ADDICTION
SSA SOCIETY FOR THE STUDY OF ADDICTION

RESEARCH REPORT
doi:10.1111/add.14470

Assessing the impact of alcohol taxation on rates of violent victimization in a large urban area: an agent-based modeling approach

Katherine M. Keyes[1,2], Aaron Shev[3], Melissa Tracy[4] & Magdalena Cerdá[5]

Department of Epidemiology, Mailman School of Public Health, Columbia University, New York, NY, USA,[1] Center for Research on Society and Health, Universidad Mayor, Santiago, Chile,[2] Department of Emergency Medicine, School of Medicine, University of California, Davis, Sacramento, CA, USA,[3] Department of Epidemiology and Biostatistics, State University of New York at Albany, Albany, NY, USA[4] and Department of Population Health, NYU Langone Health, New York, NY, USA[5]

ABSTRACT

Aims To use simulation to estimate the impact of alcohol taxation on drinking, non-fatal violent victimization and homicide in New York City (NYC). We simulate the heterogeneous effects of alcohol price elasticities by income, level of consumption and beverage preferences, and examine whether taxation can reduce income inequalities in alcohol-related violence. **Design** Agent-based modeling simulation. **Setting** NYC, USA. **Participants** Adult population aged 18–64 years in the year 2000 in the 59 community districts of NYC. The population of 256 500 agents approximates a 5% sample of the NYC population. **Measurements** Agents were parameterized through a series of rules that governed alcohol consumption and engagement in violence. Six taxation interventions were implemented based on extensive reviews and meta-analyses, increasing universal alcohol tax by 1, 5 and 10%, and beer tax by 1, 5 and 10%. **Findings** Under no tax increase, approximately 12.2% [95% credible interval (prediction interval, PI) = 12.1–12.3%] were heavy drinkers. Taxation decreased the proportion of heavy drinkers; a 10% tax decreased heavy drinking to 9.6% (95% PI = 9.4–9.8). Beer taxes had the strongest effect on population consumption. Taxation influenced those in the lowest income groups more than the highest income groups. Alcohol-related homicide decreased from 3.22 per 100 000 (95% PI = 2.50–3.73) to 2.40 per 100 000 under a 10% universal tax (95% PI = 1.92–2.94). This translates into an anticipated benefit of ~1200 lives/year. **Conclusion** Reductions in alcohol consumption in a large urban environment such as New York City can be sustained with modest increases in universal taxation. Alcohol tax increases also have a modest effect on alcohol-related violent victimization. Taxation policies reduce income inequalities in alcohol-related violence.

Keywords Agent-based modeling, alcohol, complex system, homicide, taxation, taxes, violence, violent victimization.

Correspondence to: Katherine M. Keyes, Department of Epidemiology, Mailman School of Public Health, Columbia University, 722 West 168th Street #724, New York, NY 10032, USA. E-mail: kmk2104@columbia.edu
Submitted 21 December 2017; initial review completed 22 May 2018; final version accepted 5 October 2018

INTRODUCTION

Violence and homicide continue to be endemic public health problems in the United States and are disproportionately concentrated in urban areas and large cities [1], suggesting that a public health focus on these areas in particular will have the largest impact. Further, there remain substantial socio-economic disparities in violence burden, with those in the lowest socio-economic strata most likely to be affected [2,3]. Among homicide decedents, alcohol is detected in approximately 40% of cases [4–6], which is more than all other substances of abuse combined.

Control of alcohol-related injury and violence requires population-level policy interventions [7], and in reviews of policy effectiveness for reducing alcohol-related outcomes alcohol taxation has among the most clear and compelling evidence for efficacy [7–9]. Meta-analyses and reviews combining more than 100 studies of alcohol taxation have converged on moderate effects of alcohol taxation on a diverse array of alcohol-related outcomes [10–12], including effects on violence [13–15]. The effects of alcohol tax and price on alcohol-related outcomes are typically reported in terms of price elasticity, or the extent to which buying behavior changes with changes in price. When goods are inelastic to price, then price increases will have small and diminishing effects on alcohol consumption, increase tax revenue and increase the amount of personal income spent on the good among consumers. The most recent meta-analysis indicates that, for example, the price elasticity of taxation and price on heavy drinking is approximately −0.28 [11], which indicates an approximately 3% decrease in heavy drinking given a 10% increase in price.

However, there remain important gaps in our understanding of the effects of alcohol taxation on alcohol-related health problems which existing observational data are ill-equipped to address. Elasticity through taxation varies by income [16,17], by type of beverage (beer, wine or spirit [18]) and by type of consumer (heavy drinker versus light drinker [11,19–21]). Simulation studies have estimated that heavy consumers pay as much as five times the cost of taxation compared with moderate consumers [22] per capita. Thus, alcohol taxation will affect different groups heterogeneously; while previous studies have estimated variations in elasticity across each of these groups in isolation, the conjoint effects of all three have not been considered. This is important, as cities and neighborhoods differ on average income as well as beverage practices simultaneously, and both probably modify the effectiveness of alcohol taxes. Further, the population-level effect of alcohol taxation on violence and homicide also depends on the level of violence in the community and the characteristics of social networks of drinking, which are difficult to untangle in observational data given the dyadic nature of violent interactions between a perpetrator and victim [23], and the homophily of social networks with respect to drinking levels [24]. However, these dynamics are key to understanding the potential bounds of effectiveness of alcohol taxes among different populations.

Because of the complex system in which these interactions are embedded, the assumptions of traditional approaches to assessment of these effects are often violated. Agent-based models (ABMs) [25,26] are an analytical approach that has been used to examine neighborhood and community influences on alcohol consumption as well as violence [27–29]. Because ABMs consist of simulations that follow prescribed rules about the characteristics of agents, their networks, contexts and behaviors, we can conduct simulated policy experiments without violations of model assumptions, issues of resource costs or ethical concerns. Further, ABMs allow us to specify interdependence between agents and the spread of agent behaviors, thus capturing the complexity of social networks in which alcohol and violence occur. The present study uses an ABM to estimate the impact of various approaches to alcohol taxation on drinking, non-fatal violent victimization and homicide in New York City (NYC), while incorporating social networks, neighborhood influences on alcohol use such as density of alcohol outlets and simulating the heterogeneous effects of alcohol price elasticities by income, level of consumption and beverage preferences.

METHODS

We developed an agent-based model (ABM) simulating the dynamic processes contributing to violence among adults in NYC, including the interactions between victims and perpetrators within specific geographically defined spaces, and the influence of social networks on both alcohol consumption and the risk of violence. Figure 1 illustrates the relations included in the model, which builds on our previous ABMs of violence in NYC [27–29]. Data from NYC sources were used to parameterize and calibrate the model when possible; when NYC data were not available, national or other community-based data were used (see data sources in Supporting information, Table A1). Parameter values from the data are taken as fixed, non-random quantities. Key components of the model are summarized below; additional details concerning model parameters and processes, including a description of the model following the ODD (overview, design concepts, details) protocol [30,31] (Supporting information, Appendix 1, includes statement of purpose, entities, state variables and scales, process overview and scheduling, design concepts, initialization and submodels), initialization parameters and default values (Supporting information, Table A2), flow-charts illustrating steps in the model (Supporting information, Figs A2–A3) and pseudo-code for the model (Supporting information, Appendix 2) are included in the Supporting information Appendices.

Each model step represented 1 year in time, and the model was run for a total of 10 years. At each time-step, agents could change their location, drinking status, victimization and perpetration probabilities, all based on the developed history of behaviors and location across model runs.

MODEL COMPONENTS AND INITIALIZATION

Agent population and neighborhoods

The baseline agent-based model used for initial parameterization has been described elsewhere [28,29]. Briefly, the population of 256 500 agents was initialized to approximate a 5% sample of the NYC adult population aged 18–64 years in the year 2000. Agents were assigned to each neighborhood, proportionate to size, so that distributions of age, sex, race/ethnicity and household income matched Census data for each of the 59 community districts in NYC for the year 2000 [32]. The year 2000 was chosen because most data used to parameterize agent behaviors were collected in the mid-2000s. Individual behaviors were influenced by neighborhood characteristics and vice versa. We varied the influence of neighborhoods on individual behavior in sensitivity analyses examining overall violence and alcohol-related violence, presented in Supporting information, Appendix 3.

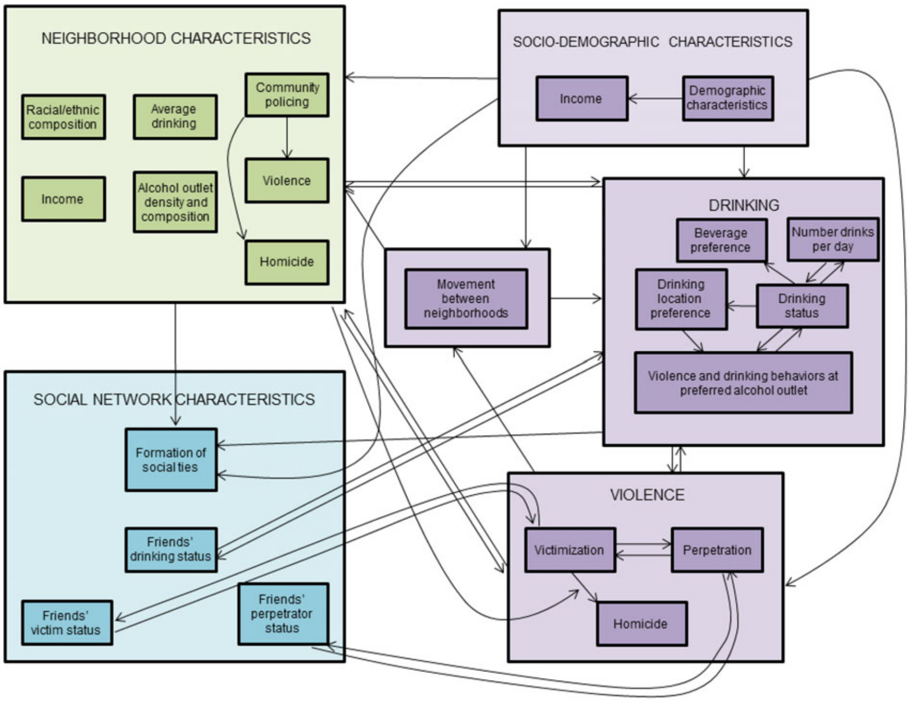

Figure 1 Diagram of relations between agent, social network and neighborhood characteristics in the agent-based model [Colour figure can be viewed at wileyonlinelibrary.com]

Alcohol outlets

Given associations between alcohol outlets and occurrence of violence [33–36], we used data from the New York State Division of Alcoholic Beverage Control (NYS Liquor Authority, 2002) to specify locations of alcohol outlets in neighborhoods, and the model was parameterized to account for variation in violence by outlet density. Details are provided in the Supporting information, Appendix 1, and a sensitivity analysis on the influence that violence near outlets could have on future violence and alcohol-related violence risk is presented in the Supporting information, Appendix 3.

Social network

Each agent was assigned a target number of close ties, with an average of three ties per agent [37]. Agents were matched based on age, sex, race/ethnicity, education, drinking status and spatial proximity, such that agents who were more similar and geographically closer to each other were more likely to become social ties [37,38]. For simplicity, social network members matched to a particular agent at baseline remained that agent's social network for the duration of the model run. Based on empirical social network literature [23], an agent's ties increased the probabilities of the agent becoming a victim of violence or a perpetrator by up to 100% if the agent was tied with other agents who were victims or perpetrators. The number of ties with agents of a given drinking status also increased the probability of transitioning to that drinking status by as much as 15%. Because empirical data verifying these estimates are relatively few, we varied the percentage of influence that the social network could have on individual drinking status and violence and examined rates of violent victimization and alcohol-related victimization in a sensitivity analysis presented in the Supporting information, Appendix 3.

Aging, mortality and movement

At each time-step, agents aged by 1 year, an empirically defined proportion of agents moved to a new neighborhood in the model, and agents died consistent with 2000 NYC adult all-cause mortality rates [39]. Agents' probabilities of moving were based on their income, duration of residence in their current neighborhood and experiences of violent victimization at the last time-step, calibrated using data from longitudinal studies in urban areas [40] and the Panel Study of Income Dynamics [41]. Each agent who died was replaced with an 18-year-old agent with the same characteristics and neighborhood location as the deceased agent, thus maintaining a constant population size and composition in the model, except for age structure.

Violence

At each time-step, each agent could perpetrate violence and/or experience non-fatal or fatal violent victimization.

Dynamics of victimization were based on a simplified routine activities model [42]. Probabilities of violent perpetration were calculated from nationally representative longitudinal data collected among adults in the United States [43], and non-fatal violent victimization probabilities were estimated from a longitudinal study of 2752 adult residents of the NYC metropolitan area with three waves of follow-up [44] (see Supporting information, Appendix 1). Homicide probabilities were informed by data from the Office of the Chief Medical Examiner in NYC [44]. Consistent with research finding important influences of social networks and neighborhood conditions on violence [23,45], social network characteristics contributed 15% and neighborhood characteristics contributed 10% of the agents' probabilities of homicide, non-fatal victimization and violent perpetration. These weights were varied in sensitivity analyses (Supporting information, Appendix 3). Homicides and violent victimization were deemed to be attributable to alcohol if the perpetrator or the victim were heavy drinkers at the time of the encounter.

Based on the aforementioned probabilities, potential victims and perpetrators were identified at each time-step. Potential perpetrators (i.e. those with a high predicted probability of perpetrating violence) searched a 15-cell radius around their location for potential victims (i.e. those with a high probability of being victimized); any such agents who had not already been victimized at that time-step were matched to a perpetrator unless a police officer was present within a two-cell radius of the victim, in which case the potential victim was protected from violence. The 15-cell radius was determined during the calibration process as most accurately achieving empirical estimates of victimization and perpetration in the model, and the cell radius for which violent perpetration could occur was varied in sensitivity analyses detailed in the Supporting information, Appendix 3.

Alcohol use

Each agent was assigned a baseline drinking status: nondrinkers, light/moderate drinkers or heavy drinkers. Drinking status was based on predictive models including individual-level characteristics, social network characteristics and neighborhood characteristics, with parameterization based on a range of NYC-centric and national data (see Supporting information, Appendix 1). In addition to drinking status, agents were also assigned an average number of drinks per day. This value was selected randomly from the empirical distribution of drinks per day for each drinking status observed in the data. At each time-step, the agent could change drinking status; transitions were predicted using individual, social network and neighborhood predictors.

Beverage types

Agents could choose to drink up to three types of alcohol: beer, wine and spirits. Calibration of beverage type was based on nationally representative data collected among adults [43] where respondents were asked how often they consume beer, wine and spirits in separate modules; frequently consumed beverage types were then predicted by demographic characteristics including age, sex, race, income, education and drinking status. Frequency of consumption of each beverage was not mutually exclusive: for example, agents could frequently consume all three beverage types or have a preference for a specific type (e.g. exclusive beer drinking).

MODEL CALIBRATION AND INTERVENTION SCENARIOS

During model calibration, ABM estimates were compared to empirical data on total and neighborhood-specific population composition. An iterative process [46] was then used to adjust predictive equations and initial conditions in the model until estimates closely matched the empirical data (see Table 1).

Each model was run for 120 time-steps. The first 110 time-steps were discarded as a 'burn-in period' [29], during which the distributions of characteristics such as age, mortality and history of violence for agents and neighborhoods converged; the length of time of the 'burn-in period' was necessary in order to obtain stability in the estimates. Only results from the final 10 time-steps were included in analyses.

We implemented alcohol taxation policies under several scenarios. First, we considered the effect of a tax on any alcoholic beverage at three levels: 1, 5 and 10% tax. The effect of these taxation levels on consumption were modeled based on empirical data sources on price elasticity ([10,11,18,19] and see Supporting information, Appendix 4). We used data from three studies to establish price elasticity: data on elasticity by beverage type (beer, wine or spirits) were drawn from Wagenaar *et al*. [11], the most updated meta-analysis of 112 studies of taxation and consumption. Wagenaar *et al*. [11] also published elasticity estimates by amount of drinking (heavy, moderate, light). Additionally, we used data from the meta-analysis by Nelson *et al*. [9], which published data on elasticity by quintiles of income. Given that elasticity across the joint distribution of all three of these variables is not available in these studies, we assumed a constant marginal effect (e.g. the elasticity estimate for beer did not vary across income levels, and the elasticity estimate by income level did not vary by beverage preference). That is, we assumed that the elasticity estimate for heavy drinking beer consumers with low income was the product of the three elasticity

Table 1 Agent characteristics and comparisons with empirically available data.

	Total		
	ABM estimates (95% CI)	*NYC estimates*[a]	*Estimates from other data sources*[b]
Baseline drinking status (%)			
Non-drinker	46.5 (46.4–46.6)	42.7 (50.6–44.8) 55.2 (52.7–57.8)	45.6 (45.0–46.2)
Light/moderate drinker	41.3 (41.2–41.4)	47.0 (44.9–49.1) 33.2 (30.9–35.6)	41.4 (40.8–41.9)
Heavy drinker	12.2 (12.1–12.3)	10.3 (9.0–11.5) 11.6 (9.9–13.4)	13.0 (12.6–13.4)
Drinking transitions (%)			
Non → light/moderate	16.3 (16.2–16.4)	20.8 (17.8, 24.1)	15.7 (15.0–16.4)
Light/moderate → non	18.6 (18.6–18.7)	15.0 (12.3, 18.3)	22.9 (21.5–24.3)
Light/moderate → heavy	9.3 (9.2–9.3)	11.8 (9.1, 15.1)	24.5 (23.0–26.0)
Heavy → light/moderate	32.8 (32.6–32.9)	35.5 (28.3, 43.4)	55.4 (54.6–56.2)
Violent victimization (%)[d]			
Past-year victimization	3.67 (3.64–3.69)	3.6 (2.3, 6.0)	1.4 (1.3–1.6); 8.0
Life-time victimization	38.1 (37.9–38.2)	32.3 (30.8, 33.9)	15.0; 19.8 (19.4–20.3); 50.8
Violent perpetration (%)[e]			
Past-year perpetration	0.56 (0.54–0.57)	NA	0.44 (0.40, 0.49); 3.2
Lifetime perpetration	11.0 (10.9–11.1)	NA	10.1 (9.7–10.5); 17.7
Homicide rate (per 100 000)[c]			
Total homicide	11.8 (10.9–12.9)	10.7	NA
Alcohol-related homicide	3.22 (2.50–3.73)	3.14	NA

[a]New York City (NYC) data sources include World Trade Center study [44], New York Social Environment Study [59] and data from the Office of the Chief Medical Examiner in NYC [39]. [b]Estimates from other data sources include National Epidemiologic Survey on Alcohol and Related Conditions (NESARC) [43], Detroit Neighborhood Health Study (DNHS) [40] and the Panel Study of Income Dynamics [41]. [c]Population estimates not drawn from sample; no confidence intervals included. [d]Past-year victimization calibration based on estimates in Potter, 2009 (8.0%) and National Epidemiologic Survey on Alcohol and Related Conditions (NESARC) [1.4%, 95% CI = 1.3–1.6]; life-time victimization calibration based on estimates in Norris, 1992 [57] (8.0%); NESARC (19.8% 95% CI = 19.2–20.3); and the Detroit Neighborhood Health Study (50.8%). [e]Past-year perpetration calibrated based on estimates in Silver, 2005 [56] (3.2%) and NESARC (0.44%, 95% CI = 0.40–0.49). Life-time perpetration calibrated based on estimates in Elbogen, 2009 [58] (17.7%) and NESARC (10.1%, 95% CI = 9.7–10.5). NA = not applicable.

estimates for heavy drinking, beer consumption and the lowest income quintile. Thus, beverage type, income and consumption each had a main effect on consumption, and we generated 30 different elasticity estimates from the 10 elasticity estimates reported in meta-analysis (shown in Supporting information, Appendix 4).

Secondly, we considered the effect of a tax on beer consumption, as it was the most prevalent type of beverage consumed. Taxation was applied throughout all neighborhoods, but the effect of taxation on drinking was allowed to vary by income, beverage type and drinking status (non-drinker, light or heavy drinker). In NYC alcohol is subjected to several taxes, including a New York State excise tax on sale or use, as well as an additional NYC excise tax on the sale or use of beer and liquor containing more than 24% alcohol by volume. Taxes on alcohol in NYC have had some adjustments over time (e.g. inclusion of a city excise tax for wine), and while taxes on high-content liquor are among the highest in the nation, taxes on beer and wine are slightly higher than the median; our tax estimates were based on overall estimates of elasticity from meta-analyses, thus changes in the NYC tax code have limited impact.

Five parameters were chosen for the sensitivity analysis. The first two are weights for the impact of neighborhood characteristics and social networks. Various events in the model, such as violent victimization and transitioning drinking status, are governed by probabilities constructed from individual agent, neighborhood and social network characteristics. The neighborhood and social network weights determine the percentage of the contribution these classes of variables have on the probabilities. Additionally, we varied the radius around an outlet within which it will be affected by a violent event, the radius for which an agent will look for an alcohol outlet, and the radius for which a perpetrator of violence will look for a victim. These latter three parameters set the distance at which outlets affect agent behaviors and agents interact with outlets and each other. Finally, we also added a sensitivity analysis in which we ran taxation interventions in a model without social network and neighborhood effects in order to determine the extent to which the model results were impacted by these layers.

The model was developed using Recursive Porous Agent Simulation Toolkit for Java (RepastJ, version 3.0), and implemented in Eclipse (version 4.2). To account for the stochastic nature of the modeling each model scenario was run 50 times, with the median, 2.5th percentile, and 97.5th percentile reported from across the 50 simulations; variation is due to the stochastic nature of the model.

RESULTS

Table 1 shows the characteristics of the agent population. The overall distributions of key parameters closely mirrored those empirically estimated from NYC-based and national data sources.

Table 2 shows the effect of taxation on the prevalence of drinking, alcohol-related violence and homicide. Universal alcohol taxes decreased the proportion of agents classified as heavy drinkers: under no tax increase, an estimated 12.2% [95% percentile interval (PI) = 12.1–12.3%] of the sample were heavy drinkers; this decreased to an estimated 11.5% at a 1% tax (PI = 11.2–11.8%) and to an estimated 9.6% (PI = 9.4–9.8%) with a 10% tax. Universal taxation also slightly decreased light drinking, from an estimated 41.3% (PI = 41.2–41.4%) under no tax increase to an estimated 40.2% (PI = 40.0–40.4%) under a 10% tax. Results were driven primarily by beer taxes; the heavy drinking prevalence decreased from an estimated 12.2% (PI = 12.1–12.3%) to an estimated 10.5% (PI = 10.2–10.7%) by only increasing beer tax by 10%.

Taxation had little impact on overall violence (see Table 2), but reduced alcohol-related violence. Alcohol-related homicide decreased from an estimated 1126.7 per 100 000 under no tax increase (PI = 1097.6–1169.6) to 870.3 per 100 000 under a 10% tax (PI = 833.0–906.5). Similar reductions were observed for alcohol-related homicide. Indeed, considering that approximately 6000 of the 15 000 homicides per year are alcohol-related, this translates into an anticipated benefit of approximately 1200 lives per year. Similar to the results on drinking prevalence, the reductions in alcohol-related violence seen in the universal tax could be almost entirely achieved through beer tax alone.

Figure 2 shows the reductions in heavy drinking achieved through taxation by level of income. Those in the highest income groups were most likely to be heavy drinkers, but were the least affected by an increase in taxation (e.g. a 10% increase in universal tax decreased the proportion of heavy drinkers in the highest income group by 0.7 percentage points). Those in the lowest income group were the most affected by taxation (e.g. a 10% increase in the universal tax decreased the proportion of heavy drinkers in the lowest income group by 3.9 percentage points).

Figure 3 shows the reductions in alcohol-related violence achieved through taxation by level of income. Similar to the results for changes in consumption by income, those in the lowest socio-economic groups experienced the highest reductions in alcohol-related violence, compared to those in the highest. At baseline, the rate of alcohol-related victimization was an estimated 1980 per 100 000 among those in the lowest income group and 480 per 100 000 in the highest. At a 10% beer tax, alcohol-related

Table 2 Simulated estimates of the prevalence of heavy, light and non-drinking, as well as violence and homicide rates per 100 000, at each level of taxation intervention, in an agent-based model of New York City, with 95% percentile intervals.

	Tax percentage increase	*Non-drinker*	*Light drinker*	*Heavy drinker*	*Alcohol violence*[a]	*Violence*[a]	*Alcohol homicide*[a]	*Homicide*[a]
No tax Increase	0%	46.5 (46.4, 46.6)	41.3 (41.2, 41.4)	12.2 (12.1, 12.3)	1126.7 (1097.6, 1169.6)	3670.7 (3644.0, 3693.7)	3.22 (2.50, 3.73)	11.8 (10.8, 12.9)
Universal alcohol tax	1%	47.2 (47.0, 47.5)	41.3 (41.1, 41.5)	11.5 (11.2, 11.8)	1058.2 (1015.2, 1102.1)	3663.1 (3633.7, 3693.9)	2.98 (2.24, 3.61)	12.0 (10.8, 12.8)
	5%	48.5 (48.3, 49.0)	41.0 (40.7, 41.1)	10.5 (10.2, 10.8)	967.5 (918.4, 1002.0)	3642.2 (3604.9, 3669.7)	2.73 (2.06, 3.37)	12.0 (10.8, 13.2)
	10%	50.3 (49.9, 50.5)	40.2 (40.0, 40.4)	9.6 (9.4, 9.8)	870.3 (833.0, 906.5)	3640.5 (3603.7, 3674.8)	2.40 (1.92, 2.94)	11.7 (10.5, 13.0)
Beer only tax	1%	47.1 (46.9, 47.3)	41.3 (41.2, 41.5)	11.6 (11.3, 11.8)	1064.7 (1032.3, 1089.7)	3659.0 (3629.6, 3694.0)	3.08 (2.46, 3.53)	11.6 (10.6, 13.1)
	5%	47.8 (47.5, 48.1)	41.2 (41.0, 41.4)	11.0 (10.8, 11.3)	1000.5 (963.4, 1042.7)	3645.0 (3621.9, 3685.9)	2.90 (2.27, 3.46)	11.9 (10.5, 13.0)

[a]Violence and homicide is rate per 100 000.

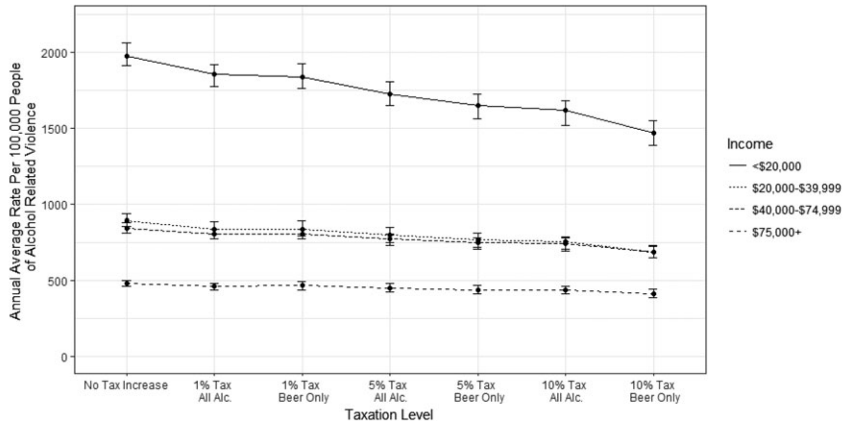

Figure 2 Estimated annual average prevalence of heavy drinking by income and level of taxation in an agent-based model of New York City

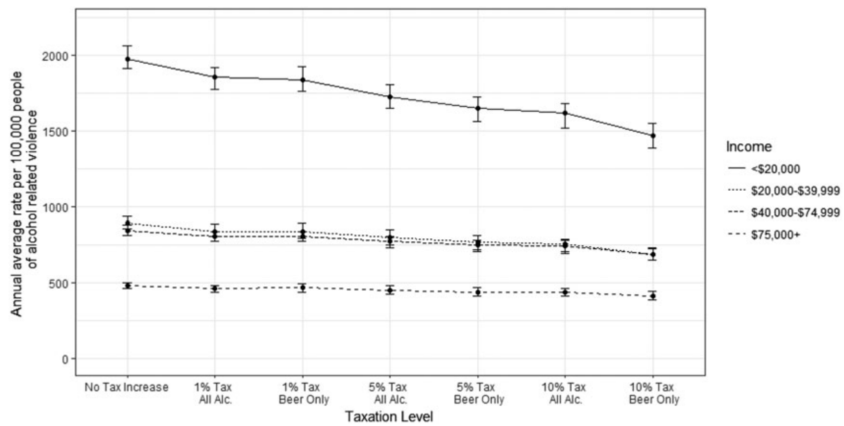

Figure 3 Estimated annual average rate of alcohol related violence by income and level of taxation in an agent-based model of New York City

violent victimization decreased to an estimated 1620 per 100 000 in the lowest income group and 440 per 100 000 in the highest. As such, there was an expected decrease of 360 cases in the lowest income group, compared to 40 cases in the highest group. Thus, compared to baseline, where the lowest income group was 4.1 times more likely to experience alcohol-related violence compared to the highest group, this relative risk decreased to an estimated 3.6 with a 10% universal alcohol tax and 3.7 with a 10% beer tax.

In Table 3, we demonstrate the change in alcohol consumption, victimization and homicide by beverage type. Universal alcohol taxes decreased the proportion of heavy drinkers among those who preferred both spirits [from an estimated 38% (PI = 37–38%) to 24% (PI = 23–26%) under a 10% tax] and beer [from 39% (PI = 39–39%) to 28% (PI = 27–30%) under a 10% tax]. Beer taxes alone were less effective than universal taxes, even among those who preferred beer [e.g. a 10% beer tax decreased the proportion of heavy drinkers among those who preferred beer from an estimated 39% (PI = 39–39% to 31% (PI = 29–32%)]. This is due to the overlap between beer and spirit consumption among beer drinkers who are also heavy drinkers. Neither universal nor beer taxes had a substantial impact on overall violent victimization or homicide among those who preferred beer, but we observed demonstrable effects on alcohol-related violent victimization and alcohol-related homicide within each group of beverage consumers. The largest decrease was observed for universal alcohol taxes on alcohol-related homicide among those who prefer spirits. In this group, alcohol-related homicide decreased from an estimated 6.5 (95% PI = 2.8–9.8) per 100 000 to 3.7 per 100 000 (95% PI = 0.33–5.97).

Description of sensitivity analyses and their results

Sensitivity of the results to the choice of key model parameters was assessed using Latin Hypercube sampling of the space of plausible parameter values [47]. The neighborhood weight parameter was correlated with the effect of taxation on light drinking ($r = -0.90$), heavy drinking ($r = 0.86$) and alcohol-related violence ($r = -0.86$), as well as moderately correlated with alcohol-related homicide ($r = -0.51$). As the neighborhood weight increases, the contribution from individual agent characteristics decreases as the sum of the weights is constrained to equal

Table 3 Simulated estimates of the prevalence of light and heavy drinking, violence and homicide, by beverage type and level of taxation in an agent-based model of New York City, with 95% percentile intervals.

	Tax percentage increase	*Light drinker (% of agent population)*			*Heavy drinker (% of agent population)*		
		Beer	*Wine*	*Spirits*	*Beer*	*Wine*	*Spirits*
No tax increase	0%	0.61 (0.61, 0.61)	0.79 (0.78, 0.79)	0.62 (0.62, 0.63)	0.39 (0.39, 0.39)	0.21 (0.21, 0.22)	0.38 (0.37, 0.38)
Universal alcohol tax	1%	0.64 (0.62, 0.65)	0.8025 (0.79, 0.81)	0.66 (0.64, 0.69)	0.36 (0.34, 0.38)	0.19 (0.18, 0.21)	0.34 (0.31, 0.36)
	5%	0.66 (0.65, 0.68)	0.81 (0.80, 0.82)	0.69 (0.67, 0.71)	0.32 (0.30, 0.34)	0.17 (0.16, 0.18)	0.28 (0.26, 0.30)
	10%	0.68 (0.67, 0.70)	0.81 (0.80, 0.82)	0.70 (0.68, 0.72)	0.28 (0.27, 0.30)	0.15 (0.14, 0.16)	0.24 (0.23, 0.26)
Beer only tax	1%	0.64 (0.62, 0.65)	0.80 (0.79, 0.81)	0.65 (0.63, 0.67)	0.36 (0.34, 0.37)	0.20 (0.19, 0.20)	0.34 (0.32, 0.36)
	5%	0.66 (0.64, 0.67)	0.81 (0.79, 0.81)	0.67 (0.65, 0.68)	0.33 (0.32, 0.35)	0.19 (0.18, 0.20)	0.33 (0.31, 0.35)
	10%	0.67 (0.66, 0.68)	0.81 (0.80, 0.82)	0.68 (0.66, 0.69)	0.31 (0.29, 0.32)	0.18 (0.17, 0.19)	0.31 (0.29, 0.33)
		Alcohol-related violence (per 100 000)			Violent victimization (per 100 000)		
No tax	0%	2355.4 (2276.6, 2426.4)	1141.6 (1072.8, 1195.4)	2155.4 (2056.2, 2234.2)	3780.1 (3710.5, 3860.8)	2659.3 (2603.9, 2739.0)	3580.6 (3452.6, 3659.2)
Universal alcohol tax	1%	2135.3 (2049.7, 2238.0)	1030.7 (951.6, 1106.3)	1862.9 (1710.3, 2038.0)	3673.8 (3606.0, 3746.8)	2620.3 (2559.6, 2684.2)	3421.9 (3310.6, 3548.9)
	5%	1853.3 (1725.8, 1956.6)	869.6 (799.1, 934.7)	1502.2 (1398.0, 1620.6)	3535.3 (3436.5, 3608.7)	2537.7 (2452.2, 2622.8)	3244.5 (3131.8, 3339.7)
	10%	1581.1 (1503.6, 1667.9)	732.2 (662.1, 800.0)	1250.0 (1146.3, 1351.6)	3398.4 (3327.1, 3452.0)	2475.3 (2370.6, 2575.0)	3120.3 (3031.4, 3217.0)
Beer only tax	1%	2172.9 (2015.9, 2250.9)	1043.3 (979.7, 1106.9)	1932.3 (1811.5, 2040.6)	3693.4 (3593.5, 3790.7)	2634.8 (2557.5, 2737.0)	3467.4 (3359.2, 3555.8)
	5%	1930.7 (1840.5, 2062.3)	989.9 (921.8, 1077.0)	1813.6 (1647.8, 1941.0)	3563.3 (3501.9, 3669.4)	2603.9 (2526.6, 2692.1)	3402.7 (3264.5, 3514.9)
	10%	1748.7 (1626.4, 1827.2)	926.9 (864.7, 1007.7)	1682.2 (1575.3, 1830.9)	3474.7 (3377.5, 3544.0)	2567.7 (2495.3, 2666.6)	3349.5 (3211.8, 3455.7)
		Alcohol-related homicide (per 100 000)			Homicide (per 100 000)		
No tax	0%	5.89 (4.10, 8.68)	2.86 (0.96, 5.15)	6.50 (2.76, 9.84)	11.20 (8.95, 14.2)	6.72 (4.30, 11.4)	11.4 (7.37, 15.1)
Universal alcohol tax	1%	6.10 (4.14, 8.42)	2.90 (0.59, 5.35)	5.63 (2.82, 9.99)	11.6 (8.34, 14.4)	7.30 (4.37, 12.2)	12.5 (8.12, 16.2)
	5%	5.01 (2.90, 6.77)	2.01 (0.50, 3.89)	3.81 (2.05, 9.37)	10.8 (7.71, 13.1)	6.49 (4.01, 10.0)	10.4 (6.42, 16.0)
	10%	3.99 (2.51, 5.77)	1.5793 (0.12, 2.64)	3.6879 (0.33, 5.97)	10.10 (7.92, 12.6)	5.80 (3.67, 10.6)	11.06 (5.49, 16.2)
Beer only tax	1%	6.11 (3.71, 8.22)	2.42 (0.97, 4.87)	5.30 (2.79, 9.08)	11.0 (8.28, 13.8)	6.75 (3.85, 10.2)	11.20 (7.99, 16.8)
	5%	5.53 (3.73, 7.74)	2.43 (0.97, 4.63)	5.3463 (2.63, 9.93)	11.2 (7.66, 14.9)	6.82 (4.02, 9.78)	12.6 (7.26, 17.1)
	10%	4.14 (2.58, 6.43)	1.97 (0.11, 3.78)	4.71 (2.02, 7.74)	10.70 (7.35, 13.1)	7.3458 (3.57, 10.9)	11.4228 (7.31, 17.3)

1. This implies that the magnitude of the effects of the interventions on the outcomes are dependent upon the amount of weight that is placed on neighborhood versus individual effects. However, allowing the parameters to change over a wide range of values produced consistent directions of results for our alcohol-related outcomes. At the level of taxation implemented in the model, the direction of the effect did not change for alcohol-related outcomes or alcohol-related violence under any parameter combination, and only under six extreme combinations did the direction of the effect for alcohol-related homicide change.

In another analysis, we evaluated the effects of taxation without neighborhood and social network effects. Under a 10% universal tax on alcohol we saw the proportion of heavy drinkers decrease by 22% (from 13.6 to 10.6%), similar to the 21% decrease (from 12.2 to 9.6%) in the main analysis. We saw a 25% decrease (1209.5 per 100 000 to 1160.2 per 100 000) in the model with no neighborhood or social network effects, similar to the 23% decrease observed in the main analysis (1126.7 per 100 000 to 870.3 per 100 000).

DISCUSSION

The present study provides the first simulated experiment of the effects of alcohol taxation on alcohol use and violent victimization, incorporating variation in elasticity across income, beverage types and overall consumption, while simultaneously allowing for alcohol use to be affected, and to affect, social networks, violent interactions and neighborhood influences on alcohol-related risk factors. Under our simulation assumptions we expect that change in alcohol consumption at the population level in a large urban environment, such as NYC, can be sustained with modest increases in universal taxation, and that beer taxes have the strongest effect on population consumption. Alcohol tax increases also have a modest effect on alcohol-related violent victimization, which comprises 30.5% of all victimization events. Importantly, alcohol taxation reduces income disparities in alcohol-related violence, given that taxes have a greater effect on those in the lowest income categories.

Taken together, these results highlight both the efficacy of alcohol taxation as a population approach to community health, and the potential for taxation to be a means to reduce income inequality in alcohol-related harm. Our estimated reductions in alcohol consumption as well as violence, while modest, are slightly greater than have been documented in previous studies. For example, Chaloupska & Wechsler [48] have estimated that increase in beer tax of 10% have an approximately 15% reduction in binge drinking among youth and 15–20% reductions in heavy drinking with substantial tax increases have also been documented elsewhere [11]. With regard to violence, Grossman & Markowitz [49] found that a 10% increase in alcohol price decreased physical fights among college students from 31.2 to 30.2% (an approximately 3% reduction). Our estimates of reductions in alcohol consumption, by contrast, indicate that a 10% increase in price is associated with decreases in heavy drinking of approximately 20% and decreases in alcohol-related violence by 30%. While the populations used in previous studies are heterogeneous (e.g. college students), and thus population compositional differences may underlie some of the observed associations, we note that dynamics in the model also contributed to differences between observed data and our simulation. For example, we allowed for neighborhoods and social networks to affect alcohol, violence and their co-occurrence, which is not only critical, given the extensive literature indicating the importance of neighborhood factors on alcohol and violence [33,35,36], but also to overcome limitations of traditional observational studies which often do not account for correlation of observations in space. While neighborhood and network effects did not substantially impact estimates of the taxation effects, they play a large role in model estimate calibration. Finally, while taxation reduces income inequalities, it does so because those with the highest incomes can afford not to be affected by taxation. As such, the balance between equity and efficiency should be considered carefully; nonetheless, alcohol taxes may have an added benefit of reducing health disparities.

In the United States alcohol taxes have been stagnant for more than 20 years, and the effectiveness of taxes has declined due to inflation at both the federal and state levels [50]. For example, since 1970, the beer tax has decreased in real dollars by more than 70% [51]. Common arguments against raising alcohol taxes is the potential for undue burden against those who are light or moderate consumers, who will not injure themselves or others due to alcohol. However, as our study and others [16,52,53] document, the burden of alcohol price increases are greatest among the heaviest consumers, who are at most risk for alcohol-related adverse consequences including violence and victimization. While those at low income are most affected by taxes in terms of consumption, the converse of this is that those in the highest income categories pay the most in alcohol taxes [22,54], as they are most likely to continue drinking even at higher price points. Alcohol tax increases would be a net gain for public health, reducing consumption and related consequences, especially if substantial, sustained and widespread.

These findings should be considered across limitations. As in all simulations, our results are dependent upon a series of modeling assumptions and the quality of the parameters that we used from existing data. For example, we assumed that the effects of taxation were constant over time, and that the only sources of variation in alcohol taxation effects were income, beverage type and level of consumption. However, we note that the available empirical literature makes similar assumptions when modeling policy effects [55]. Further, we note that alcohol taxation is a well-suited policy under which to develop an agent-based model, as meta-analytical estimates are based on more than 100 empirical studies, and that our outcomes of alcohol use and violence are well-defined and well-studied, suggesting that empirical estimates are strong in support of the model validity. While we included social network effects in our model, we assumed for simplicity that social networks were static. Thus, our model is a first step in estimating the contribution of social networks, and further elaboration of social networks over time is an important future direction. Further, the violence dynamics in our model were based on the proximity of potential perpetrators to victims, and crime was deterred only in the presence of police. Sources of informal surveillance such as number of bystanders also may deter crime, thus we do not fully represent all dynamics of crime occurrence and deterrence. Nevertheless, central dynamics of victimization based on a routine activities model [42] were represented in the model, thus our model represents again a first step in simulating violent interactions.

Data were drawn from a variety of sources; we based our data sources in NYC to the extent possible, but to the extent that parameters were not available we relied upon national (e.g. violent perpetration) sources and assumed that the strength of associations would be similar in NYC. We deviated from this general approach for several sources, including movement across neighborhoods, which was calibrated using high-quality longitudinal data from the Panel Study on Income Dynamics. As more data sources become available that allow estimation of movement specific to our model locations, we will be able to conduct more local estimation. Further, our model was calibrated to represent the population of NYC in the year 2000, because many of the data sources that we used for calibration were also collected around a similar time. Demographic changes in NYC have occurred since 2000, but are variable across all neighborhoods and buroughs, thus using data collected in 2000 applied to neighborhoods with different demographics than when data were collected may introduce bias. To the extent that population dynamics change the demographics of NYC, our results may not generalize to the current population of NYC. However, we conducted extensive calibration and sensitivity analyses of key parameters and assumptions, mitigating concerns about the dependence of the model results on assumptions. We were able to replicate distributions of key parameters. While the weight that is given to neighborhood versus individual parameters in our equations are correlated with taxation effects, the magnitude of effects decreased but the direction of results did not change among a range of sensitivity analyses. Finally, the model was specific to NYC; hence, generalizability to other contexts may be limited.

In summary, based on a simulated experiment wherein alcohol taxation increased in New York City, we were able to demonstrate robust and strong effects of taxation on alcohol consumption as well as sustained effects on alcohol-related violence when alcohol taxes are increased by at least 10%. Our results underscore that alcohol taxation remains a policy intervention that is likely to improve public health.

Declaration of interests

None.

References

1. FBI Uniform Crime Reporting. *Crime in the United States—Table 12, 2015*. Washingtin, DC: Department of Justice; 2016.
2. Hipp J. R. Block, tract, and levels of aggregation: neighborhood structure and crime and disorder as a case in point. *Am Sociol Rev* 2007; **72**: 659–80.
3. Kennedy B. P., Kawachi I., Prothrow-Stith D., Lochner K., Gupta V. Social capital, income inequality, and firearm violent crime. *Soc Sci Med* 1998; **47**: 7–17.
4. Branas C. C., Han S., Wiebe D. J. Alcohol Use and Firearm Violence. *Epidemiol Rev* 2016; **38**: 32–45.
5. Naimi T. S., Xuan Z., Cooper S. E., Coleman S. M., Hadland S. E., Swahn M. H. *et al*. Alcohol involvement in homicide victimization in the United States. *Alcohol Clin Exp Res* 2016; **40**: 2614–21.
6. Wintemute G. J. Alcohol misuse, firearm violence perpetration, and public policy in the United States. *Prev Med (Balt)* 2015; **79**: 15–21.
7. Anderson P., Chisholm D., Fuhr D. C. Effectiveness and cost-effectiveness of policies and programmes to reduce the harm caused by alcohol. *Lancet* 2009; **373**: 2234–46.
8. Babor T., Holder H., Caetano R., Homel R., Casswell S., Livingston M. *et al*. Controlling affordability: pricing and taxation. In: Babor T. F., Caetano R., Casswell S. *et al*., editors. *Alcohol: No Ordinary Commodity: Research and Public Policy*, Oxford: Oxford University Press; 2010, pp. 109–26.
9. Nelson T. F., Xuan Z., Babor T. F., Brewer R. D., Chaloupka F. J., Gruenewald P. J. *et al*. Efficacy and the strength of evidence of U.S. alcohol control policies. *Am J Prev Med* 2013; **45**: 19–28.
10. Elder R. W., Lawrence B., Ferguson A., Naimi T. S., Brewer R. D., Chattopadhyay S. K. *et al*. The effectiveness of tax policy interventions for reducing excessive alcohol consumption and related harms. *Am J Prev Med* 2010; **38**: 217–29.
11. Wagenaar A. C., Salois M. J., Komro K. A. Effects of beverage alcohol price and tax levels on drinking: a meta-analysis of 1003 estimates from 112 studies. *Addiction* 2009; **104**: 179–90.
12. Wagenaar A. C., Tobler A. L., Komro K. A. Effects of alcohol tax and price policies on morbidity and mortality: a systematic review. *Am J Public Health* 2010; **100**: 2270–8.
13. Cook P. J., Moore M. J. Economic perspectives on reducing alcohol-related violence. In: Martin S., editor. *Alcohol and Interpersonal Violence: Fostering Multidisciplinary Perspectives*,

Vol. **24**. Rockville, MD: US Department of Health and Human Services; 1993, pp. 193–212.
14. Markowitz S., Grossman M. Alcohol regulation and domestic violence towards children. *Contemp Econ Policy.* 1998; **16**: 309–20.
15. Markowitz S., Grossman M. The effects of beer taxes on physical child abuse. *J Health Econ* 2000; **19**: 271–82.
16. Holmes J., Meng Y., Meier P. S., Brennan A., Angus C., Campbell-Burton A. *et al*. Effects of minimum unit pricing for alcohol on different income and socioeconomic groups: a modelling study. *Lancet* 2014; **383**: 1655–64.
17. Jiang H., Livingston M., Room R., Callinan S. Price elasticity of on- and off-premises demand for alcoholic drinks: a Tobit analysis. *Drug Alcohol Depend* 2016; **163**: 222–8.
18. Nelson J. P. Estimating the price elasticity of beer: meta-analysis of data with heterogeneity, dependence, and publication bias. *J Health Econ* 2014; **33**: 180–7.
19. Farrell S., Manning W. G., Finch M. D. Alcohol dependence and the price of alcoholic beverages. *J Health Econ* 2003; **22**: 117–47.
20. Gmel G., Wicki M., Rehm J., Heeb J. L. Estimating regression to the mean and true effects of an intervention in a four-wave panel study. *Addiction* 2008; **103**: 32–41.
21. Heeb J. L., Gmel G., Zurbrügg C., Kuo M., Rehm J. Changes in alcohol consumption following a reduction in the price of spirits: a natural experiment in Switzerland. *Addiction* 2003; **98**: 1433–46.
22. Naimi T. S., Daley J. I., Xuan Z., Blanchette J. G., Chaloupka F. J., Jernigan D. H. who would pay for state alcohol tax increases in the United States? *Prev Chronic Dis* 2016; **13**: 150450.
23. Tracy M., Braga A. A., Papachristos A. V. The transmission of gun and other weapon-involved violence within social networks. *Epidemiol Rev* 2016; **38**: 70–86.
24. Rosenquist J. N., Murabito J., Fowler J. H., Christakis N. A. The spread of alcohol consumption behavior in a large social network. *Ann Intern Med* 2010; **152**: 426–33.
25. Auchincloss A. H., Garcia L. M. T. Brief introductory guide to agent-based modeling and an illustration from urban health research. *Cad Saude Publica* 2015; **31**: 65–78.
26. Tracy M., Cerdá M., Keyes K. M. Agent-based modeling in public health: current applications and future directions. *Annu Rev Public Health* 2018; **39**: 1–18.
27. Cerdá M., Tracy M., Ahern J., Galea S. Addressing population health and health inequalities: the role of fundamental causes. *Am J Public Health* 2014; **104**: S609–S619.
28. Cerda M., Tracy M., Keyes K. M. Reducing urban violence: a contrast of public health and criminal justice approaches. *Epidemiology* 2018; **29**: 142–50.
29. Cerdá M., Tracy M., Keyes K. M., Galea S. To treat or to prevent? Reducing the population burden of violence-related post-traumatic stress disorder. *Epidemiology* 2015; **26**: 681–9.
30. Grimm V., Berger U., Bastiansen F., Eliassen S., Ginot V., Giske J. *et al*. A standard protocol for describing individual-based and agent-based models. *Ecol Model* 2006; **198**: 115–26.
31. Grimm V., Berger U., DeAngelis D. L., Polhill J. G., Giske J., Railsback S. F. The ODD protocol: a review and first update. *Ecol Model* 2010; **221**: 2760–8.
32. US Census Bureau 2000. Summary Files 1, 3, and 4. Suitland, MD: US Census Bureau; 200.
33. Mair C., Gruenewald P. J., Ponicki W. R., Remer L. Varying impacts of alcohol outlet densities on violent assaults: explaining differences across neighborhoods. *J Stud Alcohol Drugs* 2013; **74**: 50–8.
34. Cunradi C. B., Mair C., Ponicki W., Remer L. Alcohol outlets, neighborhood characteristics, and intimate partner violence: ecological analysis of a California City. *J Urban Heal* 2011; **88**: 191–200.
35. Lipton R., Gruenewald P. The spatial dynamics of violence and alcohol outlets. *J Stud Alcohol* 2002; **63**: 187–95.
36. Livingston M. Alcohol outlet density and harm: comparing the impacts on violence and chronic harms. *Drug Alcohol Rev* 2011; **30**: 515–23.
37. Marsden P. V. Core discussion networks of Americans. *Am Sociol Rev* 1987; **52**: 122.
38. McPherson M., Smith-Lovin L., Brashears M. E. Social isolation in America: changes in core discussion networks over two decades. *Am Sociol Rev* 2006; **71**: 353–75.
39. Bureau of Vital Statistics NYCD of Health and Mental Hygeine. *Summary of Vital Statistics 2000: The City of New York*. New York, NY: Bureau of Vital Statistics NYCD of Health and Mental Hygeine; 2000.
40. Goldmann E., Aiello A., Uddin M., Delva J., Koenen K., Gant L. M. *et al*. Pervasive exposure to violence and posttraumatic stress disorder in a predominantly African American Urban Community: the Detroit neighborhood health study. *J Trauma Stress* 2011; **24**: 747–51.
41. Sharkey P. *Stuck in Place*: *Urban Neighborhoods and the End of Progress toward Racial Equality.* Chicago, IL: University of Chicago Press; 2013.
42. Cohen L. E., Felson M. Social change and crime rate trends: a routine activity approach. *Am Sociol Rev* 1979; **44**: 588.
43. Grant B. F., Stinson F. S., Dawson D. A., Chou S. P., Dufour M. C., Compton W. *et al*. Prevalence and co-occurrence of substance use disorders and independent mood and anxiety disorders: results from the national epidemiologic survey on alcohol and related conditions. *Arch Gen Psychiatry* 2004; **61**: 807–16.
44. Galea S., Ahern J., Tracy M., Hubbard A., Cerda M., Goldmann E. *et al*. Longitudinal determinants of posttraumatic stress in a population-based cohort study. *Epidemiology* 2008; **19**: 47–54.
45. Boardman J. D., Finch B. K., Ellison C. G., Williams D. R., Jackson J. S. Neighborhood disadvantage, stress, and drug use among adults. *J Health Soc Behav* 2001; **42**: 151–65.
46. Windrum P., Fagiolo G., Moneta A. Empirical validation of agentbased models: alternatives and prospects. *J Artif Soc Soc Simul* 2007; **10**: 1–21.
47. McKay M. D., Beckman R. J., Conover W. J. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Dent Tech* 2000; **42**: 55–61.
48. Chaloupka F. J., Wechsler H. Binge drinking in college: the impact of price, availability, and alcohol control policies. *Contemp Econ Policy* 1996; **14**: 112–24.
49. Grossman M., Markowitz S. Alcohol regulation and violence on college campuses. In: Grossman M., Hsieh C. R., editors. *The Economics of Substance Use and Abuse: The Experiences of Developed Countries and Lessons for Developing Countries.* Cheltenham, UK: Edward Elgar; 2001, pp. 169–98.
50. Naimi T. S. The cost of alcohol and its corresponding taxes in the U.S.: a massive public subsidy of excessive drinking and alcohol industries. *Am J Prev Med* 2011; **41**: 546–7.
51. Xu X., Chaloupka F. J. The effects of prices on alcohol use and its consequences. *Alcohol Res Heal* 2011; **34**: 236–345.

52. Chaloupka F. J., Tauras J. A. The power of tax and price. *Tob Control* 2011; **20**: 391–2.
53. Ludbrook A., Petrie D., McKenzie L., Farrar S. Tackling alcohol misuse: purchasing patterns affected by minimum pricing for alcohol. *Appl Health Econ Health Policy* 2012; **10**: 51–63.
54. Daley J. I., Stahre M. A., Chaloupka F. J., Naimi T. S. The impact of a 25-cent-per-drink alcohol tax increase. *Am J Prev Med* 2012; **42**: 382–9.
55. Marshall B. D. L., Galea S. Formalizing the role of agent-based modeling in causal inference and epidemiology. *Am J Epidemiol* 2015; **181**: 92–9.
56. Silver E., Arseneault L., Caspi A., Moffitt T. E. Mental disorder and violent victimization in a total birth cohort. *Am J Public Health* 2005; **95**: 2015–21.
57. Norris F. H., Kaniasty K. A longitudinal study of the effects of various crime prevention strategies on criminal victimization, fear of crime, and psychological distress. *Am J Community Psychol* 1992; **20**: 625–48.
58. Elbogen E. B., Johnson S. C. The intricate link between violence and mental disorder: results from the National Epidemiologic Survey on Alcohol and Related Conditions. *Arch Gen Psychiatry* 2009; **66**: 152–61.
59. New York Social Environment Study, Ahern J., Galea S., Hubbard A., Syme S. L. Neighborhood smoking norms modify the relation between collective efficacy and smoking behavior. *Drug Alcohol Depend* 2009; **100**: 138–45.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix 1 Description of ABM using the ODD protocol.

Table A1 Agent, social network, alcohol outlet, and neighborhood parameters, values, data sources, and update rules.

Table A2 Agent-based model initialization parameters and default values.

Figure A1 Flow diagram illustrating steps in model initialization.

Figure A2 Flow diagram illustrating processes occurring at each step of the model.

Appendix 2 Pseudo-code for alcohol outlet density agent-based model.

Appendix 3 Sensitivity Analysis.

Figure A3.1 Boxplots of estimated intervention effects by intervention level for all 100 sensitivity model runs.

Figure A3.2 (a) Scatter plots of estimated intervention effects on drinking status at the 10%, all alcohol intervention by parameters for all 100 sensitivity model runs. **(b)** Scatter plots of estimated intervention effects on violence outcomes at the 10%, all alcohol intervention by parameters for all 100 sensitivity model runs.

Appendix 3, Table A1 Sensitivity analysis removing neighborhood and social network effects.

Appendix 4 Estimates of price elasticity used in the agent-based model.