Is safety a cause of cycling in numbers or an effect of increased cycle use?

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ABSTRACT

Purpose: The purpose of this paper is to present an analysis of the bidirectional relationship between cycling risk and cycling rates in the Safety in Numbers phenomena. The second part consists of a discussion about when, how and why each might influence the other and where the efforts should be focused on in different life-cycle stages of a cycling community. The proposition is that cycling safety improves with numbers but first numbers increase with safety.

Design/methodology/approach: The paper uses a variety of data sets to create cycling rates and cycling risk profiles for English cities. Linear and nonlinear relations are investigated and presented in various ways. Part two consists of a literature review and discussion on whether there is a tipping point in the relationship between cycling and risk ratios.

Findings: Regression functions from both perspectives reveal powerful relationship between cycling risk and cycling rates. The effect seems to be stronger from the rates toward the risk but the strength differs for different categories of cities. However, there is a need for careful analysis and tailoring for each strategy, correlated with the level of risk and other factors such as cycling culture, infrastructure and funding opportunities.

Practical implications: The paper provides a tool for road safety strategists around the UK and abroad, offering an overview analysis and discussion points that policy makers and practitioners should be aware of before developing road safety or cycling strategies.

Originality/value: Among the first research papers to investigate SIN from a bidirectional perspective, the paper provides valuable insight, which can be used as a guide for organisations working in cycling or general road safety.

1. INTRODUCTION

1.1. SiN and vulnerable road users

Firstly described in the context of intersections in Sweden in 1993 (Brude & Larsson, 1993), Safety in Numbers (SiN) is the phenomenon by which the per-walker or per-bicyclist frequency of being struck by motorists declines as the amount of walking or bicycling on a street or in a region increases (Jacobsen, 2003). While the absolute number of walkers or bicyclists struck by motorists may increase with more people walking and bicycling, due to increase in exposure, the number of such collisions is observed to increase more slowly than the increase in the number of walkers or bicyclists, or even decrease (Jacobsen, et al., 2015). SiN advocates support the view that the number of injuries suffered by walkers or bicyclists is an imperfect indicator of the danger of walking or bicycling and that safety is indicated by the absence of danger, not by an absence of injuries (Jacobsen, et al., 2015). One important issue, from a policy makers point of view, when switching the focus from numbers to rates is the ethical aspect of it. Public health researchers and bodies have created tools to calculate the economic and health value of improving cycling and walking (Rutter, et al., 2013), which, corroborated with a lower personal risk for walkers and cyclists, allow policy makers to outface the ethical shortcomings of increasing walking and cycling policies in the context of a SiN approach, focused on rates rather than number of injuries.

Numerous studies, using a variety of data sources confirmed the existence of the SiN effect, found to apply to entire towns, cities and countries and even across time periods. Across the existing studies the estimates for cycle volume and walking volume are highly consistent and indicate that the number of accident increases less than proportionally to traffic volume (Elvik & Bjornskau, 2015). Although concluded and generally accepted that SiN effect exists, it is not clear whether this effect is causal, nor, if causal, which mechanisms generate the effect (Elvik & Bjornskau, 2015).

Possible hypothesis to explain SiN were presented and tested, having various central focuses, from street regulation, design and operations; changes in walkers or cyclists behaviour; and changes in behaviour of person driving. From an infrastructure perspective SiN was showed to operate independently of infrastructure changes (Fyhri, et al., 2014), from the perspective of changes in behaviour walker or cyclist, the results are mixed and inconclusive, leaving the perspective of changes in drivers' behaviour as the most plausible to explain SiN mechanism and effect (Jacobsen, et al., 2015).

Regarding changes in behaviour of person driving there are several hypotheses presented in literature with important and encouraging results. One of the most common ones is that motorists are themselves more likely to become walkers or cyclists and might give greater consideration to people walking and cycling. Drivers who also cycle were found 50% more likely to self-report safer driving behaviours related to sharing roads with bicyclists, than drivers who were not also cyclists (Johnson, et al., 2014).

Signal detection theory provide a possible framework for understanding SiN effect, which theorises that probability of detection depends upon (1) haw clearly the target can be detected, (2) the observer's relative frequency of experiencing the target, and (3) the consequences of detection (Nevin, 1969) . The rarity of people walking and bicycling makes them harder to detect and to require more response time than more common objects (Jacobsen, et al., 2015).

Inattentional blindness, described as the failure to detect unexpected objects is also influenced by the relative frequency of the object. Inattentional blindness is more likely when the unexpected target differs from the focus of attention in size, colour, shape and location, all associated with a person cycling or walking in an environment ruled by motor vehicles (Pammer & Blink, 2013).

Although not intending to investigate or to propose a hypothesis for how or why SiN effect creates, the present study aims to investigate the power of this effect at different levels of cycling exposure and the direction of the relation between safety and numbers for cities with high and low levels of cycling exposure. Assessing the power of SiN effect for different levels of exposure can be a very useful tool for policy makers in terms of investments efficiency and expectations as well as a guide for possible best practices to follow, corresponding to similar levels of exposure and demonstrated or expected results.

2. METHODOLOGY

The methodology presented in this paper is rather simple, having the main scope of investigating possible leads for which more complex methodologies can be employed afterwards. SiN phenomenon usually describe a negative correlation between the number of cyclists (or the size of the exposure) and the rate of injuries (or the number of injuries) among cyclists. The methodology here aims to investigate if the influence of numbers over safety is different from the influence of safety over numbers, for the whole sample and when split into two categories (cities with high and low exposure rates, corresponding for above and below the average respectively).

The study was conducted on a number of 319 English LADs (local authority districts). The study used data from three data sets in order to create cyclist injury rates and cycling exposure rates for all the 319 LADs. The datasets used were:

- Population number for each local authority district from the GB statistics, for adults (16+);
- Average adult cyclists' casualties for 2010-2014, based on residence from MAST Online. Residency is calculated based on the postcode of the casualty;

- The proportion of residents who cycle (any length) for utility purposes, at a given frequency in England, 2013-2014.

In order to obtain comparable coefficients, the database suffered two treatments:

1. Identify and eliminate the outliers and the absurd records – on the suspicion of data input errors the cities of Rotherham and Chesterfield were eliminated for presenting injury rates of 19.79% and 5.5% - unlikely high without assuming an error; Cambridge, Oxford and York were eliminated on the reason of being significantly different, in terms of cycling exposure (44%, 28% and 18% respectively), from all the other over 300 cities analysed in the study.
2. Normalise the variables for the remaining sample within the same range of variation (from 0 to 1).

The remaining sample consists of 314 records. The two variables present a range of variation between 0 and 3.26 times the average for the injury rate and between 0 and 3.30 times the average for the exposure, and similar spread of the values (see Figure 1., Figure 2.). These similarities allow for 'like-for-like' comparisons for the regression coefficients and intercepts.

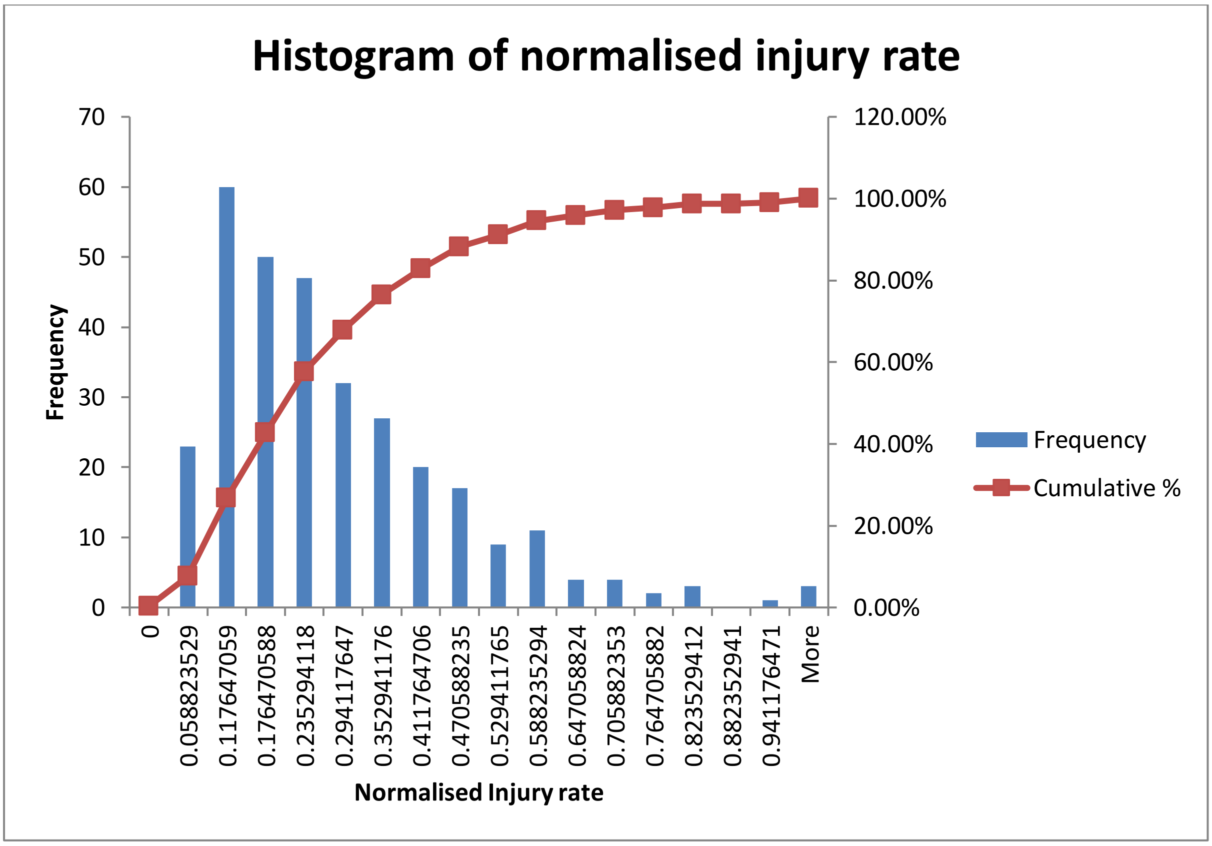

Figure 1. Histogram of normalised injury rate

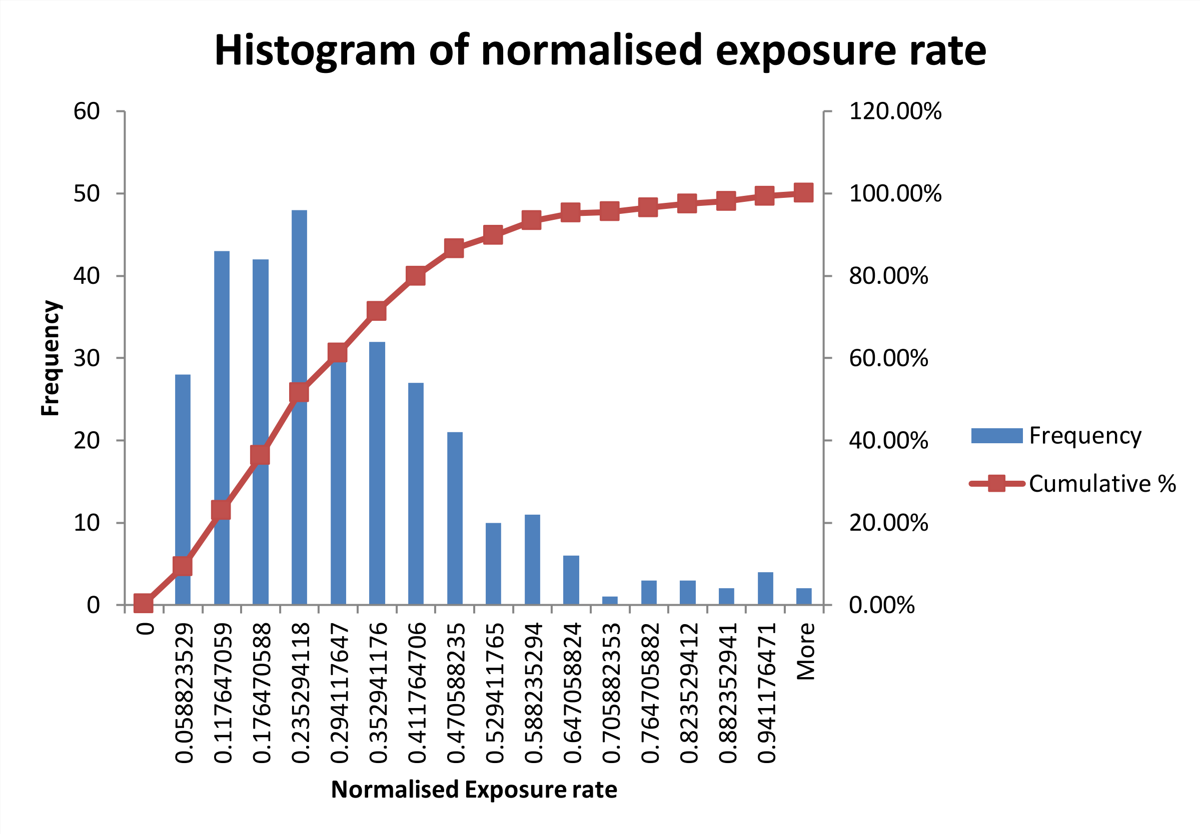

Figure 2. Histogram of normalised exposure rate

For the next step, simple linear regressions were applied to the whole sample, from both perspectives, for estimating the size of the effect each variable produce on the other, and interpretation of the results was provided.

In the final step of analysis, the sample was split in two subsets, related to their rate of exposure. The first subset represents cities with an exposure rate higher or equal to the average exposure rate (135 cities); the second subset represents cities with an exposure rate lower that the average exposure rate (179 cities). For both subsets, similar simple linear regressions were applied, from both perspectives, and interpretation of the results was provided, as well as a comparison between the two subsets.

3. RESULTS

The results are presented in order, starting with results for the total sample, followed by results for ‘cities with high cycling exposure’ subsample, and results for ‘cities with low cycling exposure’ subsample.

The results section contains only simple interpretations of the results, further analysis, links to existing research, and discussion about further development and implications being presented in the Discussion section of the research.

Total sample

Table 1. presents descriptive statistics for the normalised rates. Similarities between the two variables distributions can be observed in most of the listed statistics.

Table 1. Descriptive statistics for normalised injury rate and normalised exposure rate

Normalised_Injury_rate	
Mean	0.25143
Standard Error	0.01046
Median	0.20200
Mode	0.10000
Standard Deviation	0.18531
Sample Variance	0.03434
Kurtosis	2.27923
Skewness	1.40394
Range	1
Minimum	0
Maximum	1
Sum	78.94800
Count	314

Normalised_Exposure_rate	
Mean	0.27353
Standard Error	0.01109
Median	0.22637
Mode	0.35339
Standard Deviation	0.19643
Sample Variance	0.03858
Kurtosis	1.67555
Skewness	1.22202
Range	1
Minimum	0
Maximum	1
Sum	85.88739
Count	314

The similar distribution and the other similarities between the two variables allow for ‘like-for-like’ comparison and interpretation, when analysing regression outputs, intercepts, and coefficients from both perspectives, of the effect that injury rates manifests on exposure rates and of the effect that exposure rates manifests on injury rates.

Table 2. Exposure rate regression for total sample

Regression Statistics	
Multiple R	0.50317
R Square	0.25318
Adjusted R Square	0.25078
Standard Error	0.17002
Observations	314

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	3.05756	3.05756	105.76969	1.48E-21
Residual	312	9.01921	0.02891		
Total	313	12.07677			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.40763	0.01619	25.17936	3.89E-77
Normalised_Injury_rate	-0.53336	0.05186	-10.28444	1.48E-21

The model reveals a negative relation between the normalised exposure rate and the normalised injury rate for the total sample. The effect is significant (p<.05) and has a considerable size. Below, a very simplified way of expressing the relationship between the two variables is presented:

Normalised_Exposure_rate = 0.40763 – 0.53336 * Normalised_Injury_rate (A.1.)

A straightforward interpretation of this equation indicates that an increase of 1 for the normalised injury rate would determine a 0.53 decrease for the normalised exposure rate.

Table 3. Injury rate regression for total sample

Regression Statistics	
Multiple R	0.50317
R Square	0.25318
Adjusted R Square	0.25078
Standard Error	0.16040
Observations	314

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	2.72123	2.72123	105.76969	1.48E-21
Residual	312	8.02710	0.02573		
Total	313	10.74833			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.38127	0.01553	24.54309	7.91E-77
Normalised_Injury_rate	-0.47469	0.04616	-10.28444	1.48E-21

For the effect of the normalised exposure rate on the normalised injury rate, the model also reveals a negative relation of very similar size as in the previous case. The negative effect is also significant ($p<.05$) and of a considerable size:

Normalised_Injury_rate = 0.38127 – 0.47469 * Normalised_Exposure_rate (A.2.)

An increase of 1 for the normalised exposure rate results in a 0.47 decrease for the normalised injury rate.

Having very similar effects in direction as well as in size for both regressions, at this level we cannot make assumptions about any differences in the way either variable is shaping the other.

For the following analysis, the sample was split in two subsamples, representing cities with high cycling exposure and low cycling exposure (with normalised exposure rates equal or higher than the average normalised exposure rate, and lower than the average normalised exposure rate respectively) and similar regression techniques were deployed in order to investigate if the findings valid for the total sample are constant to these subsamples or present differences.

Cities with high cycling exposure

Table 4. presents descriptive statistics for the normalised rates for cities with high cycling exposure. Differences between the two variables and their distribution can be observed in this case.

Table 4. Descriptive statistics for normalised injury rate and normalised exposure rate for cities with high cycling exposure

Normalised_Injury_rate	
Mean	0.15615
Standard Error	0.00896
Standard Deviation	0.10415
Sample Variance	0.01848
Range	0.53600
Minimum	0
Maximum	0.53600
Count	135

Normalised_Exposure_rate	
Mean	0.45044
Standard Error	0.01443
Standard Deviation	0.16762
Sample Variance	0.02809
Range	0.73206
Minimum	0.26794
Maximum	1
Count	135

When we select only the cities with normalised exposure rates above the average normalised exposure rate, the means for the two variables are not anymore similar. The values of the two means for the subset of cities with high cycling exposure are substantially different and consistent with equation A.2., allowing to observe that, when the normalised average exposure rate increases, the normalised injury rate decreases.

Table 5. Exposure rate regression for cities with high cycling exposure

Regression Statistics	
Multiple R	0.03394
R Square	0.00115
Adjusted R Square	-0.00636
Standard Error	0.16815
Observations	135

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.00434	0.00434	0.15340	0.69593
Residual	133	3.76039	0.02827		
Total	134	3.76472			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.44191	0.02615	16.90087	6.38E-35
Normalised_Injury_rate	0.05462	0.13946	0.39167	0.69593

The regression model reveals that, for this subsample, the effect of the normalised injury rate on the normalised exposure rate is not significant, all the significant influencers being captured by the model in the value of the intercept. Although the coefficient would suggest a slight positive effect of the normalised injury rate over the normalised exposure rate (an increase in the normalised injury rate to produce an increase in the normalised exposure rate), this effect is not significant (p>.05).

Table 6. Injury rate regression for cities with high cycling exposure

Regression Statistics	
Multiple R	0.03394
R Square	0.00115
Adjusted R Square	-0.00636
Standard Error	0.10448
Observations	135

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.00167	0.00167	0.15340	0.69593
Residual	133	1.45197	0.01092		
Total	134	1.45365			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.14665	0.02587	5.66876	8.55E-08
Normalised_Injury_rate	0.02109	0.05385	0.39167	0.69593

Similar, although the coefficient would suggest a slight positive influence from the normalised exposure rate towards the normalised injury rate (an increase in the normalised exposure rate to produce an increase in the normalised injury rate), the effect is not significant (p>.05).

These two findings suggest that for cities with high cycling exposure, the exposure rate is not a significant factor in determining variation for the injury rate, and the injury rate is not a significant factor in determining variation of the exposure rate. For this category of cities there are other factors that to influence the variations of the exposure rate and injury rate.

Cities with low cycling exposure

Table 7. presents descriptive statistics for the normalised rates for cities with low cycling exposure. Differences between the two variables and their distribution can also be observed in this case too.

The means presented in this table are also consistent with equation A.2. showing that when the average mean for the normalised exposure rate decreases (when compared to the total sample or to the previous subsample), the average mean for the normalised injury rate increases (when compared to either of the previous two). Also, for the subsample of cities with low exposure level, the values of the two sets of the descriptive statistics for normalised injury rate and for normalised exposure rate respectively, are substantially different presenting very different ranges of variation, means, errors and deviations.

Table 7. Descriptive statistics for normalised injury rate and normalised exposure rate for cities with low cycling exposure

Normalised_Injury_rate	
Mean	0.32328
Standard Error	0.01497
Standard Deviation	0.20035
Sample Variance	0.04014
Range	0.98400
Minimum	0.01600
Maximum	1
Count	179

Normalised_Exposure_rate	
Mean	0.14010
Standard Error	0.00532
Standard Deviation	0.07112
Sample Variance	0.00506
Range	0.26186
Minimum	0
Maximum	0.26186
Count	179

Table 8. Exposure rate regression for cities with low cycling exposure

Regression Statistics	
Multiple R	0.71775
R Square	0.51517
Adjusted R Square	0.51243
Standard Error	0.04966
Observations	179

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.46378	0.46378	188.07695	1.24E-29
Residual	177	0.43647	0.00247		
Total	178	0.90025			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.22247	0.00706	31.50992	1.69E-74
Normalised_Injury_rate	-0.25478	0.01858	-13.71412	1.24E-29

The model reveals a significant (p<.05) negative effect from the normalised injury rate towards the normalised exposure rate. The size of the effect is moderate, an increase of 1 in the normalised injury rate resulting in a decrease of 0.25 in the normalised exposure rate.

Normalised_Exposure_rate = 0.22247 – 0.25478 * Normalised_Injury_rate (A.3.)

Table 9. Injury rate regression for cities with low cycling exposure

Regression Statistics	
Multiple R	0.71775
R Square	0.51517
Adjusted R Square	0.51243
Standard Error	0.13990
Observations	179

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	3.68083	3.68083	188.07695	1.24E-29
Residual	177	3.46404	0.01957		
Total	178	7.14487			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.60658	0.02315	26.19904	8.28E-63
Normalised_Exposure_rate	-2.02205	0.14744	-13.71412	1.24E-29

The regression model reveals a significant ($p<.05$) negative effect that the normalised exposure rate is manifesting upon the normalised injury rate variation. The size of the effect is not only significant being also of a considerable high size. An increase of 1 in the normalised exposure rate results in a decrease of 2.02 in the normalised injury rate.

Normalised_Injury_rate = 0.60658 – 2.02205 * Normalised_Exposure_rate (A.4.)

The latest two findings suggest that for cities with low cycling exposure rates SiN exists and it’s significant and substantial. Comparison between equation A.3. and A.4. suggests that for this category of cities the effect is more powerful from the numbers towards safety (in accordance with SiN hypothesis).

4. DISCUSSION AND CONCLUSION

The purpose of the paper was to present a bidirectional analysis of the relationship between cycling exposure rates and cycling risk rates, known as the SiN effect, and to investigate the existence of a tipping point where the influence from the exposure rates towards risk rates to became higher than the influence from the risk rates towards exposure rates. The results, consistent with other literature findings (Jacobsen, 2003) (Jacobsen, et al., 2015) (Elvik & Bjornskau, 2015), are indicating a strong and significant SiN effect among England’s cities, with stronger influence from the cycling exposure rates towards the cycling risk rates, than the reverse, for the total sample as well as for the two subsamples analysed.

The results seem also to indicate that there is rather a saturation point than a tipping point, a level of cycling exposure rate above which SiN effect does not significantly manifest anymore under the existing conditions (infrastructure, culture etc.). Above this saturation point other possible variables than cycling exposure should probably be investigated in the effort of improving cycling safety.

Although this paper did not propose to assess a mechanism for SiN, analysis and exploration of the effect for different cycling exposure levels allow for discussion and validation or refute of different assumptions about the mechanism.

In terms of when and where the SiN effect occur, the results seem to indicate a more powerful and significant effect for cities at the beginning of their cycling journeys. Cities with lower cycling exposure rates seem to be the ones seeing the biggest SiN effect. The results here are consistent with the literature around the likelihood of rare and ultra-rare items to be missed in visual searches (Wolfe, et al., 2005) (Mitrof & Biggs, 2014) and around relative frequency, inattentional blindness, and failure to detect factors (Simons & Chabris, 1999) (Pammer & Blink, 2013) (Biggs, et al., 2014), which suggest that the rare items or those with a rare frequency of apparition are harder to observe or even missed on visual searches. This would apply for drivers driving in environments where the cyclists are 'rare' and the result of increasing the exposure and making the cyclist more common (less 'rare') would be in them (the cyclists) being detected more often. Attempts using these types of explanations for SiN effect are also consistent with the results for the high cycling exposure subsample, where the issue of cyclists being 'rare' would not apply anymore. For those cities, SiN does not seem to appear anymore which is consistent with the assumption of rarity of the item for SiN to work.

Another hypothesis is that SiN happens where there are high cycle density growth rates (Thomson, et al., 2015) and that is also consistent with the findings. For low cycling exposure rates cities, the density growth rates can be high but, after a point (supposedly a saturation level), there is no physical space to have high density growth anymore.

Regarding how and why SiN effect occurs, the results are consistent with a growing body of literature, indicating that SiN is more likely to happen because of changes in drivers behaviour (Thomson, et al., 2015) (de Goede, et al., 2014) (Fyhri, et al., 2014) (Biggs, et al., 2014) (Elvik & Bjornskau, 2015) (Jacobsen, et al., 2015) (Johnson, et al., 2014) (Pammer & Blink, 2013) (Phillips, et al., 2011) (Fyhri, et al., 2016) (Anderson, 2006) (Sanocki, et al., 2015) and less likely to happen because of changes in cyclists behaviour (Thomson, et al., 2015) (Geyer, et al., 2006) or because of changes in street regulations, design and operations (Fyhri, et al., 2014) (Ogilvie, et al., 2004) because SiN seems to be more powerful where drivers' behaviours are more likely to be the cause for high injury rates, rates that tend to lower with the increase in the exposure rates, with the growth of the cycling phenomenon. Where the cycling exposure rates are higher and one would expect that a culture of safer cycling to arise and changes in infrastructure to become easier and more often, there the SiN effect seem to be less important in modelling the injury rates.

The paper presents also some weaknesses in terms of comprising data that, (1) for the cycling exposure rates, contains only the estimated figures cycling for utilities purposes only, and (2) for the cycling injury rates, contains only the reported data, which is argued in the literature that can be a lot lower that the real data (Juhra, et al., 2012). Arguably, because the study has been done on rates, assuming that both the proportion of cycling for utilities purposes in the total cycling and the proportion of reported collision from the total collisions remain relatively constant across the sample, the findings are still valid and, moreover, the differences that can arise are unlikely to be sufficient to change the signs, power or significance of the results.

Conclusion

In conclusion, the results suggest that safety is an effect of increased cycle use more than it is a cause for cycling in numbers.

The paper successfully evidenced the existence of SiN effect in cycling among England's cities, showing also that there is a more powerful influence from the cycling exposure rates towards cycling injury rates, especially for cities with lower exposure rates. The results also indicate the existence of a saturation exposure level, above which SiN effect is not significant anymore. The initial proposition that cycling safety improves with numbers but first numbers increase with safety, was partly disapproved. The results indicate that cycling safety improves with numbers better than numbers increase with safety until the numbers get to a saturation point where from none of them is improving the other significantly. This suggestion can be very useful for decision makers which are advised to assess cycling exposure, cycling injury rates and cycling capacity for their specific cases and take decisions accordingly. There is a danger that SiN effect could not always work well as a default solution, or not work similarly for different levels of cycling exposure. The assumption is that, at least for cities or areas with high cycling exposure rates, additional variables should be investigated in the effort of decreasing cycling risk, because just increasing numbers, even if demonstrated to work in many occasions, might not be always the most efficient or even an efficient tool.

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