# Optimising the cost-effectiveness of speed limit enforcement cameras 

Shukai Li, Boshen Jiao, Zafar Zafari, Peter Muennig

Mailman School of Public Health, Global Research Analytics for Population Health, Columbia University Mailman School of Public Health, New York City, New York, USA

## Correspondence to

Shukai Li, Global Research Analytics for Population Health, Columbia University Mailman School of Public Health, New York, NY 10040, USA; lishukai@ pku.edu.cn

Received 5 August 2017
Revised 14 November 2017
Accepted 16 February 2018
Published Online First
16 March 2018

To cite: Li S, Jiao B, Zafari Z, et al. Inj Prev
2019:25:273-277.


#### Abstract

Background Using the 140 speed cameras in New York City (NYC) as a case study, we explore how to optimise the number of cameras such that the most lives can be saved at the lowest cost. Methods A Markov model was built to explore the economic and health impacts of speed camera installations in NYC as well as the optimal number and placement. Both direct and indirect medical savings associated with speed cameras are weighed against their cost. Health outcomes are measured in terms of qualityadjusted life years (QALYs). Results Over the lifetime of an average NYC resident, the existing 140 speed cameras increase QALYs by 0.00044 units ( $95 \%$ credible interval (Crl) 0.00027 to 0.00073) and reduce costs by US\$70 (95\% Crl US\$21 to US\$131) compared with no speed cameras. The return on investment would be maximised where the number of cameras more than doubled to 300 . This would further increase QALY gains per resident by 0.00083 units ( $95 \%$ Crl 0.00072 to 0.00096 ) while reducing medical costs by US\$147 (95\% CrI US\$70 to US\$221) compared with existing speed cameras. Overall, this increase in cameras would save 7000 QALYs and US $\$ 1.2$ billion over the lifetime of the current cohort of New Yorkers. Conclusion Speed cameras rank among the most costeffective social policies, saving both money and lives.


## INTRODUCTION

Speed limit enforcement cameras ('speed cameras') have become one of the most widely used tools in wealthier nations to prevent motor vehicle collisions. ${ }^{1}$ There is evidence from meta-analysis and quasi-experimental studies that driver behaviour improves and motor vehicle collisions fall at locations near speed cameras. ${ }^{1-3}$ The effect size depends on the type of camera, the distance from the camera location and local setting characteristics. ${ }^{4}$ Fixed cameras and mobile cameras produce similar reductions in accidents in urban settings, but fixed cameras appear to be more effective in rural settings. ${ }^{4}$ For fixed cameras, the injury reduction rate declines as the radial distance from the speed camera increases. ${ }^{5}$

Speed cameras are analogous to vaccines in that, as more cameras are installed, injury rates fall and until an optimal number (analogous to 'herd immunity') is reached. After this number, further cameras produce declining returns on the investment. To show this relationship, we use New York City (NYC) as a case study to ask whether speed cameras are cost-effective, and, if so, how to optimise the number of cameras in operation. NYC has

140 speed cameras, among which 40 are mobile cameras. However, these 140 cameras can only be operated within 400 m from schools and only operate during school time. ${ }^{6}$ Moreover, the installation cost per camera is as high as US $\$ 120000$ and the maintenance cost per camera is US $\$ 30000$ each year. ${ }^{7}$ It is not clear whether these costs are worth the reductions in motor vehicle collisions that they bring. Moreover, it is not clear whether more cameras or fewer cameras would be optimal from a purely technocratic, apolitical standpoint.

To produce results that are generalisable to other cities, we modelled three different scenarios: one with no cameras installed (the previous status quo), one with the existing network of cameras (the current status quo) and one with a hypothetical scenario in which more cameras are placed in precise locations that would, in theory, maximise the return on investment ('optimal coverage'). This is meant to give policymakers a sense of whether, setting aside political concerns, it is efficient to expand, or perhaps reposition, existing networks of speed cameras.

## METHODS

## Overview

Using a prespecified willingness-to-pay threshold of US $\$ 140000$ per quality-adjusted life year (QALY) gained, we first explore the cost-effectiveness of 140 existing speed cameras (current status quo) compared with no speed camera (previous status quo) in NYC (Model 1). ${ }^{8}$ We then explore the number of cameras that would be associated with the maximum return on investment (Model 2). The maximum return on investment is defined with respect to the number of speed cameras assuming that they are placed a fixed distance apart given NYC's geography (primarily a grid, but with waterfront and greenspace). A Markov model was built in each analysis. The Markov models were based on three health states including healthy, permanently injured and dead. Both direct and indirect medical costs were modelled. Effectiveness outcomes were measured in terms of QALYs. One QALY can be thought of as a year of life lived in perfect health. In both Markov models, a simulation cohort of 36 -year-old (the median age of residents in NYC) New Yorkers was followed over their lifetimes, and the direct and indirect costs as well as the QALYs associated with the different policy scenarios were calculated. In NYC, the last camera instalment was completed in 2015, making NYC a good case study. ${ }^{6}$ All future costs and QALYs were discounted at $3 \%{ }^{9}$ The life cycle in the model was 1 year and

## Original article

Table 1 Values used in the Markov model evaluating existing speed cameras in New York City versus no speed camera

| Parameter | Value (range/SD) | Distribution | Source |
| :---: | :---: | :---: | :---: |
| Probability and HR |  |  |  |
| \% Motor vehicle injury under no speed camera scenario | 0.28\% (low: 0.26\%; high: 0.29\%) | Triangular | NYPD; Mountain et al $^{18}$; Peters et ${ }^{\text {a }}{ }^{16}$; WNYC ${ }^{19}$ |
| HR of existing speed cameras | 0.909 (low: 0.865; high: 0.955) | Triangular | Photo Enforced ${ }^{20}$; US Census Bureau ${ }^{22}$ |
| \% Case fatality rate of motor vehicle injury | 0.39\% (low: 0.34\%; high: 0.44\%) | Triangular |  |
| \% Permanent injury among non-fatal injuries | 0.18\% (low: 0; high: 0.88\%) | Triangular |  |
| Cost (US\$2016) |  |  |  |
| Camera purchase and implementation (per resident) | 1.79 | - | New York City Independent Budget Office ${ }^{7}$ |
| Annual camera maintenance (per resident) | 0.94 | - |  |
| Death cost (per case) | 8994 (SD: 6155) | Gamma | National Funeral Directors Association ${ }^{15}$ |
| Lifetime medical cost for fatal injury (per case) | 16265 (SD: 4879) | Gamma | CDC WISQARS1 ${ }^{13}$; CDC Vital Signs ${ }^{12}$; NYPD ${ }^{21}$ |
| Lifetime medical cost for non-fatal injury (per case) | 3608 (SD: 1082) | Gamma | Naumann et al ${ }^{14}$ |
| Lifetime productivity loss for fatal injury (per case) | 1277926 (SD: 383377) | Gamma |  |
| Lifetime productivity loss for non-fatal injury (per case) | 6682 (SD: 2005) | Gamma |  |
| HRQL |  |  |  |
| Individuals with permanent injury | 0.905 (SD: 0.029) | Beta | Peters et al ${ }^{16}$ |
| Individuals with short-term injury | 0.984 (SD: 0.005) | Beta | Nyman et al ${ }^{17}$ |
| Other |  |  |  |
| Population of NYC | 8625465 | - | NYCDCP ${ }^{21}$ |
| Median age | 36 | - |  |
| \% Discount rate | 3\% | - | Weinstein et al ${ }^{9}$ |

WISQARS, web-based injury statistics query and reporting system; HRQL, health related quality of life; NYC, New York City; NYCDCP, NYC Department of City Planning; NYPD, New York Policy Department.
half-cycle corrections were also employed. Details of parameters probabilistic distributions are provided in the table 1. The model was built in TreeAge Pro 2011 (TreeAge Software, Williamstown, Massachusetts, USA).

## Costs

A societal perspective was adopted in the analyses and included the indirect medical costs in concordance with the Second US Cost-effectiveness Panel. ${ }^{10}$ In the societal perspective, costs are included regardless of who pays. Therefore, the transfer of a cost from a driver to the city (eg, a speeding ticket) is not included. Typically, 'friction costs' associated with these transactions would be included. When a police officer issues a ticket he/she must stop a car, write a ticket and the ticket can be easily contested in court. A speed camera, on the other hand, merely takes a picture of a license plate and a computer prints and mails a ticket, a process with lower time costs. A speed camera ticket is difficult to refute and is issued against the vehicle rather than the driver (and is therefore a smaller penalty). The higher friction costs of human-issued tickets were assumed to be offset by the higher volume of machine-issued tickets. Major model assumptions are listed in table 2.

Monetary costs were adjusted to constant US $\$ 2016$ using the consumer price index of the USA and New York State depending on the source of the cost data. ${ }^{11}$ The lifetime direct and indirect medical cost of all types of motor vehicle injuries were obtained from the CDC's web-based injury statistics query and reporting system (CDC WISQRS) and the proportions of each type were obtained from Naumann et al and CDC vital signs. ${ }^{12-14}$ For lifetime direct medical costs of non-fatal injury, only the costs of hospitalisations or treatments in emergency department were included. The costs per person associated with death (funeral) from the 2009 National Funeral Director's survey were also included because speed cameras have the potential to reduce premature deaths and the time difference can lead to a significant difference in discounted costs. ${ }^{15}$ The implementation cost
and yearly maintenance cost per camera were obtained from the report of NYC Independent Budget Office, which reported US $\$ 26$ million for the hardware and US $\$ 36$ million for 5 years' operation and maintenance of 215 speed cameras. ${ }^{7}$

## Health state utility values

The model also incorporated the impact of injury and death on the victim's health-related quality of life (HRQL), which is required for the calculation of QALYs. HRQL after injury depends on the severity of the injury and the duration of the impact of the injury. The HRQL for permanent injury was obtained from Peters et $a l^{16}$ and the HRQL for short-term injury from Nyman et al. ${ }^{17}$ HRQL for permanent injury was based on the health of adults' longitudinal observational (HALO) study using EuroQol Five

Table 2 Major assumptions made in building the Markov model and their rationales

| Assumption | Rationale (impact on estimates) |
| :--- | :--- |
| Future productivity losses are not <br> included within the health-related <br> quality life score. | There is significant debate surrounding <br> whether EuroQol Five Dimensions <br> Questionnaire scores capture productivity <br> losses. (Favours no speed cameras.) |
| Motor vehicle collision deaths only <br> occur at the time of injury. | Injuries may lead to a higher risk of <br> future death due to the effect of injury on <br> employment and earnings. (Favours no speed <br> cameras.) |
| Friction costs are roughly equal when <br> humans issue tickets and when speed <br> cameras trigger a ticket. | While human-issued tickets are likely much <br> less efficient, the volume of tickets is much <br> high for speed cameras. (Direction of bias is <br> unclear.) |
| Speed cameras only have effects <br> within 1 km from the camera sites <br> and overlapping of coverage does not <br> increase the intervention effect. | Speed cameras have effects even beyond <br> 1 km from the camera site. Overlapping <br> areas may have more traffic injury reduction, <br> but this has not been estimated in the <br> literature. (Favours no speed camera.) |

Dimensions Questionnaire (EQ-5D) (Medical Care Research Unit, University of Sheffield; unpublished report for the Department of Health), and the HRQL value for the short-term injury was based on a time trade off (TTO) analysis. ${ }^{16}$

## Model 1 (existing speed cameras vs no cameras)

This Markov model aimed to quantify the cost-effectiveness of the existing speed cameras (current status quo) versus no speed cameras (previous status quo) in NYC. The structure and parameters of the two arms in the Markov model were the same except for the total cost of speed camera installation plus annual maintenance and the probability of motor vehicle injury. In the status quo arm, the probability of motor vehicle injury was multiplied by a HR adjusting for the reduced risk of injury associated with the presence of a speed camera.

In this Markov model, the hypothetical participants had an annual, age-specific risk of death for all causes of death other than motor vehicle injury. The participants who survived were exposed to the annual risk of fatal or non-fatal injury of motor vehicle injury. In our model, non-fatal injuries can be permanent or short term. We only incorporate motor vehicle injuries during camera operating time. Therefore, our models would underestimate the benefits that could be realised by 24 hours operation. Model inputs are presented in table 1.

We estimated the HR for the existing speed cameras (current status quo) and motor vehicle injury probabilities under a no speed camera scenario. Conservatively, injury reduction was considered only within 1 km from speed camera sites, and this reduction rate within 1 km (mean: $24 \%$, $95 \%$ CI $13 \%$ to $33 \%$ ) was obtained from Mountain et al's ${ }^{18}$ study, which quantified motor vehicle injury reduction rates within different distances from the speed camera site. In NYC, $31.79 \%$ of motor vehicle injury were found to occur within 1 km from speed camera sites, based on the geographical locations of the fixed speed cameras and all reported motor vehicle data from NYC Police Department. ${ }^{18-21}$ Weighted by the proportions of motor vehicle injury within and outside the camera coverage, the HR on average is 0.91 ( $95 \%$ CI 0.87 to 0.96 ) in NYC.

Because mobile cameras in NYC account for less than 30\% of total cameras and only operate on certain days, only 100 fixed cameras in the city were taken into consideration when calculating the HR for the existing speed cameras as a conservative estimation. ${ }^{6}$ However, the installation and maintenance costs of all 140 fixed or mobile cameras were included in our model. Speed cameras were assumed to not be able to affect traffic in areas that are separated from the camera with significant geographical factors, that is, on the other side of a river. The underlying assumptions of the modelling approach are listed in table 2.

## Model 2 (optimal coverage)

The second Markov model evaluated a sequence of hypothetically intensified speed camera programmes, where the total number of cameras was sequentially expanded to $200,250,300$,

Table 3 The cost, incremental cost (US\$2016), quality-adjusted life years (QALYs) gained, incremental QALYs gained and incremental costeffectiveness ratio (ICER) of the existing speed camera programme in New York City versus no speed camera

|  |  | Incremental <br> cost | QALY | Incremental <br> QALY | ICER |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Ctrategy | Cost | Qo speed camera | 3699 | - | 23.9397 |
| Existing speed <br> cameras | 3629 | -70 | 23.9401 | 0.0004 | Cost saving |

350, 400 and 450 . When cameras are placed closer together, injuries fall, but with diminishing effectiveness per installed camera. ${ }^{518}$ Moreover, installing more cameras in the city comes with additional implementation and maintenance costs.

To calculate the HRs associated with each 50 camera incremental increase, it was assumed that all cameras would be installed in the city uniformly (eg, without overlapping the injury reduction zones of some cameras while leaving other zones uncovered). The average coverage area and radius for each camera were calculated by dividing the total land area of NYC by the total number of cameras. The function describing the relationship between motor vehicle injury reduction and the radius of a speed camera was obtained from the literature. ${ }^{5}$ The area data of NYC was obtained from the US Census Bureau. ${ }^{22}$

## Sensitivity analysis

A probabilistic Monte Carlo simulation was performed with 10000 random samplings for our model parameters. A comprehensive one-way sensitivity analysis was performed for all parameters of the two policy models including probability of injury, HR, productivity loss, medical costs and so on.

## RESULTS

## Model 1 (existing speed cameras vs no cameras)

The results of this model are presented in table 3. Over a lifetime, the costs per person were US $\$ 3699$ for no speed cameras (previous status quo) and US $\$ 3629$ for existing speed cameras (current status quo). The existing speed cameras reduced costs by US\$70 (95\% Credible Interval (CrI) US\$21 to US\$131). In addition, the corresponding QALYs gained per person were 23.93970 for no speed cameras and 23.94014 for existing speed cameras. The existing speed cameras increased QALYs gained by 0.00044 units ( $95 \% \mathrm{CrI} 0.00073$ to 0.00027 ) per capita versus no speed camera.

## Sensitivity analysis

The one-way sensitivity analyses suggested that the most sensitive model parameters were productivity loss due to non-fatal injury, productivity loss due to fatal injury, medical costs due to non-fatal injury and the probability of motor vehicle injury. Changing the lifetime productivity loss of each non-fatal injury from US\$2673

Table 4 One-way sensitivity analyses, existing speed cameras in New York City versus no speed cameras

| Parameter | Incremental cost (US\$2016) |  | Incremental QALYs gained |  |
| :---: | :---: | :---: | :---: | :---: |
|  | Low | High | Low | High |
| Lifetime productivity loss for non-fatal injury (per case) (low: US\$2673; high: US\$10 692) | -148 | -59 | 0.0005 | 0.0005 |
| Lifetime productivity loss for fatal injury (per case) (low: US\$511 170; high: US\$2044 681) | -129 | -62 | 0.0005 | 0.0005 |
| Lifetime medical cost for non-fatal injury (per case) (low: US\$1443; high: US\$5772) | -112 | -64 | 0.0005 | 0.0005 |
| Probability of motor vehicle injury (low: 0.26\%; high: $0.29 \%$ ) | -75 | -66 | 0.0004 | 0.0005 |

The low and high values of productivity loss and medical costs were adjusted to US\$2016.
QALY, quality adjusted life year.

[^0]Table 5 Per capita costs and quality-adjusted life years (QALY) gained for scenarios with a different number of speed cameras

| Total camera <br> number | Per capita costs <br> (US\$2016) | Per capita QALY <br> gained | ICER (vs 300 cameras) <br> (US\$2016/QALY) |
| :--- | :--- | :--- | :--- |
| 0 | 3698.67 | 23.93970 | Dominated |
| 200 | 3480.01 | 23.94090 | Dominated |
| 250 | 3479.56 | 23.94094 | 64149 |
| 300 (reference | 3481.49 | 23.94097 | - |
| scenario) | 3484.85 | 23.94100 | 112234 |
| 350 | 3489.15 | 23.94102 | 153228 |
| 400 | 3494.27 | 23.94103 | 213001 |
| 450 |  |  |  |

The low and high values of productivity loss and medical costs were adjusted to US\$2016.
ICER, incremental cost-effectiveness ratio.
to US\$10 692, lifetime productivity loss of each fatal injury from US\$511170 to US\$2044681, lifetime medical costs of each non-fatal injury from US $\$ 1443$ to US $\$ 5772$ and the probability of motor vehicle injury from $0.26 \%$ to $0.29 \%$, we found the existing speed cameras (current status quo) still dominated no speed cameras irrespective of the values entered (table 4). Other model parameters did not have pronounced impact on the model outcomes.

## Model 2 (optimal coverage)

The results of this model are presented in table 5. Compared with no speed cameras, total camera instalments of up to 450 were always cost saving. When 200, 250, 300, 350, 400 and 450 cameras were installed, US\$218.7, US\$219.1, US\$217.2, US\$213.8, US\$204.4 and US $\$ 209.5$ per person were saved, respectively, over the lifetime of the cohort compared with no speed cameras. The corresponding incremental QALYs gained for these camera instalments versus no speed cameras were $0.00120,0.00124,0.00127,0.00130$ and 0.00132 and 0.00133 units, respectively. In our model, the lowest cost was achieved when additional 110 cameras were installed, bringing the total number of cameras in NYC up to 250 . The
incremental QALYs gained with 250 cameras would be 0.00124 ( $95 \%$ CrI 0.00006 to 0.00258 ) versus no speed cameras.

We also depicted the incremental cost-effectiveness ratio (ICER) for each of the 50 cameras installed (eg, 250 vs 200, 300 vs 250 ) in figure 1. The ICER is US\$64 149 ( $95 \%$ CrI cost saving to US $\$ 127$ 303) per QALY gained for 300 cameras versus 250 cameras and US\$112234 (95\% CrI US\$55 494 to US\$203 394) per QALY gained for 350 cameras versus 300 cameras.

## DISCUSSION

The speed cameras were shown to save both money and lives compared with no speed cameras. In the world of health investments, this is rare. For example, while vaccines are often found to be cost saving, for most medical treatments, one must spend tens of thousands of dollars to purchase one QALY. ${ }^{8}$

However, as with vaccines, there are declining returns on the investment as more cameras are installed. That is, there is a 'herd immunity' effect with speed cameras in which an optimal number will produce a very low accident rate, and only minuscule gains can be achieved with additional investments. NYC is used as a case study to illustrate this effect. In NYC, if the number of cameras increased from the current 140 cameras to 200 cameras, or from 200 cameras to 250 cameras, we would still realise savings along with small gains in QALYs. However, if the number subsequently increased from 250 cameras to 300 cameras, the ICER of the additional 50 cameras' instalment would reach US $\$ 50000$ per QALY gained. As the number of cameras in the reference scenario increases, the ICER of the additional 50 camera instalments rapidly crosses US $\$ 140000$ per QALY gained (figure 1), one 'rule of thumb' upper limit for cost-effective analysis. If US $\$ 140000$ per QALY gained is used as a standard for willingness to pay, then the optimal number of speed cameras is around 300 for NYC: 300 cameras in total are cost-effective (ICER’s 95\% CrI completely below US\$140 000) compared with 200 or 250 cameras, and at the same time, 350 , 400 or 450 cameras are not cost-effective compared with 300 cameras (figure 1). In this case study, however, it should be kept


Figure 1 Incremental cost-effectiveness ratio of additional 50 camera instalments in scenarios with different number of speed cameras (eg, 200 vs 250,250 vs 300 and so on). The vertical lines are $95 \%$ credible intervals. QALY, quality adjusted life years.

## What is already known on the subject

- Driver behaviour improves and motor vehicle collisions decrease at locations near speed cameras.
- The effect size of speed cameras depends on the type of camera, distance from the camera site and local setting characteristics.


## What this study adds

- Speed cameras are likely to save money and lives in most areas in which they are used.
- There are an optimal number of speed cameras, above which the return-on-investment diminishes. In New York City, the optimal number is more than double the current number in use.
in mind that 300 or even 400 cameras would still save money and lives compared with no speed camera.

Studies indicate that speed cameras reduce traffic speeds at least within 1 km of the camera. ${ }^{5}$ Currently, speed cameras cover only about one-third of NYC's usable streets, so a rough rule-of-thumb is that spacing cameras far enough apart that they cover every kilometre of NYC would be cost saving and a good public health investment. This excludes greenspace or other areas without roads. However, it is important to weigh political and ethical factors against economic factors. For example, to reduce political fallout, NYC's speed cameras only operate during school time and within school zones.

Because a ticket merely transfers costs from drivers to the government, producing no societal change, only savings from motor vehicle injuries and death costs were considered and weighted against the cost of implementation and maintenance of traffic cameras. From the perspective of a city government, traffic cameras are intuitively cost-effective, and this perspective was not included in this analysis.

A final consideration is that different cultures and localities have different tolerances for speed cameras. In some countries, speed cameras are used to 'blanket' areas. Drivers are warned before they approach them, both with road signs and navigation software. ${ }^{23}$ This is a very effective way to reduce speeds, but, based on our case study in NYC, it is unlikely to come at a good value.

## Limitations

The study was subject to a number of limitations. Foremost, the literature on the efficacy of speed cameras shows a fairly wide range of efficacy and effectiveness values. The models use a wide range of effectiveness values and suggest that we can be confident that speed cameras will produce good value when used sparingly. However, their value becomes less certain the closer one gets to an 'optimal' number of camera installations. Additionally, while the literature examining the causal impact of speed cameras on injuries is growing, it is not mature. There is more work across different contexts needed in this area. It would be useful if cities adopting speed cameras did so by rolling them out in a random fashion over time so that their efficacy could be properly evaluated.

These limitations aside, the models suggest that speed cameras should be added to the arsenal that public health practitioners have for improving population health. While we use NYC as a case study, our analysis likely underestimates the benefits that would be realised
in other locales because we add a good deal of elbow room for the cost savings and health benefits (eg, we assume that the 40 mobile cameras would have no impact, and we assume speed cameras only have effects within 1 km from the camera sites and overlapping of coverage does not increase the intervention effect). Thus, when used in moderation and in politically palatable ways, they can both save money and lives-a feat rarely accomplished in health.

Acknowledgements The authors would like to thank Amel Benzerga for helping edit the manuscript.
Contributors All the authors initiated and designed the study and participated in revising or reviewing the manuscript. All the authors have approved the final manuscript for submission. $\operatorname{SL}, \mathrm{BJ}$ and $Z Z$ designed the the model. SL and BJ supplied required simulation parameters. SL designed the HR analysis, ran the model simulations and conducted required data processing and analysis and also conducted a critical review of the manuscript for important intellectual content. ZZ and PM advised on technical implementation of simulation design.
Funding This study was funded by Global Research Analytics for Population Health at the Mailman School of Health, Columbia University. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.
Competing interests None declared.
Provenance and peer review Not commissioned; externally peer reviewed.
© Article author(s) (or their employer(s) unless otherwise stated in the text of the article) 2019. All rights reserved. No commercial use is permitted unless otherwise expressly granted.

## REFERENCES

1 Wilson C, Willis C, Hendrikz JK, et al. Speed cameras for the prevention of road traffic injuries and deaths. The Cochrane Library 2010.
2 Scott N, Janssen K, Harris D, et al. Identifying optimal sites for static speed cameras in New Zealand: a geospatial approach. Australasian Road Safety Conference 2016. Canberra, ACT, Australia. 2016.
3 Høye A. Safety effects of fixed speed cameras-an empirical Bayes evaluation. Accid Anal Prev 2015;82:263-9.
4 Gains A, Nordstrom M, Heydecker B, et al. The national safety camera programme: four-year evaluation report. 2005.
5 Hess S. Analysis of the effects of speed limit enforcement cameras: Differentiation by road type and catchment area. Transp Res Rec 2004;1865:28-34.
6 New York CIty Police Department. Vision zero year two: vision zero year two. New York City 2016.
7 New Yorl City Independent Budget Office. Transportation funds added for vision zero, traffic enforcement cameras. 2016.
8 Muennig P, Bounthavong M. Cost-effectiveness analysis in health: a practical approach. John Wiley \& Sons, 2016.
9 Weinstein MC, Siegel JE, Gold MR, et al. Recommendations of the panel on costeffectiveness in health and medicine. JAMA 1996;276:1253-8.
10 Sanders GD, ed. 2nd panel on cost effectiveness in health and medicine. The 36th Annual Meeting of the Society for Medical Decision Making. Society for Medical Decision Making, 2014.
11 US Department of Labor. Consumer Price Indexes (CPI) Bureau of Labor Statistics. 2017.

12 Center for Disease Control and Prevention. Motor vehicle crash injuries. 2014.
13 Center for Disease Control and Prevention. Web-based injury statistics query and reporting system (WISQARS), cost of injury reports 2010. National Center for Injury Prevention and Control, Centers for Disease Control and Prevention, 2014.
14 Naumann RB, Dellinger AM, Zaloshnja E, et al. Incidence and total lifetime costs of motor vehicle-related fatal and nonfatal injury by road user type, United States, 2005. Traffic Inj Prev 2010;11:353-60.
15 National Funeral Directors Assocation. 2009 National Funeral Directors' Survey. 2009.
16 Peters JL, Anderson R. The cost-effectiveness of mandatory 20 mph zones for the prevention of injuries. J Public Health 2013;35:40-8.
17 Nyman JA, Barleen NA, Kirdruang P. Quality-adjusted life years lost from nonfatal motor vehicle accident injuries. Med Decis Making 2008;28:819-28.
18 Mountain L, Hirst W, Maher M. Costing lives or saving lives: a detailed evaluation of the impact of speed cameras. Traffic, Engineering and Control 2004;45:280-7.
19 WNYC. Cartographer Speed Cameras and the City. New York City. 2015.
20 Photo Enforced. Cartographer New York City Photo Enforced Cameras Map. New York City. 2016.
21 NYPD. Motor Vehicle Collisions Open Data. In: NYPD, ed. 2017.
22 US Census Bureau. QuickFacts. 2016.
23 Kim E, Muennig P, Rosen Z. Vision zero: a toolkit for road safety in the modern era. Inj Epidemiol 2017;4:1.


[^0]:    
    

