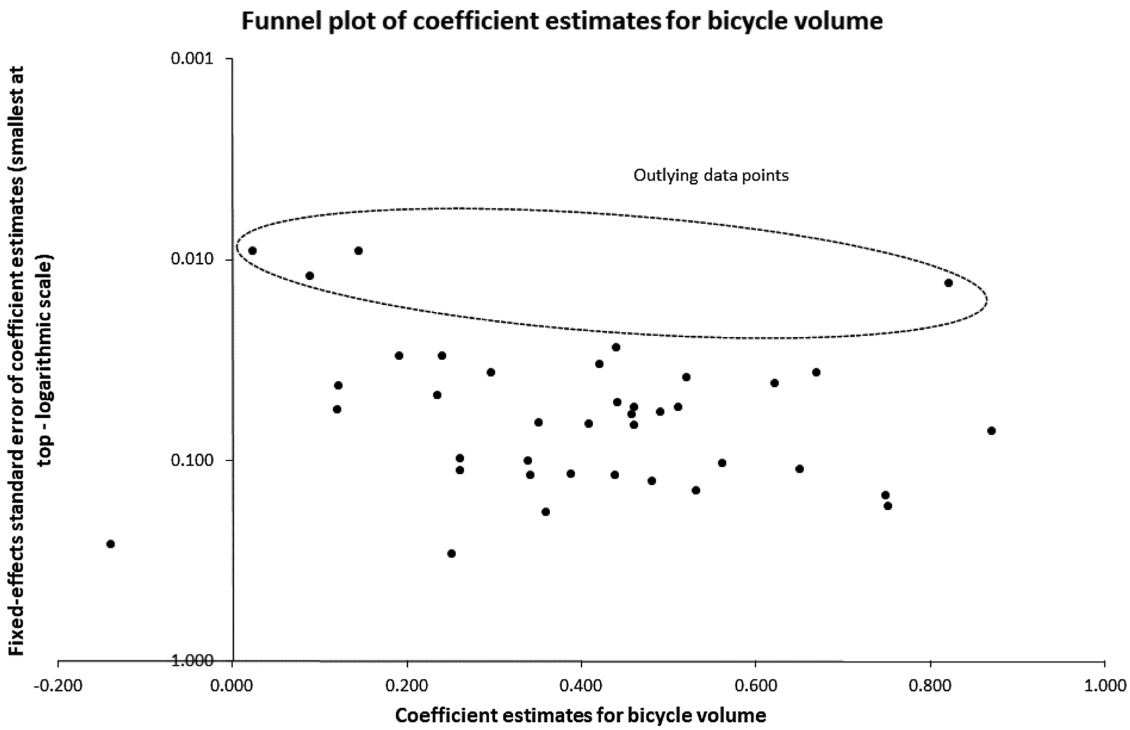

Fig. 3. Funnel plot of coefficients for bicycle volume.

consistent with safety-in-numbers. There is no evidence of such a bias in Fig. 2.

The coefficients for cycling volume are widely dispersed with no clear tendency for the more precise estimates to be closer to each other than the less precise estimates. Four data points, the four most precise estimates, were classified as outlying. Trim-and-fill produced values of 26 for R 19 for L, indicating massive publication bias. Again, however, this implies deleting the estimates that are the least consistent with the existence of a safety-in-numbers effect, which is implausible if it is assumed that researchers expect to find a safety-in-numbers effect. When all coefficients were multiplied by minus 1, R became 0 and L became negative, indicating no publication bias. A replication of the analysis, using positive coefficient values but omitting four outlying data points gave values of 0 for R and 1 for L. This shows that the initial indication of publication bias was attributable to inclusion of the outlying data points; with these omitted, there is no clear indication of publication bias.

As far as the coefficients for pedestrian volume are concerned, R

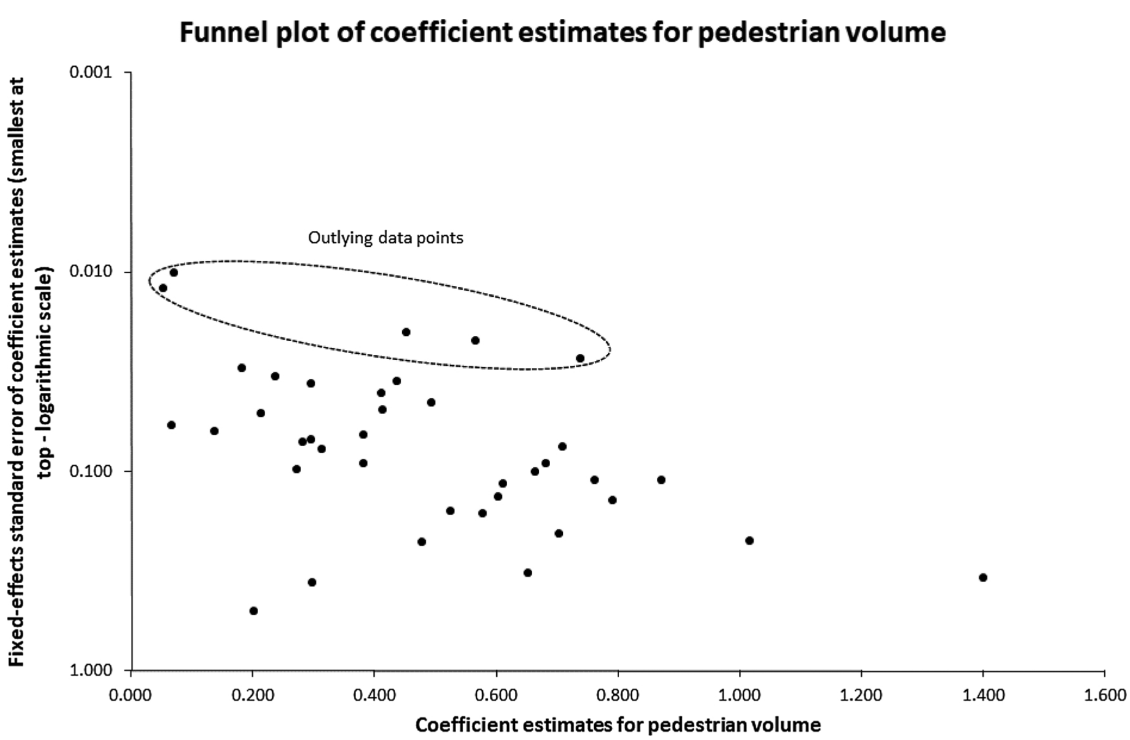

Fig. 4. Funnel plot of coefficients for pedestrian volume.

trimmed away 34 data points and L trimmed away 20. This is extreme, as there was 38 data points in total. Repeating the analysis when multiplying all coefficients by -1 R becomes 0 and L is negative. When the analysis was repeated omitting five outlying data points, both R and L became 11, thus still indicating publication bias.

A fully satisfactory analysis of the possible presence of publication is thus not possible. However, there is no obvious asymmetry in the distribution of data points in Figs. 2–4. The most obvious characteristic of the figures, particularly Figs. 3 and 4, is the very wide spread of data points that have small standard errors. There is very large heterogeneity in the estimated regression coefficients.

4.2. Outlying data points

Three data points in Fig. 2 were identified as outlying, i.e. when omitting each of these data points, and re-estimating the summary mean regression coefficient based on the remaining g – 1 estimates, the summary regression coefficient was outside the 95% confidence interval of the summary coefficient based on all g estimates. This may seem remarkable, but is nevertheless explicable, since two of the data points have the smallest standard errors of all data points. Thus, the outlying data points contributed highly to the weighted summary estimate of the regression coefficient. The summary estimate changed from 0.170 to 0.214 when the outlying data points were omitted (Table 5). All the three studies were meso-level from the USA.

Four outlying data points were identified for regression coefficients referring to cyclist volume (Fig. 3). These were located far apart and pulled in different directions. When all four were omitted, the weighted summary regression coefficient changed from 0.247 to 0.393 (Table 5). Two of these were meso-level level studies both from the US, one was macro also from the US, and one was micro from Britain. The five outlying data points identified for regression coefficients referring to pedestrian volume (Fig. 4) were also located far apart in the funnel plot, but had the smallest standard errors. Omitting them was associated with a change in the value of the summary regression coefficient from 0.230 to 0.346 (Table 5). Three of these studies were micro-level, while one was macro and one meso, and the study settings were USA or Canada.

These results suggest that meta-regression of the coefficients should be run both by including and omitting the outlying estimates, to see what difference they make to the summary estimates of the regression coefficients. In all three cases (motor vehicles, cyclists, pedestrians), removal of outliers resulted in a weaker safety-in-numbers effect.

4.3. Heterogeneity of regression coefficients

The regression coefficients are highly heterogeneous. Table 3 presents some statistics showing this heterogeneity.

The Q-statistic, a measure of variance, is large in all three groups. The I^2 statistic is based on Q and shows how much of the variation in estimates that is systematic (as opposed to purely random sampling variance between the coefficients estimated in different studies). It is stated as a percentage and shows that nearly all the variation between regression coefficients is systematic. Finally, the values of the variance component used in random-effects meta-analysis are also large. Inclusion of this component reduces the statistical weights by 97.9% for coefficients referring to motor vehicle volume, by 99.1% for coefficients referring to cyclist volume and by 98.3% for coefficients referring to pedestrian volume. When there is so large heterogeneity, some would question whether a meta-analysis makes sense. It may perhaps be uninformative to estimate a single weighted mean regression coefficient for motor vehicles, cyclists or pedestrians. It is, however, meaningful to perform a meta-regression analysis to identify sources of the large heterogeneity of coefficient estimates.

Table 3
Heterogeneity in estimates of regression coefficients.

Group	Number of coefficients	Outlying estimates	Q-statistic	I^2 statistic (%)	Tau^2
Motor vehicles	75	3	1733.06	95.85	0.0214
Cyclists	39	4	3476.41	98.91	0.0823
Pedestrians	38	5	1528.36	97.71	0.0583
All groups	152	12	6962.72	97.89	0.0383

4.4. The stability of regression coefficients across model specifications

There are many ways of specifying accident prediction models. If the coefficients referring to the traffic volume variables are found to be unstable with respect to different model specifications, that suggests either that there is: (1) A co-linearity problem, meaning that traffic volume is highly correlated with another independent variable and that coefficients may changes values depending on whether the correlated variable is or is not included in the model; (2) Omitted variable bias, by which the coefficients for traffic volume capture the effect of one or more omitted variables in addition to traffic volume.

If estimates of regression coefficients vary greatly across model specifications, that suggests the presence of one or both of these problems, making meta-analysis difficult. Analysts would have to choose one of the estimated coefficients, and if their values differ a lot, the choice may influence the results of meta-analysis. Some of the primary studies included in this meta-analysis report coefficient estimates for several model specifications. Table 4 lists these estimates for three studies.

Models have been listed from the simplest to the more complex. In general, the models to the right in Table 4 (models numbered 5, 6 or 7) contain more variables than models listed to the left. The values of the estimated regression coefficients are quite stable across model specifications. A tendency can be seen for the coefficients referring to motor vehicle volume to become smaller as models include more variables. On the other hand, the coefficients for cyclist volume and pedestrian volume remain remarkably stable across model specifications. It is concluded that, to the extent the stability of regression coefficients across model specifications can be evaluated, the coefficients are quite stable and therefore possible to include in a meta-analysis.

5. Results

5.1. Regression coefficients

The following analyses have been made to obtain mean regression coefficients and identify factors influencing their values:

1 Fixed-effects meta-analysis, including all data points and omitting outlying data points
2 Random-effects meta-analysis, including all data points and omitting outlying data points
3 Meta-regression analysis, including all data points and omitting outlying data points

Table 5 summarises the results of these analyses. It is seen that the weighted mean coefficients in the fixed-effects analysis vary substantially depending on whether the outlying data points are included or not. In the random-effects model, the treatment of the data points that were found to be outlying according to the fixed-effects model made a smaller difference to the weighted mean regression coefficients. In the random-effects analysis, the summary regression coefficients were found to have almost the same values for motor vehicles, cyclists and pedestrians. An overall mean value was therefore estimated.

A meta-regression was run (Lipsey and Wilson, 2001), applying an SPSS macro written by David Wilson. The meta-regression software fits four types of models to the data: (1) A fixed-effects model fitted by

Table 4
Test of stability of regression coefficients across different model specifications.

Study	Group	Regression coefficients estimated in different models						
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Cai et al., 2016	Motor vehicles	0.145	0.142	0.155	0.154	0.112	0.103	
	Pedestrians	0.067	0.065	0.052	0.056	0.057	0.060	
	Motor vehicles	0.190	0.162	0.186	0.164	0.168	0.148	
	Cyclists	0.109	0.070	0.110	0.088	0.108	0.071	
Elvik, 2016	Motor vehicles	0.190	0.150	0.143	0.078	0.082	0.050	0.048
	Cyclists	0.138	0.132	0.135	0.136	0.126	0.127	0.120
	Pedestrians	0.062	0.054	0.054	0.075	0.071	0.061	0.066
Aldred et al., 2017	Motor vehicles	1.31	1.32	1.32	1.15			
	Cyclists	0.82	0.72	0.85	0.86			

Table 5
Weighted mean regression coefficients.

Model of analysis	Data points included	Mean regression coefficients estimated in different models of analysis (standard errors) (N)			
		Motor vehicles	Cyclists	Pedestrians	All groups
Fixed-effects model	All	0.171 (0.003) (75)	0.247 (0.004) (39)	0.231 (0.006) (38)	0.203 (0.002) (152)
	Outlying points omitted	0.214 (0.006) (72)	0.393 (0.009) (35)	0.346 (0.011) (33)	0.275 (0.004) (140)
Random-effects model	All	0.401 (0.022) (75)	0.401 (0.048) (39)	0.449 (0.043) (38)	0.410 (0.018) (152)
	Outlying points omitted	0.443 (0.032) (72)	0.420 (0.032) (35)	0.446 (0.035) (33)	0.436 (0.019) (140)
Meta-regression model	All (micro-level, 2019)	0.454 (0.085) (152)	0.459 (0.095) (152)	0.409 (0.096) (152)	
	All (macro-level, 2019)	0.255 (0.110) (152)	0.260 (0.118) (152)	0.210 (0.119) (152)	
	Outlying omitted (micro)	0.420 (0.110) (140)	0.400 (0.126) (140)	0.369 (0.128) (140)	
	Outlying omitted (macro)	0.273 (0.147) (140)	0.252 (0.158) (140)	0.221 (0.160) (140)	

Table 6
Coefficients in meta-regression analysis.

Term	Model including all data points (148)			Model excluding outlying data points (136)		
	Estimate	Standard error	P-value	Estimate	Standard error	P-value
Constant	0.7397	0.0847	0.0000	0.7270	0.1107	0.0000
Dummy for cyclists	0.0048	0.0431	0.9118	−0.0206	0.0600	0.7314
Dummy for pedestrians	−0.0454	0.0452	0.3155	−0.0516	0.0631	0.4163
Dummy for meso-level	0.0085	0.0455	0.8509	0.0190	0.0618	0.7578
Dummy for macro-level	−0.1989	0.0693	0.0041	−0.1474	0.0958	0.1239
Dummy for North-America	−0.0435	0.0475	0.3594	0.0067	0.0689	0.9222
Dummy for rest of world	0.0215	0.0730	0.7685	0.096	0.0946	0.3096
Ratio MV to CYCL or PED	−0.0001	0.0000	0.0866	−0.0001	0.0001	0.0709
Number of covariates	−0.0104	0.0041	0.0107	−0.0029	0.0070	0.6839
Year (count; 1979 = 1)	−0.0059	0.0027	0.0315	−0.0073	0.0037	0.0477

means of ordinary least squares regression; (2) A random-effects model fitted by the method of moments; (3) A maximum likelihood random-effects model; and (4) A restricted maximum likelihood random-effects model. The method of moments and maximum likelihood models are fitted by an iteration routine that minimises the value of the residual variance component; i.e. the adjusted statistical weights assigned to each estimate are determined so as to minimise residual variance. Meta-regression estimates in Table 5 are based on the mean number of covariates controlled for (4.645), the median value of the ratio of motor vehicles to cyclists or pedestrians (13.5), and the last year included in the study (2019 = year count = 40). Estimated coefficients and their standard errors are shown in Table 6 for the best fitting model, having the smallest value of the residual random effects variance component. When all data points were included, a random-effects model estimated by the method of moments fitted best. When outlying data points were omitted, a maximum-likelihood random-effects model fitted best.

Dummies were created for group of road user (motor vehicles, cyclists, pedestrians), for level of analysis (micro, meso, macro) and for region of the world (Europe, North America, rest of world). The number of covariates controlled for was entered as a count (range 0–23; mean value 4.645). The ratio of the number of motor vehicles to the number of cyclists or pedestrians was entered with two decimals (e.g. 15,000 motor vehicles and 700 cyclists = 15,000/700 = 21.43). Year was also entered as a count (1–40). When running the models, the dummies for motor vehicles, micro level and Europe were omitted to avoid co-linearity. The best fitting model including all estimates had a residual variance component of 0.03009. The crude variance component was 0.03834. The model therefore explained only 21.5% of the systematic variation in estimates of the regression coefficients.

Table 6 shows that the regional dummies were non-significant. This is reassuring, as it indicates that studies have found the same results no matter where they have been made. Results for the meso-level of analysis were not statistically significantly different from the micro-level (used as reference). The negative coefficient for macro level (Table 6) indicates a stronger safety-in-numbers effect at the macro level than at the micro level. There was a tendency for the safety-in-numbers effect to be stronger in more recent studies than in older studies and stronger the more covariates a study controlled for. The latter finding shows that the safety in numbers effect does not vanish in comparatively well-controlled studies.

Nevertheless, merely counting the number of potentially confounding variables a study has controlled for does not say which

Table 7
Infrastructure characteristics and strength of safety-in-numbers effect for cyclists.

Study	Coefficient for cyclist volume	Accident modification factors associated with infrastructure elements								
		Presence or density of junctions	Presence of bus lane or stop	1 metre or lane added crossing width	Adding a leg in junction	Presence of raised median	Presence of/ 1 km/ mile added bike lane	1 km/mile added sidewalk	Presence of/ 1 km/ mile added bike path	Density of bike lanes
Strauss et al., 2014	0.87					0.71				
Aldred et al., 2017	0.82	3.33	0.92							
Prato et al., 2014	0.67	1.04					1.06		0.75	
Strauss et al., 2015	0.51		1.60	1.01		0.62				
Osama, Sayed 2016	0.46						0.95			1.02
Heydari et al., 2017	0.41		1.94				1.51			
Tasic et al., 2017	0.30	1.01					1.30			
Daniels et al., 2011	0.26						0.58			
Kaplan, Prato 2015	0.23	2.16					0.80		0.50	
Yao, Loo 2016	0.19								1.34	
Elvik, 2016	0.12	1.43		1.21	1.08					
Cai et al., 2016	0.09	1.23						1.26		

confounding variables are associated with a stronger safety-in-numbers effect. The next section examines how the strength of the safety-in-numbers effect is related to variables characterising infrastructure design and traffic control.

5.2. Relationship to infrastructure design and traffic control

There are two main hypotheses about how a safety-in-numbers effect may arise. One of them states that the effect is related mainly to the number of cyclists and pedestrians. The more numerous they become, the more accustomed drivers of motor vehicles become to interacting effectively and safely with cyclists and pedestrians. The other hypothesis can be labelled numbers-in-safety. It proposes that the quality of infrastructure and traffic control influences the attractiveness of cycling or walking. The better the facilities provided, the more people will cycle or walk. What looks like safety-in-numbers is therefore a reflection of the quality of infrastructure.

It is impossible to determine the direction of causality in cross-sectional studies, as all studies included in this paper are, with one exception (Aldred et al., 2017 was both cross-sectional and longitudinal). It is, however, possible to study whether the strength of the safety-in-numbers effect is related to infrastructure variables that have been included in the accident prediction models. If the quality of infrastructure is the main contributor to safety-in-numbers, one would expect that:

1 Infrastructure variables included in models are associated with accident reductions; i.e. these variables make cycling or walking safer,
2 By making cycling or walking safer, infrastructure safety measures are associated with a stronger safety-in-numbers effect (low coefficient values).

Table 7 probes these predictions for cyclists. Studies that included one or more infrastructure variables in addition to cyclist volume have been sorted from those showing the weakest safety-in-numbers effect for cyclists (coefficient values close to 1) to those showing the strongest safety-in-numbers effect for cyclists (coefficients close to 0).

It is seen that most studies have included few infrastructure variables. Table 7 shows the accident modification factors associated with these variables. An accident modification factor of, for example, 0.80 indicates an accident reduction of 20%. Conversely, 1.20 indicates an increase of 20% in the number of accidents. The picture is untidy. It is not the case that a strong safety-in-numbers effect is associated with safer infrastructure, at least judging by the accident modification factors listed in Table 7. Table 8 shows similar findings for pedestrians.

Estimates of the effects of infrastructure elements are scarce and scattered. Few studies include more than one or two characteristics of infrastructure. In the two studies with the lowest coefficients for pedestrian volume, indicating the strongest safety-in-numbers effect, all infrastructure variables are associated with an increase in the number of accidents. These studies indicate that the safety-in-numbers effect persists despite a hostile traffic environment, in which multiple lanes, signalised junctions, and traffic entering from many directions at crossing locations make walking demanding.

6. Discussion

The safety-in-numbers phenomenon – the tendency for the number of accidents to grow less than in proportion to traffic volume – has attracted considerable research interest in recent years. Most of the studies reviewed in this paper are quite recent. While nearly all studies find evidence of safety-in-numbers, i.e. regression coefficients with values less than one, the coefficients are very diverse and have tended to become increasingly so over time. There is no convergence towards a common value or a smaller range of values; quite the opposite. This is illustrated in Fig. 5.

Table 8
Infrastructure characteristics and strength of safety-in-numbers effect for pedestrians.

Study	Coefficient for pedestrian volume	Accident modification factors associated with infrastructure elements								
		Presence or density of junctions	All red signal phase	1 metre or lane added crossing width	Adding a leg in junction	Presence of pedestrian signal	Presence of bus stop	1 km/mile added sidewalk	Presence of raised median	Presence of refuge
Osama and Sayed, 2017a, 2017b, 2017c, 2017d	0.87	1.19						0.97		
Tulu et al., 2015	0.65								0.66	
Strauss et al., 2014	0.57		0.54							
Tasic et al., 2017	0.49	1.15								
Elvik et al., 2013	0.31	1.62		0.93	1.11					
Heydari et al., 2017	0.30					0.72	2.14			
Guo et al., 2017	0.24	1.09								
Xu et al., 2017	0.21					0.69				
Elvik, 2016	0.07	1.43		1.21	1.08					1.09
Nashad et al., 2016	0.07	1.34						1.31		
Cai et al., 2016	0.05	1.29						1.28		

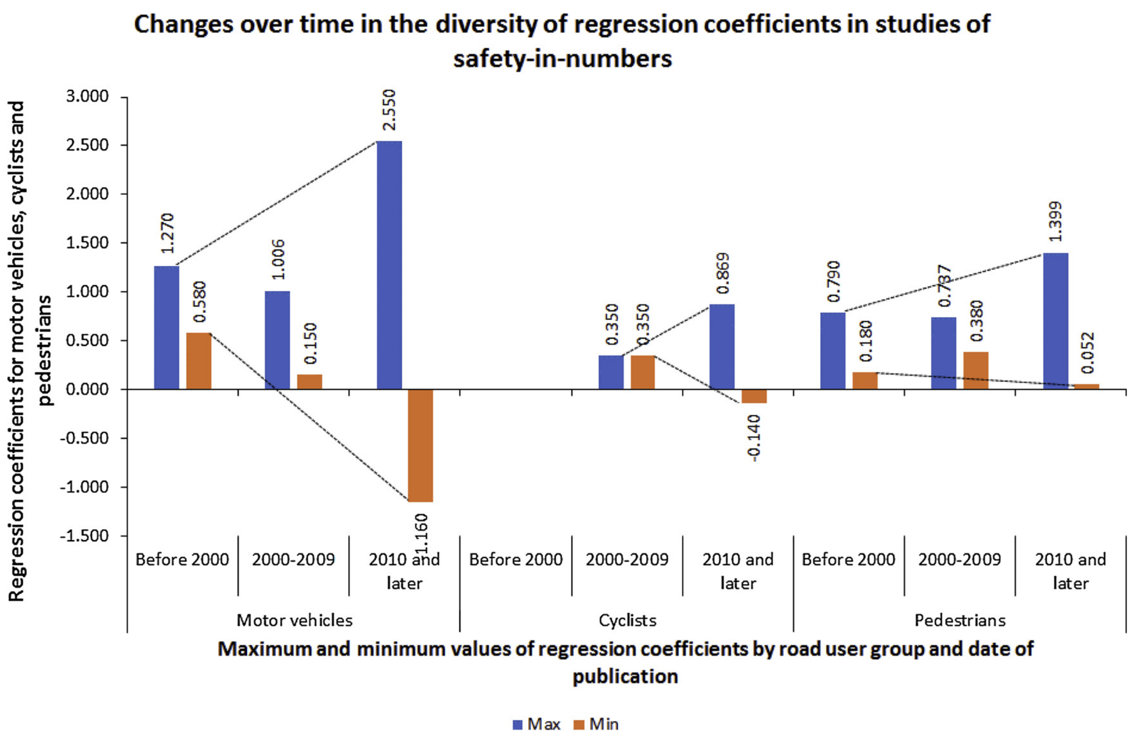

Fig. 5. Changes over time in the diversity of regression coefficients in studies of safety-in-numbers.

Fig. 5 shows the maximum and minimum values of regression coefficients reported in studies published either before 2000, between 2000 and 2009 and from 2010 and later. The tendency for the range of estimated values of the coefficients to become wider over time is most evident for motor vehicles, but it is found for cyclists and pedestrians as well. This increasing diversity creates problems for meta-analysis. Funnel plots of regression coefficients show no tendency for less dispersion between precisely estimated coefficients than between less precisely estimated coefficients. The distribution of coefficient estimates is not well-behaved as that concept is usually applied on meta-analysis. Adding to this problem is the fact that outlying estimates are found, even among those that are most precise.

Meta-regression was performed to identify sources of the large heterogeneity in coefficient estimates. The five factors that were found to be most clearly associated with the values of the regression coefficients were:

1 Road user group: Stronger safety-in-numbers effect for pedestrians than for motor vehicles and cyclists.
2 Level of analysis: Stronger safety-in-numbers effect at the macro-level (city) than at the micro-level (pedestrian crossing, junction).
3 Ratio of the number of motor vehicles to the number of cyclists or pedestrians: The higher the ratio, the stronger the safety-in-numbers effect.
4 Control for potentially confounding factors: Stronger safety-in-numbers effect the more potentially confounding factors a study controlled for.
5 Publication year: Stronger safety-in-numbers effect in the most recent studies.

It is particularly interesting that the safety-in-numbers effect does not vanish when a study controls for more confounding variables. There is an alternative hypothesis: Safety-in-numbers is really numbers-in-safety, meaning that once infrastructure measures have made it safe to walk or cycle, more people will be doing so. Unfortunately, it is not possible to test this hypothesis by means of the studies reviewed in this paper. The studies are all cross-sectional and causal direction cannot be determined. Most studies include very few variables describing infrastructure. It is not the case that studies finding the strongest safety-in-numbers effect also provide evidence of a safe infrastructure. On the contrary, studies showing strong safety-in-numbers effects for cyclists and pedestrians include infrastructure-related variables that appear to increase the number of accidents. Thus, the safety-in-numbers effect is found, despite the fact that the infrastructure contains elements that increase the number of accidents, like more travel lanes to cross, signalised junctions and traffic entering from multiple directions at crossing locations.

The main source of the safety-in-numbers effect is therefore probably not the safety of infrastructure, but the changing dynamics of interaction between drivers of motor vehicles and cyclists or pedestrians as the latter groups become more numerous. Fyhri et al. (2017) exploited the huge seasonal variation in cycling in Norway. They found that when cyclists became more numerous, they reported less often being overlooked by cars and less often that cars did not yield to them. The number of traffic conflicts was also found to decline when the number of cyclists increased. Interactions between cyclists and motorists were observed at the same locations three times during the summer season; infrastructure remained unchanged and the findings cannot therefore be attributed to infrastructure measures.

Results along similar lines are reported in a series of papers by Thompson et al. (2015, 2016, 2017). The first paper generated a safety-in-numbers effect by varying bicycle density by means of traffic simulation. Bicycle density is the number of bicycles within an area of a given size at any point in time. The second paper applied learning theory to model how drivers adapt behaviour as the number of cyclists increases. The third paper also applied learning theory but allowed for the possibility of forgetting what has been learnt if cyclists are provided with a separate path and thus interact more rarely with drivers. It was shown that cyclists not using the separate path may be at increased risk, because drivers do not expect to see cyclists in the driving lanes once a separate facility has been provided.

Clearly, more research is needed to fully understand the mechanisms producing safety-in-numbers. The studies reviewed in this paper are statistical models of accident occurrence only and give no insight into why safety-in-numbers occurs or whether one may create or reinforce a safety-in-numbers effect by improving infrastructure facilities.

7. Conclusions

The main conclusions of the research presented in this paper can be summarised as follows:

1 Nearly all regression coefficients showing the relationship between traffic volume and the number of accidents indicate a safety-in-numbers effect for cyclists and pedestrians.
2 There is wide dispersion in the values of regression coefficients, even for coefficients with high statistical precision. Coefficients with outlying values are found both for motor vehicle volume, cyclist volume and pedestrian volume.
3 According to a random-effects meta-analysis, the weighted mean values of the regression coefficients are close to 0.40 for all groups of road users.
4 A meta-regression analysis found a stronger safety-in-numbers effect for pedestrians than for motor vehicles and cyclists, and a stronger safety-in-numbers effect at the macro level (e.g. a city) than at the micro level (e.g. in junctions).
5 There is no clear relationship between the strength of the safety-in-numbers effect and the quality of infrastructure facilities for cycling or walking. Most studies evaluating the safety-in-numbers effect include only a few variables describing infrastructure.

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