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Development of a computational modeling laboratory for examining tobacco control policies: Tobacco Town

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Abstract

A key focus of recent policy efforts to curb tobacco product usage has been the role of place—specifically the density of retail and advertising and the resulting spatial pattern of access and exposure for consumers. Policies can alter the environment by reducing density or shifting distribution of tobacco retail and thus limiting access and exposure. Since little empirical evidence exists for the potential impact of these policies across potentially heterogeneous places, we develop and apply an original spatial computational model to simulate place-based retail tobacco control policies. The model is well-grounded in theory and available empirical evidence. We apply the model in four representative settings to demonstrate the utility of this approach as a policy laboratory, to develop general insights on the relationship between retailer density, retail interventions, and tobacco costs incurred by consumers, and to provide a framework to guide future modeling and empirical studies. Our results suggest that the potential impact on costs of reducing tobacco retailer density are highly dependent on context. Projected impacts are also influenced by assumptions made about agent (smoker) purchasing decision-making processes. In the absence of evidence in this area, we tested and compared three alternative decision rules; these interact with environmental properties to produce different results. Agent properties, namely income and cigarettes per day, also shape purchasing patterns before and after policy interventions. We conclude that agent-based modeling in general, and Tobacco Town specifically, hold much potential as a platform for testing and comparing the impact of various retail-based tobacco policies across different communities. Initial modeling efforts uncover important gaps in both data and theory and can provide guidance for new empirical studies in tobacco control.

Keywords

Tobacco control; Tobacco retailer density; Agent-based modeling; Chronic disease prevention; Systems science

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Appendix A. Supplementary data
Supplementary data to this article can be found online at https://doi.org/10.1016/j.healthplace.2019.102256

1. Introduction

Design and implementation of public health policy, including tobacco control policy, is often informed by evidence from experiments, natural observations, and statistical models. The last decade has seen increasing uptake of computational modeling approaches from complex systems science as a complement to these traditional policy design aids. Such models are now used to inform policy choices or intervention design in control of communicable disease (Burke et al., 2006; Epstein, 2009; Lee et al., 2010; Yang et al., 2009; Ferguson et al., 2006), land-use and agricultural policy (Berger et al., 2006; Brady et al., 2009; Guzy et al., 2008; Happe et al., 2006, 2008), ecosystem and natural resource management (Heckbert et al., 2010; Schluter and Pahl-Wostl, 2007), and increasingly in chronic disease prevention (Zhang et al., 2015; Hammond, 2014; Li, 2016). Complex systems approaches offer the opportunity to consider potential policy intervention effects across diverse contexts or populations and over long time horizons, to capture potential interactions or tradeoffs among multiple intervention actions within a package of policies, and to address the role of adaptive response by actors within the system in shaping a policy's net impact (Hammond, 2015)– all of which would be difficult if not impossible to address with traditional observational or experimental policy study designs (Luke and Stamatakis, 2012). In addition, these modeling approaches allow consideration of spatial elements that are difficult to capture in other dynamic modeling frameworks. These are particularly important at present given the emphasis of policymakers on retail-density-based policy options, and the limited statistical evidence base to inform design of such policies.

In this paper, we describe the design and application of a new model for simulating place-based retail tobacco policies. While smoke-free and tax policies along with access to cessation services remain the corner-stones of tobacco control strategies, retail-focused interventions are quickly becoming a priority for tobacco control programs across the US. Despite growing interest in this strategy, a body of evidence for retail policies has been slow to emerge (Moreland-Russell et al., 2015; Luke et al., 2016). Opportunities to test multiple competing variants of retail interventions in real-world settings are limited, and analysis of policy impact is challenging given the inherently spatial nature of the policies, the high degree of heterogeneity across likely settings, and the need for longitudinal tracking to capture adaptive responses by consumers and retailers alike to an altered retail environment.

Our model, entitled *Tobacco Town*, is intended to address this gap, serving as a 'policy laboratory' for retail tobacco interventions (Hammond, 2015). We use a technique known as agent-based modeling (ABM) (Bonabeau, 2002; Gilbert and Gilbert, 2008; Taylor, 2014), in which individual actors in a system and a spatial context are represented in a computational framework that allows simulation of dynamics driven by decentralized interactions of actors with each other and with their environments. ABM offers particular advantages for the study of retail-oriented tobacco control policies. Since such policies are inherently spatial (e.g., regulating location and concentration of tobacco retailers through zoning), sufficiently detailed representation of geography and contextual heterogeneity is essential for any model —and capture of spatial elements is a particular strength of ABM (IOM, 2015). The technique also offers an effective way to study interaction between individual behavior and a co-evolving environmental context, or even social interactions between individuals themselves (Bruch et al., 2015). Finally, because ABM is an individual-level simulation technique and does not require aggregation to study relatively large populations, it can yield important insights into distributional effects and health disparities (Langellier, 2016; White et al., 2012). Previous uses of ABM to study spatial dynamics and interventions in public health include work on physical activity and walkability (Kumanyika et al., 2019; Yang et al., 2014) and control of communicable disease epidemics (Burke et al., 2006; Epstein, 2009; Lee et al., 2010; Yang et al., 2009; Ferguson et al., 2006).

This paper is intended to introduce the TobaccoTown approach and provide a broad framework that is flexible enough to accommodate future advances in behavioral and empirical science in the field of tobacco control and bring these insights into a policy arena. Unlike our other experiments with the TobaccoTown concept, the model presented here allows for heterogeneity in individual decision-making behavior surrounding tobacco purchase (an area in which science is rapidly evolving) and allows for greater generalizability and extension in future work (discussed in section 4.1).

Below, we describe the design of Tobacco Town and the sources of data and social science theory used to ensure that it is well-grounded using the best available evidence. We outline multiple uses for the model, and apply it to representative abstract settings to demonstrate its utility and to develop broad insights into the potential impacts of retail policies. We report generalized results on the relationship between retailer density, retail interventions, and tobacco costs incurred by consumers (including both travel and price costs), along with sensitivity analyses that put these results in context. We also highlight important gaps in both theory and empirical evidence uncovered by the modeling effort, and provide guidance for new empirical studies in tobacco control. We conclude by describing the potential for future work using Tobacco Town as a platform, and by connecting this work to broader emergent themes in public health policy and chronic disease prevention.

2. Methods

Tobacco Town is an agent-based simulation model, which draws on key concepts and structures from our experience and from the growing evidence base for place-based tobacco control policies, particularly retailer density (Ribisl et al., 2017; Cohen and Anglin, 2009; Leatherdale and Strath, 2007). These are operationalized into constructs appropriate for the agent-based model framework in accordance with standard best practices for using ABMs to inform tobacco regulatory policy (Hammond, 2015). We then apply the model to abstract contexts intended to represent plausible real-world settings, modeling the impact of generalized retailer density reduction to generate a set of initial insights and to demonstrate the utility of the model.

2.1. Model design

Our general approach was to build an agent-based model of a hypothetical environment, Tobacco Town, populated by individuals (‘agents’) who are current cigarette smokers. The town consists of a basic grid geography, containing a street network, key locations where agents spend time (workplaces and homes), and tobacco retailers. Agents travel around the town between home and an assigned destination (referred to as a ‘workplace’, although this is an abstract category that reflects any daytime destination), making choices along the way about whether to purchase cigarettes—and if so, where and how many. The model design is focused on key and actionable parameters (distance, cost, and supply) aligned with place-based retail policies. In this section, we provide an overview of the model’s basic design as well as the data that were used to parameterize it. See Appendix for more technical details about model construction and execution.

2.2. Incorporating place: the environment

Individual tobacco users’ experience of retail-density policies is mediated through place—namely, through the reshaping of the environment which governs access and exposure to tobacco retail. To allow for examination of place-based tobacco control policies on health behavior with maximum generalizability, four different abstract settings were defined in the model to represent typical community environments: Urban Rich, Urban Poor, Suburban Rich, and Suburban Poor. Each community type was informed by realistic data from a prototypic California city, although the cities are not modeled in geographic detail. Cities were selected from a dataset containing all California cities and census-defined places with between 30,000 and 130,000 residents, and were chosen based on their population density and median household income (US Census Bureau, 2012) (see Appendix) to serve as archetypes of the four communities. California cities were chosen because of access to accurate retailer density data and matched to nationally representative census places by median household income where current cigarette price data were available. Both the California retailer data and the nationally-representative cigarette price data were obtained from a related study funded by the National Cancer Institute (U01 - CA154281). Each community is an abstract square grid of streets representing 10 square miles.

Every simulation run of the Tobacco Town model generates a virtual town based on a set of specified parameter values and input data, chosen to represent aspects of the environment that are most important for retail policies. These include the spatial density of several different types of tobacco retailers (convenience stores, drug stores, tobacconists, grocery stores, liquor stores, and mass merchants) and the distributions of cigarette prices across these retailer types (Feld, 2016). Densities of schools and workplaces are also represented, along with income, demographics, and the mix of transportation types among the population. Based on these parameters, retailers are created, assigned types and cigarette prices, and stochastically placed at intersections in the uniform street grid. School and workplaces of defined density, from federal data sources for the archetype cities (US Census Bureau, 2018; National Center for Education Statistics, 2018), were created and placed as well. Finally, agents are created (with properties that are discussed below) and placed in residences that are also located on intersections.

2.3. Incorporating individual heterogeneity: the agents

In our Tobacco Town model, agents represent individual adult cigarette smokers. For the initial model, we leave aside the question of initiation and cessation (see Limitations) and focus on purchase decisions and costs incurred to obtain tobacco among current active smokers. These decisions and costs may change under different retail policy regimes. Each agent has a set of attributes assigned at the outset of every simulated run (which remain fixed throughout the duration). These include: residence and work locations (randomly selected from all available points in the town), a travel route between these locations (randomly selected upon initialization from the set of shortest paths between agents' residences and workplaces), and a constant daily smoking rate. Agents also have income levels, and a fixed type of transportation (i.e. walking, biking, or driving). The parameter values used to determine agent and environment properties in our model are grounded in empirical data taken from the US Census and other sources (US Census Bureau, 2012; Knoblauch et al., 1996; US Environmental Protection Agency, 2012; US Environmental Protection Agency, 2018) that are described in detail in the Appendix.

2.4. Dynamics

During each simulated day, agents travel from home to their assigned workplace and back again along their assigned fixed travel route. If an agent has fewer cigarettes on hand than they will smoke that day, they purchase more by visiting a retailer during their commute (which may involve deviation from their standard shortest route between home and work).[1] The key outcomes of the model are the price and travel costs incurred by agents each time they make a purchase; the specific retailer chosen is also recorded for each purchase. To calculate a total per-pack cost metric for each agent, we sum the price paid and the travel cost involved in deviating from their typical commute to visit the retailer, and divide by the number of packs purchased. This *total* cost per pack metric serves as a proxy for the accessibility of tobacco products, where accessibility can be modified by appropriate tobacco control policies that make it harder or more expensive to obtain tobacco products (Ashe et al., 2003). The total cost metric combining travel and purchase costs was chosen for two important reasons. First, this is consistent with fundamental behavioral and economic theories and studies demonstrating that people will prefer to minimize costs and travel times for purchasing commodities (https://cdn2.hubspot.net/, 2637; Andreyeva et al., 2010) Second, the purchase and travel metrics are aligned well with actual and proposed tobacco control policies that work by increasing tobacco product costs (via taxes and setting minimum prices, for example) or reducing tobacco retailer density (which increases travel times and costs) (Chaloupka et al., 2011; Henriksen, 2012; Kirst et al., 2019). See Appendix [1] for equations governing these costs.

Agents can trade off price cost and travel cost—choosing for example to travel further out of their way to visit a retailer with cheaper advertised prices. The core dynamics of the model are thus determined by the spatial distribution of agents and retailers with various characteristics (including prices) and by the retailer-selection decision process employed by the agents. Changes in retail policy will cause changes in the spatial distribution of retailers, which will lead some agents to adapt their behavior, making different choices and incurring different costs.

[1]In the real world, individuals make purchases at other times (e.g., with their groceries). We make this simplifying assumption based on available data and for the sake of model parsimony. Ultimately, we believe it is a meaningful representation of tobacco purchase behavior.

An important evidence gap uncovered by the Tobacco Town modeling project concerns decision models for tobacco purchase among consumers. Only very limited existing tobacco-specific data or research is available to guide our characterization of either retailer selection decisions or purchase quantity decisions (Cohen and Anglin, 2009)—this is discussed further below. For the initial model, we created three stylized strategies that draw directly on well-supported theoretical and empirical literatures in social and behavioral science more generally. We use the simulation platform to compare different assumptions about decision-making and characterize the impact of each on overall purchase behavior and policy effects. Briefly, the three decision rules are:

Rational.—Agents have full information about current retailer locations and prices within the town, consider all available retailers when choosing where and how much to purchase, and optimize their choice to minimize costs (see below). This rule is consistent with canonical models of decision-making in economics (Elster et al., 1994).

Two-phase.—Agents have full information about retailer locations and prices, but consider a limited set of retailers when choosing where and how much to purchase. The consideration set of retailers is reduced by applying one of the following heuristic filters:

- A maximum price the agent is willing to pay
- A maximum distance the agent is willing to travel
- A type of retailer which the agent will not consider

If the consideration set contains no retailers, then agents choose the best retailer with regard to the specified metric (*e.g.*, the closest retailer if consideration is limited by a maximum distance). This rule is inspired by recent research in cognitive science and marketing (Bruch and Feinberg, 2017).

Learning.—Agents begin each simulation with limited information. Initially, they expect cigarettes at all retailers to be priced at the mean price for the town. Through local sampling (*i.e.*, as they make their initial purchases at specific retailers or directly observe prices at retailers that they pass), they update their information about prices through a standard learning rule. This rule is consistent with learning theory as applied to consumer choice behavior (Tellis and Gaeth, 1990; Swait and Adamowicz, 2001).

All agents in any particular simulation run use the same decision strategy. Regardless of strategy, agents' purchase behaviors are determined using the following algorithm:

1. *Calculate expected optimal purchase quantity for each potential retailer*. This is defined as the quantity that results in the minimum expected total per-pack cost for a retailer. Total cost is a combination of a) expected cigarette pack prices at a retailer; b) travel costs (*e.g.*, fuel); and opportunity costs (i.e., the value of the time that agents would spend deviating from their daily travel route and making purchases, based upon the agents' hourly incomes). Every ten packs of cigarettes are bundled into a carton (which is less expensive than ten separate packs). Agents consider cigarettes that will be consumed on subsequent days as

having lower value (*i.e.* having higher cost). Finally, purchases are capped at an upper limit of 100 packs, or 10 cartons.

2. *Select the retailer with the lowest expected purchase cost.* This is based on a comparison of the total per-pack costs of purchasing optimal quantities of cigarettes. The model allows for stochastic noise in this step: there is a small probability of an alternative retailer being selected instead. This increases retailer sampling, which is essential when agents employ the learning rule described above.

3. *Travel to selected retailer.* Agents will then follow a randomly selected shortest path from their daily travel route to the retailer. Under the learning rule, the path chosen shapes the exposure of the agent to retail options, and thus the trajectory of learning (and future decisions).

4. *Purchase cigarettes.* Purchase the expected optimal quantity of cigarettes from the selected retailer.

Agents will smoke their daily smoking rate's worth of cigarettes between simulated days, reducing starting inventory on the next day. During each model run, detailed data are collected on agents' purchase behavior individually (including timing of purchases, sequence of retailers chosen, and cost incurred) and in aggregate (*e.g.*, distributions across agent types and across retailers and retailer types).

2.5. Application

The model is designed to allow comparisons between a status quo base case and a variety of potential simulated policy changes intended to reduce density of retailers (Cohen and Anglin, 2009). These might include removal of: a proportion of existing retailers at random, all retailers of a specific type, retailers within a specified radius of schools, and retailers within a specified distance of another retailer.

The model also allows for variation in assumptions regarding agent decision-making about tobacco purchase (i.e., the three separate algorithmic decision rules described above). Co-variation of policy parameters, town type, and decision rule define a multi-dimensional parameter space within which we generated and analyzed results (presented below). A full description of the parameter space explored and simulation runs undertaken is provided in the Appendix.

Each model run consisted of 30 simulated days, and each parameterization was run 40 times to allow for stochastic variation. Stochastic elements in the model include random placement of retailers and agents' homes and worksites. Standard errors for important metrics were low across runs and across late time periods, indicating this number of simulations and simulation length were sufficient to capture variation.

3. Model calibration & results

The initial version of Tobacco Town reported here is a proof of concept to be used in the future with more detailed geographies for place-specific policy simulations; we do not directly test policy projections retrospectively or prospectively in this paper. To build confidence in the model, we ground as many of our assumptions and starting parameters as possible in empirical data and fully-explicated, commonly-used theory (see above), and then demonstrate that the model produces output that is both internally consistent and can reproduce patterns in observed data. The first set of model run outputs were used for both model calibration and to assess face validity. For example, we compared baseline outputs from Tobacco Town to data from the most recent National Adult Tobacco Survey (NATS) (CDC, 2018) to check whether the patterns of tobacco purchase generated by the model match those observed in surveillance systems. Fig. 1 provides an example comparison and shows reasonable agreement between aggregated agent behavioral patterns and survey data– the majority of both real-life smokers and the model's agents made purchases at convenience stores or gas stations. The largest difference between model output and empirical data was found for drug and convenience stores, with 10–15% more purchases in the model shifted to drug stores instead of convenience stores. The empirical store audit data in our cities showed that on average, prices at drug stores were slightly lower than those at convenience stores, so agents occasionally purchased more at drug stores in the model. Overall, purchase proportions among store types are in agreement between the empirical and model data.

An important early contribution of the Tobacco Town model is to highlight data gaps in the tobacco control literature—for example, to our knowledge, no data is available that directly measures travel costs incurred for tobacco purchase, nor evidence that would allow us to directly adjudicate between decision-making assumptions for tobacco purchase used here. Future work to collect this type of data would allow further testing and calibration of the simulation model.

3.1. Generalized density reduction: nonlinearity and context-dependency

Our initial analysis with Tobacco Town focused on understanding the impact of variations in density between different town types and the potential effects of generalized (randomly distributed) density reductions. We varied retailer density across wide ranges, in different town type settings and across a large number of runs, and uncovered two important findings. First, the relationship between retailer density (retailers per square mile) and total cost incurred for purchases (averaged across all individuals in the town) is *nonlinear*, and suggests the presence of a threshold effect (Fig. 2). When tobacco retailers are relatively abundant, small or moderate density reductions have minimal projected impact on cost. By contrast, when retailers are relatively scarce, density reductions of the same magnitude can have dramatic impacts. This is potentially important guidance for policy decision-making. Second, since town types exhibit characteristic differences in initial retailer abundance, density reductions are likely to have different impacts (with concomitant different slopes) in different types of settings. This also has important potential implications for policy planning and for disparities. The shaded areas in Fig. 2 represent the distance between the 15th and 85th percentiles in density for each community type. While urban and suburban poor areas potentially see just 7% and 6% increases in cost by dramatically reducing retailer density, their higher-income counterparts may see 12% or 14% cost increases.

3.2. Impact of individual decision rules on dynamics and key outcomes

As an ABM, Tobacco Town is an individual-based simulation model, allowing both for distributional results in addition to population averages (see next section below) and for consideration of the role of individual decision-making in determining overall dynamics. As discussed above, no direct studies of tobacco user purchase decision-making exist so we have relied on broader literature in social and cognitive science to explore three different styles of decision-making in Tobacco Town. We conducted systematic analysis within the model to ascertain the impact that different assumptions about individual decision-making have on our key outcomes (purchase price distribution, travel cost distribution, and total cost distribution).

Fig. 3 compares the composition of costs across transportation modes and towns under two different decision rules, the *rational* rule and a particular parameterization of the *two-phase* rule under which agents refuse to travel more than one half mile off their home-to-work route to buy cigarettes. The results show that rank ordering of costs across transportation modes is consistent across town types and decision rules, that is, travel costs are always lowest for drivers and highest for walkers. In addition, while agents with restrictions on distance they travel always incur higher overall costs than unrestricted agents, travel costs for restricted agents are always lower, but purchase prices are higher. Finally, we see that purchase prices are more variable when agents' distances are unrestricted.

Our third type of decision-rule—the *learning* rule—produces changes through time in agent choices even within a fixed environment. Agents using the learning rule have changing information as a function of specific geographic location and routing, as well as the frequency with which they will sample new information by purchasing from retailers whose prices are not the anticipated lowest available. Sampling, and the incorporation of new information into future decisions, are controlled by individual learning parameters (see Appendix). Learning dynamics are thus a joint product of individual and environmental settings.

Fig. 4 illustrates typical trajectories through time for cost outcomes experienced by individuals using the rational and learning rules in different town settings. Costs under the learning rule are always higher than those experienced under the rational rule in each town type, but those under the learning rule decrease relatively rapidly at first, then become more stable over time. The up and down oscillation, seen more under the rational decision rule, is due to pack-a-day carton purchasers, many of whom buy a carton approximately every 10 days. At the model start, when these agents are rational with perfect information, they purchase cartons for the lowest price, hence the relatively large uptick in average cost under this decision rule after day zero when single- or multiple-pack purchasers comprise the majority of buyers. The same uptick is not seen under the learning decision rule as carton buyers purchase from a larger variety of retailers under imperfect information. As the model continues, all agents learn about the distribution of prices and purchases converge on lower-priced retailers. Dynamics produced by learning have important implications for policy impact interpretation (see Discussion)—estimated effects of an intervention may differ in the short-run and the long-run.

3.3. Impact of agent characteristics and environment on outcomes

Regardless of the choice of decision rule, agent and environmental characteristics affect dynamics and key outcomes. An important feature of Tobacco Town is its ability, as an individual-based model, to draw out these differences across individuals and uncover potential distributional consequences of policies.

Agents in our model differ in ways that affect the prices that they experience during the course of a simulation. These differences include geography (*i.e.*, proximity of retailers to agents' routes between home and work), wages, transportation, and discount rate. Taken together, these sources of heterogeneity across agents can produce meaningful heterogeneity in our outcomes of interest.

Figs. 5 and 6 compare average model outputs by particular agent characteristics across town types and among decision rules. Fig. 5 considers the lowest- and highest-earning agents (bottom and top income quartiles in each town type) and compares the average number of packs purchased and distance traveled per retailer visit. In each environment, the lowest earners consistently purchase fewer packs per visit but travel longer distances to do so. The difference in number of packs purchased on average between income groups is greatest in the urban rich town type, while the difference in distance traveled is greatest in suburban rich. This makes intuitive sense and is also consistent with behavioral economic theory– people with lower incomes are willing to trade time to save money, while higher income agents are less price sensitive.

Fig. 6 shows differences in travel cost and distance traveled across agents by cigarettes smoked per day. In general, heavier smokers are incentivized to travel longer distances and to buy in bulk to offset travel costs. The slope of the nonlinear relationship between cigarettes per day and travel costs is mediated by the town type (i.e., the underlying density of retailers and agents).

4. Discussion

Tobacco Town is a computational model designed to serve as a *spatial policy laboratory*, providing insight into the potential impacts of tobacco control policies that aim to alter the retail environment at the point of sale. Unlike other policy simulation models in the tobacco control field (IOM, 2015), the role of place and spatial structure are a central focus here— the distribution of retailers of different types across the space through which individuals move shapes the dynamics of search and purchase. As we demonstrate above, differences in place drive differences in outcomes across individuals, settings, and policies. The emphasis on spatial dynamics is facilitated by the approach taken here, agent-based modeling. This approach also offers other advantages for tobacco control policy implementation and for place-based policies more generally. For example, the individual-based approach to modeling allows us to examine important differences between individuals and groups within the modeldifferences in decision-making, smoking rate, transportation choices, or demography such as presented above. Coupled with an explicit representation of individual decision-making, the dynamic nature of the simulation model allows us to address adaptive behavior by actors (as in the learning rule). Above, we demonstrate that this can lead long-run outcomes to differ from short-run outcomes. This has important implications for policy design and evaluation, which does not always consider adaptive dynamics (Hammond, 2015).

Although many existing tobacco models and policies emphasize individual characteristics, health and health disparities are generally driven by differential distributions across communities (White et al., 2012), and complex dynamics that arise through interaction between adaptive individuals and their co-evolving environments. ABM allows us to explore these co-evolutionary dynamics, and to effectively bridge from the individual level to the population level (and back again) (Bruch et al., 2015). The approach to policy design and implementation we present here is thus of increasing importance not only for tobacco control and regulations, but for physical activity, (Kumanyika et al., 2019) healthy cities (Yang et al., 2011), obesity (Gillman and Hammond, 2016), violence (Bhavnani and Miodownik, 2009), and other areas of population health research.

4.1. Limitations and future work

The Tobacco Town model was built using the best available empirical evidence and theory, including assumptions about individual tobacco consumer characteristics and behaviors, retailer characteristics, and environmental settings. The model can reproduce key stylized patterns of tobacco purchasing in plausible data-based contexts. We have also highlighted gaps in our current understanding as a field of tobacco decision-making and behavior, uncovered by the modeling process—these are necessarily limitations of our model. We see identification and discussion of these gaps as important contributions in advancing future work, drawing attention to the micro-foundations of population level patterns that are the more traditional focus of tobacco control research.

Also, as suggested earlier, this first proof-of-concept Tobacco Town model has been deliberately kept simple to follow best practices in model development (Hammond, 2015). For example, the abstract transportation grid and the assumption that agents always go to the same place to purchase tobacco products clearly do not perfectly match reality. However, these simplifying assumptions allow us to build a first model and test the fundamental dynamics of density, travel, and tobacco purchasing. Future studies will develop extended versions of Tobacco Town that will use more realistic city geography and incorporate more dynamic travel patterns.

We also intentionally limit the types of behavior that we model in this initial model, while incorporating design elements in the framework to permit future expansion. Most importantly, we do not simulate initiation and cessation. We do this because although these behaviors are almost certainly linked to outcomes that we do model (i.e. direct and indirect purchase costs), it is unclear how best to specify those relationships (e.g. their strength, linearity, or moderating influences). We also make necessary assumptions in this model regarding when smokers purchase cigarettes: given available data, we cannot comfortably characterize “opportunistic” purchases along with other items. Assumptions about how consumers purchase tobacco products include: we only consider a single product type; we use a simple characterization of time and travel distance valuation as well as temporal discounting; and we have homogeneous decision-making strategies within a given simulation run.

5. Conclusions

To illustrate the potential utility of Tobacco Town as a computational laboratory, and the types of insights it can produce, we applied it to four stylized representative settings and uncovered some generalized results. There is a nonlinear relationship between retailer density and individual outcomes (costs) in the model, as well as important differences across the four town type contexts. The central insight following from these results is that density reduction as a tobacco control measure should not be expected to necessarily have consistent results across settings. Instead, the impact of any given magnitude or style of density reduction may depend crucially on setting and timing. We also unpack our general findings to show how specific settings (environments) interact with individual characteristics (smoking rate and demography) and decision-making to form heterogeneous outcome distributions across the population. This illustrates the role Tobacco Town can play in helping assess distributional consequences of retailer policies, including impact on potential disparities.

This paper is intended to provide an introduction to Tobacco Town, its technical underpinnings, and its potential uses. We have begun application of the model to specific policies (Luke et al., 2017) and settings (Mahoney et al., 2016). Other future work will include expansion of the model to consider geographical data-driven (GIS) settings, retailer dynamics, tobacco initiation and cessation, and underage tobacco use, and to further expand the exploration of behavioral decision rules begun here (particularly as more evidence becomes available). The Tobacco Town project also fits within a broader agenda of *precision prevention* (Gillman and Hammond, 2016)—the tailoring of generalized evidence-based strategies to specific contexts to enhance effectiveness, avoid unintended consequences, and promote sustainable implementation.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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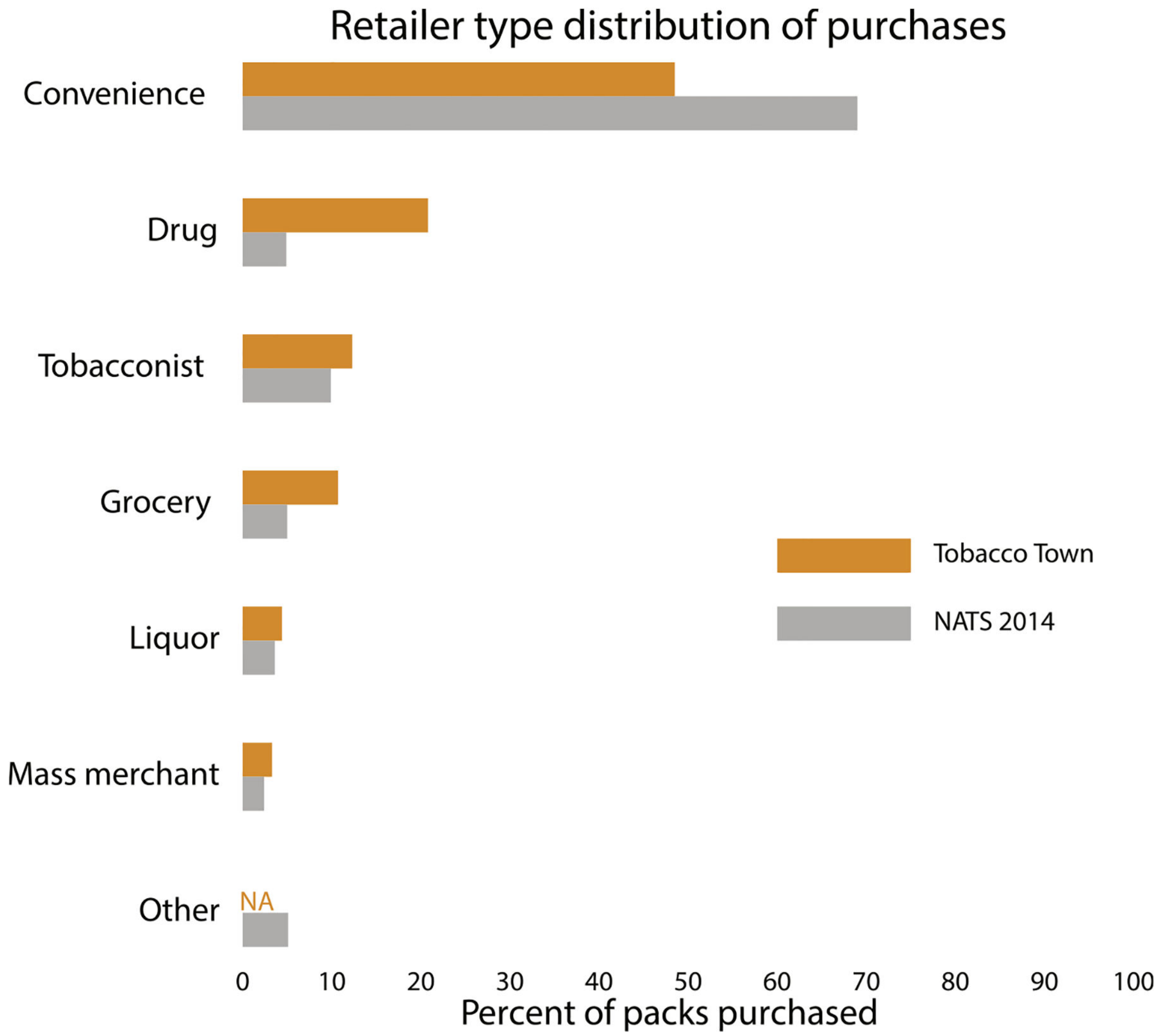

Fig. 1. Comparisons of Tobacco Town outputs and National Adult Tobacco Survey (NATS).
Aggregated simulation output of 1120 runs represented in orange, NATS data in grey. Overall patterns of purchasing are similar; the largest difference is observed for drug stores and convenience stores, where approximately 15% of purchases are shifted to drug stores in Tobacco Town.

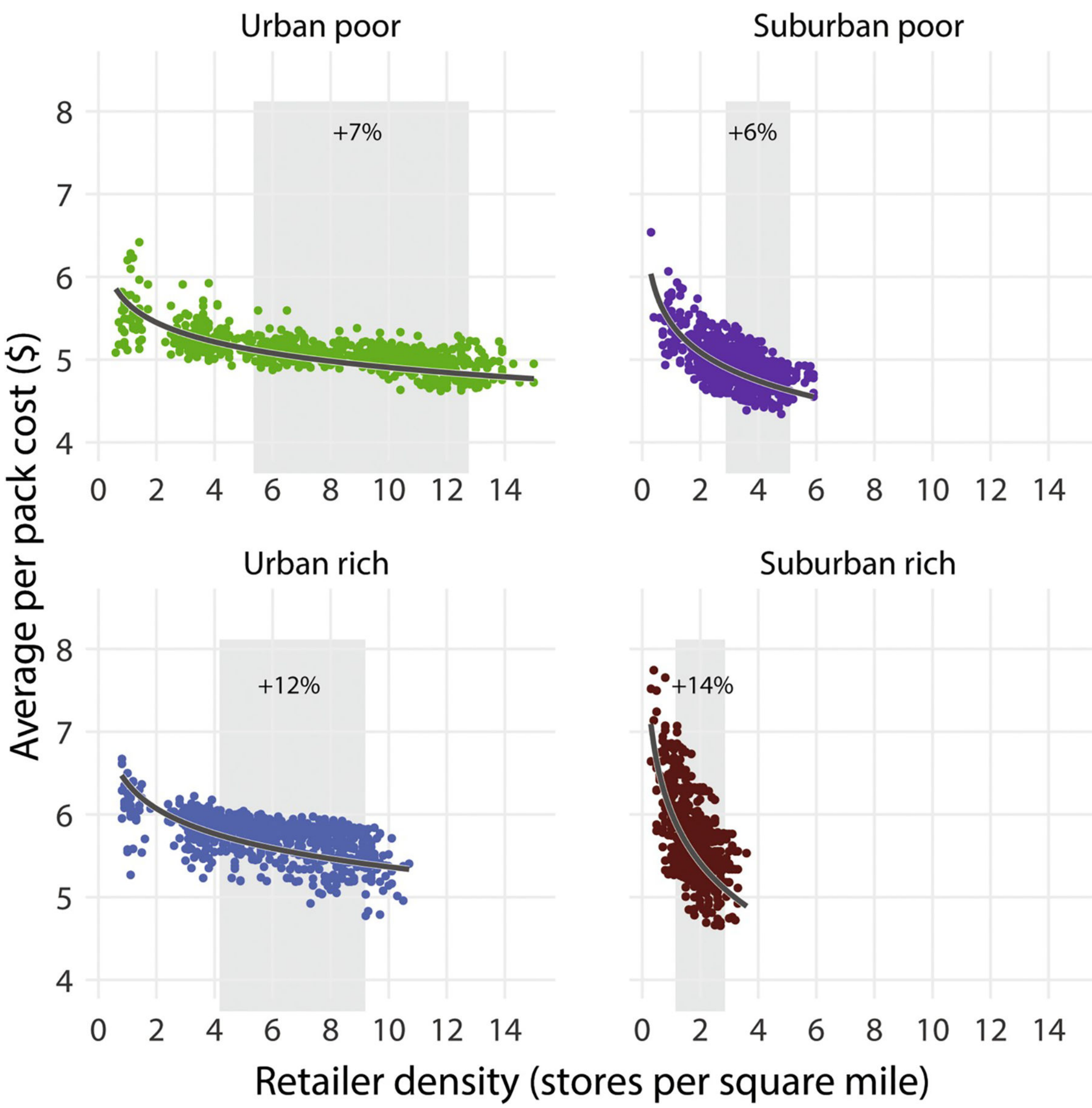

Fig. 2. Relationship between density and total cost across town types.

2560 simulation runs were conducted across 4 different town types with stochastic variation observed in retailer density (x-axis). Overall total cost (travel plus purchase cost), averaged across agents in each simulation, is shown on the y-axis. The shaded areas in each plot represent the 15th through the 85th percentiles of retailer density, and the percentages shown within each are the predicted increase in overall costs per pack of cigarettes.

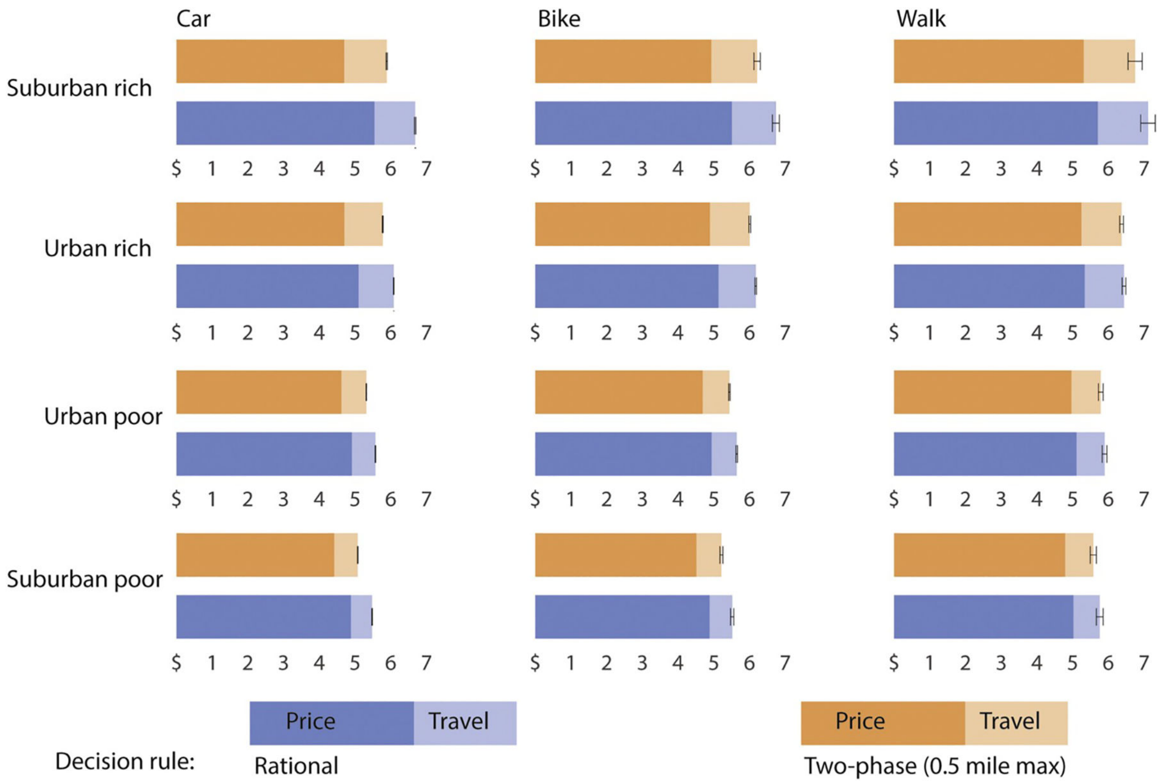

Fig. 3. Average total travel plus purchase costs by town type for two decision rules.

Comparison of components (travel and purchase price) of per pack cost across three transit modes and two decision rules comprising 84 runs. The blue bars show costs under the rational decision rule and the orange bars show costs under the two-phase rule wherein agents first restrict the additional distance they will travel for cigarettes to 0.5 miles, and then choose among the stores that meet this criterion. While costs are similar under both rules, they are always higher with the two-phase restricted distance rule.

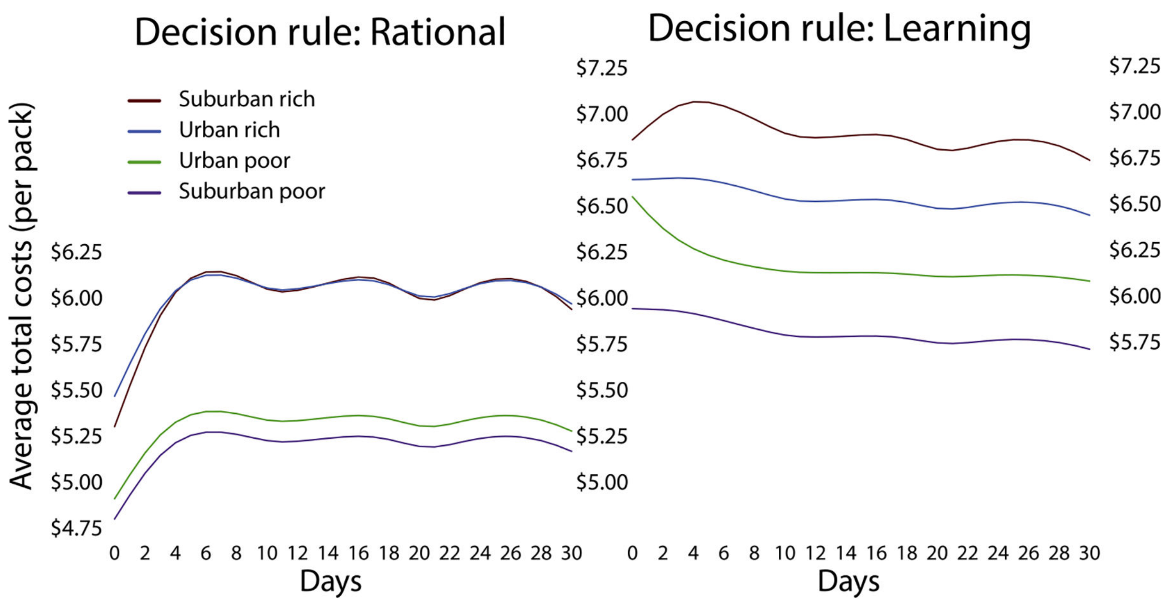

Fig. 4. Average total costs ($ per pack) for two decision rules by town type over time.

Simulated output (smoothed) of average daily costs per pack (travel plus purchase price) over 160 runs (80 per each decision rule) by town type. Costs incurred are always higher for the learning rule compared to those under the rational rule for each town type.

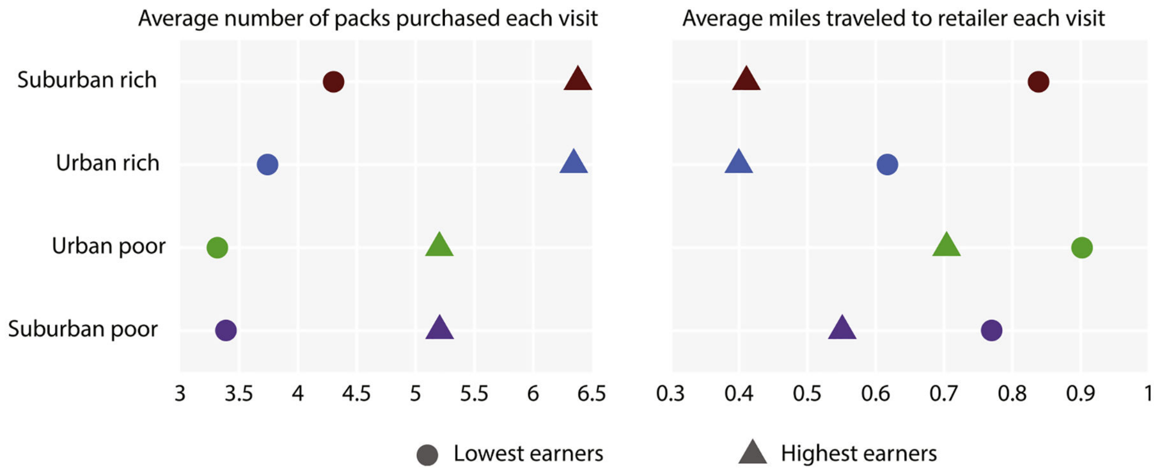

Fig. 5. Average purchase characteristics for lowest and highest income quartiles by town type.

Average number of packs purchased and miles traveled for agents in the lowest and highest income quartiles for each town type from simulation results in 84 runs. Highest earners consistently purchase more packs at shorter distances while lowest earners travel farther and purchase fewer packs on average.

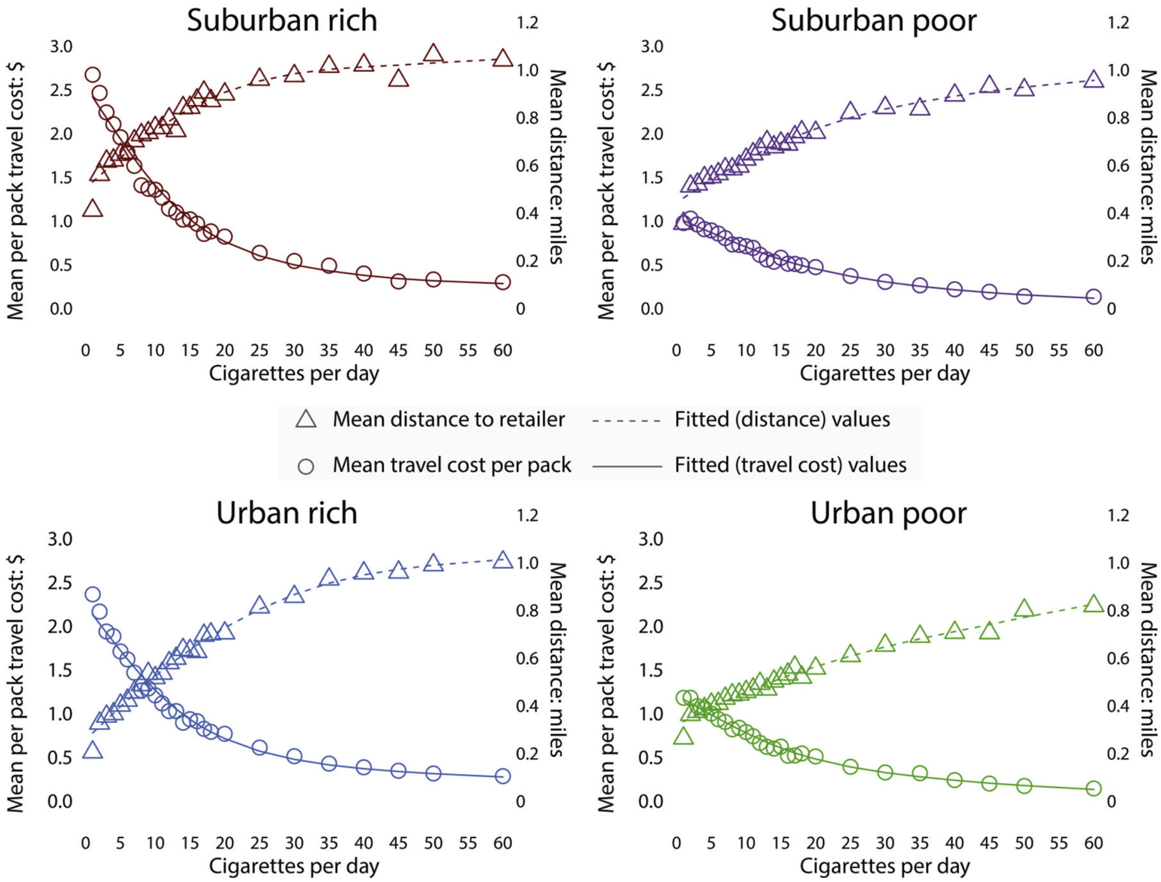

Fig. 6.

Average distance & travel costs by cigarettes per day and town type. Simulation results from 84 runs by town type showing average travel cost and distance traveled by agent smoking rate (cigarettes per day). Heavier smokers travel farther but reduce overall travel costs by purchasing in bulk.