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Exploring factors influencing the strength of the safety-in-numbers effect

Rune Elvik

Institute of Transport Economics

Gaustadalleen 21, 0349 Oslo, Norway

E-mail: re@toi.no

ABSTRACT

Several studies have found a so-called safety-in-numbers effect for vulnerable road users. This means that when the number of pedestrians or cyclists increases, the number of accidents involving these road users and motor vehicles increases less than in proportion to the number of pedestrians or cyclists. In other words, travel becomes safer for each pedestrian or cyclist the more pedestrians or cyclists there are. This finding is highly consistent, but estimates of the strength of the safety-in-numbers effect vary considerably. This paper shows that the strength of the safety-in-numbers effect is inversely related to the number of pedestrians and cyclists. A stronger safety-in-numbers is found when there are few pedestrians or cyclists than when there are many. This finding is counterintuitive and one would expect the opposite relationship. The relationship between the ratio of the number of motor

vehicles to the number of pedestrians or cyclists and the strength of the safety-in-numbers effect is ambiguous. Possible explanations of these tendencies are discussed.

Key words: Safety-in-numbers; moderating factors; pedestrian volume; cyclist volume

1 INTRODUCTION

Safety-in-numbers is a phenomenon which has attracted considerable research interest in recent years. The concept is mainly used to refer to a protective effect for pedestrians and cyclists as their number increases. Safety-in-numbers means that when the number of pedestrians or cyclists increases, there is a less than proportional increase in the number of accidents involving these road users and motor vehicles. In other words, the more pedestrians and cyclists there are, the safer becomes travel for each pedestrian or cyclist. In a recent literature review and meta-analysis, Elvik and Bjørnskau (2017) found that the studies reviewed have produced very consistent results. They concluded that a safety-in-numbers effect exists, but it is still not clear whether it is causal or what causal mechanisms bring it about.

While studies are highly consistent in finding a safety-in-numbers effect, the strength of the effect varies considerably between studies. Little is known about factors associated with variation in the strength of the safety-in-numbers effect. One can think of several factors that can influence the strength of the safety-in-numbers effect:

1. The number of pedestrians or cyclists: When there are many pedestrians or cyclists, drivers of motor vehicles will expect to encounter them and interact with them. This can strengthen the safety-in-numbers effect.
2. The number of motor vehicles: When there are many motor vehicles, pedestrians or cyclists may find it more difficult to attend to all of them. A high ratio of the number of motor vehicles to the number of pedestrians or cyclists may weaken the safety-in-numbers effect.

3. Characteristics of pedestrians or cyclists: Inexperienced pedestrians or cyclists may be less able to interact effectively with motor vehicles than more experienced pedestrians or cyclists. Tolerance of risk (e.g. how small gaps one tolerates when crossing a road) varies between individuals. If a large share of pedestrians or cyclists are inexperienced and/or willing to accept small safety margins, the safety-in-numbers effect may become weaker.
4. Characteristics of the traffic environment: If pedestrians or cyclists to a large extent are physically separated from motor vehicles, and interact with them at points where motor vehicles are forced to stop or slow down, this may strengthen the safety-in-numbers effect.

Unfortunately, none of the studies of safety-in-numbers reviewed by Elvik and Bjørnskau (2017) included all these factors. A few studies included some variables describing the traffic environment. No study included any data on the characteristics of pedestrians or cyclists. Based on these studies, it is therefore only possible to evaluate how the number of pedestrians or cyclists and the ratio of the number of motor vehicles to the number of pedestrians or cyclists influences the strength of the safety-in-numbers effect. The main objective of this paper is therefore to explore the influence of two factors on the strength of the safety-in-numbers effect: (1) the number of pedestrians or cyclists, and (2) the ratio of the number of motor vehicles to the number of pedestrians or cyclists.

Before exploring the influence of these factors, an explanation is given of what is meant by the strength of the safety-in-numbers effect. Next, relevant studies are identified, before the tendencies found in these studies are explored.

The paper is based on the studies reviewed by Elvik and Bjørnskau (2017), but differs from that paper by: (1) focusing primarily on variation in the strength of the safety-in-numbers effect, (2) adding new studies, and (3) discussing whether the tendencies found in cross-sectional studies are also found in longitudinal studies.

2 THE STRENGTH OF THE SAFETY-IN-NUMBERS EFFECT

All studies that were reviewed by Elvik and Bjørnskau (2017) estimated the safety-in-numbers effect by means of count regression models, in general negative binomial regression models, of the following form:

$$\text{Number of accidents} = e^{\beta_0} MV^{\beta_1} CYCL^{\beta_2} e^{(\sum_{n=1}^i \beta_n X_n)} \quad (1)$$

In equation 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 ($e^{(\sum \beta_n X_n)}$) is a set of predictor variables (X) other than traffic volume, which may influence the number of accidents. All the studies reviewed by Elvik and Bjørnskau (2017) were cross-sectional.

If a model of the form shown in equation 1 has been fitted to the data, a regression coefficient for traffic volume (MV , $CYCL$ or PED) with a value less than one indicates that the number of accidents increases less than proportionally to traffic volume. The closer to 0 the coefficient is, the stronger is the safety-in-numbers

effect. This is illustrated in Figure 1, which shows how cyclist risk changes for two different values of the coefficient.

Figure 1 about here

The two curves in Figure 1 are based on the highest (0.669) and lowest (0.085) coefficients for cyclist volume found in the studies reviewed by Elvik and Bjørnskau (2017). Cyclist volume in Figure 1 is assumed to vary between 100 and 10,000. According to the upper curve, risk at the highest cyclist volume is reduced to 25 percent of the risk level at the lowest cyclist volume. According to the lower curve, risk at the highest cyclist volume is reduced to only 1.5 percent of the risk level at the lowest cyclist volume.

3 STUDY RETRIEVAL AND CODING

Studies reviewed by Elvik and Bjørnskau (2017) were included if they stated motor vehicle volume, pedestrian volume and cyclist volume. In addition to the studies reviewed by Elvik and Bjørnskau, the following additional studies were included.

A study by Daniels et al. (2011) of factors influencing safety in roundabouts was included. This study ought to have been included in the review of Elvik and Bjørnskau (2017), but was missed because its main topic was the safety of roundabouts. Three studies have been published after Elvik and Bjørnskau completed their review (the review was completed in late 2014, but published in 2017). The first is the PhD dissertation of Krøyer (2015). The second is a paper by Abou-Senna et al. (2016) presented at the conference “Road Safety on Five

Continents”. The data given in that paper was re-analysed by means of negative binomial regression. Finally, a recent paper by Elvik (2016) was included. Table 1 lists key data for the papers included in this study.

Table 1 about here

Many studies are listed more than once, since several estimates of the safety-in-numbers effect were extracted from them. For each study, the following information was extracted:

1. Publication year
2. Country of origin
3. Years data refer to
4. Mean motor vehicle volume for study sites
5. Mean pedestrian volume for study sites
6. Mean cyclist volume for study sites
7. Coefficient for motor vehicle volume
8. Coefficient for pedestrian volume
9. Coefficient for cyclist volume
10. Ratio of number of motor vehicles to number of pedestrians
11. Ratio of number of motor vehicles to number of cyclists

Traffic volume is stated as AADT (Annual Average Daily Traffic) in all studies, i.e. the mean daily number of motor vehicles, pedestrians or cyclists during one year.

The coefficients for motor vehicle volume, which are not of primary interest in this study, vary substantially, ranging from -0.32 to 1.62. Most of the coefficients are less than 1, which is consistent with a safety-in-numbers effect. All coefficients for

pedestrian volume are consistent with safety-in-numbers and range between 0.07 and 0.79. All coefficients for cyclist volume are also consistent with safety-in-numbers and range from 0.09 to 0.65. Although all coefficients for pedestrian or cyclist volume indicate a safety-in-numbers effect, it is seen that the coefficients vary substantially. There is, in other words, considerable variation in the strength of the safety-in-numbers effect.

4 EXPLORATORY ANALYSIS

The exploratory analysis consists of examining the bivariate relationships between: (1) Pedestrian or cyclist volume and the coefficients for pedestrian or cyclist volume, and (2) The ratio of motor vehicle volume to pedestrian or cyclist volume and the coefficients for pedestrian or cyclist volume. The purpose of the exploratory analysis is to look for patterns in the data that can be analysed more rigorously in the main analysis.

Figure 2 shows the relationship between pedestrian volume and the coefficient for pedestrian volume estimated in count regression models. It is seen that the curve fitted to the data points is strongly influenced by the two data points in the lower right corner of the diagram, which are labelled as potentially outlying in Figure 2.

Figure 2 about here

When these two data points are omitted, the curve in Figure 3 emerges. It shows, contrary to what was expected, that the safety-in-numbers effect gets weaker when

the number of pedestrians increases. The data points are, however, widely spread around the curve fitted to them.

Figure 3 about here

It is obviously not correct to omit data points based on the visual impression of a diagram. A formal test of whether the data points are outlying has therefore been made and is reported in the next section of the paper. Figure 4 shows the relationship between cyclist volume and the coefficient for cyclist volume estimated in count regression models.

Figure 4 about here

Figure 4 indicates that the safety-in-numbers effect for cyclists becomes weaker the larger the number of cyclists. This is contrary to what was suggested in the introduction. Figure 5 explores the relationship between the ratio of motor vehicle volume to pedestrian volume and the strength of the safety-in-numbers effect.

Figure 5 about here

The data points are widely spread, but there is a tendency for the safety-in-numbers effect to become stronger the larger the number of motor vehicles per pedestrian is. This is not consistent with prior expectations. Figure 6 shows the same relationship for cyclists.

Figure 6 about here

A negative relationship is found, meaning that the safety-in-numbers effect for cyclists gets stronger the larger the number of motor vehicles per cyclist is.

5 META-REGRESSION ANALYSIS

The exploratory analysis examined bivariate relationships only and did not account for the fact that the data points plotted in the diagrams have different statistical weights. To assess the relationships indicated by the exploratory analysis more rigorously, meta-regression analysis has been performed. Four models have been developed:

1. A model containing all data points for pedestrian volume, including the two that seemed out of place in Figure 2.
2. A model omitting the two data points for pedestrian volume that looked as though they might be outlying in Figure 2.
3. A model based on all data points for cyclist volume.
4. A model based on all data points for both pedestrian and cyclist volume.

By comparing models 1 and 2, one may determine whether the two data points omitted from model 2 were in fact outlying. By comparing models 1 and 3, one may determine whether the coefficient for pedestrian volume differs from the coefficient for cyclist volume. A t-test applicable to unequal sample sizes and unequal variances was used in order to test whether the coefficients were different.

The meta-regression analysis included only data points for which the statistical weights were known. There were 23 data points for pedestrian volume. The inverse-variance statistical weight could be estimated for 20 of these data points. There were 10 data points for cyclist volume. The inverse-variance statistical weight was known for 7 of these data points. Thus, the sample size for the meta-regression was quite small.

The exploratory analysis indicated that the relationships between the traffic volume variables and the coefficients representing the safety-in-numbers effect were best described by means of power functions or exponential functions. In the meta-regression models, all variables were therefore converted to natural logarithms. Table 2 shows the estimated coefficients and their standard errors.

Table 2 about here

In model 1 a positive coefficient is estimated for pedestrian volume, indicating that the safety-in-numbers effect becomes weaker as pedestrian volume increases. Note that this applies when controlling for the ratio of the number of motor vehicles to the number of pedestrians (since both variables were included in the model). The coefficient for the ratio of the number of motor vehicles to the number of pedestrians is also positive, suggesting that an increasing ratio is associated with a weakening of the safety-in-numbers effect, which is inconsistent with the exploratory analysis. The coefficients are not statistically significant, but the coefficient for pedestrian volume is closest to being so.

Model 2 omits the two data points that seemed to be outlying in Figure 2. The values of the coefficients change somewhat, in particular the coefficient for pedestrian volume. A t-test confirms that the coefficients for pedestrian volume are significantly different in models 1 and 2, thereby confirming that the two data points are indeed outlying. Nevertheless, the general shape of the relationship between pedestrian volume and the strength of the safety-in-numbers effect is the same in both models, as shown in Figure 7.

Figure 7 about here

In view of the limited sample size, it is preferable to include all data points. As can be seen from Table 2, inclusion of all data points (20 pedestrian, 7 cyclist) means that the coefficients for pedestrian volume (0.2920) and cyclist volume (0.2848) are very close in value. A t-test confirms that there is no statistically significant difference between these coefficients. The results for cyclist volume are similar to those for pedestrian volume, but the coefficient for the ratio of the number of motor vehicles to the number of cyclists is negative, which is consistent with the exploratory analysis. The coefficient is, however, far from statistically significant and its sign cannot be given any substantive interpretation.

In model 4, all data points were included, irrespective of whether they refer to pedestrians or cyclists. As expected, the coefficient for pedestrian or cyclist volume was close to the values found in models 1 and 3. The coefficient for the ratio of the number of motor vehicles to the number of pedestrians or cyclists is positive, but far from statistically significant. The positive sign of the coefficient implies that an increasing ratio, i.e. an increasing imbalance between the number of motor vehicles and the number of pedestrians or cyclists is associated with a weaker safety-in-numbers effect. Holding pedestrian or cyclist volume constant at its weighted mean value (1353), the coefficient for the ratio of the number of motor vehicles to the number of pedestrians or cyclists implies that the coefficient for pedestrian or cyclist volume increases from 0.38 at a ratio of 1.5 to 0.56 at a ratio of 940 (this is the range of values found in the data).

The lack of statistical significance of the coefficient for the ratio of the number of motor vehicles to the number of pedestrians or cyclists can perhaps be attributed to

the fact that there is fairly high negative correlation between this ratio and the number of pedestrians and cyclists, in particular when both variables are defined as natural logarithms. Figure 8 shows this.

Figure 8 about here

When there are few pedestrians or cyclists (lower right part of Figure 8), the ratio of the number of motor vehicles to the number of pedestrians or cyclists is large. It is perhaps not surprising to find such a negative relationship, since a high number of motor vehicles may deter people from walking or cycling. However, the fact that there is a negative correlation raises questions regarding the origins of the safety-in-numbers effect and the interpretation of it. These issues are discussed below.

6 DISCUSSION

It is well-known that an entirely spurious safety-in-numbers effect can arise as a result of how the accident involvement variable is defined (Elvik 2013). In particular, if accident involvement is defined as accidents per kilometre travelled (A/KM) and exposure is defined as kilometres travelled per inhabitant (KM/INH), there will by definition be a negative relationship between the variables that looks like a safety-in-numbers effect. Can a similar spurious safety-in-numbers effect arise if motor vehicle volume is negatively correlated with pedestrian or cyclist volume? Sites with many pedestrians or cyclists will have comparatively few cars; hence pedestrians or cyclists are protected, not simply because they are numerous, but because there are few cars that may strike them. Conversely, if there are many cars, there will be comparatively

few pedestrians or cyclists, but each of them may be at high risk because there are many cars that may strike them.

While this is in principle possible, it cannot explain the variation in the strength of the safety-in-numbers effect found in this paper. That variation goes in exactly the opposite direction of the pattern suggested above. Contrary to what one would expect, the safety-in-numbers effect appears to be weakest when there are many pedestrians or cyclists. The relationship between the strength of the safety-in-numbers effect and the degree of imbalance between the number of motor vehicles and the number of pedestrians or cyclists is unclear. While the coefficient for the ratio of the number of motor vehicles to the number of pedestrians or cyclists was positive in three of the four meta-regression models, it had a low value and was nowhere near statistically significant in any of the models. This suggests that any relationship is weak, certainly weaker than the relationship between pedestrian or cyclist volume and the strength of the safety-in-numbers effect.

The results regarding pedestrian or cyclist volume are inconsistent with prior expectations. It should be noted that the analyses are based on cross-sectional studies only and confounding by omitted variables cannot be ruled out. Thus, Fyhri et al. (2016) found clear indications that the strength of the safety-in-numbers effect is related to characteristics of cyclists, in particular their experience and willingness to take risks. If the population of pedestrians or cyclists differs between studies with respect to these characteristics, it may confound the results of the analyses, since none of the studies included any data on pedestrian or cyclist characteristics.

No well-controlled longitudinal studies of the safety-in-numbers effect have been found. However, data for New York City for the period 2000-2014 (Trottenberg 2015) show that from 2000 to 2014, the annual number of cycling trips increased from 55 million to 153 million. The number of killed or seriously injured cyclists per million trips decreased from 8.34 to 2.35. This trend is consistent with a safety-in-numbers effect becoming stronger as the number of cyclists increases. The data do not state how motor vehicle volume developed in the same period, nor if there have been improvements in cycle facilities. Despite this, the tendency is the opposite of the one found in this paper, suggesting that cross-sectional and longitudinal studies may not give consistent results as far as the safety-in-numbers effect is concerned.

7 CONCLUSIONS

The main conclusions of the study reported in this paper can be summarised as follows:

1. Cross-sectional data show a tendency for the safety-in-numbers effect to be weaker the larger the number of pedestrians or cyclists. The paper did not include any study that has evaluated whether the safety-in-numbers effect becomes stronger or weaker over time as the number of pedestrians or cyclists changes.
2. The strength of the safety-in-numbers effect has no clear relationship to the ratio of the number of motor vehicles to the number of pedestrians or cyclists.

3. These findings reflect statistical relationships only. It was not possible to examine all factors that may influence the strength of the safety-in-numbers effect.
4. Longitudinal studies of changes over time in pedestrian or cyclist volume and changes in accidents involving these road users and motor vehicles would provide additional evidence on the strength of the safety-in-numbers effect.

ACKNOWLEDGEMENT

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Table 1:

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Figure 1:

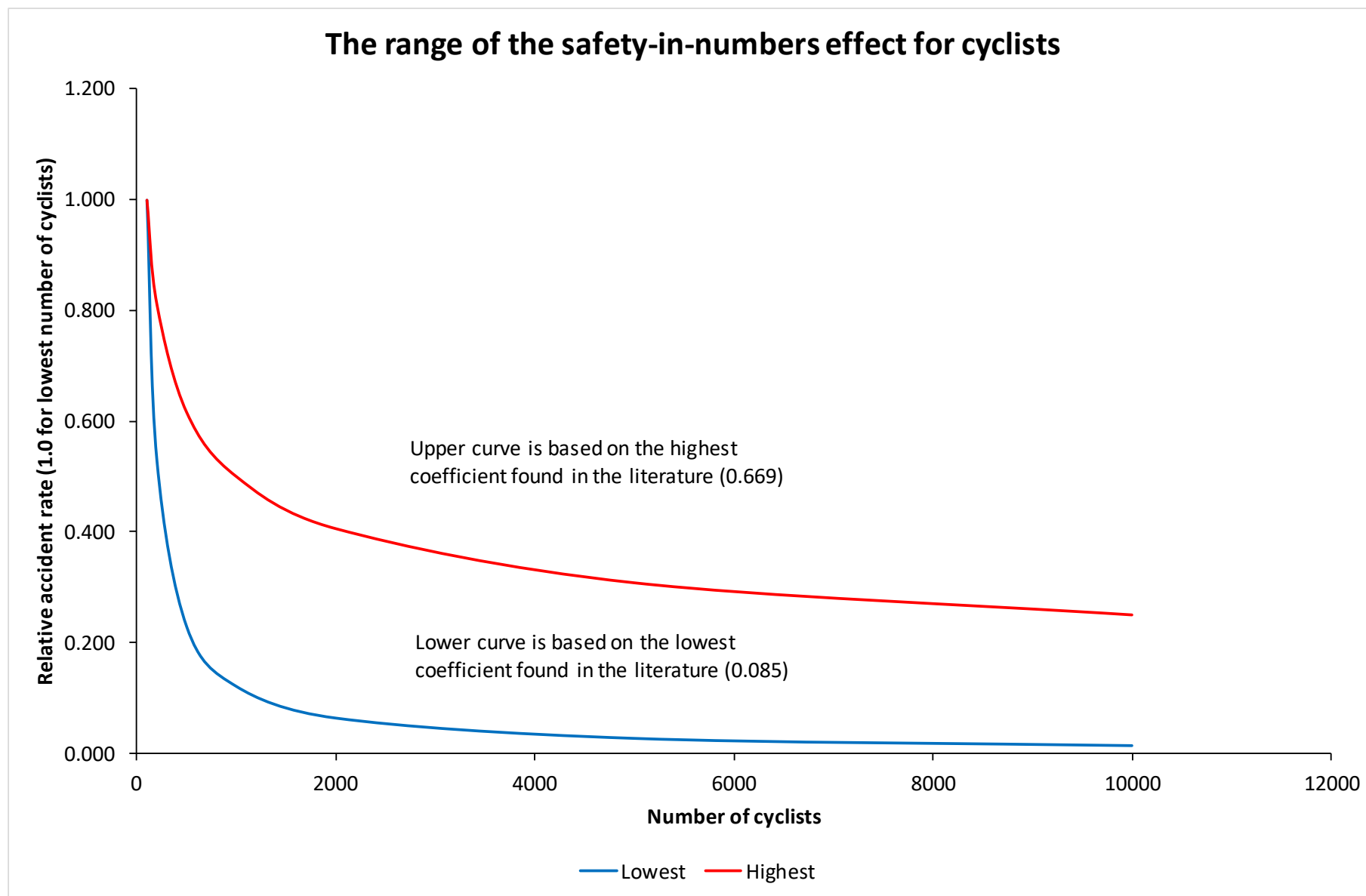


Figure 2:

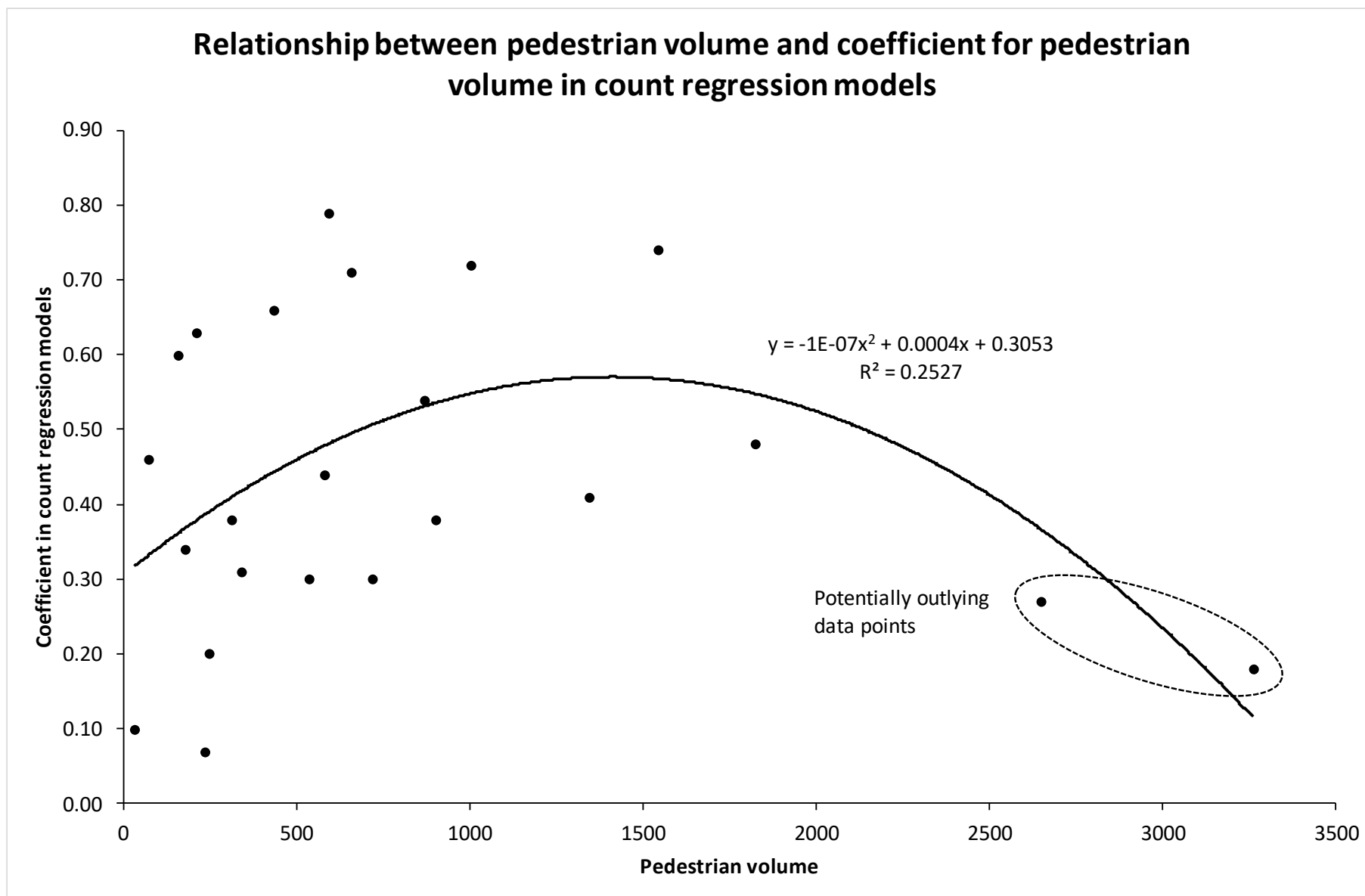


Figure 3:

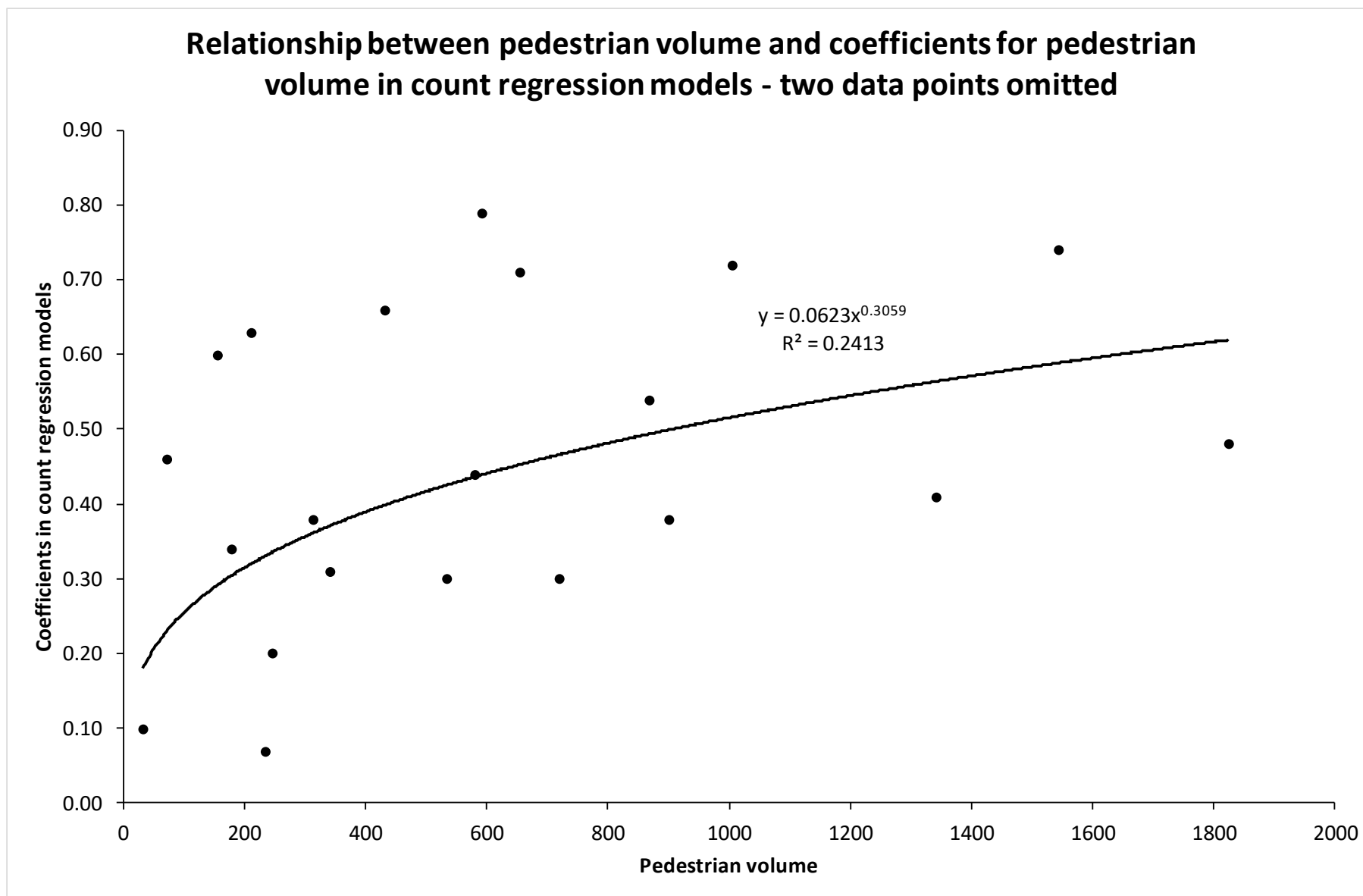


Figure 4:

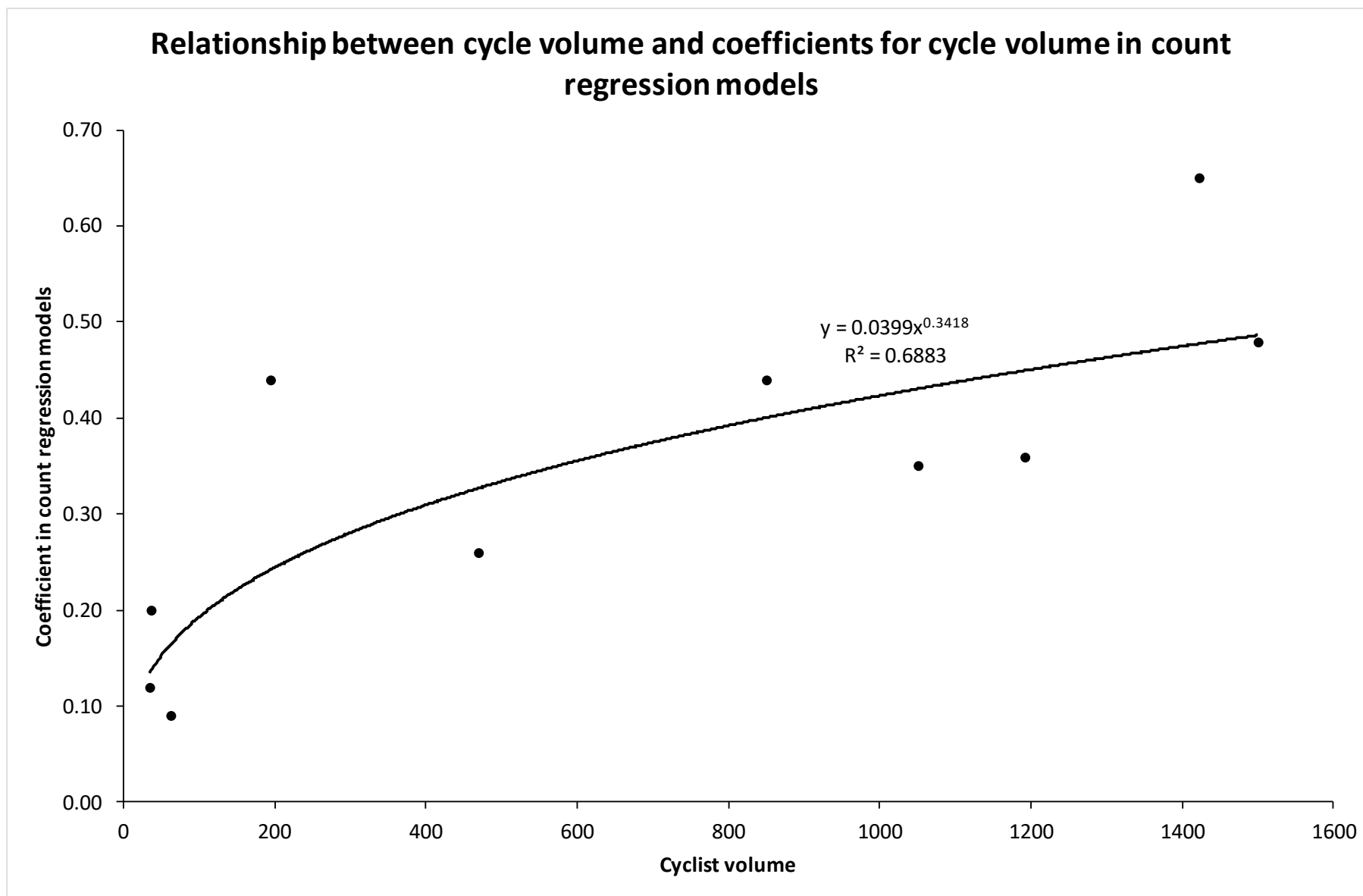


Figure 5:

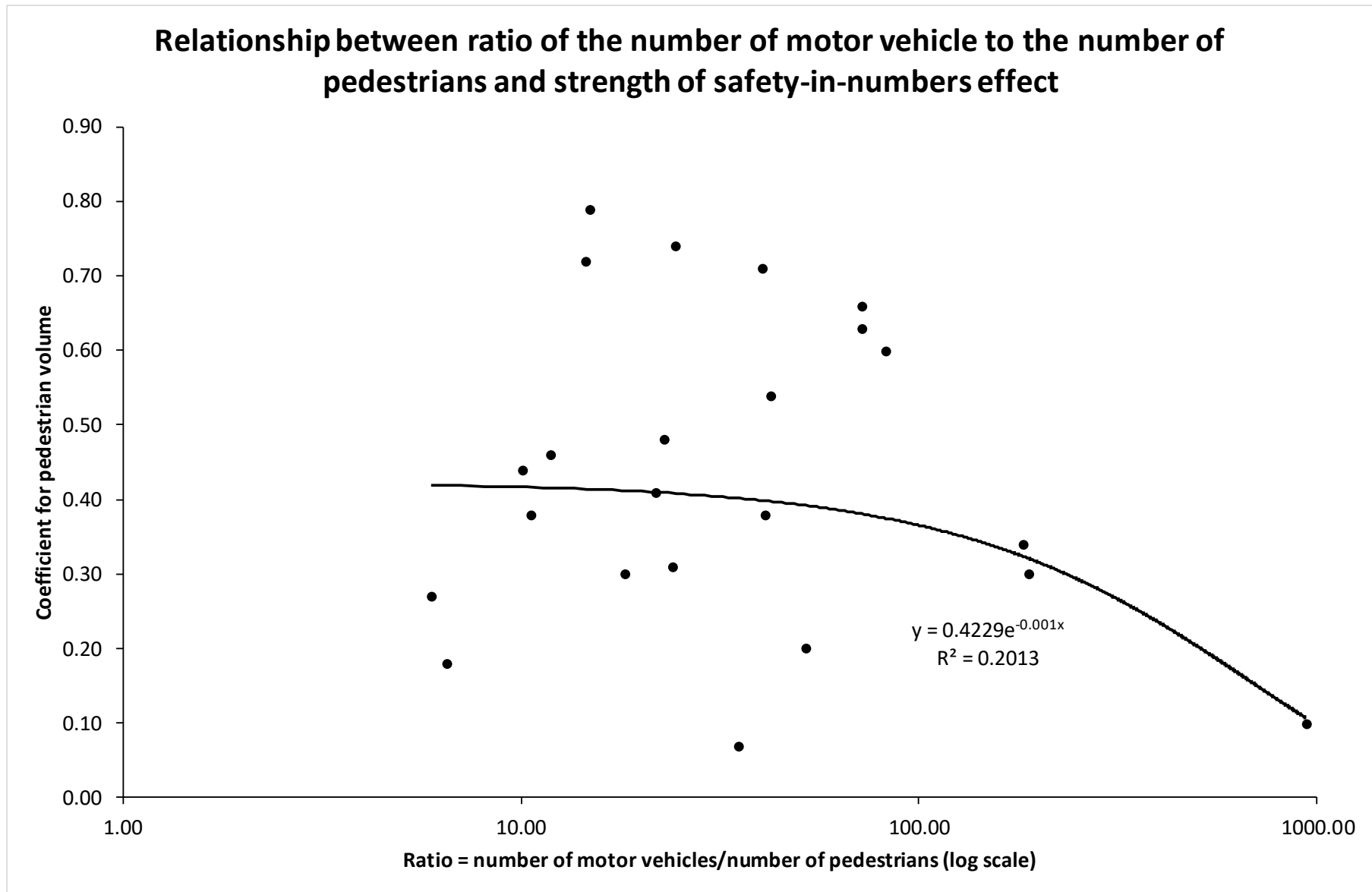


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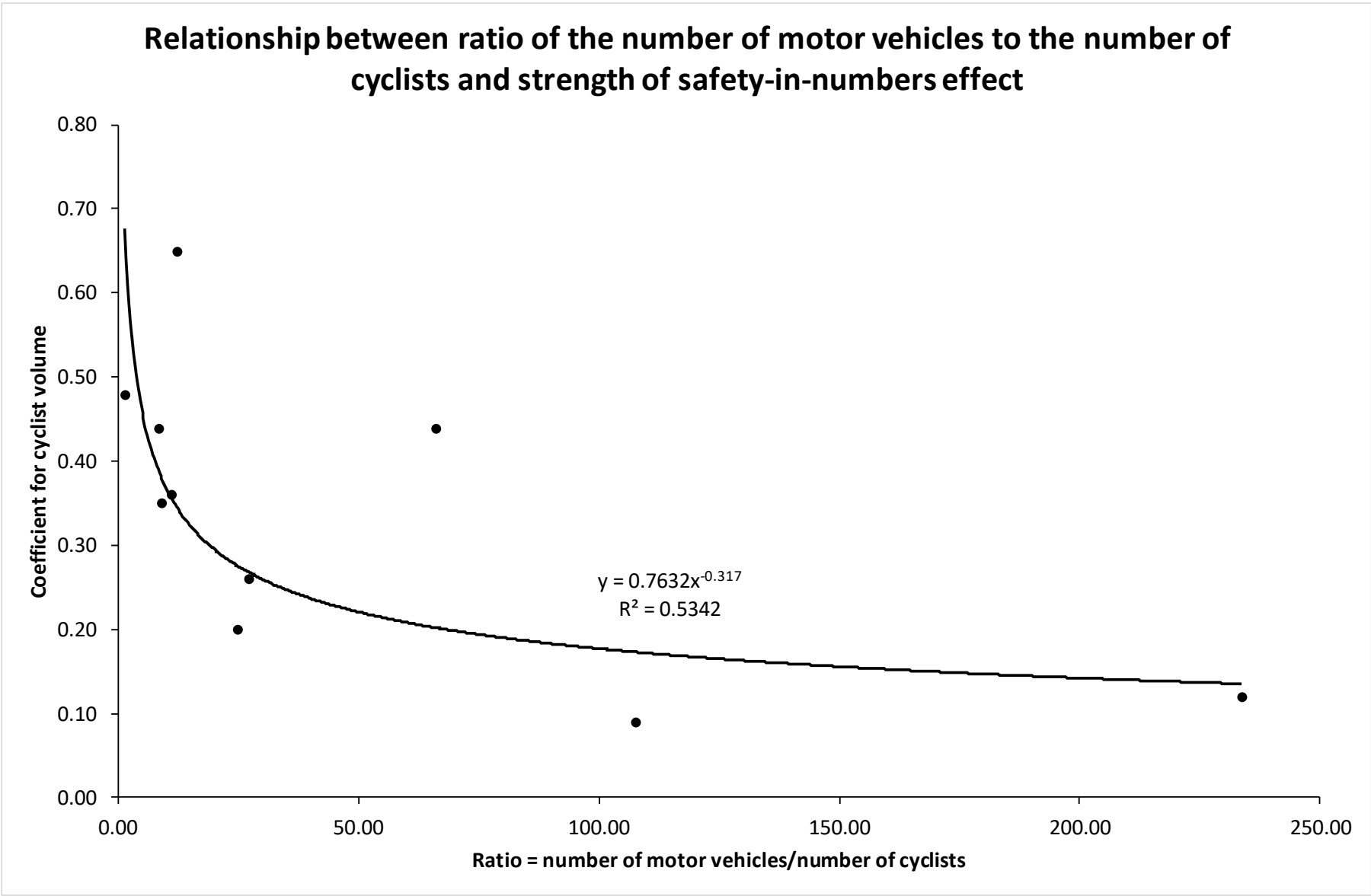


Figure 7:

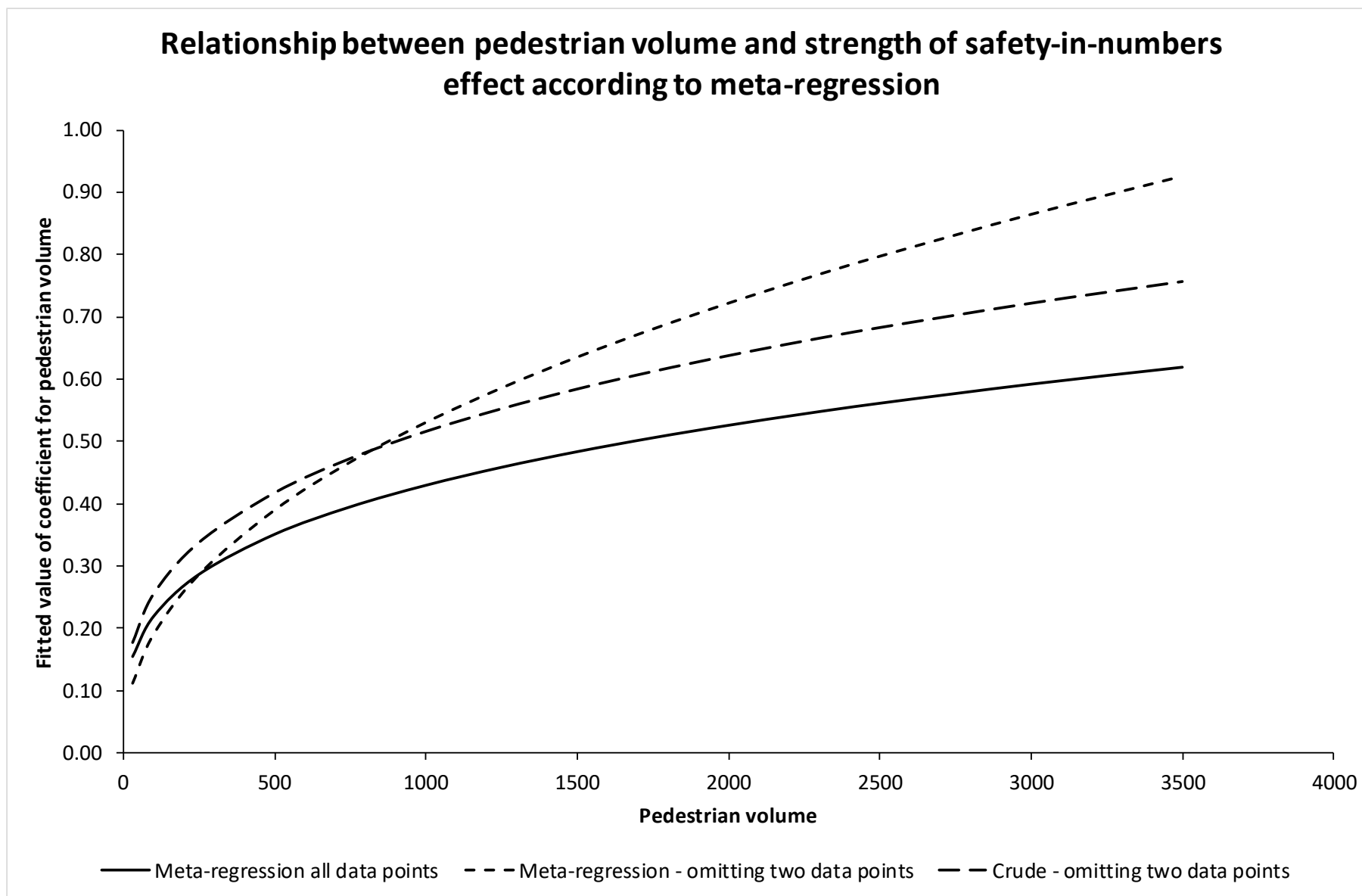


Figure 8:

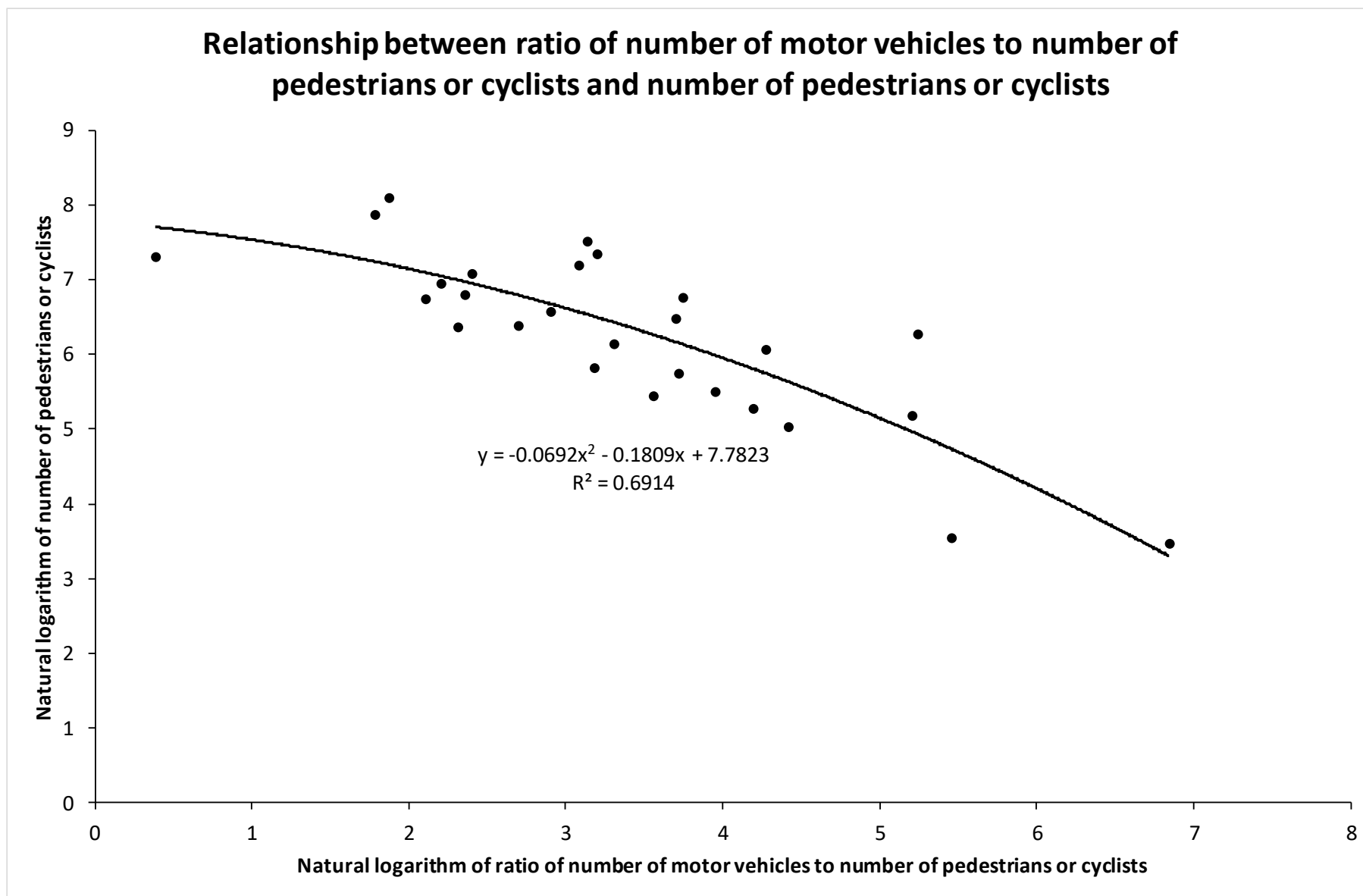


Table 1:

Authors	Country	Year	Years for data	Motor vehicle volume	Pedestrian volume	Cyclist volume	Coefficient for motor vehicles	Coefficient for pedestrians	Coefficient for cyclists	Ratio motor vehicles/ pedestrians	Ratio motor vehicles/ cyclists
Inwood, Grayson	Great Britain	1979	1973-1978	15687	2646		0.92	0.27		5.93	
Inwood, Grayson	Great Britain	1979	1973-1978	8751	591		0.58	0.79		14.81	
Hall	Great Britain	1986	1979-1982	21180	3260		1.27	0.18		6.50	
Brüde, Larsson	Sweden	1993	1983-1988	14548	1004		0.50	0.72		14.49	
Brüde, Larsson	Sweden	1993	1983-1988	17465		1423	0.52		0.65		12.27
Summersgitt, Layfield	Great Britain	1996	1983-1988	5820	579		0.72	0.44		10.05	
Lyon, Persaud	Canada	2002	1985-1995	37705	1544		0.57	0.74		24.42	
Lyon, Persaud	Canada	2002	1985-1995	29285	1342		0.40	0.41		21.82	
Lyon, Persaud	Canada	2002	1985-1995	30999	432		0.53	0.66		71.76	
Lyon, Persaud	Canada	2002	1988-2000	26356	655		0.58	0.71		40.24	
Jonsson	Sweden	2005	1998-2002	9500	900		0.83	0.38		10.56	
Jonsson	Sweden	2005	1998-2002	9500		1050	0.76		0.35		9.05
Turner	New Zealand	2006	1994-2003	6783		63	0.29		0.09		107.67
Turner	New Zealand	2006	1994-2003	894		36	0.36		0.20		24.83
Turner	New Zealand	2006	1994-2003	15116	210		0.80	0.63		71.98	
Turner	New Zealand	2006	1994-2003	838	71		0.56	0.46		11.80	
Zegeer et al	United States	2006	1994-1998	12828	312		1.01	0.38		41.12	
Zegeer et al	United States	2006	1994-1998	12817	155		0.30	0.60		82.69	

Table 1:

Authors	Country	Year	Years for data	Motor vehicle volume	Pedestrian volume	Cyclist volume	Coefficient for motor vehicles	Coefficient for pedestrians	Coefficient for cyclists	Ratio motor vehicles/ pedestrians	Ratio motor vehicles/ cyclists
Harwood et al	United States	2008	1997-2005	36617	867		-0.32	0.54		42.23	
Harwood et al	United States	2008	1997-2005	41708	1823		0.38	0.48		22.88	
Harwood et al	United States	2008	1997-2005	29984	32		0.62	0.10		937.00	
Harwood et al	United States	2008	1997-2005	32465	178		0.18	0.34		182.39	
Daniels et al	Belgium	2011	1991-2001	12782	246		1.62	0.20		51.96	
Daniels et al	Belgium	2011	1991-2001	12782		470	0.91		0.26		27.20
Miranda-Moreno et al	United States	2011	2000-2008	12893		195	0.40		0.44		66.12
Schepers et al	Netherlands	2011	2005-2008	2200		1500	0.73		0.48		1.47
Schepers et al	Netherlands	2011	2005-2008	7000		850	0.70		0.44		8.24
Elvik et al	Norway	2013	2004-2010	8186	340		0.59	0.31		24.08	
Kröyer	Sweden	2015	2008-2012	13100	719		0.64	0.30		18.22	
Kröyer	Sweden	2015	2008-2012	13100		1192	0.71		0.36		10.99
Senna et al	United States	2015	2009-2014	100588	533		0.36	0.30		188.72	
Elvik	Norway	2016	2003-2010	8181	233	35	0.05	0.07	0.12	35.11	233.74

Table 2:

Terms	Model 1: Pedestrian coefficients, all data points (n = 20)		Model 2: Pedestrian coefficients, two data points omitted (n = 18)		Model 3: Cyclist coefficients, all data points (n = 7)		Model 4: Pedestrians and cyclists in same model (n = 27)	
	Estimate (standard error)	P-value	Estimate (standard error)	P-value	Estimate (standard error)	P-value	Estimate (standard error)	P-value
Constant	-3.2217 (1.9336)	0.0957	-3.8953 (1.6189)	0.0161	-2.8543 (1.8518)	0.1232	-3.1222 (1.3734)	0.0230
Ln(pedestrian volume)	0.2920 (0.2131)	0.1706	0.4444 (0.1836)	0.0155				
Ln(ratio motor vehicles/pedestrians)	0.0944 (0.1881)	0.6158	0.0504 (0.1570)	0.7483				
Ln(cyclist volume)					0.2848 (0.2200)	0.1954		
Ln(ratio motor vehicles/cyclists)					-0.0131 (0.1825)	0.9428		
Ln(pedestrian or cyclist volume)							0.2945 (0.1567)	0.0602
Ln(ratio motor vehicles/peds or cyclists)							0.0620 (0.1319)	0.6384
Comparison of models 1 and 2	Pedestrian coefficient in model 1 versus model 2: t = -2.3676, df = 35.94, p = 0.0117							
Comparison of models 1 and 3	Pedestrian coefficient in model 1 versus cyclist coefficient in model 3: t = 0.1022, df = 10.24, p = 0.5397							
Comparison of models 1 and 4	Pedestrian coefficient in model 1 versus pedestrian or cyclist coefficient in model 4: t = -0.0442, df = 33.36, p = 0.4825							
Comparison of models 3 and 4	Cyclist coefficient in model 3 versus pedestrian or cyclist coefficient in model 4: t = -0.1128, df = 7.76, p = 0.4566							