URBANSCAPE: AN AGENT-BASED MODEL OF FAST FOOD RESTAURANTS WITHIN AN URBAN CONTEXT

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Introduction

The underlying putative causal pathways driving the spread of obesity in the United States fall into two main mechanisms: social contagion, and homophily. These processes are in part driven by food buying and consumption preferences as they relate to compositional and contextual effects. On one hand, social contagion is the process by which compositional factors – individual behaviors, preferences, and attitudes – propagate through social ties via influence, adoption, or persuasion (Christakis et al., 2007). On the other hand, homophily explains how individuals with similar attributes tend to cluster around similar physical and social milieus. Since food buying and consumption patterns are to a great extent tied to one's immediate surroundings, 'obesogenic' contextual factors could illuminate one of the mechanisms by which low-income minority communities suffer higher rates of obesity and diabetes (Kwate et al., 2009). Such factors include supermarket availability, food advertising, and park space accessibility, all of which ultimately shape food and exercise-related behaviors (Kwate et al., 2009).

With the steady progression of urbanization in the US and around the world, the multilevel dynamics that drive food and exercise-related behavior are of particular interest in the context of cities. In New York City, for instance, 2005 estimates place 53% of adults in the overweight or obese category as measured by BMI (Roberts et al., 2005). Of more concern is the finding that, as of 2004, 43% of New York City children are overweight, with an estimated obesity prevalence of

24%. Cases of obesity are particularly prevalent among Hispanic and Black children, which mirrors the distribution of obesity and its related comorbidities in the broader population (Thorpe, 2004).

The obesity epidemic is a daunting public health challenge primarily because the relevant actors and mechanisms operate at such a wide range of scales. These include micro and macro processes at the biophysical, behavioral, social, economic, political, and environmental levels. These often heterogeneous and autonomous parts interact to constitute a complex adaptive system (CAS), which is characterized by nonlinear, unpredictable outcomes (Hammond, 2009). Agent-based Modeling (ABM) is a relatively recent method for the study of CASs, and is particularly apt in the case of obesity as it relates to the food environment.

In this paper, I outline the basic architecture of the Urbanscape ABM in order to investigate how contextual factors drive obesity in an urban context. I begin by summarizing some of the contemporary literature vis-à-vis the relationships between income, food expenditure, mobility (as a measure of disability), obesity and diabetes, supermarket accessibility, and fast food restaurant density. Using these relationships, I conceptualize the basic parameters, variables, and rules by which fast food and grocery store agents interact with the urban context.

This schema of interrelated parts is the framework from which I construct the 'Urbanscape' ABM. While the initial output and analysis of preliminary simulations indicate a clustering of fast food exposure in low and low-middle income areas under certain initial conditions, the ABM in its current form is clearly inchoate. A major flaw in the assumptions of the model relates to the fact that the economics behind the operation and startup costs of food source agents are not grounded in empirical data. Due to the dearth in the peer-reviewed literature of the specifics of fast food and grocery store operations, the economic rules that govern agent behavior have instead been determined by the putative common sense notion of that fast food outlets generally have lower costs than and grocery stores. In acknowledging this limitation, it is important to note, however, that the main purpose of this ABM is to provide the rudimentary architecture upon which future inquiry can develop.

Obesity & Diabetes: A Structural Perspective

Much research has been done regarding the contextual correlates of obesity, so much so that the term 'obesogenic environment' has come into popular circulation. I will use 'obesogenicity' as defined by Swinburn et al. (1999), which is the combination of circumstances, exposures, and influences that promote obesity in individuals or within populations. According to their ecological model of obesity, biological and environmental factors shape behavioral attributes in an individual level, which then act on mediators – namely energy intake and expenditure – to ultimately modulate body fat composition (Swinburn et al., 1999). Studies in New York City specify city-scale properties that are useful as indicators of obesogenicity.

Rundle et al. (2009) found an inverse association between BMI and the density of BMI-healthy food outlets in the individual's neighborhood, but found no significant association between BMI and the density of BMI-unhealthy outlets. Underlying this urban topology of obesogenic factors is the economy of food expenditure and consumption, which is the primary focus of the Urbanscape ABM.

According to the US Department of Agriculture/Economic Research Service, the percentage of Food Away From Home (FAFH) expenditures have increased from 3.6% in 1970 to 4.1% in 2011 (US Department of Agriculture/Economic Research Service). Furthermore, Fast Food (FF) expenditures as a percentage of FAFH expenditures have likewise increased, from 21.2% in 1972 to 36.3% in 2011. Data from the Bureau of labor statistics show a more granular stratification of FAFH expenditure by income before taxes. Those in the income bracket of $5,000 or less spend approximately 56% of their income on FAFH, while those in the income bracket of $150,000 or more spend a factor of 10 less, at approximately 4% (US Department of Labor). Work done by Fanning et al. (2010) posits a decision-making model that produces predicted probability curves of per-day consumption of Food at Home (FAH), Fast Food (FF), and Other Food Away From Home (OFAFH). These predicted probabilities are based on a matrix of socioeconomic and demographic factors, notably age, sex, income, and household size. Relevant to the Urbanscape model is the predicted consumption probability of FF across income; the curve approximates an inverted parabola peaking at roughly $60,000 per year at a probability of 0.37 in males and 0.28 in females. While including consumer choices is outside the scope of the Urban Scape ABM, this predicted probability curve mirrors data taken from the continuing survey of food intakes by individuals (CSFII) of 1994-1996 and will be used to approximate the percent of income spent on FF per year.

While these consumption patterns account for obesogenic behaviors at the individual level, food providers embedded within the built environment interact with these preferences to influence both energy intake and expenditure. It would be useful, at this point, to introduce the notion of 'Food Deserts' as a relevant obesogenic construct. Much work has been done to characterize 'Food Deserts' (FDs) as neighborhoods that lack supermarkets and 'Food Oases' (FOs) as neighborhoods that have them in abundance (Furey et al., 2001, Pearce et al., 2007, Walker et al., 2012). However, it would be additionally useful to extend the definition of FDs as a combination of supermarkets, bodegas, fast food restaurants, junk food carts, and fruit/vegetable carts, along with their concomitant advertising schemes within the neighborhood context.

Examining one of these food providers, Kwate et al. (2009) links fast food exposure to predominantly Black and Latino neighborhoods in New York City, which in turn correlates with the prevalence of obesity and diabetes. As an important biological proxy for obesity, mobility disability is becoming highly prevalent among older populations, especially in middle-aged and older women (Vincent et al., 2010). While the chronic effects of childhood obesity are poorly understood at the moment, studies on the relatively proximal impairments of childhood obesity on motor and cardiovascular functions suggest an accompanying detriment to quality of life and life chances (Tsiros et al., 2011). Furthermore, current estimates of the economic costs of obesity place the aggregate yearly medical expenditure and productivity loss at 73.1 billion USD (Finkelstein, 2010).

These costs are exacerbated by the fact that obesity is a strongly correlated risk factor for type II diabetes and coronary heart disease, which themselves incur negative externalities to quality of life (Eekel et al., 1998; Mokdad et al., 2003). The current thinking regarding obesity and its impact on the individual and populations is that individual-level behaviors operate within environmental bounds that are themselves shaped by social norms, legislation, and economic factors. This review of obesity-related studies would suggest that the relationships outlined above establish and perpetuate a positive feedback loop that clusters fast food exposure in low-income neighborhoods.

Urbanscape as the Environmental Context

Drawing from the literature, a simplified causal model of obesity can inform the Urbanscape ABM, which is written in the Python programming language. The environmental context in which agents act is defined as a square grid of n x n squares that represent residential city blocks. Urbanscape is a time-discrete model, running on an annual time scale, with each block containing exogenous and endogenous attributes that represent aggregated variables. The key exogenous factor is the average cost of living per block defined as ‘rent’; the distribution of rent in the urbanscape is an immutable attribute that is preset as an initial condition. The initial experiments delineated in this paper establish the initial rent distribution using the 'centralbusinessdistrict_distribution' (CBD), 'random_distribution' (random), and 'vertical_distribution' (vertical) methods (see **Supplemental Materials**, lines 298-308, 239-241, and 216-224 respectively). The average income per block 'i' is an endogenous variable, which is defined by the function:

$$f(r) = 4r \times \mu \tag{1}$$

where r denotes rent and, $\mu \in \mathbb{R}$: $\mu_{min} \leq \mu \leq 1$

μ denotes the average 'mobility' of residents, which is the biophysical proxy of obesity that reduces income by some factor, the value of which is a determined by the logistic decay function:

$$f(x) = \alpha + \left(\frac{1-\alpha}{1+\beta^{(x-\lambda)}} \right) \tag{2}$$

where x denotes 'externalities', $\alpha \in \mathbb{R}$: $0 \leq \alpha \leq 1$,
$\beta \in \mathbb{R}$: $\beta > 1$, *and* $\lambda \in \mathbb{Z}$: $\lambda > 0$

x in this case denotes negative externalities, which is a tally of exposure to FFAs and GSAs, which is described in more detail in the next section. The parameter α defines the possible values that μ can assume, ranging from α to 1. β defines the rate of decay and λ defines the inflection point of the logistic decay function. Thus, *x* is a crude measure of the total amount of exposure that a particular block has endured in the number of time steps t.

Each block in the Urbanscape also spends some fraction of its income on FAFH, FF, and FAH. The percent of income spent on FAFH is determined by the power function (3) and percent of income spent on FF is determined by the quadratic function (4.1) for $h(i) \geq 0.075$. Due to a dearth of granular data on fast food expenditures beyond an income level of 100,000 per year, a major assumption in the model is that any income value for which $h(i) \leq 0.075$ follows the randomized linear function described in equation (4.2).

$$g(i) = \theta i^{-\eta} \rho \tag{3}$$

where i denotes income and $\theta,\eta,\rho \in \mathbb{R}$

$$h(i) = -(\delta i - \varepsilon)^2 \rho \tag{4.1}$$

limited to a range of $h(i) \geq 0.075$, *and where* $\delta,\varepsilon,\rho \in \mathbb{R}$

$$f(i) = 0.075\rho \tag{4.2}$$

for all $h(i) < 0.075$

$$k(i) = \kappa i^{-\gamma} \rho \tag{5}$$

where i denotes income and $\kappa,\gamma,\rho \in \mathbb{R}$

Equations (3), (4.1), (4.2), and (5) include a random variable ρ, which is a random multiplier such that $0.75 \leq \rho \leq 1.25$. This introduces an element of stochasticity to the percent expenditures on FAH, FAFH, and FF. From these percentage values, we can derive the average income spent on FAFH, FF, and FAH, which are defined by the equations (6), (7), and (8) respectively:

$$i_{FAFH} = g(i) \times i \tag{6}$$

$$i_{FF} = h(i) * i_{FAFH} \tag{7}$$

$$i_{FAH} = k(i) * i \tag{8}$$

This model assumes that the percent of income spent on food at home is synonymous with grocery expenses, and that exposure to GSAs decreases exposure to negative externalities from FFAs. The endogenous variables of income, mobility, negative externalities, and expenditure on FF and FAH are shaped by the FFAs and GSAs that populate the Urbanscape based on their location on the grid, their effect radius, and the rule by which their location is determined. The next section delineates the Agent creation rule for determining which static location each Agent occupies.

Negative Externalities & the Profit Motive

The parent class for all agents in Urbanscape is called 'Agent', whose two attributes keep track of its location on the n x n grid and its wealth. FastFoodAgent (FFA) and GroceryStoreAgent (GSA) are subclasses of this parent class, and they share similar attributes but differ in operation costs and externality effects. One of the core rules of the Urbanscape ABM is that a maximum of one FFA and one GSA can occupy a city block at any particular time.

The annual total operation cost of FFAs and GSAs are defined as the rent of the particular block b_i that they occupy, plus a predetermined integer value that is not empirically-based but was determined by initial experimentation with different values (see **Supplementary Materials**, lines 371-399). Qualitatively, the operation costs of a grocery store are putatively much higher than that of a fast food restaurant. Therefore, the yearly operation cost of a GSA is set at $200,000 plus location rent, and the operation cost of a FFA is set at $50,000 plus location rent. Starting at some initial wealth, their revenues determine whether or not they remain in business or go bankrupt. Once bankrupt, agents are removed from the Urbanscape grid.

The effect radius of FFAs and GSAs is a parameter that is preset to '2', which defines a Moore neighborhood that extends two blocks in all directions from the central location. Each Agent has an immutable set of coordinates defined by the effect radius function (see **Supplementary Materials,** lines 69-75). These coordinates delineate the blocks from which the FFA and GSA can 'capture' the income spent on fast food in each block within the Agent's radius. To account for competition, the total amount of the fast food expenditures is split evenly among all other FFAs of the same type whose effect radii include b_i. Similarly, the total amount of expenditures spent on food at home is divided among GSAs that share the particular block $b_{i.}$ The 'fast food capture number' ('grocery store capture number') of each block denotes the value by which FF (FAH) expenditures are split at a particular time *t*. Therefore, the 'negative externalities' of the Urbanscape represent a tally of the total fast food capture number minus the total grocery store capture number of each block at total time *T*.

Agents are created in the Urbanscape based on a probabilistic rule, which assesses the potential profits that would be garnered if the Agent were to establish itself in a particular block. The potential profits for each block are directly proportional to the probability with which the Agent starts its business. If more than one block is 'chosen' as a candidate location, a single coordinate is randomly picked (see urbanscape.py, lines 444-557).

Simulations & Results:

Scaling Rent vs. Non-Scaling Operation Costs

I tested two versions of Urbanscape — urbanscape_v3 and urbanscape_v4 — that have one distinct rule difference. In version 3, the Non-Scaling Operation Costs (OCs) rule is as follows: the operation costs of FFAs and GSAs are fixed, regardless of average rent r_b at $(x,y)_i$ where $(x,y)_n$ is the block location of agents i = {1, 2, 3, ..., n} (Figures 1A-E, 2A-E, 3A-E). The projected profits in the probability create rule will favor locations in high income areas. In version 4, the Scaling OCs rule are defined such that the operation costs of FFAs and GSAs scale linearly with r_b, meaning that operation costs increase at a proportional rate to block rent cost increases (Figures 1F-J, 2F-J, 3F-J). This would diminish the difference in potential profits between setting up in lower and higher income areas. For each rule set, I ran simulations with the 'CBD', 'random', and 'vertical' rent distribution methods.

While an inverse association between negative externality exposure and block income level are discernible in all simulation experiments, the relationship is clearer in ‘CBD’ rent distribution experiments (Figure 1A,F) than in the ‘random’ and ‘vertical’ rent distribution experiments (Figure 2A,F and 3A,F respectively). The plateauing of externality exposure in the ‘random’ and ‘vertical’ experiments compared to its sustained increase in the ‘CBD’ experiments could possibly be explained by complex system dynamics. The positive feedback loop between food expenditures and potential agent profits favors the establishment of FFAs and GSAs in low-income and high-income areas respectively. It is possible that the differential localization of FFAs (Figure 1D,I) and GSAs (Figure 1E,J) reinforces this feedback loop in ‘CBD’ rent urbanscape distributions.

A worry in considering this hypothesis would be that the dose dependence of negative externalities on income is an artifact of the model; in other words, the rules of the model necessarily leads to the differential in localization of FSAs and GSAs. However, the observation that income affects on externalities are discernible in ‘random’ and ‘vertical’ experiments even with the apparent co-localization of FFAs (Figure 2D,I and Figure 3D,I) and GSAs (Figure 2E,J and Figure 3E,J) suggests the possibility of a statistically detectable positive feedback loop in micro pockets of the Urbanscape. Further analysis is needed to support this hypothesis, and a hint may lie in the observation that there exist pockets of low mobility even with relatively uniform localizations of FFAs and GSAs under the ‘random’ distribution regime (Figure 2C,H).

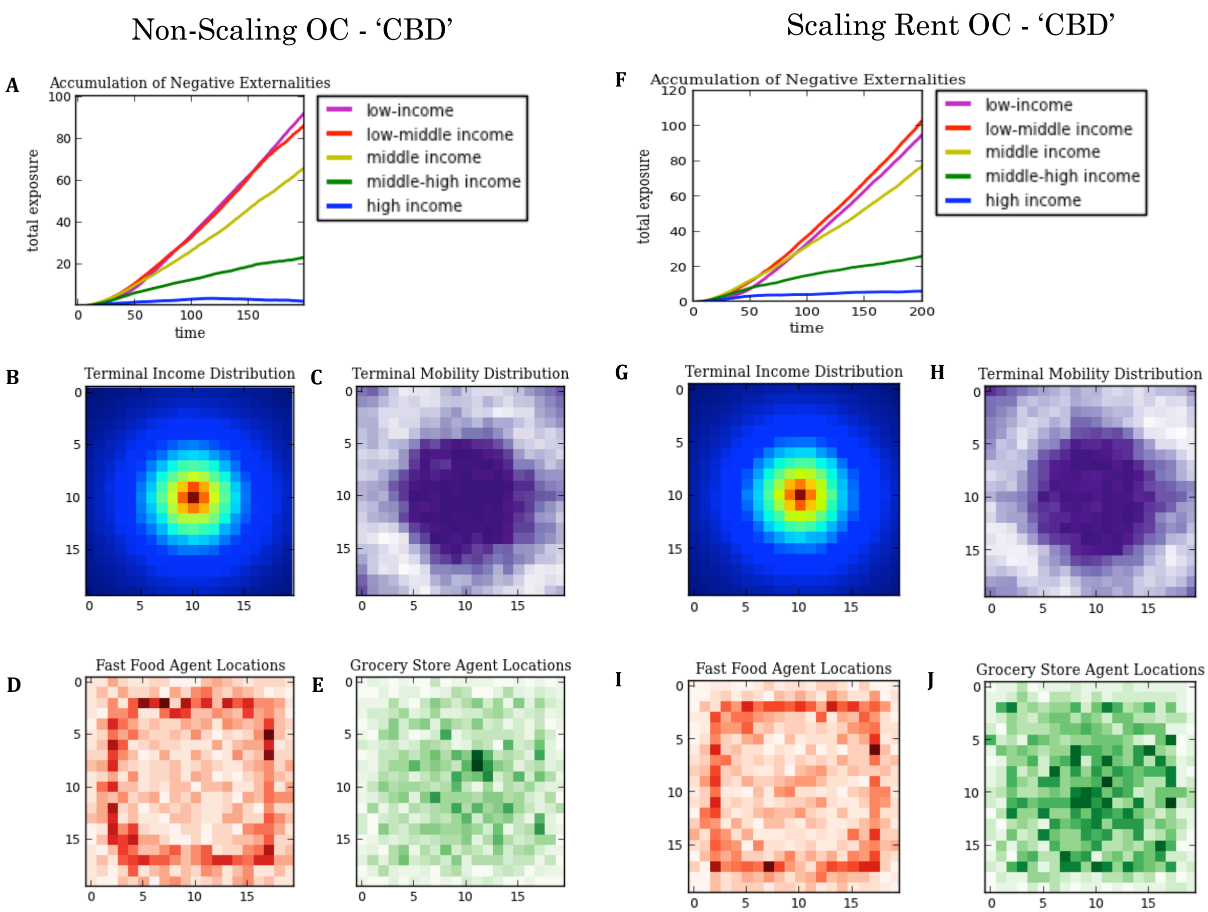

Figure 1. Plots show the values of each measure averaged over 50 experiments, each with time steps t = 200. The plot of exposure to negative externalities are broken down by income quintiles, showing a greater accumulation of negative externalities in lower income blocks **(A,F)**. The income distribution t = 200 across experiments show the delineation of income boundaries **(B,G)**. Mobility at t = 200 seems to be positively correlated with income distribution **(C,H)**. FFAs at t = 200 are chiefly localized at the in GSA localization between the Non-Scaling **(D,E)** and Scaling OC rule **(I,J)** is that the clustering of GSAs in the former is more contrasted than the latter.

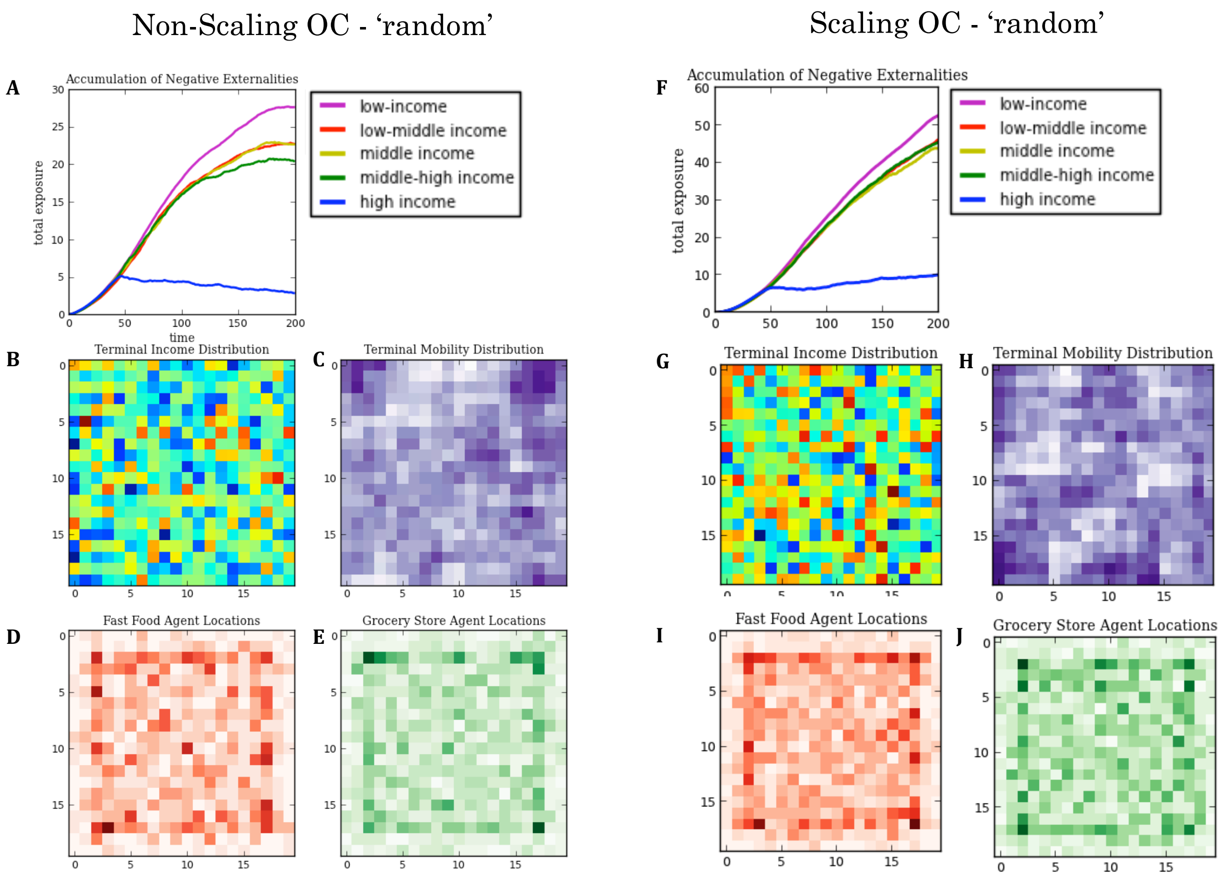

Figure 2. Plots show the values of each measure averaged over 50 experiments, each with time steps t = 200. The plot of exposure to negative externalities are broken down by income quintiles. Externalities in high income blocks plateau at t = 50, while those of lower income blocks begin to level off at t = 100. The differences in externality accumulation in blocks of middle-high income and lower are less prominent with the ‘random‘ rent vs. ‘CBD‘ rent distribution **(A,F)**. The income distribution t = 200 across experiments **(B,G)**. Mobility at t = 200 seem to cluster to a particular region under both Non-Scaling and Scaling OC rules **(C,H)**. FFAs and GSAs at t = 200 seem to preferentially localize at the corners of the periphery **(D,E,I,J)**.

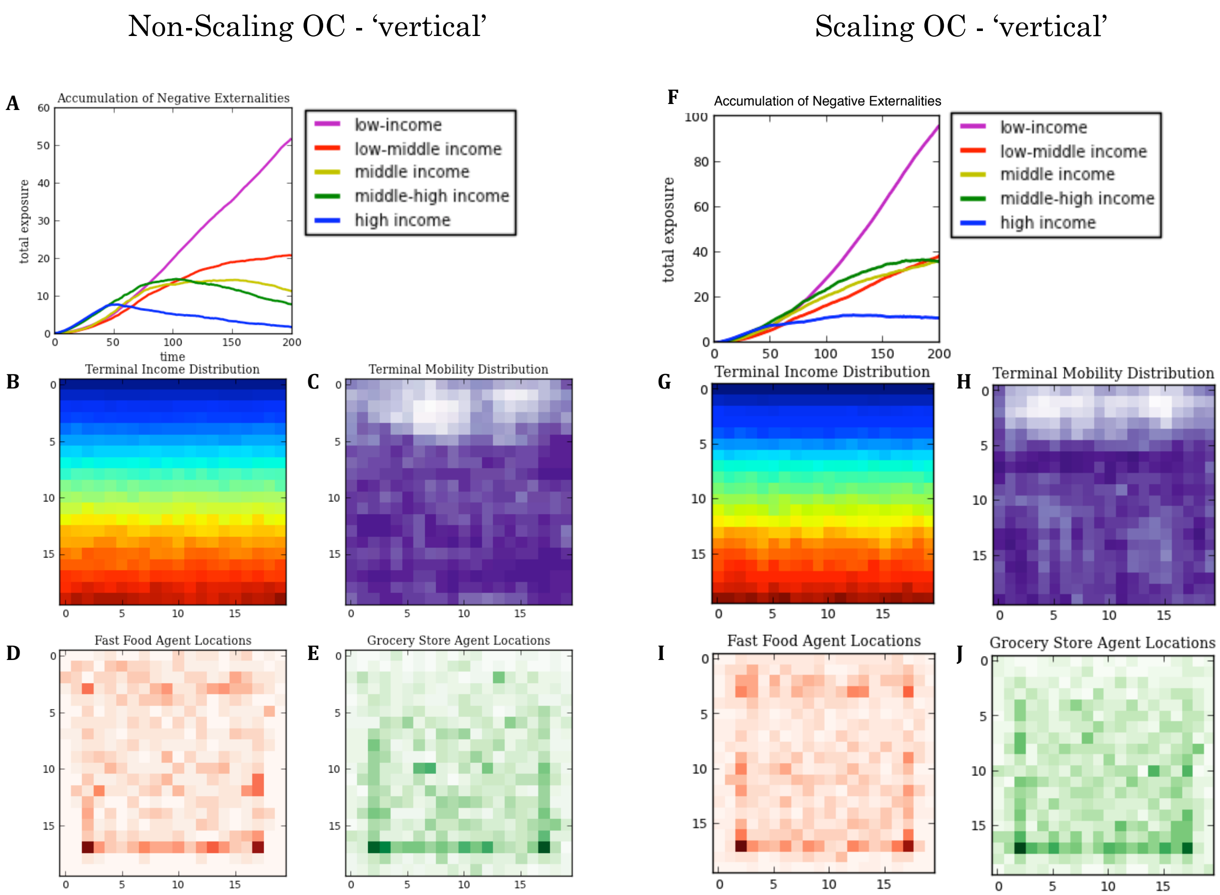

Figure 3. Plots show the values of each measure averaged over 50 experiments, each with time steps t = 200. The plot of exposure to negative externalities are broken down by income quintiles. Externalities in high income blocks plateau at t = 50, while those of lower income blocks begin to level off at t = 100. There are discernible gradients under both rule sets, although quintiles 2-4 seem to be converge with the Scaling OC rule **(A,F)**. The income distribution t = 200 across experiments show a uniform distribution of incomes across the urbanscapes **(B,G)**. The lower incomes suffer low levels of mobility at t = 200 **(C,H)**. FFAs and GSAs at t = 200 preferentially localize at the high income blocks. There seem to be slightly more FFAs in the lowest income (blue) region and slightly more GSAs in the middle income region **(D,E,I,J)**.

Discussion & Future Directions

The initial results and tentative analysis of the Urbanscape ABM are promising in that there seems to be a gradient across income quintiles in exposure to negative externalities, defined as the balance between FFA and GSA exposure. Further experimentation and statistical testing will determine whether this result is consistent across different initial conditions, creation rules, and parameter values. The model as outlined above gives rise to the expected dynamic in which pockets of the Urbanscape become 'food deserts' with lower-income blocks being disproportionately burdened. Whether this effect is an artifact or emergent behavior from the actions of autonomous agents within the urbanscape context remains open to further inquiry and statistical analysis.

Models, including ABMs, are by nature laden with (perhaps unrealistic) assumptions and subject to many limitations, and here I will focus on four major flaws. Firstly, the Urbanscape ABM includes only one of the environmental factors that drive the formation of 'food deserts' as defined by Swinburn et al. (1999). Namely, only energy intake is built in as a major mechanism of driving obesity. The other key aspect driving obesity is energy expenditure, of which 'mobility' is the only biophysical proxy measure. It is well known that the availability and accessibility of parks and exercise facilities also promotes the maintenance of a healthy weight (Swinburn et al., 1999, Simon et al., 2008). A promising direction for future research could attempt to synergize the Urbanscape ABM with an ABM that simulates the daily walking activities of adults in a city environment, which is described by Yang et al. (2011).

Secondly, although the relationship between mobility and annual income are strongly correlated, it remains unclear whether this effect is prominent across gender, income brackets and other cultural and socioeconomic factors; the existing evidence only points to an association across age (Fanning et al., 2010). Using mobility as a modifier of income level across sociodemographic factors may be an unrealistic assumption. Furthermore, expenditure decisions made by people in different household sizes, cultures, and educational backgrounds are more nuanced than the simple quadratic function in this ABM (equation 4.1) (Fanning et al., 2010). A multi-agent model that incorporates block residents and probabilistic decision-making algorithms could readily account for income and energy expenditure behaviors as a function of these various socioeconomic and environmental factors.

Thirdly, major features of the urban environment are absent from the model; these include recreation spaces, transportation systems, and food and health advertising. Findings from a multilevel analysis that relates obesity to the built environment suggest that mixed land-use, bus stop density, subway stop density, and population density are inversely associated with BMI, adjusted for sociodemographic factors at the individual- and neighborhood-level (Rundle, 2007). Transportation architecture could be integrated into the Urbanscape ABM to not only modulate individual-level decisions, but also expand the effect size of FFAs and

GSAs to cover regions that increase human traffic flows around central business districts.

Finally, the underlying distribution of the population, living costs, and food prices are static in this model. There is no accounting for inflation, migration of city residents, gentrification, and urban decay, all of which are macro-level determinants. These processes shape the distribution of socioeconomic variables and behavioral composition of residents in a city. By assigning dynamic state variables to the model, such as urban decay, growth, and gentrification, the model would better capture the evolving nature of a cityscape.

With these limitations in mind, the scope of this paper is to outline the basic architecture for an agent-based model that defined agents as food providers that operate within the context of an urban environment. Developing this architecture and experimenting with different parameter regimes and Agent subclasses could prove fruitful in investigating questions relating to how homophily, socioeconomic, and environmental factors shape the obesogenic behaviors of individuals and populations. I conclude with the notion that ABMs and simulation experiments provide a methodology for rigorously testing and examining our models of how the interactions of micro and macro-level phenomena produce complex adaptive systems. Developing realistic obesity-related ABMs that empirically correspond to geospatial and socioeconomic data would allow for not only a deeper understanding of the obesity epidemic, but also the identification of leverage points in the system to inform the policy-making process.

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