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Social Determinants of Population Health: A Systems Sciences Approach

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Abstract

Population distributions of health emerge from the complex interplay of health-related factors at multiple levels, from the biological to the societal level. Individuals are aggregated within social networks, affected by their locations, and influenced differently across time. From aggregations of individuals, group properties can emerge, including some exposures that are ubiquitous within populations but variant across populations. By combining a focus on social determinants of health with a conceptual framework for understanding how genetics, biology, behavior, psychology, society, and environment interact, a systems science approach can inform our understanding of the underlying causes of the unequal distribution of health across generations and populations, and can help us identify promising approaches to reduce such inequalities. In this paper, we discuss how systems science approaches have already made several substantive and methodological contributions to the study of population health from a social epidemiology perspective.

Keywords

Social determinants of health; social conditions; systems analysis; systems theory

Introduction

The structural factors that shape societies influence the health of populations within those societies. In the 19th century, Durkheim observed that the rapid industrialization of European cities paralleled a shift from collectivism to individualism, a shift that was associated with population variations in suicide rates among these societies [1]. Nearly a century after Durkheim, Geoffrey Rose reminded epidemiologists that “(s)ociety is not merely a collection of individuals but also a collectivity, and the behavior and health of its members are profoundly influenced by its collective characteristics and social norms” [2, p. 62]. It is social epidemiology’s interest in understanding the influence of such phenomena (e.g.,

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collectivity, social arrangements, norms) on population health that differentiates it both epistemologically and often analytically from the more general field of epidemiology.

The field of social epidemiology has amassed a substantial body of literature examining associations among social structures, public policy, health, and illness [3-5]. Many of these findings have maximized techniques such as multilevel regression, which model the independent and interactive effects of variables across multiple levels of causes on health and illness [5]. These models consider the nested sources of variability within groups of people (e.g., households in neighborhoods), but they are not necessarily able to explore how the structure and interconnectivity of these relationships produce this common variance. Social learning theory [6, 7] and social impact theory [8], among other theoretical frameworks, suggest that group norms are simultaneously shaped by and shape the behaviors of individuals within the group. While regression models may be appropriate to evaluate the unidirectional, linear, effects that social structures have on individual health outcomes, the feedback processes common in the mechanisms that drive population health patterns often produce unpredictable, nonlinear, effects and violate regression model assumptions. Hence, traditional regression models often offer inadequate tools to examine feedback processes between factors at multiple levels and mechanisms by which these processes are translated into disease and disorder.

This constraint inherent to traditional regression model has generated an interest in applying systems science approaches to understanding population health. A systems science approach to epidemiology begins with the assumption that societies form a complex adaptive system. Scott Page [9] explains that these system are characterized by “situated, adaptive, diverse individuals whose interactions produce higher-order structures (self-organizing) and functionalities (emergence).” Each system is situated within spatial and temporal boundaries that influences how people both interact and learn behaviors from others. The interaction among people and social structures over time determines the dynamics of the system, consequently driving population health. Therefore, a systems science approach to epidemiology provides the theory and analytics necessary to examine the social production of health and illness [10, 11].

Recent reviews have comprehensively discussed the systems science armamentarium, including: social network analysis [12-15], systems dynamics models [16, 15, 14], and agent-based models (ABM) [12, 14, 15]. We do not aim here to replicate this work or to provide a systematic review of this literature but rather to discuss key papers that exhibit both the methodological and substantive contributions that a systems science approach has already made to social epidemiology. In this paper, we first introduce the key methodological contributions that the systems science armamentarium can make to the study of population health, including: (1) modeling processes of assortative selection and social transmission of disease; (2) addressing issues of interference among people that alter intervention effects; and (3) modeling latency periods and feedback processes. We then examine substantive contributions that a systems science approach can make to understanding three aspects of population health: (1) processes that generate inequalities in health; (2) feedback processes between individuals and societies that shape population

health; and (3) hypothetical points of interventions that can obtain optimum improvement in population health.

Methodological contributions

The burgeoning use of systems approaches to model interdependence is an exciting area of scholarship in epidemiology. These methods represent an evolution from earlier mathematical techniques (e.g., differential equations) and have been employed since the late 1990s in infectious disease epidemiology [17-20] and are now increasingly incorporated in chronic disease [21] and social epidemiology [22]. Because system science methods are well suited to model the complex social phenomenon that drive population health patterns, these methods have been used to address key methodological constraints that arise in the study of population health. We discuss three methodological issues that systems science methods address, including: (1) assortative selection and social transmission of health behaviors; (2) the influence of interference in health interventions; and (3) time lags and feedback between system structures that shape population health patterns.

Assortative selection and social transmission of health behaviors

Although it is well known that health behaviors and disease aggregate through social networks, the processes that give rise to social networks and how those processes in turn also influence health remain less clear. Networks often form, but not always, based on similar backgrounds and life experiences [23]. This affinity for individuals within a system to live amongst people with similar characteristics can create homogenous sub-groups and alter ecological landscapes. In addition, niche theory has been applied in several fields of science [24-27] to describe a generalized feedback process whereby people responding to available resources begin to actively shape those same resources, creating specialized “niche” relationships between person and resource. Paul Gruenewald [27] has used niche theory to explain how sub-groups, with homogenous consumer alcohol preferences, have contributed to a segmented commercial market where drinking venues (e.g., bars, pubs, nightclubs) must compete for an ever more specific part of the population. As drinking venues market their services towards a very particular clientele, they promote homophily among their patrons, a phenomenon that Gruenewald has called assortative drinking [27]. These venue-based clusters of drinkers share social norms and behaviors. As such, niche theory suggests that high-risk drinking venues will arise that segregate and reinforce risky drinking behaviors within drinking networks.

Gorman and colleagues [28] used an ABM to illustrate the role of niche venues in the assortative processes of selection into social networks. Susceptible drinkers, current drinkers, and former drinkers moved around a simulated grid one step at a time. When both a susceptible and current drinker became co-located, “social influence” converted susceptibles to drinkers. As susceptible drinkers transitioned into current drinkers based on social influence, current drinkers transitioned into former drinkers through a random process. Simulation results indicated that current drinkers moving at random will spread evenly over the entire area and that a single current drinker in an area would eventually convert all susceptibles to current drinkers over time. In the second experiment a “bar” was introduced

to the grid to attract current drinkers (i.e., current drinkers were more likely to move towards the bar), which altered the distribution of drinkers throughout the grid. This feedback between individual selection of contexts and interactions due to personal preferences, and environmental influences on the individual, shaped individual-level behaviors and population disease burden.

Model processes of interference that influence intervention effects

In epidemiology, we identify causes of disease in order to then mitigate their effects. However, the impact of an intervention to reduce the consequences of a cause on a potential outcome is often not only defined by an isolated effect on an individual, but also by the effect such an intervention has on a set of interconnected individuals. Systems science approaches offer us tools to explicitly model the contribution that interference makes to intervention effects. Inference, in most epidemiological contexts, refers to the process through which an individual's exposure status in the study influences another's outcome value; traditional regression techniques assume that there is no interference between units [29], but that is often not a realistic assumption.

A series of recent studies that evaluated interventions to promote active travel (e.g., walking, cycling) illustrate the potential of systems science approaches to account for the role of interference in shaping intervention outcomes. Yang and colleagues employed an ABM to simulate several structural interventions that could target the walking behaviors of both school-aged children [30, 31] and adults [32, 33]. Interventions ranged from improving traffic safety [30, 31] to reducing residential segregation [33]. These simulations showed that the impact of the interventions depended on the changes in behavior it produced in the local social network. For example, in one study that examined several hypothetical interventions targeting children's walking behavior to and from school, each household's decision to either drive their child or allow their child to walk to school evolved over time as a function of their child's attitudes towards walking, traffic safety, and distance to school [31]. Furthermore, children's attitudes about walking were shaped as a function of the total proportion of children who walk to school—the study conceptualized this dynamic process between the proportion of children walking to school and each child's attitudes about walking as alterations to social norms [31]. This study found that an intervention strategy that targeted a small area around schools with greater intensity proved more effective at increasing active travel among students than interventions that targeted a greater area with lower intensity. The study findings suggest that the targeted high-intensity strategy converted those students living closest to school from drivers to walkers, and with more children walking to school, the school's social norms about walking changed [31]. This finding that peer networks contributed substantially to the effectiveness of interventions is well supported in the empirical literature [34, 35], and illustrates how modeling processes of interference (rather than assuming they do not exist) can give us greater insight into the mechanisms through which interventions can have an impact, and into the transportability of interventions across different settings and populations.

Model latency periods and feedback processes

Systems science approaches can be used to model the influence that different assumptions about latency periods and feedback processes can have when examining the influence of social exposures on health. Latency periods and feedback processes are closely linked. The latency period refers to the period of time that follows first exposure or intervention and ends with measureable effects. During this time, feedback processes may alter social structures to influence population dynamics. Because structural interventions often require from months to years to reach optimum benefits, systems science methods can be used to compare the latency periods for competing interventions.

Marshall and colleagues [36], for example, used an ABM to compare both the effectiveness and time lag of four hypothetical intervention scenarios and “high-impact” combination prevention scenario on reducing HIV incidence in an urban population. Each agent in this model was assigned to be either an injection drug users, non-injection drug users (i.e., used drugs, other than marijuana, through noninjection modes of consumption), or non-drug users in proportions that matched the sexually active adult population in New York City. The study modeled assortative linking between agents, such that partnerships were weighted to favor the formation of links between agents with similar characteristics, and linked agents could transmit HIV to each other either through engaging in sexual intercourse and, if both agents used injection drugs, sharing syringes. Persons in the acute stage of HIV infection had the highest risk for HIV transmission. Each of four potential intervention strategies (i.e., increased HIV testing, improved access to substance abuse treatment, increased use of needle exchange programs, scaled-up treatment as prevention) and high-impact combination scenerio was evaluated to estimate HIV incidence from 2012 to 2040. The study found the high-impact combination prevention to offer the greatest reduction in HIV incidence over time. Furthermore, the reduction observed from the high-impact combination prevention in 15 years was greater than the reduction from any single intervention over 28 years. Systems analytics could provide a useful tool for chronic disease epidemiology because of the long latency periods inherent to chronic diseases [21]; however, this has yet to be fully realized.

Case study: The role of system science in evaluation of the drivers of health disparities

A central goal of epidemiological practice is to identify, describe, and explain health inequalities both within and between populations. Epidemiologic theories such as ecosocial theory [37], eco-epidemiology [38], or social-ecological systems perspective [39], provide the framework to understand the causes and processes that drive variations in population health and disorder. What these theories share in common is an explicit multi-level, dynamic process, whereby population health is shaped by the social structures that contain it. As such, health inequalities arise from social, economic, and political practices that different populations are born into, develop, and function within throughout their life course.

The drive to understand the processes that shape population health, and to identify the pathways that connect macrosocial factors to patterns of health, have traditionally relied on a range of archival and survey data on social factors and health conditions at multiple levels,

and on the use of analytic approaches such as multilevel models for the investigation of linear, unidirectional, relationships between these factors and individual health states. Yet the relation between macrosocial factors and population health is not necessarily unidirectional. Rather, from the collective actions of individuals, social structures and population dynamics emerge, that then influence the individuals who comprise them.

A systems science framework can make three critical contributions to understanding the macrosocial production of health, it can help us: (1) model how health inequalities shape population health; (2) understand feedback between micro- and macro-level processes; and (3) identify targets for intervention to reduce inequalities in health. These contributions are not mutually exclusive properties existing within systems science, but rather steps that can be taken by epidemiologists who employ systems science to identify health inequalities, determine what causes these inequalities, and provide informed prevention strategies to ameliorate such health inequalities.

Identifying health inequalities

Health inequalities are differences in health states that arise from differences in biology, environment, and social interactions among people or groups. Inequalities that arise from the social, economic, and political practices that create differential access to resources and opportunities have been of central interest in social sciences including social epidemiology. Systems science approaches can help us identify these underlying determinants of illness to address population health and health inequalities. They can do so in two ways. First, in systems approaches, macro-level patterns of health are not defined, but emerge from the characteristics and behaviors of individuals embedded in different contexts and defined by their relations to each other. In this way, such approaches force us to identify the processes at multiple levels that give rise to observed patterns of inequality. Second, with systems approaches, we can simulate a series of counterfactual scenarios, holding everything in the model constant and varying only one parameter. By doing so, we can identify contextual factors that modify an intervention's effect on population health.

A recent study we conducted on the neighborhood drivers of racial/ethnic inequalities in homicide illustrated how contextual factors, such as residential segregation, might reduce the effectiveness of more proximal interventions in reducing inequalities [40]. From 2009 through 2013, the annual rate of homicide among African Americans was over five times higher than their non-Hispanic white counterparts [41]. Sampson and colleagues [42] have argued that associations between racial segregation and violence are largely mediated by collective efficacy, defined as “social cohesion among neighbors combined with their willingness to intervene on behalf of the common good”. We created an ABM that reflected the sociodemographic characteristics of the adult population in New York City and evaluated whether increasing collective efficacy across all neighborhoods (i.e., a population-based strategy) or focusing on the most violent neighborhoods (i.e., high-risk prevention strategy) resulted in greater reductions in overall rates and ethnic inequalities in violent victimization. Although simulations showed that a population-based prevention strategy lowered overall rates of violent victimization, neither the population-based nor high-risk prevention strategy reduced inequalities. We were concerned that this failure to reduce inequalities in homicide

may be due to segregation of Blacks into low-income neighborhoods, which would, in the long term, reduce collective efficacy and continue to drive higher rates of homicide. We thus simulated the same interventions under three alternative scenarios: (1) complete racial/ethnic residential segregation across the city; (2) intermediate segregation; and (3) no segregation. Racial/ethnic inequalities in victimization were only reduced through the elimination of residential segregation. This study illustrates how, by using a system science approach to simulate a series of different interventions under a range of counterfactual scenarios of segregation (something we would never be able to observe in the real world), we were able to visualize how targeting proximal risk factors could fail to reduce health inequalities if we did not address the fundamental drivers of health inequalities [43].

Understanding feedback

Systems science analytics are particularly well suited to understand the influence of feedback between micro- and macro-level processes on population health and health inequalities. Ladyman and colleagues [44] explains that “(a) part of a system receives feedback when the way its neighbors interact with it at a later time depends on how it interacts with them at an earlier time.” Consider a series of neighborhoods, comprised of heterogeneous households, where each household prefers to live near neighbors that share a recognizable characteristic (e.g., African American v white). Each household’s decision to stay in their current neighborhood or re-locate to a new neighborhood depends on the characteristics of their current neighbors, but after the household makes a decision to stay or relocate, its neighbors will make a similar decision in response to their neighbors’ movement. An early example of the application of systems science approaches to the generation of residential segregation dynamics illustrated this process [45], showing how household preferences about location can give rise collectively to population segregation and neighborhood tipping points. In this model, every unit membership was assigned into one of two permanent and recognizable groups (i.e., black and white ethnicity). Through a series of discrete intervals each unit evaluated their current situation and decided whether to stay in their current location or re-locate to a new area based on whether the color mixture in their current space was acceptable. This study contributed two important findings about the drivers of residential segregation. First, each unit is constantly affected by the decisions of others; irrespective of a unit’s decision to stay or re-locate, everybody else’s movements will affect each unit’s location prior to the next interval, precipitating future movement. Second, it is through this iterative process that the behavior of micro-level units give rise to macro-level phenomena (segregation).

Several studies have used systems science approaches to examine the influence of place-related factors on creating health inequalities [46, 47, 28]. An illustrative example relates to the influence of place-related factors on food preferences. It has been proposed that reduced access to healthy and affordable foods in low-income neighborhoods likely helps shape differences in food preferences between low- and high-income households [48, 49], forming a feedback loop between individual behavior and neighborhood markets whereby availability drives preferences, which then affect availability. To identify the drivers of income inequalities in diet, Auchincloss and colleagues [47] employed an ABM that assigned households and stores behaviors based on their access to healthy foods and

customers, respectively. In this model, each household's decision to shop at a store was driven by food price, distance, and preferences for healthy foods, whereas stores decided to change location and food type in response to their customer base. Through this feedback, Auchincloss and colleagues refuted the hypothesis that inequalities in diet reflect difference in food preferences between low- and high-income households by finding that only under a starting condition of total segregation was this true. Next, Auchincloss and colleagues used the segregation scenario where income differentials in diet emerged (i.e., total segregation) to examine under what conditions healthy food prices and preferences could overcome or exacerbate the effects of segregation on healthy diet. In this series of experiments, the currently patterned segregation of healthy food stores to high-income areas could be reversed by simultaneously changing food preferences among low-income households and reducing food prices. Although these models do not require the explicit specification of interventions that can simultaneously shift both food preferences and prices, they provide evidence that synergistic interventions will be required to ameliorate the currently patterned health inequalities.

This *in silico* experiment by Auchincloss and colleagues [47] examined the interdependencies between household choices and business decisions, and that dynamic feedback over time between the changes in household choices and business decisions give rise to either salubrious or deleterious household health-behaviors. In addition, studies have documented that these re-enforcing feedback cycles produce and maintain contextual factors that influence physical activity and built environment (e.g., walking routes) [46, 32], violent victimization and racial/ethnic segregation [40], and alcohol consumption and density of alcohol retailers [27]. As these examples illustrate, systems science methods can be used to ask questions about the dynamic mechanisms through which macrosocial determinants of population health produce health inequalities.

Improving interventions

Finally, systems science can help us identify targets for intervention to reduce inequalities in health. While many of the previous examples have tested plausible policy interventions to reduce health inequalities related to violent victimization [50], physical activity [31], and diet [47], the following models were explicitly built to optimize interventions and inform future policy decisions. Several of these models were built to represent a very specific population or geographic area [51-53]; however, this specificity comes at a cost to generalizability—that is, the closer a model is built to represent a specific population or location, the less likely its findings will be generalizable to other societies with different mobility patterns, structural factors, and distributions of individual-level risk factors. As such, some studies aim to examine more fundamental processes to increase their generalizability.

Systems sciences approaches can be used to identify hypothetical points of intervention that will obtain optimum improvement in population health. Previous models have compared individual- versus structural-level interventions [31, 54, 55], active versus passive interventions [56], and primary versus tertiary prevention [50, 57, 58]. In one study, we investigated whether a population-level violence prevention intervention (i.e., hot-spot

policing) or an individual-level treatment intervention (i.e., cognitive behavioral therapy [CBT]) contributed to a greater reduction in the burden of violence-related posttraumatic stress disorder in urban areas [50]. In this model, we observed an equally slight reduction in the annual prevalence of violent victimization from implementing either hot-spot policing for 10 years or increasing CBT by 100% for 30 years; however, the joint implementation of hot-spot policing and a 50% increase in CBT resulted in a similar reduction in just five years. Our observation that interventions can work synergistically to obtain optimum improvement in population health has been replicated across several similar studies that have employed systems science methods [57, 46, 33, 47, 59]. Because the development, implementation, and long-term evaluation of community health interventions can be costly, ABMs have provided a particularly attractive opportunity to sequentially evaluate several competing interventions to determine those most likely to provide population health benefits.

Conclusions

Traditionally in public health and other sciences we have looked to behavioral risk factors that vary within populations as potential manipulable exposures that cause poor health, and there have been calls to move even further “downstream” to examine individual differences in biological factors. Yet such approaches fail to consider the drivers of risk factors, macrosocial determinants of health that create and maintain inequalities. System science approaches offer both the theory and the tools to examine structural and macrosocial factors, allowing us to hypothesize and theorize about the fundamental drivers that shape health and how we might intervene on them in effective ways both to improve population health overall and to reduce health inequality. Further, without systems approaches to analyses, we violate assumptions regarding independence, interference, and linear effects, potentially leading to the wrong answers to questions of public health relevance. The years to come will be an exciting time for complex systems modeling in social and chronic disease epidemiology, as more scholars are trained in these methods and technical and methodological innovation continue to push the field forward. Increasing recognition that the systems that underlie the generation of our data are critical to answer questions regarding how to improve population health will improve our science and our ability to intervene for a healthier society.

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References

Papers of particular interest, published recently, have been highlighted as:

* Of importance

** Of major importance

1. Berk BB. Macro-Micro Relationships in Durkheim's Analysis of Egoistic Suicide. *Sociological Theory*. 2006; 24(1):58–80.

2. Rose G. The strategy of preventive medicine. The strategy of preventive medicine. 1992
3. Beckfield J, Krieger N. Epi + demos + cracy: linking political systems and priorities to the magnitude of health inequities--evidence, gaps, and a research agenda. *Epidemiol Rev.* 2009; 31:152–77. doi:10.1093/epirev/mxp002. [PubMed: 19474091]
4. Kramer MR, Hogue CR. Is segregation bad for your health? *Epidemiol Rev.* 2009; 31:178–94. doi: 10.1093/epirev/mxp001. [PubMed: 19465747]
5. Oakes JM, Andrade KE, Biyoow IM, Cowan LT. Twenty Years of Neighborhood Effect Research: An Assessment. *Current Epidemiology Reports.* 2015; 2(1):80–7. doi:10.1007/s40471-015-0035-7.
6. Bandura, A. *Social Learning Theory.* Prentice-Hall; Englewood Cliffs, NJ: 1977.
7. Bandura, A. *Social foundations of thought and action: A social cognitive theory.* Prentice-Hall; Englewood Cliffs, NJ: 1986.
8. Latane B. The psychology of social impact theory. *Am Psychol.* 1981; 36(4):343–56.
9. Page SE. What Sociologists Should Know About Complexity. *Annu Rev Sociol.* 2015; 41(1):21–41. doi:10.1146/annurev-soc-073014-112230. *This qualitative review outlines existing literature with respect to complexity in the social sciences.
10. Galea S, Riddle M, Kaplan GA. Causal thinking and complex system approaches in epidemiology. *Int J Epidemiol.* 2010; 39(1):97–106. [PubMed: 19820105]
11. Marshall BD, Galea S. Formalizing the role of agent-based modeling in causal inference and epidemiology. *Am J Epidemiol.* 2014 kwu274. **This paper makes a case for agent-based models to be used to simulate counterfactual outcomes in the presence of complexity.
12. El-Sayed AM, Scarborough P, Seemann L, Galea S. Social network analysis and agent-based modeling in social epidemiology. *Epidemiol Perspect Innov.* 2012; 9(1):1. doi: 10.1186/1742-5573-9-1. *This qualitative review describes the application of systems science methods in epidemiology, focusing on network analysis and agent-based models. [PubMed: 22296660]
13. Butts CT. Social network analysis: A methodological introduction. *Asian Journal Of Social Psychology.* 2008; 11(1):13–41. doi:10.1111/j.1467-839X.2007.00241.x.
14. Speybroeck N, Van Malderen C, Harper S, Muller B, Devleeschauwer B. Simulation models for socioeconomic inequalities in health: a systematic review. *Int J Environ Res Public Health.* 2013; 10(11):5750–80. doi:10.3390/ijerph10115750. [PubMed: 24192788]
15. Luke DA, Stamatakis KA. Systems science methods in public health: dynamics, networks, and agents. *Annu Rev Public Health.* 2012; 33:357–76. doi:10.1146/annurev-publhealth-031210-101222. [PubMed: 22224885]
16. Homer JB, Hirsch GB. System dynamics modeling for public health: background and opportunities. *Am J Public Health.* 2006; 96(3):452–8. doi:10.2105/ajph.2005.062059. [PubMed: 16449591]
17. Garnett GP, Anderson RM. Sexually transmitted diseases and sexual behavior: insights from mathematical models. *J Infect Dis.* 1996; 174(Suppl 2):S150–61. [PubMed: 8843245]
18. Ghani AC, Swinton J, Garnett GP. The role of sexual partnership networks in the epidemiology of gonorrhea. *Sex Transm Dis.* 1997; 24(1):45–56. [PubMed: 9018783]
19. Potterat JJ, Rothenberg RB, Muth SQ. Network structural dynamics and infectious disease propagation. *Int J STD AIDS.* 1999; 10(3):182–5. [PubMed: 10340199]
20. Rothenberg RB, Potterat JJ, Woodhouse DE, Muth SQ, Darrow WW, Klovdahl AS. Social network dynamics and HIV transmission. *AIDS.* 1998; 12(12):1529–36. [PubMed: 9727575]
21. Smith BT, Smith PM, Harper S, Manuel DG, Mustard CA. Reducing social inequalities in health: the role of simulation modelling in chronic disease epidemiology to evaluate the impact of population health interventions. *J Epidemiol Community Health.* 2014; 68(4):384–9. doi:10.1136/jech-2013-202756. [PubMed: 24363409]
22. Diez Roux AV. Complex systems thinking and current impasses in health disparities research. *Am J Public Health.* 2011; 101(9):1627–34. doi:10.2105/ajph.2011.300149. [PubMed: 21778505]
23. McPherson M, Smith-Lovin L, Cook JM. Birds of a feather: Homophily in social networks. *Annu Rev Sociol.* 2001; 27:415–44.

24. Wiens JJ, Graham CH. Niche conservatism: Integrating evolution, ecology, and conservation biology. *Annu Rev Ecol Syst.* 2005; 36:519–39.
25. Vandermeer JH. Niche theory. *Annu Rev Ecol Syst.* 1972; 3:107–32.
26. Loureiro ML, Hine S. Discovering niche markets: A comparison of consumers willingness to pay for local (Colorado grown), organic, and GMO-free products. *Journal of Agricultural and Applied Economics.* 2002; 34(3):477–88.
27. Gruenewald PJ. The spatial ecology of alcohol problems: niche theory and assortative drinking. *Addiction.* 2007; 102(6):870–8. doi:10.1111/j.1360-0443.2007.01856.x. [PubMed: 17523980]
28. Gorman DM, Mezic J, Mezic I, Gruenewald PJ. Agent-based modeling of drinking behavior: a preliminary model and potential applications to theory and practice. *Am J Public Health.* 2006; 96(11):2055–60. doi:10.2105/ajph.2005.063289. [PubMed: 17018835]
29. Tchetgen Tchetgen EJ, VanderWeele T. On causal inference in the presence of interference. *Stat Methods Med Res.* 2010; 21(1):55–75. [PubMed: 21068053]
30. Yang Y, Diez-Roux A, Evenson KR, Colabianchi N. Examining the impact of the walking school bus with an agent-based model. *Am J Public Health.* 2014; 104(7):1196–203. doi:10.2105/ajph.2014.301896. *This paper presents evidence from an agent-based model on factors that influence intervention effects in the presence of interference among units. [PubMed: 24832410]
31. Yang Y, Diez-Roux AV. Using an agent-based model to simulate children's active travel to school. *Int J Behav Nutr Phys Act.* 2013; 10:67. doi:10.1186/1479-5868-10-67. [PubMed: 23705953]
32. Yang Y, Diez Roux AV, Auchincloss AH, Rodriguez DA, Brown DG. Exploring walking differences by socioeconomic status using a spatial agent-based model. *Health & place.* 2012; 18(1):96–9. doi:10.1016/j.healthplace.2011.08.010. [PubMed: 22243911]
33. Yang Y, Auchincloss AH, Rodriguez DA, Brown DG, Riolo R, Diez-Roux AV. Modeling spatial segregation and travel cost influences on utilitarian walking: Towards policy intervention. *Comput Environ Urban Syst.* 2015; 51:59–69. doi:10.1016/j.compenvurbsys.2015.01.007. [PubMed: 25733776]
34. Christakis NA, Fowler JH. The spread of obesity in a large social network over 32 years. *N Engl J Med.* 2007; 357(4):370–9. doi:10.1056/NEJMsa066082. [PubMed: 17652652]
35. Fowler JH, Christakis NA. Estimating peer effects on health in social networks: a response to Cohen-Cole and Fletcher; and Trogdon, Nonnemaker, and Pais. *J Health Econ.* 2008; 27(5):1400–5. doi:10.1016/j.jhealeco.2008.07.001. [PubMed: 18692263]
36. Marshall BD, Friedman SR, Monteiro JF, Paczkowski M, Tempalski B, Pouget ER, et al. Prevention and treatment produced large decreases in HIV incidence in a model of people who inject drugs. *Health Aff (Millwood).* 2014; 33(3):401–9. doi:10.1377/hlthaff.2013.0824. *This paper is a model for investigating time lags using agent-based models. [PubMed: 24590937]
37. Krieger N. Epidemiology and the web of causation: has anyone seen the spider? *Soc Sci Med.* 1994; 39(7):887–903. [PubMed: 7992123]
38. Susser M, Susser E. Choosing a future for epidemiology: II. From black box to Chinese boxes and eco-epidemiology. *Am J Public Health.* 1996; 86(5):674–7. [PubMed: 8629718]
39. McMichael AJ. Prisoners of the proximate: loosening the constraints on epidemiology in an age of change. *Am J Epidemiol.* 1999; 149(10):887–97. [PubMed: 10342797]
40. Cerda M, Tracy M, Ahern J, Galea S. Addressing population health and health inequalities: the role of fundamental causes. *Am J Public Health.* 2014; 104(Suppl 4):S609–19. doi:10.2105/ajph.2014.302055. [PubMed: 25100428]
41. Centers for disease control NCfHS. Underlying cause of death 1999–2013 on CDC WONDER online database, released, 2015. Data are from the Multiple Cause of Death File, 1999–2013, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program. 2015
42. Sampson RJ, Raudenbush SW, Earls F. Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science.* 1997; 227(5328):918–24. [PubMed: 9252316]
43. Link BG, Phelan J. Social conditions as fundamental causes of disease. *J Health Soc Behav.* 1995:80–94. Spec No. [PubMed: 7560851]
44. Ladyman J, Lambert J, Wiesner K. What is a complex system? *European Journal for Philosophy of Science.* 2013; 3(1):33–67.

45. Schelling TC. Dynamic models of segregation. *Journal of Mathematical Sociology*. 1971; 1:143–86.
46. Yang Y, Diez Roux AV, Auchincloss AH, Rodriguez DA, Brown DG. A spatial agent-based model for the simulation of adults' daily walking within a city. *Am J Prev Med*. 2011; 40(3):353–61. doi: 10.1016/j.amepre.2010.11.017. [PubMed: 21335269]
47. Auchincloss AH, Riolo RL, Brown DG, Cook J, Diez Roux AV. An agent-based model of income inequalities in diet in the context of residential segregation. *Am J Prev Med*. 2011; 40(3):303–11. doi:10.1016/j.amepre.2010.10.033. [PubMed: 21335261]
48. Story M, Kaphingst KM, Robinson-O'Brien R, Glanz K. Creating healthy food and eating environments: policy and environmental approaches. *Annu Rev Public Health*. 2008; 29:253–72. doi:10.1146/annurev.publhealth.29.020907.090926. [PubMed: 18031223]
49. Leonard T, McKillop C, Carson JA, Shuval K. Neighborhood effects on food consumption. *Journal of Behavioral and Experimental Economics*. 2014; 51:99–113. doi:10.1016/j.socec.2014.04.002.
50. Cerda M, Tracy M, Keyes KM, Galea S. To Treat or to Prevent?: Reducing the Population Burden of Violence-related Post-traumatic Stress Disorder. *Epidemiology*. 2015; 26(5):681–9. doi: 10.1097/ede.0000000000000350. *This paper presents agent-based model that compares the effectiveness of two potential interventions on population health. It offers important substantive insight and introduces the role that these models can have in future policy decisions. [PubMed: 26237744]
51. Wilson DP, Blower SM. Designing equitable antiretroviral allocation strategies in resource-constrained countries. *PLoS Med*. 2005; 2(2):e50. doi:10.1371/journal.pmed.0020050. [PubMed: 15737005]
52. Verguet S. Efficient and equitable HIV prevention: A case study of male circumcision in South Africa. Cost effectiveness and resource allocation : C/E. 2013; 11(1):1. doi: 10.1186/1478-7547-11-1. [PubMed: 23289923]
53. Matsumoto M, Ogawa T, Kashima S, Takeuchi K. The impact of rural hospital closures on equity of commuting time for haemodialysis patients: simulation analysis using the capacity-distance model. *International journal of health geographics*. 2012; 11:28. doi:10.1186/1476-072x-11-28. [PubMed: 22824294]
54. Blok DJ, de Vlas SJ, Bakker R, van Lenthe FJ. Reducing Income Inequalities in Food Consumption: Explorations With an Agent-Based Model. *Am J Prev Med*. 2015; 49(4):605–13. doi:10.1016/j.amepre.2015.03.042. [PubMed: 26232897]
55. Mahamoud A, Roche B, Homer J. Modelling the social determinants of health and simulating short-term and long-term intervention impacts for the city of Toronto, Canada. *Soc Sci Med*. 2013; 93:247–55. doi:10.1016/j.socscimed.2012.06.036. [PubMed: 23123169]
56. Dray A, Perez P, Moore D, Dietze P, Bammer G, Jenkinson R, et al. Are drug detection dogs and mass-media campaigns likely to be effective policy responses to psychostimulant use and related harm? Results from an agent-based simulation model. *Int J Drug Policy*. 2012; 23(2):148–53. doi: 10.1016/j.drugpo.2011.05.018. [PubMed: 21742481]
57. Marshall BD, Paczkowski MM, Seemann L, Tempalski B, Pouget ER, Galea S, et al. A complex systems approach to evaluate HIV prevention in metropolitan areas: preliminary implications for combination intervention strategies. *PLoS One*. 2012; 7(9):e44833. doi:10.1371/journal.pone.0044833. [PubMed: 23028637]
58. El-Sayed AM, Seemann L, Scarborough P, Galea S. Are network-based interventions a useful antiobesity strategy? An application of simulation models for causal inference in epidemiology. *Am J Epidemiol*. 2013; 178(2):287–95. doi:10.1093/aje/kws455. [PubMed: 23696107]
59. Soerjomataram I, Barendregt JJ, Gartner C, Kunst A, Moller H, Avendano M. Reducing inequalities in lung cancer incidence through smoking policies. *Lung Cancer*. 2011; 73(3):268–73. doi:10.1016/j.lungcan.2011.01.009. [PubMed: 21333375]