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Title:

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Date:

2015

Citation:

Thompson, J., Savino, G. & Stevenson, M. (2015). Reconsidering the Safety in Numbers Effect for Vulnerable Road Users: An Application of Agent-Based Modeling. *Traffic Injury Prevention*, 16 (2), pp.147-153. <https://doi.org/10.1080/15389588.2014.914626>.

Persistent Link:

<https://hdl.handle.net/11343/337642>

Reconsidering the Safety in Numbers Effect for Vulnerable Road Users: An Application of Agent-Based Modeling

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Received 21 August 2013, Accepted 9 April 2014

Objective: Increasing levels of active transport provide benefits in relation to chronic disease and emissions reduction but may be associated with an increased risk of road trauma. The safety in numbers (SiN) effect is often regarded as a solution to this issue; however, the mechanisms underlying its influence are largely unknown. We aimed to (1) replicate the SiN effect within a simple, simulated environment and (2) vary bicycle density within the environment to better understand the circumstances under which SiN applies.

Methods: Using an agent-based modeling approach, we constructed a virtual transport system that increased the number of bicycles from 9% to 35% of total vehicles over a period of 1,000 time units while holding the number of cars in the system constant. We then repeated this experiment under conditions of progressively decreasing bicycle density.

Results: We demonstrated that the SiN effect can be reproduced in a virtual environment, closely approximating the exponential relationships between cycling numbers and the relative risk of collision as shown in observational studies. The association, however, was highly contingent upon bicycle density. The relative risk of collisions between cars and bicycles with increasing bicycle numbers showed an association that is progressively linear at decreasing levels of density.

Conclusions: Agent-based modeling may provide a useful tool for understanding the mechanisms underpinning the relationships previously observed between volume and risk under the assumptions of SiN. The SiN effect may apply only under circumstances in which bicycle density also increases over time. Additional mechanisms underpinning the SiN effect, independent of behavioral adjustment by drivers, are explored.

Keywords: safety in numbers, cycling, risk, agent-based modeling, density, accident

Introduction

In the absence of safe or segregated road infrastructure, safety for vulnerable road users remains a genuine concern (Elvik 2009a; Pucher, Garrard, and Greaves 2011; Teschke, Reynolds, et al. 2012). Despite the relatively high risk of injury and deaths that arise per kilometer traveled for cyclists and pedestrians (Elvik 2009a), many global cities proactively encourage the up-take of active transportation (European Environmental Agency 2008; Hickman et al. 2011; Reynolds et al. 2010). Though it may appear counterintuitive to promote more hazardous transport modes, concerns regarding cyclist safety are often discounted based on an assumption that the safety in

numbers (SiN) effect will prevail (Jacobsen 2003; Robinson 2005).

The SiN effect proposes that increasing volumes of cycling or pedestrian activity results in a reduced per capita risk of road injury. An array of studies (Bhalla et al. 2007; Elvik 2009a, 2009b; Jacobsen 2003; Kopits and Cropper 2005; Robinson 2005; Tin et al. 2011) have expressed this effect, generally in the form $I \propto E^b$, where I is the road injury risk (e.g., number of collisions), E is the proportional volume (defined variously by absolute numbers, distance travelled, or the number of trips) of cyclists, and b is the exponent. For cycling, the exponent has been estimated to average around 0.4 with a range between 0.3 to 0.6 (Jacobsen 2003).

For cycling proponents (e.g., The National Cycling Charity 2009; Safe Cycling Australia 2013), SiN offers a convenient argument for simultaneously advocating increased bicycle use while also achieving improved cyclist safety. This virtuous cycle has been broadly promulgated in both scientific (Pucher et al. 2010) and popular media (University of New South Wales 2008) leading to widespread adoption by cycling activists and incorporation into various city and region-based transport plans and strategies (City of Yarra 2010;

Associate Editor Clay Gabler oversaw the review of this article
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Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/gcpi.

Department for Transport Energy and Infrastructure 2006; Department of Transport 1997).

However, despite consistent findings from published studies investigating its effect across both micro- and macroscopic traffic situations (Elvik 2009b), the employment of aggregated, inductive methodological approaches (Kopits and Cropper 2005; Robinson 2005) used to study SiN means that the mechanism by which it operates remains unclear (Bhatia and Wier 2011; Teschke, Harris, et al. 2012; Teschke, Reynolds, et al. 2012; Wegman et al. 2012). Behavioral adaptation by drivers due to increased exposure to cyclists has been offered as a likely explanation (Jacobsen 2003); however, little published evidence (Phillips et al. 2011) exists to support this contention. Recent figures from London and San Francisco also demonstrate a sharp rise in serious injuries among cyclists (San Francisco Municipal Transportation Agency 2012; Stordy 2013) at rates that cannot be explained by commensurate increases in bicycle volumes alone (San Francisco Municipal Transportation Agency 2011; Transport for London 2011). Consequently, an assumption that greater numbers of cyclists will reduce road injury risk under all circumstances may be overly simplistic. Further, a promotion of cycling that relies on SiN to increase safety may potentially lead to passivity and thwart efforts to improve cyclist safety by removing focus from additional interventions that may truly contribute to reduced risk (Bhatia and Wier 2011; World Health Organization 2013).

One possible explanation for SiN that has not been widely explored is bicycle density, referring to the number of cyclists located within a given radius of other cyclists. Conditions that increase density such as perceived safety (Lawson et al. 2013), close proximity to destinations (Owen et al. 2010), and provision of cycling infrastructure that is either segregated or bicycle friendly (Reynolds et al. 2009; Wegman et al. 2012; Winters and Teschke 2010) may increase cyclist numbers. However, by reducing exposure of individual cyclists to danger, bicycle density may provide the mechanism through which the safety benefit derived from increased bicycle numbers is achieved.

The aim of this article is therefore two-fold: to (1) investigate the relationship between the number of cyclists and the per capita risk of collision within a simulated transport system and (2) explore the robustness of the SiN effect under conditions of variable local bicycle density.

Materials and Methods

Design of the Virtual Transport System

To explore the SiN effect, an agent-based modeling (ABM) approach was used. ABM is a technique that has demonstrated its value within complex system fields as diverse as biochemistry (Zhang et al. 2011), workforce culture (Marin et al. 2006), biology (Morrell et al. 2010), traffic simulation (Bo and Cheng 2010; Khalesian and Delavar 2008; Li 2006; Sarvi and Kuwahara 2007), crowd simulation (Turner and Penn 2002), and health (Laskowski et al. 2011).

In transportation and traffic modeling, representation of systems and interactions between vehicles has generally varied between broad macroscopic and fine microscopic levels

(Hoogendoorn and Bovy 2000). The utilization of ABMs in transportation literature has often taken the latter approach, attempting as far as possible to mirror the temporal and spatial elements of real-world systems and assess behavioral responses to proposed built infrastructure or traffic management strategies via scaled microsimulations (e.g., Bonomi et al. 2009; Ehlert and Rothkrantz 2001; Sarvi and Kuwahara 2007).

In contrast, we present here a simulation designed not to strictly represent temporal or spatial system elements, nor to assess detailed vehicle dynamics as they relate to potential collisions (Savino et al. 2013), but to assist in disaggregation of the general phenomenon of the SiN effect. Our model has been designed to demonstrate a basic mechanism potentially underlying the SiN effect by reproducing simple, rule-based microlevel behavior (i.e., avoidance of collisions and traffic) among vehicles while controlling two major variables of interest: (1) growth in the number of bicycles entering the system and (2) the density of cycling activity along established routes. In this respect, the model departs from that typically produced using specialized traffic modeling software packages (e.g., Barceló and Casas 2005; Gomes et al. 2004) and is more akin to approaches used in other traffic, crowd, and social phenomena (e.g., Gilbert 2008; Luo et al. 2008; Nagel and Schreckenberg 1992; Shiwakoti et al. 2010).

System Architecture and Parameters

The virtual transport system (VTS) was of an area 132×132 distance units (17,424 area patches) produced using Netlogo (Wilensky 2013). Because ABMs operate within virtual environments, units of measurement (distance, time, speed, etc.) are abstract. A schematic flowchart of the simulation operation (Shiwakoti et al. 2010) is presented in the Appendix (see Fig. A1, online supplement).

At baseline (time 0), the VTS included 2,000 cars and 200 bicycles distributed randomly on a grid-based, bidirectional road system. The maximum ($v_{\max}$) and minimum ($v_{\min}$) velocity of cars and bicycles were scaled to approximate an urban environment where cars had higher maximum (1 unit per time step) but lower minimum velocities (0 units per time step) than cyclists (0.3 units per time step/0.05 units per time step). A summary of units associated with the VTS can be found in the Appendix (see Table A1, online supplement).

Cars' headings were randomly allocated to cardinal directions and did not change for the duration of the simulation. In order to avoid collisions, vehicles demonstrated simple give-way behaviors; if the area of road 1 distance unit in front of their current heading was occupied by another vehicle, they decelerated to the velocity of that vehicle minus 0.1 velocity units per time step until they had reached $v_{\min}$ for their vehicle type (see Appendix, Table A1). Once a vehicle's immediate heading was no longer impeded, they again accelerated by 0.1 velocity units at each subsequent time step until they reached $v_{\max}$.

To examine the effect of an increase in bicycle volume on the number of potential collisions within the VTS, we modeled an initial high-density scenario (HiDens) that increased cycling activity by 1 unit per time step over a period of 1,000 time steps. Data recorded at each time step (t_k , with k index varying from

1 to 1,000) represented movement of a set of N vehicles of classes a and b from geographic coordinates $x_{1,2,\dots}$ and $y_{1,2,\dots}$ under various conditions of bicycle density (D).

To reflect the encouragement of bicycle use within bicycle-friendly routes, a snowballing effect based on the gain or loss of utility function (UF) units was applied. As individual bicycles moved around the system, they gained 1 UF unit per time step if the route traveled on was bicycle friendly. Green, bicycle-friendly routes were those where other bicycles had recently traveled on and no cars had since ventured. When bicycles ventured outside bicycle-friendly routes (grey areas), they received no UF units for doing so. Further, they also risked interaction with cars, which reduced their stock of UF by 5 units. If a bicycle's UF reached above 15 units, it was eligible to introduce another bicycle into the system at a position up to 20 distance units behind its current location, with an identical heading. If a bicycle's UF units fell below 0, it was removed from the system. These incentives had the effect of encouraging increased bicycle travel along routes conducive to cycling and discouraging bicycles along routes dominated by cars or where few other bicycles existed.

The calculation of utility function units for bicycles at each time step can be expressed in the equation

$$UF_i(t_k) = UF_i(t_{k-1}) + \alpha_i(t_k) \cdot (C_1) - \gamma_i(t_k) \cdot (C_2), \quad (1)$$

where UF is the utility function of the i th bicycle at time t_k , α is the presence at a position (1 = present, 0 = not present) in the VTS that is bicycle friendly, and γ is the presence of cars at their current location (1 = present, 0 = not present). For the purpose of this experiment, the weighting coefficients C_1 and C_2 were values of 1 and 5, respectively.

In addition to the manipulation of bicycle activity based on the loss or gain of UF units, bicycles were subject to an exploration factor that controlled the likelihood that bicycles would continue at their current heading or turn left/right by 90° at random intersections in pursuit of alternative routes. This setting was designed to reflect the extent to which bicycle policy encouraged cyclists to move beyond more established cycling routes into new areas of the system. In effect, it acted as a counterbalance to the encouragement of bicycles to coalesce along established routes through UF units. The exploration factor was held at 1% within the initial scenario.

Under the rules of the simulation, potential collisions (P) were most likely to occur when cars and bicycles were crossing paths at intersections. In such situations, if either a car or bicycle looked ahead and saw the area in front of them to be empty, both vehicles attempted to move into the empty space at the same time. Alternatively, if either vehicle looked ahead and saw another vehicle or object ahead of them, they decelerated in order to avoid collision in a basic give-way maneuver. The decision-making process of individual vehicles in relation to avoiding collisions with other vehicles is presented in Fig. A2 (see online supplement).

Potential collisions were recorded at each time step and were defined as those that occurred when cars and bicycles were logged at identical locations within the system (i.e., they had failed to give way) and cars were not stationary. Collisions

(C) between cars and cyclists were recorded as;

$$C = P \cdot r, \quad (2)$$

where P = is the potential collision event and r was a constant risk ratio of 1. Although this 1:1 ratio would not hold true under real-world circumstances, changes to this ratio were beyond the scope of interest because, whilst relevant to absolute numbers, the value of r would not affect the shape of relationship between bicycle numbers and collisions proposed under the SiN effect.

Monitors within the VTS produced measures at each time step of total number of vehicles, total number of bicycles and cars, number of collisions experienced by bicycles, and mean bicycle density,

$$D_i = \frac{B_n}{L^2}, \quad (3)$$

where D is the bicycle density evaluated for the i th bicycle, the environment being divided into a number N of overlapping squares with edge L ($N = 17,131$, $L = 3$ distance units), and B is the number of bicycles in the n th area where the i th bicycle is located. Each simulation was repeated over 1,000 time steps, with results reported as mean outputs from 5 trials.

Results

Experiment 1

Figure 1 shows a visualization of the VTS at the conclusion of the simulation from one of the 5 HiDens trials. Importantly, our model demonstrated that although the number of bicycles was higher within the system at a constant rate, the pattern of aggregation among bicycles was not uniform. Rather, bicycles coalesced along select, bicycle-friendly routes over time.

Analysis of the relative risk associated with increased bicycle volume within the HiDens scenario was consistent with patterns observed in previous real-world studies (Elvik 2009b; Jacobsen 2003; Robinson 2005). The mean exponent (b) for the power relationship between bicycle volume (E) and collision numbers (I) was 0.34 (see Fig. 2a). As bicycle numbers doubled, mean total collision numbers among bicycles increased by around 27% and per capita risk of collisions among bicycles decreased by around 37% (see Fig. 2b).

The relationship between bicycle numbers and collision risk was sensitive not only to the number of bicycles within the system but also the mean local bicycle density at each time step. During the early stages of the HiDens scenario (<time step 300), bicycle density was relatively low and the per cyclist risk of collision between cars and bicycles was relatively high ($\geq$ around 10%). Over time, cyclists became discouraged from traveling in car-oriented areas and coalesced along bicycle-friendly routes, leading to a rapid rise in cyclist density. This was mirrored by a relatively rapid, nonlinear decline in collision risk for bicycles (see Fig. 3).

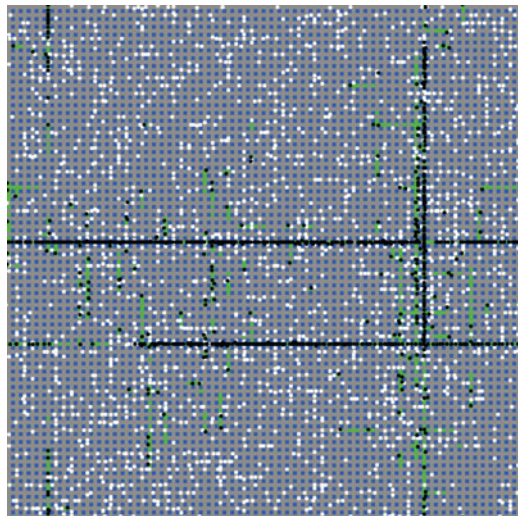


Fig. 1. Visualization of travel patterns within the VTS under the HiDens scenario showing an aggregation of bicycles (black) along specific bicycle-friendly routes area and the remaining routes largely dominated by cars (white).

Experiment 2—Sensitivity Analysis

Method

We conducted a sensitivity analysis including 3 additional scenarios of identical growth in bicycle numbers over time with reduced density growth: medium density (MedDens), low density (LowDens), and very low density (VLowDens). To reduce

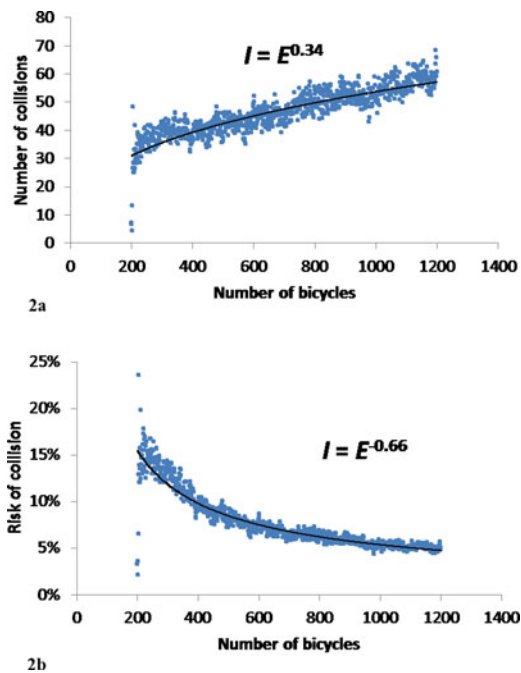


Fig. 2. Observed relationship between bicycle numbers and number of collisions and relationship between bicycle numbers and per capita risk of collision within the HiDens scenario.

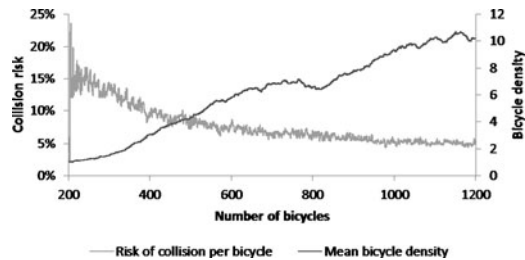


Fig. 3. Associations observed between relative risk of collision, cyclist growth, and mean cyclist density over time averaged under the HiDens scenario.

density growth of bicycles, we made alterations to the model’s exploration setting. This progressively increased the likelihood that bicycles chose to deviate from their set heading in pursuit of alternative routes from 1% under the original (HiDens) scenario to 2% (MedDens), 3% (LowDens), and 4% (VLowDens), respectively.

It was anticipated that increases in bicycle numbers under conditions of progressively lower growth in bicycle density would result in increased per bicycle collision risk and increased total collision numbers. Further, because density within each of the 3 scenarios was more likely to stabilize at a constant, lower rate, it was expected that the SiN effect would be progressively negated.

Results

Table 1 and Figs. 4a, 4b, and 4c show results of the MedDens, LowDens, and VLowDens scenarios, demonstrating that the total number of collisions between cars and bicycles was higher in lower density scenarios despite consistent bicycle number growth. The association between bicycle numbers and collisions also became more linear under progressively lower-density scenarios.

Figure 5 shows an example of the pattern of aggregation of bicycles from one of the VLowDens trials. In contrast to patterns observed under high-density conditions (see Fig. 1), bicycle route choice was more dispersed with cyclists more inclined to deviate away from established routes.

Table 1. Mean collisions, cyclist density, cyclist volume, and power relationship between bicycle numbers and number of collisions in each scenario over 3 trials

Scenario	HiDens	MedDens	LowDens	VLowDens
Mean collisions (SD)	46.6 (9.0)	75.9 (4.6)	80.9 (1.5)	88.4 (2.3)
Mean density (min, max)	3.4 (0, 12.5)	1.9 (0, 3.1)	1.6 (0, 2.3)	1.3 (0, 1.6)
Mean bicycle volume	700	700	700	700
Mean power relationship (bicycle volume to collisions)	.34	.72	.78	.86

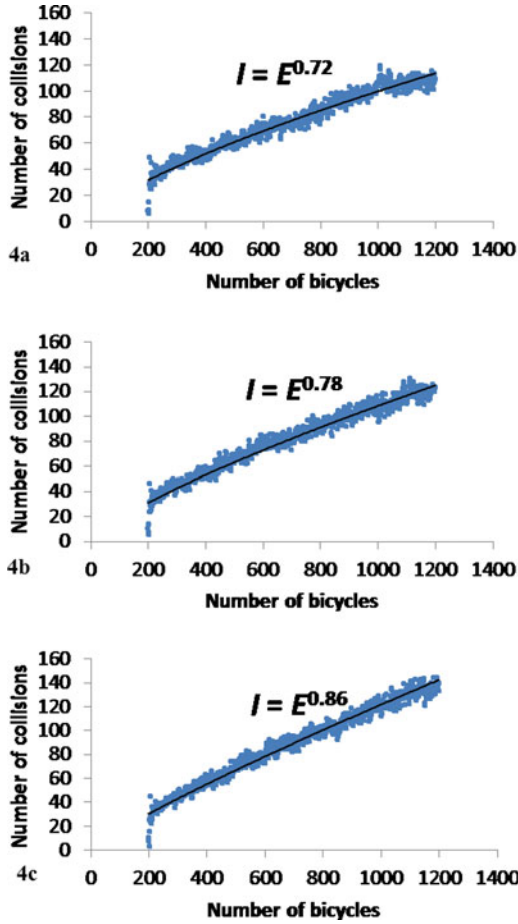


Fig. 4. Relationship between increasing bicycle volume and rate of accidents under the (a) MedDens, (b) LowDens, and (c) Very-LowDens scenarios.

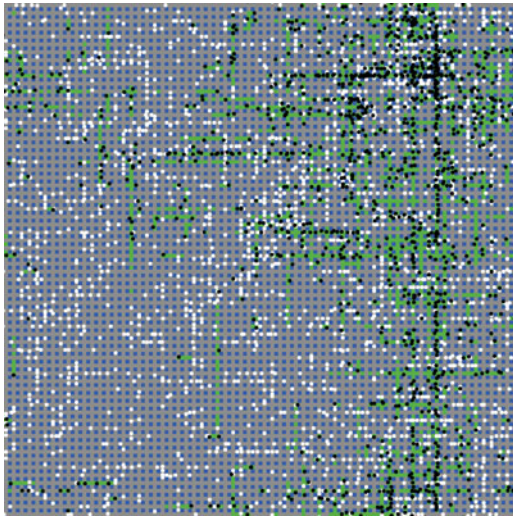


Fig. 5. Visualization of travel patterns within the VTS under the VLowDens scenario showing greater dispersion of bicycles (black circles) around bicycle-friendly routes and the remaining area dominated by cars (white circles).

Discussion

The findings from this study demonstrate that replication of the SiN effect for vulnerable road users is possible through agent-based simulation of a generic transport system employing simple, rule-based behaviors of collision avoidance and travel route preference that increases bicycle density. Furthermore, they suggest that the circumstances within which the SiN effect applies may be contingent upon the density of bicycles more so than their numbers alone. The emergent pattern of bicycle aggregation along particular routes within the simulation is qualitatively similar to that observed in real-world commuter cycling studies where favorable cycling conditions produce heightened activity along specific routes (Hood et al. 2011; Howard and Burns 2001; Sener et al. 2009; Stinson and Bhat 2003). This emergent, macrolevel behavior of bicycle activity provides additional validation (Gilbert 2008) and confidence that patterns modelled here may reflect mechanisms underlying the SiN effect.

In simulated scenarios where bicycle density increased over time alongside increasing bicycle numbers, per capita risk of collision decreased. Conversely, where growth in bicycle density was lower, per capita collision risk decreased more slowly with increasing bicycle numbers. Further, when bicycle density growth was low and remained relatively stable over time, the association between increasing bicycle numbers and collisions more closely resembled a linear relationship, effectively nullifying the SiN effect.

Underlying the SiN effect, Jacobsen (2003) and others (e.g., Adams 1987) have suggested that behavioral adjustment, including increased awareness and care demonstrated by drivers, may contribute to the reductions in risk observed with increasing cyclist or pedestrian volume. However, similar SiN effects have been demonstrated here among virtual vehicles that demonstrate no behavioral adaptation over time or change in behavior with increasing exposure. Although this tends to not support a behavioral adaptation hypothesis, we must be cautious with our interpretation given that it is not based on observed empirical data. Consequently, the findings from this study should be viewed in relation to the imposed and implicit limitations of the system's design. This restriction, however, has also enabled a consistent, observable environment to be created that enabled conduct of sensitivity analysis through modification of a single parameter (density) over many thousands of time points and potential collision events, areas of methodological limitation that have been highlighted in previous real-world designs (Bhatia and Wier 2011; Minikel 2012).

We propose 2 alternative mechanisms outside of behavioral adjustment for consideration that may underlie the SiN effect. Firstly, increasing bicycle density coinciding with increasing volume may have the simple consequence of reducing the proportion of surface area per cyclist exposed to danger from cars. Just as the overall number of collisions increases with an approximate 0.4 power to cyclist volume in observational studies and between the 0.34 to 0.86 power in this study, the circumference (C) of a circle increases proportionally to the square root of its area (A), represented in the form

$$C \propto A^{0.5}. \quad (4)$$

This simple explanation accords directly with the proposed relationship between deaths and motorization forwarded by Smeed (1949) and may account for the consistent patterns of results described here and elsewhere (Elvik 2009b; Jacobsen 2003; Robinson 2005).

A second, closely related explanation drawn from the biological sciences is the influential selfish herd theory proposed by Hamilton (1971) and explored by others (e.g., De Vos and O'Riain 2012; Hirsch and Morrell 2011; Morrell et al. 2010). This theory proposes that increased density brought about through aggregation (e.g., bird flocking, fish schooling, etc.) is an adaptive mechanism that reduces risk of predation by minimizing high-risk exposure at the periphery of groups (Bumann et al. 1997). Applied to vulnerable road users, this theory would suppose that each cyclist is subject to risk from predators (vehicles) at a rate proportional to the size of their domain of danger (DOD), or half the distance between each cyclist and his nearest neighbor. The smaller each cyclist's DOD is in relation to other cyclists (i.e., by increasing bicycle density), the smaller their relative risk. Cyclists, aware of danger posed by motor vehicles (Bauman et al. 2008), are likely to aggregate along safe and convenient urban routes (Pucher, Dill, and Handy 2011; Teschke, Harris, et al. 2012; Winters and Teschke 2010), thereby reducing the size of their individual DOD and reducing individual risk.

Bicycle density as described here may be just one of the mechanisms that underlie volume–risk associations observed in the real world. For example, our models were not specifically designed to mimic segregated bicycle infrastructure. It is plausible that density represents the effect of safe, segregated infrastructure to the extent that it separates cyclists from cars and hence reduces potential exposure to threat. Further limitations of these results relate to the accuracy with which they depict real-world events. Our models of collision risk were based on very simplified representations of vehicle movement and collision avoidance. We did not scale the size of vehicles themselves, vary intersection types, or vary other potentially influential factors.

In cities where increases in cycling numbers have not been met with comparable decreases in collisions predicted by the SiN effect (San Francisco Municipal Transportation Agency 2012; Stordy 2013), research may wish to determine whether patterns of cycling resemble those observed under the medium or low-density scenarios modeled here. It is possible that cycling activism and desire to reclaim territory from cars (Aldred 2010; Furness 2007) in cities where cycling has experienced a relatively recent cultural renaissance (Pucher, Behler, and Seinen 2011) may inadvertently play a role in increasing exposure to risk.

This study has demonstrated that agent-based modeling may be a useful mechanism for disaggregating and understanding the SiN effect for cyclists. Low-density travel by cyclists among motor vehicle traffic may expose individuals to per capita risks of collision that are not counteracted by the number of cyclists in the remainder of the system. Alternatively, growing, stable, or even decreased numbers of bicycles within a system accompanied by increased cyclist density may have the potential to not only decrease per cyclist risk but to also decrease collision numbers in absolute terms. If the re-

sults presented here bear relationship to the real world, there is potential that the safety in numbers message may be best substituted by safety in density.

Funding

M.S. is supported by a National Health and Medical Research Council (Australia) Fellowship. G.S. is supported by the European Community's Seventh Framework Programme FP7/2007–2013 under the Grant Agreement No. 328067.

Supplemental Materials

Supplemental data for this article can be accessed on the publisher's website.

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