# Bicycle Helmet Laws, Safety-in-Numbers, and Bikeshares

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**Abstract**

Active transportation (walking and bicycling) dramatically improves wellbeing through numerous mechanisms including health, empowerment, social equity, childhood cognitive development, resilience, pollution reduction, scalability, and sustainability. The popularity of cycling is modulated by safety and convenience. The safety of cyclists is strongly correlated with the number of cyclists, with both mechanistic and empirical support for bidirectional safety-numbers causality. Bikesharing can quickly increase the convenience of cycling, especially for new and occasional riders.

Helmet laws have two competing effects on safety: they protect some cyclists during collisions, but also reduce the number of bicycle trips, especially impacting bikesharing. This paper sketches some likely causal loops that link helmet laws and safety-in-numbers to bicycle modeshare and, ultimately, to life expectancy, which we use as a proxy for wellbeing. Three interacting feedback loops are included, modelling the dynamic interactions between safety, convenience, and bikeshare system size. The model illustrates that, at best, helmet laws slow and limit bicycle adoption, and at worst they push bicycle modeshare into a death spiral. The results presented here are not intended to be predictive, but rather to demonstrate a potentially dangerous system behaviour, and to motivate more detailed study.

## 1 Introduction

Urban transportation systems designed around active mobility—walking and bicycling—show high potential for simultaneous co-optimisation of health, wellbeing, local and international social justice, climate, resilience, childhood cognitive development, good use of urban public space, local air quality, global sustainability... [WCA and ECF, 2016; Macmillan et al., 2020]

Danger and inconvenience are often cited as the main reasons people choose not to bike [Daley and Rissel, 2011; Claudy and Peterson, 2014; Fishman, 2016; Macmillan and Woodcock, 2017; Branion-Calles et al., 2019]. Efforts to reduce danger generally follow two approaches. One approach focuses on transportation system design: since most serious bicycle injuries and fatalities are caused by collisions with cars, the emphasis is on reducing the kinetic risks posed by cars, e.g., through physical separation and lower car speed limits. The other approach attempts to convert fatal collisions into non-fatal collisions by increasing the use of bicycle helmets. These two approaches are often framed as complementary, and it is often argued that greater efforts should be made to increase helmet use, especially among bikeshare riders, where helmet use is especially low (e.g. Graves et al. [2014]; Chen et al. [2021]).

While each safety intervention has been studied in depth, the temporal dynamics of interactions between them have largely been neglected. This paper investigates the consequences of increasing cyclist safety primarily through the safety-in-numbers effect [Robinson, 2005; Elvik and Goel, 2019]: when the number of cyclists increases, the risk to cyclists is reduced, presumably through mechanisms such as drivers learning to accommodate cyclists, and greater political and financial incentives to build bike-friendly infrastructure (the emergence of political forces opposing good bicycling infrastructure is a damping influence, but will be ignored here). Conversely, requiring helmets reduces the number of trips by bicycle, for reasons of inconvenience, discomfort, money, ideology, helmet-hair, etc. This effect is especially damaging for bike-sharing systems.

We use life expectancy as a proxy for healthy ageing and wellbeing. We estimate how that number varies as a function of the rate of bicycling, incorporating the health benefits of physical activity and the risks of fatal collisions:

- More active lifestyle → Increased life expectancy
- Helmet requirement → Greater crash survivability
- Helmet requirement → Fewer trips by bike

We model the dynamics of the desirability of bicycling based on three feedback loops:
**Safety-In-Numbers:** More biking ⇆ Safer biking
**Convenience:** More biking ⇆ More bike-friendly destinations, facilities, routes, etc...
**Bikeshare business:** More biking ⇆ More bikeshare stations
By reducing the complexities of bicycle modeshare to these three representative feedback loops, we explore how policies that increase the number of cyclists can quasi-exponentially increase cyclist safety. In contrast, not only can helmets never improve safety by more than a constant factor, but helmet requirements also activate these feedback loops in the opposite direction, with the unintended consequence of exponentially increasing risk to cyclists.

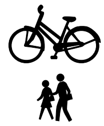
## 2 Background

We assume that the goal of policy is to increase access to *intrinsic goods*—things that are *good for their own sake* rather than proxy quantities, and that society-wide wellbeing metrics or average healthspan measures such as QALY/DALY/LEGPH approach this ideal. While there is more to life than not being dead, we take life expectancy as sufficiently close to an intrinsic good, since it is highly correlated with the more sophisticated wellbeing metrics and easier to measure.

Active transportation can improve social equity, access to community resources such as education and food, air quality, climate stability, universal autonomy, childhood cognitive development, economic productivity, etc... [WCA and ECF, 2016; Macmillan et al., 2020; Bruntlett and Bruntlett, 2021] We consider these not to be ends in themselves, but rather proxy goods to the extent that they facilitate wellbeing. Similarly, encouraging bicycling is valuable because of the many mechanisms by which it improves wellbeing / healthspan (which we approximate here as life expectancy) of the average member of the population:

| Objective | Correlate | Mechanism | Technology |
|---|---|---|---|

$$\textit{Wellbeing} \leftarrow \left\{\begin{array}{c}\textbf{Lifespan}\\ \text{QALY}\\ \text{DALY}\\ \text{LEGPH}\\ \text{Gini}\\ \text{SDGs}\\ \vdots\end{array}\right\} \leftarrow \left\{\begin{array}{c}\textbf{Active lifestyle}\\ \textbf{Mobility safety}\\ \textbf{Clean air}\\ \text{Mobility equity}\\ \text{Childhood cognitive development}\\ \text{Reduced parental burdens}\\ \text{Pleasant ``third space''}\\ \text{Economic efficiency}\\ \text{Low resource use}\\ \text{Stable ecosystem}\\ \text{Stable climate}\\ \text{Global equity}\\ \vdots\end{array}\right\} \leftarrow$$



We focus on the first three (boldfaced) mechanisms. The remaining ones are connected to healthspan and wellbeing, but quantitative research on effect sizes is lacking. Due to the bicycle's versatility, popularity, benefit/cost ratio, and interdependence with mobility infrastructure, we focus on cycling as a good indicator of active transportation (cycling, walking, running, handcycles, wheelchairs, etc...). And because, compared to private ownership, bikeshare systems greatly lower the barriers to entry, we focus on those.

> ...the major barriers to bikeshare relate to a lack of convenience and competitive advantage with other modes, safety concerns and anything that impedes spontaneity. [Fishman, 2016]

## 2.1 Convenience

Convenience is consistently found to be a primary factor in mode choice [Claudy and Peterson, 2014; Bachand-Marleau et al., 2012; Fishman et al., 2015; Fishman, 2016; Kabra et al., 2020]. Convenience may include such factors as:

- Distance: in many cities, most trips are under 5 kilometres (km), at low speed, and will take a similar amount of time by car or bicycle. The number of such trips is subject to gradual change, through emergent response to demand or intentionally through new city technologies such as 15-Minute Cities [Moreno et al., 2021; Pozoukidou and Chatziyiannaki, 2021]. The convenience of longer trips is more dependent on specialised infrastructure such as access to high-average-speed routes or easy integration with public transportation [Jonkeren et al., 2021].
- Terminal costs: time and cost of parking, distance to destination, ability to secure a bicycle vs. theft...

- Pleasantness of the route for the chosen mode.
- Ability to carry common loads (groceries, children. . . )
- In hot climates, availability of showers or changing rooms.
- Availability of equipment, including suitably equipped bicycles (e.g. fenders, racks, cargo boxes) at the location of need and anything required by law (e.g., lights, helmet).

#### 2.1.1 Bikeshares

Whereas bicycle ownership requires overcoming various obstacles to purchase (choice, cost, outfitting), logistics (maintenance, storage), and use (restricted to home–[. . . ]–home trips, concerns anent theft), bikeshare systems [Fishman et al., 2015; Fishman, 2016] that are easy to join and that offer dense coverage [Bachand-Marleau et al., 2012; Kabra et al., 2020] can reduce all of these barriers. When combined with cyclist-friendly infrastructure, they can quickly increase ridership, and can facilitate multimodal trips. And while they compete against public transportation and walking, they can also reduce trips by car [Cheng et al., 2022; Cordeau, 2023].

### 2.2 Traffic safety

The UK, Germany, Denmark, and the Netherlands kill on the order of one cyclist per 100 million km ridden [Buehler and Pucher, 2021]. At an average moving speed of 20 km/h (reasonable for regular commuters [De Geus et al., 2007]), this is one death every 5 million hours of cycling. If the average age of a cyclist killed in a collision is ∼25, and the life expectancy is ∼80, then approximately 500,000 life-hours are lost per 5 million.

The USA is more hostile to cyclists: as of Buehler and Pucher's [2021] analysis, the USA was killing 6 cyclists per 100 million km, and rising. This reduces the benefit/cost ratio, but even in the USA the benefits generally outweigh the costs (§2.3).

#### 2.2.1 Safety-in-numbers

As the number of cyclists (or, more precisely, bike use) increases, the risk per cyclist decreases. Much research includes car, bike, and pedestrian traffic and examines other factors (see Elvik and Goel's [2019] comprehensive meta-analysis), but the simplest form suffices here:

$$\frac{\text{number of collisions}}{\text{baseline number of collisions}} \sim \left(\frac{\text{number of cyclists}}{\text{baseline number of cyclists}}\right)^{\beta} \tag{1}$$

When $\beta < 1$, the number of collisions grows more slowly than the number of cyclists. Elvik and Goel [2019] include studies that put $\beta$ as low as -0.14 and as high as 0.87. They estimate a city-level average of $\beta \approx 0.25$, but on the scale of individual junctions they find $\beta \approx 0.4$. Using $\beta = 0.4$ as a conservative example, if the number of cyclists (or kilometers cycled) doubles, the number of collisions increases by a factor of only $2^{\beta} \approx 1.3$, so the risk to each cyclist (or for each km) decreases by $1 - \frac{2^\beta}{2} = 1 - 2^{\beta-1} \approx 34\%$. If $\beta = 0.25$, then if bicycle use doubles, risk decreases by 40%.

Causal directionality is debated. Is the observed effect simply due to more people choosing to bike in response to extrinsic safety improvements—"numbers-in-safety"? Elvik and Goel [2019, sec. 5.2] provide an argument that their results are consistent with safety-in-numbers, and others (see also §2.1.1) argue persuasively that more cycling immediately raises awareness and teaches motorists what to look for, while on long timescales more bicycling creates more pressure for infrastructure improvements [Macmillan and Woodcock, 2017]. And since risk is such a commonly reported reason for choosing not to bicycle, as safety improves, so should the number of cyclists (§2.2.2). The presence of arguments and evidence in both directions supports exploring a feedback model.

A nice piece of evidence was accidentally published by Graves et al. [2014] in an article arguing for more helmet use. Their data on 5 intervention and 5 control cities show that in cities that implemented or greatly expanded their bikeshare systems, rates of serious injuries among cyclists dropped by 28% while rates in control cities increased by 2%—although the authors ignored this result, and it took others to point it out [Fishman et al., 2015].

We believe that the reasoning behind the safety-in-numbers hypothesis is sufficiently sound, and that there is sufficient supporting evidence, to warrant this investigation of potential consequences.

### 2.2.2 Perception of safety

The health benefits from active transportation usually outweigh the risks (§2.3.1). But perceptions, not data, drive daily decisions. The choice not to bicycle is often due to a belief that bicycling is dangerous [Claudy and Peterson, 2014; Carstensen et al., 2014; Aldred and Crosweller, 2015; Fishman, 2016; Macmillan and Woodcock, 2017]. Since statistics generally show that bicycling is safe, we can dismiss the hypothesis that the decision not to bike is based on mortality data.

What, then, generates the perception of safety? Infrastructure such as separated bike lanes [Branion-Calles et al., 2019; Hardinghaus and Weschke, 2022; Fishman et al., 2015; Fishman, 2016; Manton et al., 2016; Fosgerau et al., 2023], slow car traffic [Hardinghaus and Weschke, 2022], experience [Fishman, 2016; Manton et al., 2016] informed by direct learning from conflicts with motorists:

> Thus in the UK, reported deaths, serious injuries, slight injuries, and self-report injuries might be of the rough magnitude of around 50; 1000; 6000; and 20,000 per billion miles cycled respectively. This research suggests that, per billion miles cycled, one might by contrast expect 25,000,000 'very scary' near miss incidents—a completely different metric and one that can contribute to our understanding of why people apparently over-estimate the risks of cycling. [Aldred and Crosweller, 2015]

It also seems likely that the presence of cyclists serves not just to make the system safer, but also as a vote of confidence in the system.[1]

It has been argued that since helmets are worn for dangerous sports but not for most transportation modes, requiring helmets on bicycles sends the signal that, unlike "regular" transportation, bicycling carries risk on par with dangerous sports [Gerhard, 2023]. However, since the psychological effect size is unknown, we do not include this separately, but assume that the decrease in bicycling due to helmet laws includes this effect.

### 2.2.3 Helmets

The degree to which helmets protect cyclists is controversial. Few analyses do a convincing job of controlling for exposure or other concurrent traffic-safety interventions. Still fewer take into account the fact that severe head injuries are rare in the first place, so any cost-benefit analysis finds little benefit [Taylor and Scuffham, 2002; Robinson, 2007; de Jong, 2012]. Rather than reviewing that literature, we note that the debate is far from settled, so we will sidestep it entirely by assuming that helmets provide perfect protection against all possible head injuries (§3.2.1).

Helmet laws reduce the amount of bicycling. While the size of the effect is also debated, plausible estimates for users of their own bikes are that an enforced helmet law reduces the number of bicycle trips by 10–40% [Komanoff, 2001; Robinson, 2006; Rissel and Wen, 2011; Hoye, 2018; Gerhard, 2023]. The effect on bikeshares is more extreme [Fishman et al., 2015; Fishman, 2016], and indeed bikeshares in areas with helmet laws struggle. This paper partially sidesteps the problem of establishing effect size: due to system feedbacks, even a small impact on cycling is amplified over time. However, better estimates of the magnitude and timescale of this effect would allow refinement of the model.

Developing Komanoff's [2001] suggestion, de Jong [2012] showed that even under unrealistically optimistic assumptions about helmet effectiveness, the small decrease in ridership caused by helmet laws increases the burden of diseases of inactivity to the point that it usually overwhelms the gains achieved by perfect helmets. Here, we consider how safety-in-numbers feedbacks might amplify this effect over time.

## 2.3 Health

### 2.3.1 Diseases of inactivity

While lethal cycling collisions are spectacular, they are rare: the leading causes of death are lifestyle diseases caused primarily by lack of physical activity.[2] The physical and mental health benefits of frequent activity (functional movement, play, exercise. . . ) reduce the prevalence and severity of many—even most—diseases [WHO, 2010; Reimers

[1]Perhaps especially when cyclists match the observer's demographic, or represent vulnerable groups.
[2]The burden of lifestyle diseases due to diet is comparable, but it is beyond the scope of this work.

et al., 2012; USA. DHHS, 2018; Lieberman, 2021; Garcia et al., 2023], arguably including ageing itself: at the volumes and intensities typical of transportation (4–7 METs [De Geus et al., 2007; Herrmann et al., 2024]), 1 hour of cycling yields a life expectancy gain of ∼2–3 hours (broadly consistent with the typical finding that 150 minutes/week of moderate exercise increases life expectancy by 3 years, assuming the habit is maintained for 50 years; see also [Leskinen et al., 2018; Yang, 2019]). The greatest gains are at the lowest levels—those going from no activity to a small amount [Powell et al., 2019; Garcia et al., 2023], which amplifies the public-health effects of bikeshares if they nudge occasional trips—but the benefits continue to accrue at much higher doses [USA. DHHS, 2018; Lieberman, 2021; Lee et al., 2022].

Recalling §2.2: if 5 million hours of bicycle commuting result in the loss of 500,000 life-hours due to fatal collisions, but the recovery of ∼15 million life-hours by treating lifestyle diseases, then the expected gain is 30 times greater than the loss. This simplistic calculation yields a number roughly consistent with those from more sophisticated analyses [de Hartog et al., 2010; de Jong, 2012; Kelly et al., 2014; Tainio et al., 2016].

### 2.3.2 Pollution

Air pollution from fossil fuels may decrease life expectancy by an average of ∼1 year worldwide [Lelieveld et al., 2020], and can be many times higher in densely populated areas. Not all of this is caused by personal vehicles, so the potential life expectancy gain at optimistic levels of modeshare shift (at least in regions with strong tailpipe emissions laws) might be on the order of minutes per day—not just for cyclists but for all residents. Vehicles also make a significant contribution to non-exhaust particulates [Oroumiyeh and Zhu, 2021], including toxic compounds from e.g. tire and brake dust, but we do not include this. Cyclists consume more car pollution than motorists, but de Hartog et al. [2010] found that the benefits usually outweigh the risks. We note that the health effects of stricter tailpipe emissions controls may be amplified not only by increasing the cost of cars, but also through the feedback loop reducing the pollution-consumption disincentive of bicycling, but we leave this as future work.

## 3 Methods

We present a differential-equation (compartment) model[3] that simulates the evolution of the population-wide outcome of interest. Life expectancy increases due to the light exercise provided by bicycling (assuming that our baseline is the current prevalence of diseases of inactivity), and decreases due to air pollution and deadly collisions. The model represents average (probabilistic) travel behaviour—so, for example, the average change in life expectancy is the change expected due to making a trip by bicycle multiplied by the probability of a trip being made by bicycle.

We will assume that, on average, one hour per day is dedicated to transportation. This is broadly consistent with average commute times worldwide. The faster people

[3] The Vensim model sin.mdl is at `https://github.com/bwpearre/public/tree/main/2024-08_ISDC`

can travel, the greater their tolerance for commute distance, consistent with induced demand and the fact that our lives are limited not in distance but in time. Probably coincidentally, if commuting uses an active mode, this number aligns well with health recommendations (§2.3.1).

A trip is made by bicycle if that is the most convenient option, not seen as too risky, and the traveller has access to the equipment (private or public bike, and helmet if required). Otherwise the trip is made by car.[4] Thus we have (ignoring helmets for now):

$$\Pr(\text{bike}) = \Pr(\text{convenient}) \Pr(\neg \text{ deterred by risk} \mid \text{access to bike}) \Pr(\text{access})$$

For example, if bicycling is the most convenient mode for 20% of trips, 10% of the population has access to a bike, and those believe that half of all trips are sufficiently safe, then 1% of trips will be made by bike.

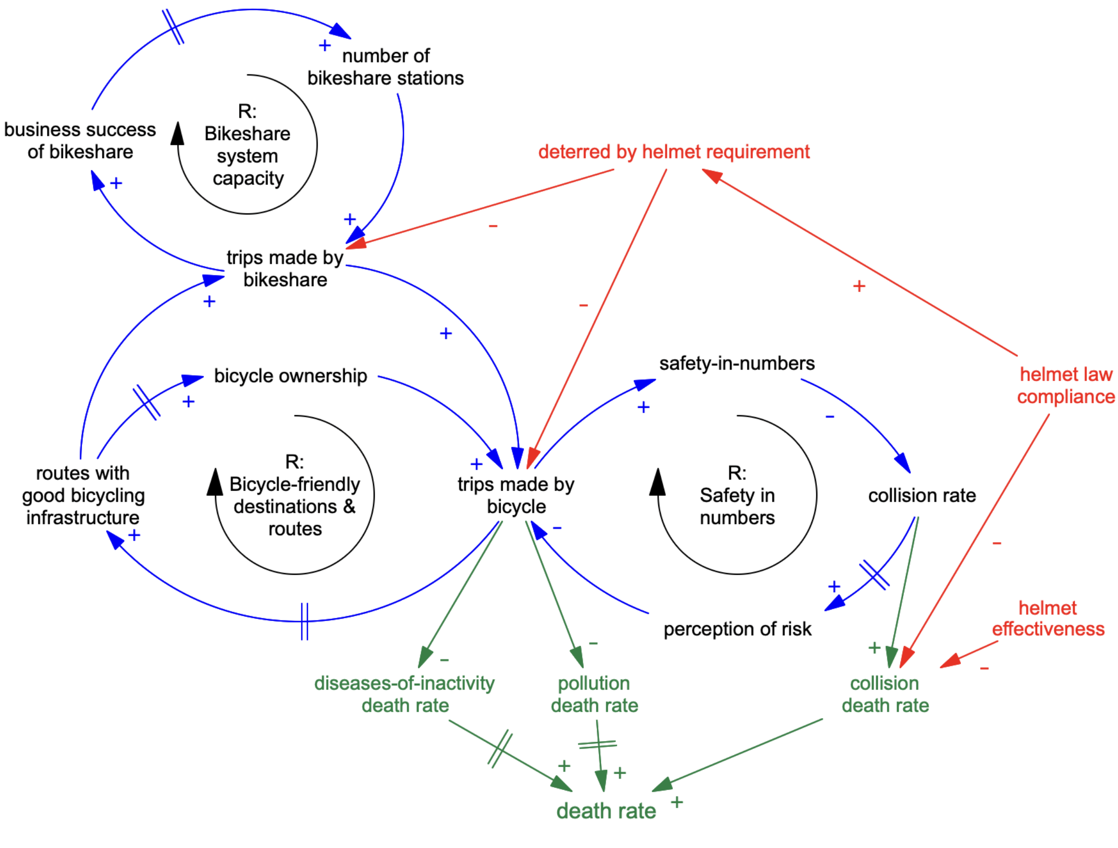



**Figure 1:** The modelled relationships between cycling, safety, infrastructure, bikeshare systems, and death rate. The model's feedback loops are shown in blue and black, the health calculator in green, and the effects of helmet laws in red.

[4]Not modelled here: it has been observed that when public transportation is available, bicycles compete with that as well as with cars, but see Cordeau [2023].

A simplified causal-loop diagram is shown in Fig. 1, sketching how the model connects these factors. Crucially, we assume that more bicycling leads to increased safety (§2.2.1).

Working through an example, if a bicycle helmet law reduces the number of bike trips by 20% (§2.2.3), assuming from §2.2.1 $\beta = 0.4$, then the risk of collision per kilometre increases by $0.8^{\beta-1} \approx 14\%$. Assuming helmets ∼25% of all cyclist deaths—roughly 100% of deaths due to head injury—the risk of death per km would initially decrease by $1 - (0.75 \cdot 1.14) \approx 14\%$. Meanwhile, the 14% increase in crashes and close calls per km would scare more potential cyclists away, leading to a further increase in risk for those who remain. Decreased demand for all kinds of cyclist-friendly infrastructure (§2.1) gradually makes it less likely that a bicycle will be the most convenient mode for any given trip. Most importantly, as physical activity slowly declines, lifestyle diseases proliferate, with profound consequences to life expectancy.

## 3.1 State variables

### 3.1.1 Convenience

One probability, Pr(trip is most convenient by bike), represents all of the factors described in §2.1. We assume that the aggregate of these factors responds slowly to changing demand, and that if infrastructure is not maintained, it slowly decays over time. There will always be some trips that are inconvenient by bicycle, so we cap convenience at 70%, perhaps achievable with mature implementations of the 15-Minute City [Moreno et al., 2021; Pozoukidou and Chatziyiannaki, 2021] or Superblocks [Mueller et al., 2020]. We acknowledge that this may lead to both induced bicycle traffic and induced demand [Lee et al., 1999] but leave this effect for future work.

### 3.1.2 Safety and risk

In the model, only the safety-in-numbers effect controls the rate of potentially deadly collisions (§2.2.1). The probability of death given a severe collision is only affected by helmet use and effectiveness.

As described in §2.2.2, we assume that perceived risk rises and falls with actual risk, following Eq. 1 with an information delay. We choose a baseline in range with reported values (e.g. [Aldred and Crosweller, 2015; Fishman et al., 2015]): the initial probability of non-cyclists being deterred by potential risks Pr(deterred by risk | no bike access) = 0.7. Those who have access to a bike are less likely to be deterred by danger than those who do not [Fishman et al., 2015], so:

$$\Pr(\text{deterred by risk} \mid \text{bike access}) = 0.7 \cdot \Pr(\text{deterred by risk} \mid \text{no bike access})$$

How to estimate the effect of perceived risk on behaviour? Since even a small absolute risk has a high probability of deterring a bike trip, and since multiplying a probability by a scalar is not valid, we use the odds ratio:

$$\frac{\Pr(\text{deterred}) / \Pr(\neg\text{deterred})}{\Pr_{\text{base}}(\text{deterred}) / \Pr_{\text{base}}(\neg\text{deterred})} = \frac{\Pr(\text{crash}) / \Pr(\neg\text{crash})}{\Pr_{\text{base}}(\text{crash}) / \Pr_{\text{base}}(\neg\text{crash})}$$

Safety-in-numbers and helmet laws interact through perceived risk and ability and willingness to bike. Unrealistically, infrastructure improvements are not taken to directly improve safety, simply because the number of additional free parameters exceeds the number of papers examining the relationship. Rather, in this simplified model, infrastructure leads to greater safety only because more convenient bicycle routes induce demand for cycling, which enhances safety through numbers (we leave incorporation of the detailed estimates of induced demand developed by Fosgerau et al. [2023] as future work). We also ignore the potential vote-of-confidence (bandwagon) effect of seeing many other cyclists on the road. Both of these effects would have approximately the same structure as the safety-in-numbers perception, albeit probably with different time constants.

#### 3.1.3 Access to a bicycle

Bicycles can be privately owned, or borrowed through a bikeshare. Each time a trip is most convenient by bicycle and the potential rider is not deterred by safety concerns, a bike owner or bikeshare member will bike, and someone without access will, with some probability, join a bikeshare if one is available, or (generally with much lower probability (§2.1.1)), buy a bike. These are treated as uncorrelated: bikeshare members can also be bike owners. Bikeshare memberships are maintained in proportion to the probability that they are used, and unused private bikes slowly rust (artificially, at a rate equal to the initial rate of acquisition).

For a non-cyclist, the initial decision to bike is a big step both psychologically and materially. Once that step has been taken, further trips by bike are more likely [Fishman et al., 2015]. We have not modelled this explicitly, but note that recent riding closely parallels the risk-assessment structure described in §3.1.2: the initial decision to arrange access to a bicycle is an excellent proxy for the decision to make a first trip by bike, and thus the deterrence factor described above could contain both of these effects.

#### 3.1.4 Bikeshare system capacity

Well-appointed bikeshares drastically lower barriers of entry for would-be cyclists due to their low upfront cost and potential availability for any segment of a trip.

By default, the model assumes that a bikeshare is introduced to the world at a certain time, with some initial station density $\delta$ (e.g. $\delta = 1$ station/km$^2$).

What is the probability that a bikeshare bike is nearby? Kabra et al. [2020] find a linear decrease in bikeshare utility of 0.194%/m as a user needs to walk up to 300 m, and a much steeper one beyond that. We take 200 m to be a reasonable average for our simple threshold model. Using the $L_1$ norm, this suggests that a bikeshare station serves 0.08 km$^2$, and thus the probability of a station within 200 m is $0.08\,\delta$. To account for imperfect tiling and to constrain probabilities to $[0, 1]$ we somewhat arbitrarily use $\tanh(\cdot)$.

$$\Pr(\text{bikeshare is nearby}) = \tanh(0.08\,\delta)$$

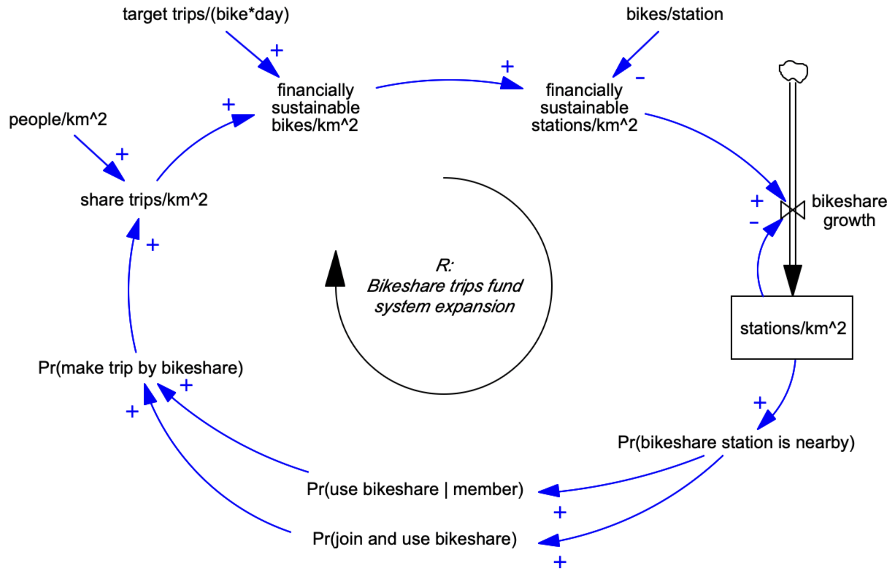



**Figure 2:** The bikeshare model expands and contracts continuously in response to demand, with the goal that each bike will serve e.g. 4 trips/day.

$$\frac{\text{bikeshare trips}}{\text{km}^2 \cdot \text{day}} = \frac{\text{population}}{\text{km}^2} \cdot \frac{\text{trips}}{\text{day}} \cdot \Pr(\text{would use bikeshare}) \cdot \Pr(\text{bikeshare is nearby})$$

Pr(would use bikeshare) varies with perceived risk and convenience infrastructure. Eyeballing data published in [Fishman, 2016], we assume that as demand varies, the density $\delta$ of bikeshare locations in the system is increased or decreased until each bicycle is serving e.g. 4 trips/day. We deal only with station-based bikeshares with a fixed number of bikes (by default, 10) per station, and make the optimistic assumption that bikeshare stations are always suitably stocked. Freund et al. [2019] provide a thorough review of the literature on rebalancing, and Kabra et al. [2020] describe interesting relationships between the number of bikes at a station and the decision and habituation processes of potential users: is it worth going to the bikeshare in hopes of finding a working bike? We leave these refinements for future work.

Different bikeshare systems offer different levels of convenience of joining and use [Fishman, 2016], represented as Pr(join bikeshare | want), which multiplies

$$\Pr(\text{most convenient by bike}) \Pr(\neg \text{ deterred by risk}) \Pr(\neg \text{ bikeshare member})$$

to produce a probability per day of joining the bikeshare. Helmet laws further modulate this probability as described in §3.2.1.

### 3.2 Interventions

#### 3.2.1 Helmets

A helmet law changes the average cyclist's behaviour to some degree $\lambda \in [0 \ldots 1]$, from $\lambda = 0$ (no behavioural effect) to 1 (absolute respect for the law). The present model ignores the fact that some cyclists already wear helmets and will likely not change their behaviour in response to a law. The error thus introduced would have an effect on the numeric predictions of a data-calibrated model, but matters little for the system behaviours shown here—especially since so few bikeshare riders wear helmets [Fishman et al., 2015].

We dodge the debate on how effective helmets may be by making an assumption that maximally favours helmet laws: "idealised" helmets that entirely eliminate lethal head trauma—roughly 25% of all serious cyclist injuries [de Jong, 2012; Graves et al., 2014]. This assumption is for devil's-advocate realism, but as we will see, even "magical" helmets that prevent 100% of all cyclist deaths do not significantly affect the results.

Helmet laws affect bike owners and bikeshare members differently. Owners are deterred from making a trip by bike with a low probability $0.2\lambda$ (from a conservative reading of [Robinson, 2006]), whereas potential bikeshare riders are far more likely to be deterred since they are prohibited from making spontaneous trips [Fishman et al., 2015; Fishman, 2016]. A different factor (by default $0.8\lambda$) controls this, and helmet requirements probably deter first-time bikeshare users even more severely (default $0.9\lambda$). The size of the deterrent effect of helmets is poorly studied and tightly linked to other agendas, but our qualitative results hold if helmets disincentivise cycling at all.

## 4 Results

In these example scenarios, convenience infrastructure responds to demand, which responds to perceived safety, which follows actual safety-in-numbers (Fig. 1). The time constants are somewhat arbitrary, so the time scale is useful for comparison to other results, but not predictive of absolute change rates. However, while some parameters—especially rates of change—are uncertain, every effort has been made to use published values, especially for safety and health outcomes.

### 4.1 A bikeshare is introduced, no helmets required

Assume an initially steady scenario in which a constant 10% of people own bikes, 20% of trips are most convenient by bike, and safety concerns and access barriers result in the bicycle being chosen for 1% of trips. At 10,000 cycling hours between crashes (typical for the USA), our initial lifespan benefit of bicycling is around 8 times greater than the risk (probably an unusually pessimistic starting point—see (§2.2). Collisions and pollution kill a few people, but averaged across the whole population, the trips by bicycle still raise the population average life expectancy by a minute per day above that of a car-only city. This is the starting point of Fig. 3.

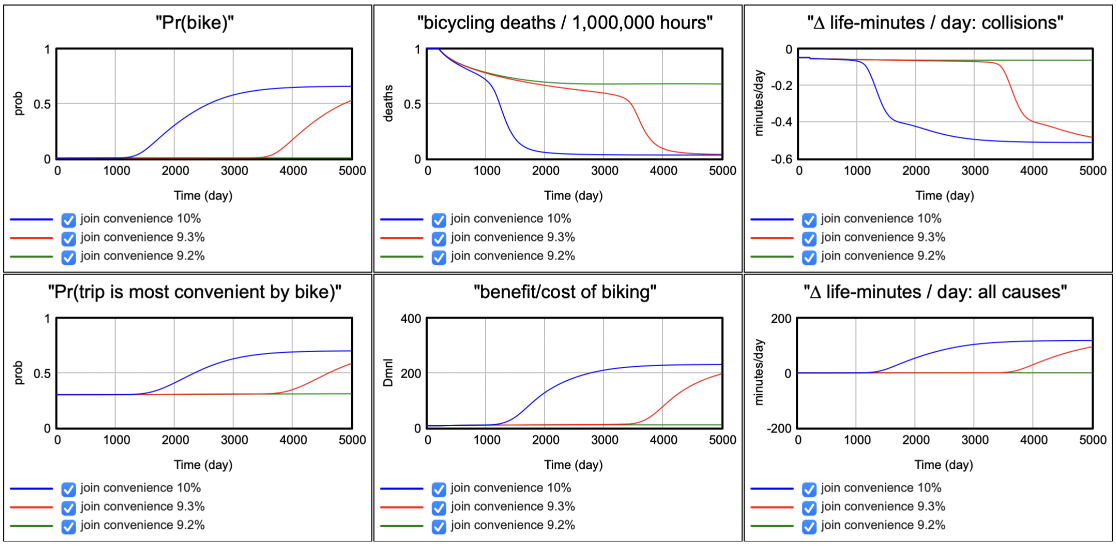



**Figure 3:** Introduction of a bikeshare on day 200. Under default assumptions (base), the system improves slowly at first, followed by s-curve growth as the feedback loops activate each other. Behaviour is sensitive to many parameters; here we vary the convenience of joining the bikeshare. As this is reduced from 10%, the dynamics change gradually at first, but a sharp boundary appears around 9.3%, below which the bikeshare system does not attract enough members to maintain itself or stimulate significant infrastructure improvements. The graphs show: *Pr(bike):* the probability that any trip will be made by bike. *Pr(trip is most convenient by bike):* the probability that any trip is most convenient by bike. *bicycling deaths / 1,000,000 hours:* the expected number of cyclist deaths in traffic for every million hours of bicycle travel time. *benefit/cost of biking:* life expectancy gain (exercise) / loss (fatal collisions). Δ *life-minutes / day: collisions:* If $\beta > 0$, then more bicycling leads to more crashes (§2.2.1, here $\beta = 0.4$), and thus to more "newsworthy deaths"—which should be compared to Δ *life-minutes / day: all causes:* combining life expectancy change due to traffic deaths, air pollution, and light exercise from cycling, distributed over the whole population.

On day 200 a bikeshare system is introduced, which makes bicycles more easily available. In Fig. 3's "join convenience: 10%" scenario, the bikeshare is easy enough to use that 10% of people who notice that biking would be the most convenient mode for a given trip, and are not deterred by danger, obtain a membership, after which they are likely to use the system when convenient and safe. At an initial density of one station per km$^2$, only around 8% of people are within 200 m of a station when they need it. For these people, due to the low barrier of entry, membership grows, allowing the installation of more stations, serving a greater number of people. As the equipment barrier is removed and more trips are made by bike, responsive improvements to infrastructure encourage more people to organise access to bikes. At the same time, real and perceived risks decline, encouraging further growth. As mobility infrastructure changes to cater to this new mode, bicycling becomes the most convenient mode for more trips, equipment barriers are further reduced, risk declines to less than a tenth of its initial value, and the probability of choosing to bike approaches its maximum (it is limited to 70% as noted in §3.1.1). Pollution declines (not shown, as it tracks Pr(bike)), but we estimate that it contributes under a minute/day, although this varies drastically across cities and countries. When 70% of trips are by bike, safety has improved to the point that the lifespan gains due to exercise are over 200 times greater than the costs due to risk of fatal collision. Distributing the costs and benefits over the whole population, life expectancy of the average resident increases by two hours every day.

### 4.1.1 Instability and convergence

This model starts in an unstable equilibrium, and is nudged by the introduction of the bikeshare system. The feedbacks between convenience (infrastructure) and safety may attract enough new riders to support the bikeshare system's maintenance needs, but this outcome depends on many of the model's parameters.

For example, three values of *join convenience* ("Pr(join share | want)" in the model, representing how easy it is to join the bikeshare) are shown in Fig. 3. Below 9.3% the rate of people joining the bikeshare dips below the rate of people who let their memberships lapse. Ridership shrinks, the safety-in-numbers effect is reduced, and the bikeshare system deteriorates.

In this case, the short-lived demand-driven investment in convenience infrastructure can inspire a few people to buy their own bicycles. Even after the collapse of the bikeshare, this additional ridership can, in the absence of any disincentive, drive the system towards the bike-friendly stable state. But the higher cost of entry and lower convenience of personal bicycles make this happen far more slowly (and far less equitably).

If risk is driven down by safety-in-numbers and bike supply rises to meet demand, asymptotic behaviour is governed by the maximum number of trips that are most convenient by bike. Many of the model's parameters change only the speed of convergence to this eventual stable state.

## 4.2 Introduction of helmet law

Fig. 4 shows a scenario initially similar to §4.1, with the bikeshare introduced on day 1. On day 3000, a mandatory helmet law is introduced. Many would-be spontaneous cyclists now find themselves downtown without a helmet. At 70% law compliance, ridership immediately drops by over 50%, so with $\beta = 0.4$ the collision risk to the remaining cyclists rises by around 50%. Helmets temper the blow—risk of death only increases by $\sim$25%. However, in this example the discouragement of active transportation reduces the potential life expectancy gain from almost 120 to 50 minutes per day. With 100% law compliance, the further reduction in cycling exaggerates the result—reducing life-expectancy gains to only $\sim$23 minutes. With magical helmets that prevent *all* cyclist deaths (including, e.g., fatal blows to the torso), with these parameters, the law's 100-minute/day lifespan reduction is moderated by only $\sim$20 seconds.

The new equilibrium seen in Fig. 4 is driven by the fact that biking is still more convenient, safer, and more accessible than it was. As before, asymptotic behaviour is governed by the maximum number of trips that are most convenient by bike. Now

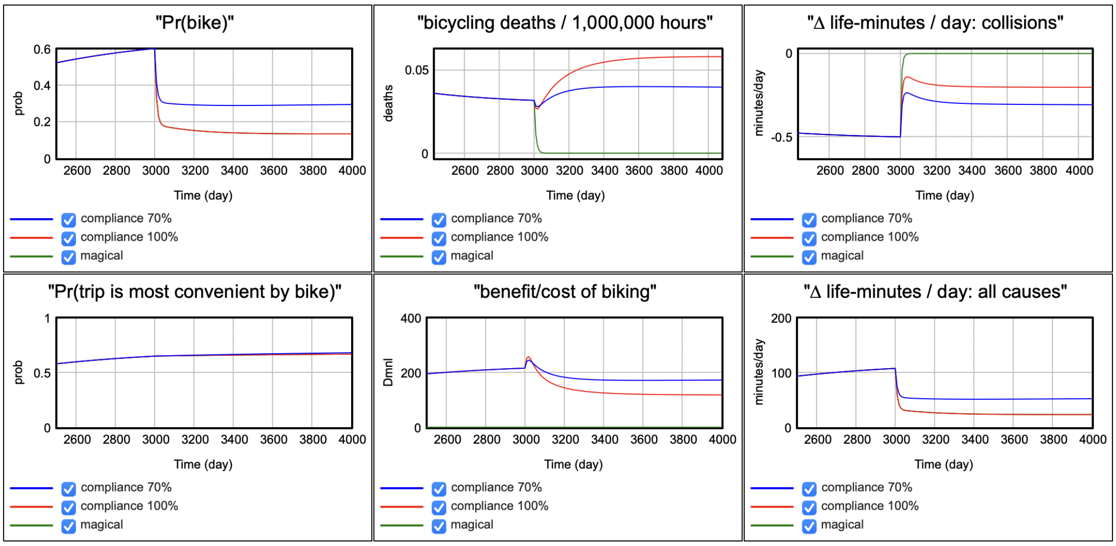



**Figure 4:** An established bikesharing culture (day 2999) encounters a helmet law on day 3000. Behaviour is shown with 70% and 100% compliance with the law. Also shown: a "magical" scenario, with 100% compliance and helmets that prevent 100% of cycling deaths. For most of the output variables—notably "Δ life-minutes / day: all causes"—the magical scenario is almost indistinguishable from "100% compliance" with idealised helmets (perfect protection from the ~25% of collisions that involve head injuries §3.2.1). "benefit/cost of biking" goes to ∞ since we are only considering death; if we included serious injury, this would not be the case.

convenience is modulated by the probability that a rider—or someone considering joining or using the bikeshare—is carrying a helmet, is willing to risk a police encounter, or does not find rental helmets unappealing.

### 4.2.1 Bistability

The helmet law is a nudge away from bicycling, allowing the feedbacks that previously activated a virtuous cycle of bikeshare availability, safety, convenience, and health to reinforce in the other direction toward an attractor that is hostile to cyclists. The boundary between attractors is determined by many parameters, whose relative importances vary over the parameter space. Compliance with the law usually has a powerful effect, as shown in Fig. 4. Fig. 5 shows another example, in which the growth of a bicycling culture can be merely slowed and handicapped, or even killed entirely, depending on the degree to which bicycling culture has established itself. §4.4 contains a more detailed discussion.

## 4.3 Helmet law repealed: worse before better

What happens when a helmet law is repealed? This is dangerous—mainly to politicians. The number of lethal collisions—in time, not normalised for exposure—tracks Fig. 6's "Δ life-minutes / day: collisions". The law's introduction (assuming idealised helmets)

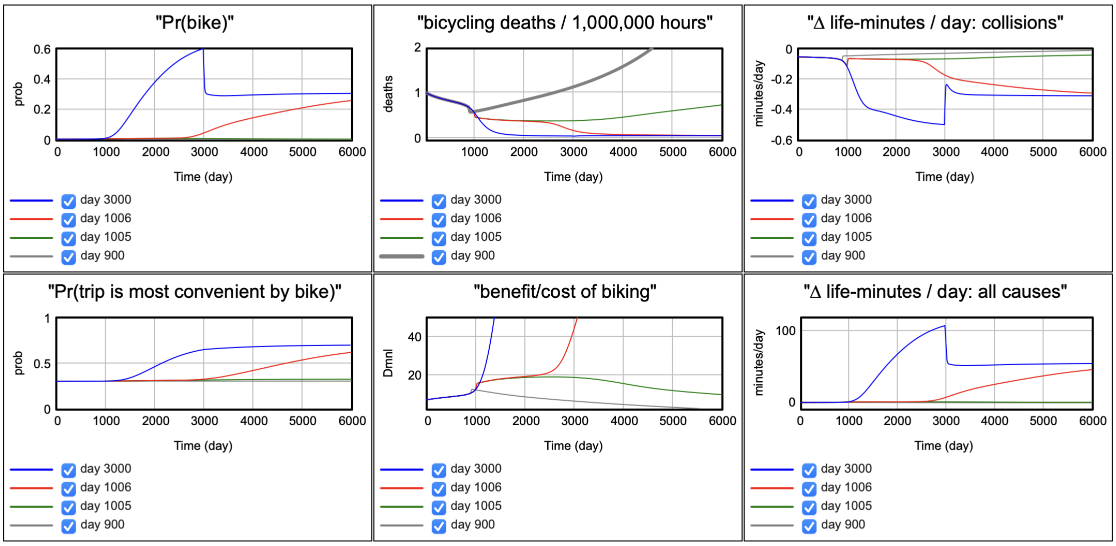



**Figure 5:** If a helmet law is introduced after a robust biking culture is established, the new law will damage public health, but the damage may be limited. However, such a law can also drive the system into the car-centric attractor. Here, if the bikeshare system has had 1006 days to grow, then the helmet law (at 70% compliance) merely reduces the benefit and converges to the same equilibrium shown in Fig. 4, but if the law is introduced one day earlier, then cycling culture collapses. The split in trajectories is shown most clearly in "benefit/cost of biking".

reduces the number of these newsworthy deaths. When the law is repealed, the total number of crash fatalities spikes (here, it more than doubles), and (if $\beta > 0$) never returns to the low level seen during the helmet-law era. The size of the effect depends somewhat on the effectiveness of helmets, but is due mostly to the changes in the number of cyclists. Even the risk per hour spikes before falling to new lows (if $\beta < 1$) as the safety-in-numbers effect catches up.

As the increase in collisions poses a political risk, Fig. 6 suggests a possible policy intervention. Collisions can spike if ridership—which in this model instantly tracks helmet law compliance—increases faster than the safety-in-numbers effect can keep pace with. But if law compliance changes more gradually (shown from 0.1/day to 0.003/day; the safety-in-numbers effect's change rate is 0.01/day), then the spike in collisions is reduced or even eliminated.[5] Hence the possibility that political risk could be minimised by e.g. gradually reducing bareheaded-riding fines before eliminating them entirely, or quietly ending enforcement.[6] The health benefits, which closely follow ridership numbers, also accrue more slowly, but the question of how to balance slower convergence to maximal health benefits vs. lessened risk of political backlash during the worse phase of the worse-before-better dynamic is beyond the scope of this work.

[5]The risk profiles of riders who most quickly choose to return to cycling after a helmet law's repeal may be a confound, but is not addressed here.

[6]The optimal rate is probably not easy to determine from published results, since the rate of change of the safety-in-numbers effect is not well studied, and involves behaviours on several timescales.

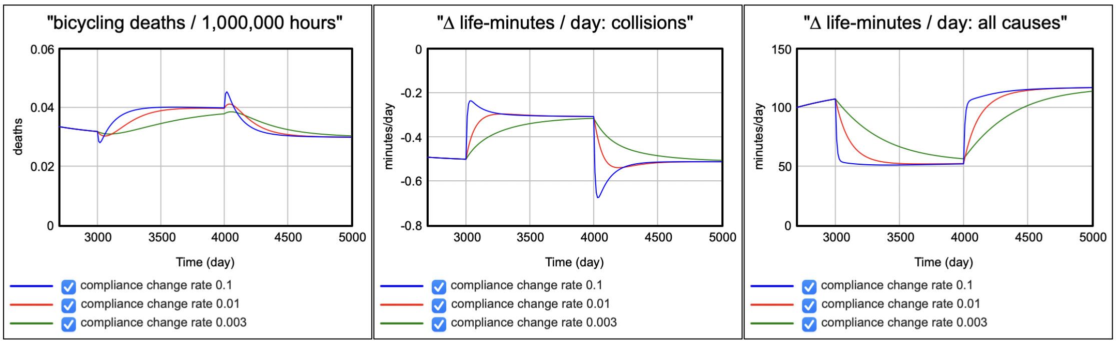



**Figure 6:** The trajectory of Fig. 4, with a helmet law introduced on day 3000 (70% compliance) and repealed on day 4000. The different lines show the effect of different rates of behavioural-adjustment to the legal changes. The rate of change of the safety-in-numbers effect is fixed at 0.01/day.

### 4.4 General observations anent sensitivity

Near the boundary between attractors, the outcome is highly sensitive to many of the model's parameters. The ones that flip the system vary somewhat according to where in the parameter space the system starts, but some trends may be observed. Moving further from the boundary, some parameters change the eventual equilibrium Δ lifespan/day, and some change only the rate of convergence to that equilibrium. Here are a few general observations (parameter names given for comparison with the figure, or with the model):

**Helmet law compliance:** As increased helmet law enforcement decreases ridership, especially among potential bikeshare users, the system's feedbacks cause this to affect life expectancy far more dramatically than documented in previously published static analyses. The time constants for this change include safety-in-numbers adjustments, safety perceptions, investment in infrastructure, and bikeshare capacity adjustment.

**Perceptions of safety:** The model assumes that perception of risk is a constant (if delayed) multiple of true risk. In this case, the safety-in-numbers effect is sufficient to activate the safety → infrastructure → convenience → ridership → bikeshare growth → safety loop, even without any explicit assumption of infrastructure improving real or perceived safety.

**Convenience:** Increasing the upper limit on the number of trips that are most convenient by bike is beneficial in this simple model, and it would be more powerful if individual cyclist demographics were separated or measures such as social equity or child mobility were examined. This model wraps many potential convenience improvements, and many possible timescales, into one loop. We leave a more nuanced analysis for future work.

**Infrastructure:** Quickly building and rigorously maintaining infrastructure can make the system more resistant to the negative impact of a helmet law. Furthermore, the long initial period during which growth is almost imperceptible is due largely to the slow response time of infrastructure, and can thus be greatly accelerated by a preemptive infrastructure project that immediately increases convenience—and, not modelled but true in the real world, the perception of safety.

**Convenience for new and occasional bikeshare users:** Making bikeshare systems easy to join can amplify small bikeability improvements by facilitating an immediate response in ridership. Lowering the costs of maintaining active membership makes ridership more robust to perturbations.

**Transport hours:** Amusingly, increasing the hours of transport per day generally increases health. Only when most people use cars, pollution is high, and collisions are frequent is this effect reversed. This result relies on the model's assumption that increasing transportation hours would not affect mode choice, and at very high levels, the linearised exercise–health dose-response, and ignores the immediate opportunity costs of transportation time.

**Bikeshare bikes/station:** In the model, this parameter affects access: 10 bikes at 2 5-bike stations gives twice as many people access as 10 bikes at a single station. In the real world this is complicated by unmet demand, limited placement opportunities, increased difficulty of rebalancing, users learning how often an operable bike will be at the closest station...

**Target trips/(bike·day):** The fewer trips per bike per day required to make the system financially viable, the faster the system can expand—assuming that profits are reinvested.

**People/km$^2$:** Higher-density cities increase the number of people near any given station. Not modelled: higher-density cities put more destinations within easy reach of bikes, generate more political pressure to address difficulties with car-first systems (which can push towards making them bikeable, more pressure for EVs of various sizes, turning bike infrastructure into car infrastructure...), or can even put most destinations close enough that biking is less appealing than walking.

**safety-in-numbers exponent $\beta$:** Varying $\beta$ (§2.2.1) by 10%, as Vensim's Sensitivity2All does, is misleading, since it is an exponent, and since the dynamic response of the model to variations in $\beta$ is markedly nonlinear across its range. That said, $\beta$ can have a profound impact on the safety of cyclists, and thus on the evolving dynamics of bicycle infrastructure and demographics. Future work will investigate what factors are responsible for the large spread in values found by Elvik and Goel [2019], and search for policies that might lower $\beta$ on different timescales.

Especially early, when the system is sensitive to perturbations in either direction, making large changes to as many parameters as possible will activate feedbacks that make convergence to the chosen equilibrium more likely.

# 5 Discussion

This simple model aggregates or ignores many subsystems—for example, different kinds of infrastructure (convenience, safety, pleasantness...) for various trip types (commuting, errands, children's mobility needs, socialisation, leisure...), modes (car, bike, rail, scooter...), and interventions that operate on different spatial and temporal scales (driver education, policing, bike storage, separated lanes, superblocks, zoning, and other incentives for different modes...). We have attempted to capture the essence of the behaviour without creating too many degrees of freedom, but even so, many parameters (especially time constants) are just educated guesses. Additional complexity may offer additional insights at the cost of more guesswork and a combinatorial explosion in parameter space.

Here, the competitive advantage of bicycling was represented only by convenience infrastructure. A more detailed model of competitive advantage may offer insight into nudges *away* from driving, such as parking restrictions, congestion charges, rerouting of through-traffic, etc.

The choice between driving and biking was made through a pared-down model of cyclist convenience and safety, comparing only those two modes. The metric of interest—life expectancy—was only modulated by exercise, collisions, and air pollution. Important future work would expand the pool of transportation users to include those who cannot drive—children, economically disadvantaged, those to whom car parking is not available; and those who cannot bike—especially the large subgroup who are so out of shape that they can only use active modes for very short distances at first, before regaining basic functional health.

The case of children is especially interesting, since not only do independently mobile children reduce the burden of parenting, but the ability to independently explore a city seems likely to facilitate processes by which children turn into competent adults [Bruntlett and Bruntlett, 2021; Silonsaari et al., 2024]. A long-term consequence of weakness in this system has been called the "backseat generation"—children and adolescents who have only experienced mobility from the back seat of a car, and thus have been denied an opportunity for several kinds of cognitive development.

Data are available for the implementation of various bikeshare systems under various infrastructure-development and legal frameworks. Given the number of parameters that can be constrained by the research, it may be possible to fit this model to data and begin to make quantitative predictions.

### 5.1 Stability

This paper examines a bistable system initialised to an unstable equilibrium, so any intervention is interesting. Some of the delays are large: people change habits slowly, in most countries the convenience of cars has been the primary goal of transportation planners for decades resulting in a system requiring extensive modification for some of the more important factors that encourage bicycling, and bikeshare systems and the supporting infrastructure—and mindshare—take many years to permeate a city. Given these long timescales, even an unstable system may appear stable.

However, a few balancing feedback loops must exist. These hypotheses will be explored in future work:

**Car traffic flow rates:** Traffic congestion arises when the demand for road exceeds supply, and since each car creates far more demand than each bike, the system supports many fewer trips by car. As people turn from cars to bikes for more trips, less demand on road systems results in more efficient traffic flows, reducing the traffic cost and terminal cost of trips by car, thus increasing their appeal. On the other hand, improving travel times by car increases the number of trips by car even in the absence of alternatives, through induced demand [Lee et al., 1999; Fosgerau et al., 2023]. Since car traffic delays are highly nonlinear in car traffic volumes, these loops were omitted for simplicity.

**Bicycle theft:** A supply of bicycles supports an ecosystem of thieves, which disincentivises cycling, although bikeshares are less susceptible than bike ownership [Pucher and Buehler, 2008; Handy et al., 2010; Kabra et al., 2020].

**Bike safety perception spread through media:** An interesting possibility explored by Macmillan et al. [2016] is that media preferentially report cyclist killings. Since more cycling usually ($\beta > 0$) results in more killings, to the extent that safety perceptions come from media reports, the appeal of cycling will be self-limiting.

**Bike safety perception spread through social networks:** Early stages of bicycle adoption are frequently facilitated by social interactions. Social-graph structures in which growth connects formerly disconnected components could allow the number of people who hear news of perceived risks to grow faster than the growth of the community. Could this increase the perception of risk fast enough to limit growth?

Change always involves loss. Moving a system towards active transportation tends to be strongly resisted by those who have, through disuse, lost the confidence, willingness, or ability to do even mild physical activity. In this model, this can be somewhat explored by lowering the probability of joining a bikeshare or buying a bike despite logical reasons to do so, and by reducing infrastructure responsiveness. Each of these affects rates of change throughout the system. When these rates are close to rates of decline (e.g. infrastructure decay), the system's asymptotic behaviour becomes sensitive to initial conditions. A more grounded study of these effects could guide acceptable interventions.

### 5.2 Social pressure to wear helmets

As expected for a social-approval–seeking species such as ours, community pressure to wear a helmet may behave similarly to a law. This suggests an interesting possibility: that helmet publicity campaigns and social mores may reduce long-term safety. It is conceivable that such campaigns—which always implicitly and sometimes explicitly exaggerate the dangers of cycling—send a stronger signal than a law that bicycling is dangerous, at the same time stealing attention from the interventions that activate virtuous cycles [Gerhard, 2023]. Furthermore, social norms can broadcast the same message [Ledesma et al., 2019]. If this is the case, then even an individual's choice to wear a helmet may trade a possible increase in safety today for increased risk in the years to come. Perhaps the best choice for an individual is to wear a helmet while discouraging others from doing so.

## 5.3 The big picture

The transition from car-based to active mobility is closely tied to other, larger processes, affecting many of the UN Sustainable Development Goals. Although speculative, feedbacks with the broader social framework could potentially have dramatic and far-reaching effects:

- Childhood autonomous mobility not only reduces parental burden, but is important for both physical and cognitive development, e.g. spatial reasoning, executive control, independence, socialisation, gumption, happiness, etc [Carstensen et al., 2014; Bruntlett and Bruntlett, 2021; Silonsaari et al., 2024].
- We speculate that both presentation of self and recognition of other road users as non-threatening humans rather than as potentially lethal machines [Hennessy and Wiesenthal, 1999; Ellison-Potter et al., 2001] may reduce exposure to fight-or-flight stresses, further reducing burden of disease and improving individual and social health.
- Availability of effective transportation at low cost reduces barriers to mobility, economic hardship, and inequality, thus potentially improving many measures of individual and societal wellbeing [Wilkinson et al., 2019].
- While reduction and avoidance of $CO_2$ emissions is *sine qua non* for humanity, the spatial and temporal health consequences of carbon pollution mitigation are too great, and too timing-dependent, to be easily mapped onto changes in life expectancy. What is certain is that transitioning away from fossil fuels and intensive manufacturing and mining, towards mobility systems that can be rapidly scaled to serve billions, is urgent. Thus, the ratio of mobility and health benefits to societal and environmental costs of bicycle-centric transportation systems, especially given the simplicity and maturity of the technology and expected worldwide urbanisation trends, deserves our attention.

## 5.4 Conclusion

The safety-in-numbers effect is strongly correlated with the risk of bicycle riding, and the arguments and evidence pointing to causal feedback loops are too great to ignore. Assuming increased bicycling increases cyclist safety, we have sketched a model illustrating some potential dynamics of this effect. Initial efforts to increase ridership can activate reinforcing feedback loops, resulting in superlinear (quasi-exponential) gains to life expectancy, healthspan, and wellbeing. As famously described by Meadows [1999], increasing the gain around reinforcing feedback loops is a reasonably effective intervention—in this case potentially adding 2–5 years to cyclist life expectancy, and bringing that benefit to a large proportion of the population. In contrast, helmet laws do nothing to avert car-bike crashes, and cannot improve collision survival by more than a (small) constant factor—the least effective of Meadows' leverage points, consistent with an increase in life expectancy on the order of a few weeks for cyclists, while limiting the number of people to whom that benefit applies, thus reducing population life-expectancy gain to days.

If pressure to wear helmets even slightly suppresses feedback loops that affect ridership, that pressure is expected to erode life expectancy and health far more severely than can be restored even by perfect helmets. Extant static estimates of the public health effects of helmet laws are likely to dramatically underestimate the long-term harm done by unintended consequences, which can push the cost:benefit ratio of helmet laws well beyond 100:1. Given even the remote possibility of this, the potential size of the effects and the far-reaching societal consequences make it vital that any bicycle helmet policy be examined with extreme care.

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