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Impact of Different Policies on Unhealthy Dietary Behaviors in an Adult Population of Los Angeles County: An Agent-Based Simulation Model

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Impact of Different Policies on Unhealthy Dietary Behaviors

in an Adult Population of Los Angeles County:

An Agent-Based Simulation Model

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Health Services

by

Donglan Zhang

2014

ABSTRACT OF THE DISSERTATION

Impact of Different Policies on Unhealthy Dietary Behaviors

in an Adult Population of Los Angeles County:

An Agent-Based Simulation Model

by

Donglan Zhang

Doctor of Philosophy in Health Services

University of California, Los Angeles, 2014

Professor Frederick J. Zimmerman, Chair

A typical American diet is comprised of too much high-calorie foods and insufficient fruits and vegetables. Many theories and models targeting unhealthy dietary behaviors focus exclusively on people as individuals, while behavior theories such as multi-level theory of population health emphasize the social component in human cognitive habits and behaviors, providing an alternative paradigm to understand dietary behaviors. This dissertation incorporates those behavioral theories into an agent-based

simulation model (ABM) to generate insights about how an individual makes food choices in the context of social network and external food environment, for the purpose of simulating policy interventions that are potentially effective in changing unhealthy dietary behaviors in an adult population of Los Angeles County.

Chapter 2 describes the model structure, process overview and model settings. Chapter 3 focuses on empirical estimation of model parameters and tests the model using face validation and sensitivity analysis. Data from the 2007 Food Attitudes and Behaviors Survey and other empirical studies are used to estimate model parameters, and data from Los Angeles County Health Survey 2007 are used to validate the model predictions at baseline. Based on the validated model, Chapter 4 contrasts the potential effects of various policies on individuals' dietary decisions using model simulation. The model shows that a 20% increase in taxes on fast foods would lower the probability of fast-food consumption by 3 percentage points, whereas improving the visibility of positive social norms by 10%, either through community-based or mass-media campaigns, could improve the consumption of fruits and vegetables by 7 percentage points and lower fast-food consumption by 6 percentage points. Zoning policies has no significant impact on food consumption in a moderately-dense urban neighborhood since people have easy access to both healthy and unhealthy food outlets. Chapter 5 concludes that interventions emphasizing healthy eating norms have the great potential to create sustainable behavior change, and may be more effective than directly targeting food prices or regulating local food outlets. Agent-based modeling may be a useful tool for testing the population-level effects of various policies within complex systems.

The dissertation of Donglan Zhang is approved.

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2014

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CHAPTER 1. INTRODUCTION

How do people make food choices? If people recognize the detrimental health outcomes of obesity and don't want to be obese, why do they consume obesogenic foods? Many theories and studies to date assume that certain incentives, particularly financial incentives govern human behaviors including dietary behaviors (Ebhohimhen & Avenell, 2008; Wall, et al., 2006), and they quickly reach a conclusion that people choose unhealthy and energy-dense foods because those foods are cheaper and tastier (Drewnowski & Darmon, 2005). However a number of exceptional observations in real life cast doubt on this assumption. For example, a public health student may carefully read nutrition labels for each food option when making purchasing decision, while only a few people reported that they noticed the calorie labeling when they chose food (Elbel, et al., 2009; Kolodinsky & Green, 2008). An Asian immigrant may consider a typical US diet not palatable, and prefer a home-cooked meal even if it's less convenient (Brown, et al., 2010). An employee eating at the same food court may always pick up the same food, no matter how many new options are available to her (Macht, 2008).

Small deviation from this assumption may potentially produce considerable difference to the population-level predictions (Akerlof & Yellen, 1985). Without a comprehensive understanding of food decision-making, interventions are likely to fail. Behavioral theories such as how consumers learn (Witt, 2001), habits of mind (Hodgson, 2004), evolution of social learning and norms (Watts & Strogatz, 1998) and multi-level theory (Zimmerman, 2013) provide alternative insights into a more in-depth understanding of the mechanism of dietary behaviors. This study aims to incorporate new insights into a computer-based simulation model to better represent how people make

dietary choices in a real world, for the purpose of identifying policy interventions that are potentially effective or ineffective. To test the model empirically, data on an adult population from five different neighborhoods in Los Angeles County were used.

1.1 Change in the American Diet and Its Consequences

For over a century, the American diet has been changing constantly. From 1879 to around 1958, as cited in Farnsworth and Wickizer, Bennett and Peirce estimated that per capita consumption of animal products was within the range of 1200 – 1300 calories per day, while consumption of vegetable products decreased from 2500 to below 1900. Within this period, from around 1900 to the 1930s, the per capita consumption of sugary foods rose by 285 calories per capita and then flattened after 1930. Consumption of fatty and meaty foods increased slightly during this period, while wheat flour continued to fall in per capita consumption of calories (See Figure 1.1) (Farnsworth & Wickizer, 1960).

From 1970 to 1997, based on data from the U.S. Department of Agriculture, a steep rise in consumption of carbonated soft drinks has been witnessed along with a decrease in consumption of beverage milk (See Figure 1.2). In 1997, Americans drank nearly two-and-a-half times more soda than milk. During the same period, meat consumption increased 19 pounds above the 1970 level to 196 pounds in 1998 (Putnam & Gerrior, 1994). Moreover, a notable change in American's dietary behaviors from 1970 to 1990s has been the rising consumption of food away from home. Between 1977-78 and 1994-96, consumption of food away from home including fast food, snacks and meals in restaurants increased from 18% to 32% of total calories (Guthrie & Lin, 2002). On any given day about one-quarter of the adult population visited a fast food restaurant (Schlosser, 2004). Americans not only consumed fast food with high energy densities,

but also were exposed to large portion sizes. Young and Nestle estimated the average number of daily calories created in the American food supply rose from 3,300 per person in 1970 to 3,800 in the late 1990s (Young & Nestle, 2002).

On the positive side, the average consumption of fruits and vegetables among Americans has been rising steadily since 1970. Per capita consumption of fruits and vegetables increased from 573 pounds in 1970 to 711 pounds in 1995 (See Figure 1.3). From 1994 through 2005, however, intake of fruits and vegetables ceased to rise. Data from both the Behavioral Risk Factor Surveillance System (BRFSS) and the National Health and Nutrition Examination Survey (NHANES) showed that the proportion of American adults eating fruits or vegetables for five or more times per day was largely unchanged after 1994 (Blanck et al., 2008; Casagrande et al., 2007).

This trend in dietary intake has led to the rapid increase in obesity since about 1980 (Ljungvall & Zimmerman, 2012). The age-adjusted prevalence of obesity increased from 12% in 1980 to 35.5% in 2009-2010 among adult men, and from 17% to 35.8% among adult women in the United States (Flegal et al., 2012). Obesity is associated with increased risk of several diseases including diabetes, cardiovascular diseases and cancers. Obesity-related illness is estimated to carry an annual cost of $190.2 billion and is projected to increase medical costs by $48–66 billion per year in the 2030s (Wang et al., 2011). In contrast to an unhealthy diet, it has been well-documented in the literature that maintaining a healthy diet such as adequate intake of fruits and vegetables has a beneficial effect on the risks of total mortality, incidence of coronary artery diseases (Dauchet et al., 2006; Steffen et al., 2003), risk of type 2 diabetes (Carter et al., 2010), risk of ischemic stroke (Joshipura et al., 1999) as well as cognitive decline (Kang et al.,

2005). Recently, the Institute of Medicine called national attention to accelerating progress in obesity prevention (IOM, 2012). Greater public health efforts and approaches are needed to alter American's unhealthy dietary behaviors to address this major health problem.

* Data from Merrill K. Bennett and Rosamond H. Peirce, adapted by author
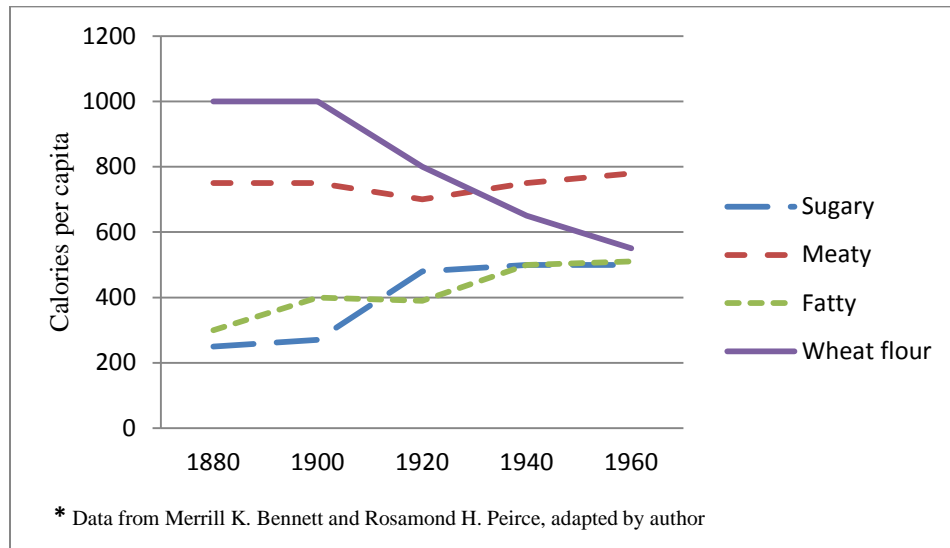
Figure 1. 1. Calories Consumed Per Capita Per Day By Food Groups, 1880 – 1960 *

* Data from Judy Putnam and Shirley Gerrior, adapted by author
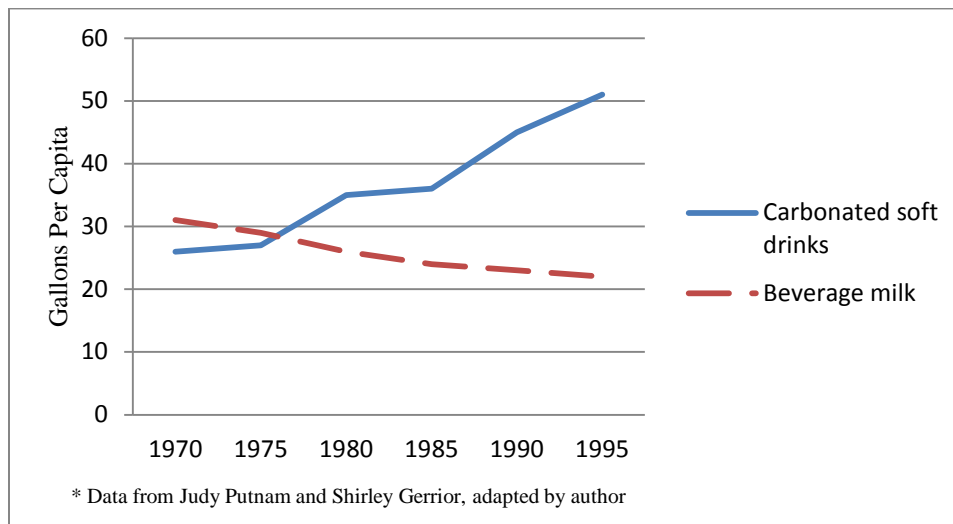
Figure 1. 2. Consumption of Carbonated Soft Drinks vs. Beverage Milk, 1970-1995 *
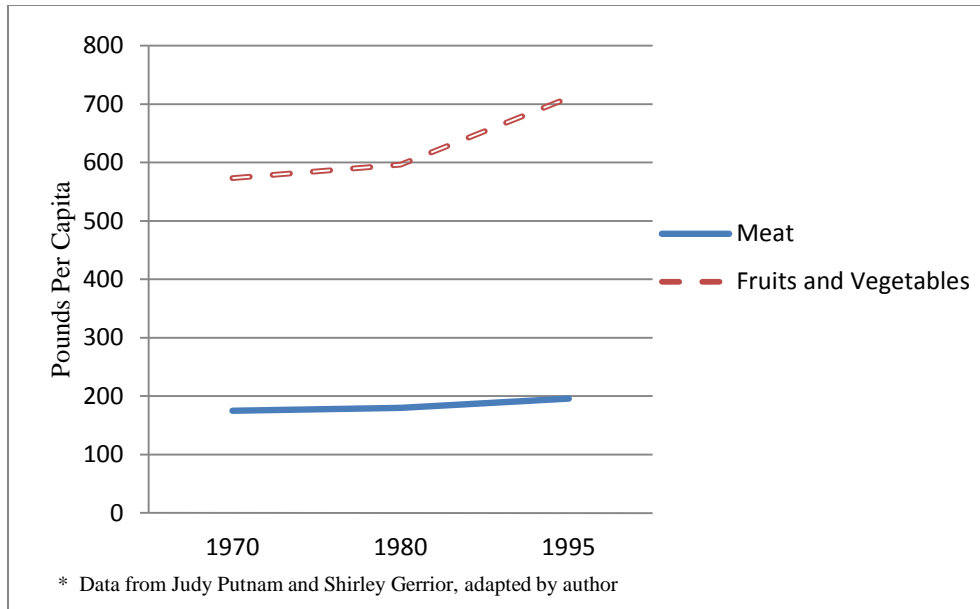
Figure 1. 3. Total Per Capita Consumption of Meat vs. Fruits and Vegetables, 1970-1995 *

1.2 Policy Interventions Targeting Unhealthy Eating Behaviors in Adults

The literature about policy interventions to address obesogenic dietary behavior among US adults can be divided into three distinct categories. One such category is the use of economic measures to alter food consumption, such as taxing unhealthy ingredients and subsiding healthy foods (Brownell et al., 2009; Mytton et al., 2012; Powell et al., 2009), in light of studies that have shown the price of a calorie obtained from unhealthful foods is lower than a calorie from more healthful foods (Drewnowski & Darmon, 2005; Drewnowski, 2005). A recent meta-analysis found that the healthiest diets, for instance, diets rich in fruits and vegetables cost $1.54 per 2000 kcal more on average than the unhealthiest diets such as the diets that rich in processed foods (Rao et al., 2013), whereas price differences between healthier options and unhealthier options were smaller and non-significant among certain food groups such as snacks/sweets, grains and fats/oils.

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Generally, the association between food prices and food consumption was small in magnitude, although the effect may be larger for certain low-income groups (Powell et al., 2009).

The second category of obesity policy is to target the food environment through zoning polices, including increasing healthy food vendors in food-desert communities (Song et al., 2009) and restricting the opening of new fast-food restaurants (Sturm & Cohen, 2009). Studies have found from cross-sectional analysis that proximity to certain food establishments, i.e., fast-food restaurants, convenience stores and vending machines that sell energy-dense snaking foods, is associated with unhealthy eating patterns and increased body mass index (Block et al., 2011; van der Horst et al., 2007). However, the evidence is not consistent across different geographic regions and populations. For example, a study conducted among California youth identified no significant relation between those food establishments in both school and residential neighborhood and dietary behaviors (An & Sturm, 2012) .

The third category is related to combating unhealthy eating norms, following research showing the power of food marketing to change dietary behavior and proposing restrictions on the time, place, and manner of marketing of obesogenic foods (Harris et al., 2009; Nestle, 2006; Zimmerman, 2011). Conversely, pro-nutritional marketing focuses on education as a means of increasing consumer awareness of dietary health. Such educational approaches include improving health literacy (Nelson et al., 2009), requiring nutrition disclosure on menus (Roberto et al., 2009) and issuing dietary guidelines on nutrition (Willett & Ludwig, 2011).

1.3 Models for Dietary Behaviors

1.3.1 Theoretical Framework

Research has to date focused on identifying a single biological, behavioral, or environmental explanation of this health problem based on different theoretical frameworks. For example, an increasing number of studies have adopted the substance use model that conceptualizes overeating as a food addiction problem with corresponding brain changes. These studies hypothesize that many people, particularly those who are obese, have lost their ability to control consumption of high-calorie foods (Ifland et al., 2009). However, the empirical evidence in support of this hypothesis has been inconsistent (Ziauddeen et al., 2012).

A large number of health studies, albeit not explicitly stated, adopted the idea that people are rational and make conscious choices to maximize a utility function (Köster, 2003). Studies using this theoretical foundation have empirically tested and found an association between actual food choice and food price (Andreyeva et al., 2010; Duffey & Gordon-Larsen, 2010), taste preference (Drewnowski, 1998), convenience orientation (Candel, 2001; Scholderer & Grunert, 2005) and health concerns (Sun, 2008). A negative association between the concepts of "unhealthy" and "tasty" was also identified (Raghunathan et al., 2006). But there is still plenty of room for debate on what "rationality" is (Harbaugh et al., 2001). The assumptions of this theory that preferences are pre-determined and that consumers can consistently calculate the true utility of each food option every time they make a food choice may not hold in a real food market (Ariely, 2003; Zimmerman, 2013). If preferences and ranking of those preferences were

pre-determined and remained constant throughout a person's life time, food choices would have been fully determined, and interventions would have been rather straightforward, conforming to those preferences by either reducing the prices for healthy food or making healthy choices more convenient. However, a large literature has shown that preferences are not biologically preset and could easily be modified in certain contexts (Ariely, 2003; Ariely, et al. , 2006; Ariely & Norton, 2008). The development of taste preference is one example. Taste sense is known to be developed in as early as the prenatal stage and matured in early childhood, affected by family environment, and linked with experiences of types of flavors and foods. For some people, the similar taste preferences continue until young adulthood, while changes in taste preference can happen any time during adolescence (Nicklaus et al., 2004), across the course of pregnancy (Bowen, 1992), when trying a new flavor with peers (Yeomans, 2008). A satisfactory experience after a purchase would increase the likelihood of repurchase the food product (Grunert, 2002). Additionally, the impact of taste on food intake depends on sex and age and is modulated by eating disorders and other pathologies of eating behavior (Drewnowski, 1997). Contradictory to the rational-choice theoretical framework, consumers in a real setting are heterogeneous, may have incomplete or biased information, and have endogenous preferences. They can learn from experiences and are more likely to choose the flavors and foods they have known, and may use rules of thumb instead of deliberative calculation to make food-consumption decisions (Gibson, 2006; Köster, 2009). They also interact with others in decision-making, making buying choices based on their friends' advice or their social network (Feunekes et al., 1998).

A multi-level theory of population health provides an alternative paradigm for individual decision-making. This theory argues that individual beliefs and behaviors are influenced by preferences and incentives, as in rational-choice theory, but are also shaped by cognitive habits, which have a social dimension because they are both shared and reinforced within a social network (Zimmerman, 2013). According to this paradigm, individual decision-making incorporates both conscious and subconscious forces. A consumer might deliberatively choose a food option that corresponds best to his/her preferences, but cognitive habits evolve as the individual learns from his/her previous experience when making food choices. So the next time when the consumer sees the same food option, he/she makes less conscious efforts and applies habits to optimize choice. Habits are malleable and easy to adapt to custom and norms in the social environment, and can be distorted by the power of social institutions, such as food marketers or the government. This theory is more comprehensive than rational-choice theory because it conceptualizes human decision-making as a dynamic and evolutionary process, while it is also a more complex paradigm that poses new challenges for empirical testing and parameterization.

1.3.2   Agent-Based Modelling and Its Applications in Public Health

Many empirical studies have focused on the effects of various interventions on eating behaviors using statistical techniques that rely on the stable unit treatment value assumption (SUTVA), which states that there are no interactions among people who experience the intervention that would alter the effectiveness of the intervention (Rubin, 2005). Yet as in infectious disease studies (Halloran & Struchiner, 1995), SUTVA is

known to be violated in obesity-related behaviors (i.e., an individual's choice influences and can be influenced by other individuals' food choices in the same social network) (Christakis & Fowler, 2007; VanderWeele, 2011). For example, in obesity intervention studies, involvement of the spouse in the intervention often increased the effectiveness of weight-loss interventions, and interventions on both parents and children have been shown to result in a greater extent of behavior change (McLean et al.,2003). An effect of social reinforcement enhances similarities in eating behaviors in a social group (Lieberman et al., 2001). What is therefore not clear from existing regression-based work is what the magnitude of the population-level impact of these policy interventions might be if they were implemented in the real world.

Agent-based modeling (ABM) is a new analytical method for the social sciences, and is being increasingly used to study problems with a complex adaptive system feature where there is heterogeneity among members of the population and when behavior changes is a result of interaction between individuals and/or with their environment (i.e., adaptation) (Maglio & Mabry, 2011; Horst et al., 2007). A simulation model can get at the causal mechanism directly, albeit hypothetically. ABM uses both deductive and inductive reasoning for the purpose of deriving knowledge about the causal mechanism and increasing understanding of the real-world system. First, similar to the deductive approach used in regression-based analysis, based on empirical literature and individual-level behavioral theories, agents' decision-making rules are developed using information obtained from empirical data sets. Second, ABM modelers use an inductive approach by simulating the agents' interactions to see what kind of patterns will evolve, and whether these patterns reflect some macro-level stylized facts observed in the real world,

providing new insights for the existing theories (J. M. Epstein, 1999). This approach is sometimes called diagnosis, or abduction (Bromley, 2008; Paavola, 2006).

ABM has a long history within the social science arena, particularly within segregation studies (Schelling, 1971; Schelling, 2006), innovation diffusion studies (Berger, 2001), as well as studies on wealth disparity (Zimmerman & Carter, 2003). In his 1971 paper, Thomas Schelling built an abstract ABM to examine the extent to which individual preferences for not being in the minority group of a neighborhood can lead to collective segregation. His model only has one parameter, the individual's tolerance of minority status. It assumes that if an individual of a given race lives in a neighborhood where his/her race is of minority status that is below the tolerant limit, the individual chooses to move out of the neighborhood. The model shows that even a small preference for living with neighbors of the same race (great tolerance of minority status) could collectively result in extreme segregation. Schelling's finding that the endogenous interaction between individual and society leads to non-linear macro-level phenomenon was influential in the social science and computational economics fields. But his segregation model was very abstract, and was deployed to explain a theory based on simple rules, rather than to fit it empirically to a real world setting.

More recently, empirically testing a computational model has become mainstream, which is largely attributable to the rapid development of computational technology. Berger applied an ABM with integration of a spatial component to simulate social and spatial interactions between heterogeneous farm-households. Their model aimed to understand the process of technology diffusion in agriculture. By empirically parameterizing the model to various data sources on an agricultural region in Chile, their

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model was able to predict the diffusion of specific innovations based upon rules of micro-motives of households and their interactions. Zimmerman & Carter (2003) developed a dynamic model to illustrate how initial asset disparity can deepen wealth disparities between the rich and the poor, even in a model with rational, perfectly forward-looking agents and convex technologies (i.e., with decreasing marginal returns). Their model had a distinctive feature that the price of the productive asset was endogenously determined and evolved in response to households' decisions. The action in the model was driven by the need for the poor to eat to maintain labor productivity, a modest and realistic assumption that nonetheless produced counterintuitive results. The model derived key parameter values from empirical data in developing regions and reproduced a real-world situation where the poor households could hardly lift themselves out of poverty and wealth inequality worsened with a positive feedback between initial wealth disparity and rate of return on wealth. Model parameters were derived from data collected in three regions of Burkina Faso from 1981 – 1985, and the model was validated using other studies in this area. Both of these studies used agent-based modeling to reproduce a complex, interactive and non-linear phenomenon.

In the public health field, ABM has been widely applied in the studies of infectious disease epidemic and control (Carpenter & Sattenspiel, 2009; Eubank et al., 2004; Lee et al., 2010; Lee et al., 2010), and recently in drinking behavior (Gorman et al., 2006), adolescent sexual initiation (Orr & Evans, 2011), health care management (Huang et al., 1995) and obesity and dietary behavior (Auchincloss et al, 2011; Hammond & Dubé, 2012; Malhi et al., 2009, Giabbanelli et al., 2012). For instance, Lee's study was intended to determine the effects, timing and prioritization of employee vaccination

during a H1N1 influenza epidemic in the Washington, DC metropolitan region. They developed an ABM based upon the traditional Susceptible-Infected-Recovered (SIR) model, and were able to empirically test parameters in the model. But in contrast to the SIR model that is basically an aggregate differential-equation model, their model simulated individual agents with a set of socio-demographic characteristics and behaviors, and assumed agents move among various locations in a virtual space in the computational model. Gorman et al. extended the SIR model and applied it to examine the agent-environment interactions in the development of drinking behavior. Their ABM explicitly modeled the interaction between drinkers and nondrinkers over time. The model showed a non-linear population-level development and maintenance of drinking behaviors through individual-level social interaction. However, unlike modeling infectious disease, the appropriateness of applying the SIR framework to study drinking behavior is a great concern, and the study offered little insight in explaining drinking behavior in an empirical context and no efforts were made to validate the model. Although the above two studies both used an SIR framework, the purpose of modeling was different. Lee's model was to inform and promote evidence-based policy making, whereas Gorman's study was to develop potential explanatory hypotheses for mechanisms driving stylized patterns observed in the world.

Recently, systems thinking has been introduced to study obesity and obesity-related behaviors (Hammond, 2009). Concepts such as social contagion (Burke & Heiland, 2006; Burke & Heiland, 2007), obesity networks (Christakis & Fowler, 2007), an ecological model of obesity (Story et al., 2008) and obesity system maps (Finegood et al., 2010), are developed by viewing obesity as a complex adaptive system. In modeling

obesity and dietary behavior, Auchincloss et al. constructed an ABM to assess the hypothesis that residential segregation contributes to the dietary disparity related to household income. Their model had two types of agents – households and food stores. They assumed that households made their food choices by maximizing a utility function and food stores could choose to move in/out. While insightful, there were two important concerns in their model. First, they did not validate the model to match empirical data. The reason was, as the authors claimed, that there were no data available to test the model's validity. Yet calibration is important to validate the model and to show generalizability of the results. Second, they oversimplified one scenario by assuming that food preferences were perfectly correlated with income, and this assumption determined the magnitude of the outcome measure to a considerable degree. While preferences may be shaped by food environment and social networks, their assumption of perfect association between preferences and income may be a bit far from the reality. Hammond et al. and Giabbanelli both used an ABM framework to model obesity and found social influence to be a significant factor in obesity epidemic, but Giabbanelli also included the interaction between social networks and environmental factors. He used a threshold approach to model individual behavior, which assumed that individual behavior could be influenced by friend's network and external environment, and assumed a change happens when the influence was beyond a given threshold. He matched the model outputs against the data measured by the National Longitudinal Survey of Youth. The threshold approach was a simple way to model individual decision-making, but this may be a concern since individual decision-making is a much richer process in which beliefs and historic

experiences should be taken into consideration. Additionally, the threshold was not evidence-based but set subjectively, which is another important limitation in the study.

1.4 Dissertation Overview

As discussed above, the ABM approach can be useful for studying complex systems such as dietary behavior, where decisions are influenced by a multi-level interplay of socioeconomic, psychological, and physiological forces. It is a method for simulating the actions and interactions of autonomous agents – usually referred to as individuals in a defined space to assess their effects on the system as a whole (Homer & Hirsch, 2006). In this dissertation study, I use ABM as a virtual laboratory for testing policies, as in a randomized experiment study we randomize a group of subjects to either a treatment group or a control group in the hope that the difference between the two groups are negligible (Greenland & Robins, 1986), we can intervene or not intervene the same group of people in a computer experiment study without making the assumption of randomization, the difference between the two outcomes under two scenarios are the true net effectiveness of the intervention.

I develop an ABM that explicitly represents how each individual makes dietary decisions in the context of their social network and food environment, in order to project the potential impact of various policies on food consumption in an adult population in the Los Angeles County, California.

This research has several important purposes. First, it aims to provide a uniform framework within which to compare the relative effectiveness of various proposed solutions on unhealthy eating behaviors in a population of interest. Second, the study

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begins the process of developing an agent-based policy simulation model that can be used to better understand the evolution of population-level obesity-related behaviors and health outcomes as well as the potential impact of various possible policy solutions.

The study is presented in the following chapters. Chapter 2 describes the model structure, theories, settings and assumptions. Chapter 3 presents empirical parameterization and validation of the model. In Chapter 4, the results of simulations are reported and the potential of different interventions to influence population-level outcomes is compared. Chapter 5 assesses the implications and limitations of the ABM simulation and concludes the dissertation.

CHAPTER 2.   AN AGENT-BASED MODEL OF DIETARY CHOICES IN THE CONTEXT OF SOCIAL NETWORK AND FOOD ENVIRONMENT

As Tesfatsion and Judd noted in their book Handbook of Computational Economics – Agent-Based Computational Economics (Tesfatsion, 2006),

*"A system is typically defined to be **complex** if it exhibits the following two properties:*

- *The system is composed of interacting units;*

- *The system exhibits emergent properties, that is, properties arising from the interactions of the units that are not properties of the individual units themselves."*

The food system is one example of complex adaptive systems, where a large number of micro-agents, i.e., consumers, food stores, and restaurants interact with each other and make daily decisions, giving rise to global phenomenon such as obesogenic dietary patterns, socioeconomic disparities in diet, food deserts in some areas and eating norms and culture. Such global phenomena in turn influence the interaction between the micro-agents.

The following ABM is built on the basis of the multi-level theory of population health (Zimmerman, 2013). First, individuals' food choices are influenced by a few of values and incentives, each of which is assumed to have independent impact (they are not correlated). Second, some values are modeled as individual cognitive habits that can adapt to the collective habits, or in other words, social norms (Vendrik, 1993). Third, the model accounts for the endogenous association between individual consumers and food

outlets in which the food environment affects individual's food- purchase decisions, and at the same time also adapts to consumers' consumption changes.

The chapter is structured as follows. Section 2.1 introduces the model structure and describes the agents and their behaviors. Section 2.2 presents the development of agents' behavioral rules and assumptions underlying the agent's decision-making process. Section 2.3 presents the initial setting of the ABM.

2.1 Model Structure

2.1.1 Agents and Attributes

The ABM contains two kinds of agents: individuals and food outlets. Individuals consume foods sold and marketed by the food outlets, and food outlets adapt to consumers' choices. One time-period in the model represents one day and each simulation runs for over 3 years (1100 days). Each of the major elements is now described in turn:

- *Individuals* have demographic characteristics (age, gender, educational attainment). The model accounts for both spatial and social aspects as individuals are assigned a home location and a set of friends, both assumed constant throughout the 3-year period.

- *Food Outlets* sell either fresh fruits and vegetables (FV) or fast foods (FF). These two options are stylized extremes representing healthy and unhealthy food choices for the purposes of modeling. Each food outlet has a constant location, and sells only one

type of food in each period. Food outlets may change the type of food they sell from one quarter (i.e., 90 days) to the next.

2.1.2 Agents' Behaviors

Individuals make food choices each period based on their own taste preferences, health beliefs, food-price indices, sensitivity towards the food prices, food accessibility, and demographic factors of age, gender, and education, corresponding to behavioral theories and findings in empirical studies (Drewnowski, 1998; Sun, 2008). The relative importance of each factor on food choices is determined by parameters of weights. Weights have meaning only relative to each other, for instance, if the weight on health belief is larger than that on taste preference, health belief is then more influential than taste in affecting the consumer's food choices. The weight parameter assigned to each factor is based on estimates from the Food Attitudes and Behavior (FAB) Survey (National Cancer Institute, 2007) and other empirical studies (Chapter 3 presents detailed estimation of those parameters).

Importantly, the model relaxes the restrictive assumption that each factor is predetermined and constant, i.e., that preferences are fixed and exogenous, and instead allows individuals to update their taste preferences (the stronger the preference, the more the individual likes sugary/salty taste) and their health beliefs (the stronger, the more the individual cares about the healthiness of food). This updating of preferences occurs based on the individual's previous-period habits, the influence of friends, and food-marketing strategies used in the broader environment.

When making food choices, the individual also evaluates the accessible food within walking distance, defined variably as food that is sold within 0.25 - 1 miles of the individual (Moore et al., 2009). The person also considers the price indices of the foods – both FF and FV sold in the environment, and then computes two probabilities, as was measured in the FAB dataset: the weekly probability of consuming more than 1 meal from a FF restaurant, and the daily probability of consuming more than 2 servings of FV. Finally, individuals consume FV and/or FF in proportion to their calculated probabilities.

In this model, therefore, consumers do not make food choice decisions directly, but instead determine their probability of eating particular types of food and then their actual behavior is drawn from their probability distribution. The probability function is modeled as a latent utility function that governs an individual's actual food choice.

A food outlet evaluates consumers' food consumption in the environment and decides whether to sell FV or FF. This evaluation takes place quarterly (i.e., once every 90 time-steps, or days) since companies like McDonald's usually evaluate and submit a revenue report on a quarterly basis (Bloomberg Businessweek, 2014). The model tracks the consumption for the food-type sold by the outlet. The probability of switching food-type is assumed to be proportional to the decline between the current quarter's consumption compared to that of the previous quarter (e.g., if the average fast-food consumption decrease by 75% then a FF outlet has a 75% chance to switch to FV). Outlets do not switch types if their sales remain constant or increase.

2.2 Process Overview

2.2.1 Generating Social Networks

Ideally, the model could have been built based upon empirical data on how people are connected in the population of interest. However, the various types of social networks such as family network, friend's network, community network and online network (Coelho & Néda, 2005; Lewis et al., 2008) makes precise measurement less efficient, if not impossible. In addition, thanks to the rapid development in network theories and techniques, the features and properties of many social networks have been mathematically described (Barabási & Albert, 1999; Girvan & Newman, 2002). This study uses computer algorithms to generate most commonly-used social network structures based upon those properties among the agents.

Research on complex networks has demonstrated that individuals do not typically be-friend others entirely at random. Instead, they tend to (1) form dense groups of friends, in which members of a group are linked to each other by a large number of one-to-one friendship ties, known as a high *clustering coefficient* feature, and (2) some within the group also have social ties to individuals belonging in other groups such that anyone in the network is only a few contacts away from anyone else, which is called a small *average distance* feature. The presence of both features is referred to as the *small-world* property (Girvan & Newman, 2002; Newman, 2001). A wide variety of models have been developed to create social networks with the small-world property. Among them, the Watts-Strogatz model is one of the most often-used (Watts & Strogatz, 1998). Family, friends and community networks are examples of small-world networks. An alternative social network called random network also has a small average distance but a much lower clustering coefficient (Newman et al., 2002). The most widely-used random network is the Erdos-Renyi model, which creates a social tie between any pair of individuals

uniformly at random (Erdos & Rényi, 1960). Some online networks have the features of random networks (Centola, 2010).

In this ABM, first, a small-world network was generated using the Watts-Strogatz model. As in a real community, individuals belong to groups of friends, and some also have friendship ties to members of other groups. The model began by connecting individuals into dense communities to obtain a high clustering coefficient and then introduced a small amount of random change in social ties to obtain a small average distance. Secondly, a random network using the Erdos-Renyi model was also generated to compare with the small-world network. These two network types will be employed in this model in separate simulations as a form of sensitivity testing.

To perform simulations on social networks produced by either the Watts-Strogatz or Erdos-Renyi model, the parameters of both models must be tuned so that the resulting networks are comparable. Networks can be comparable when they have the same number of individuals, and when individuals have the same average number of friends, defined as the *average degree* (Giabbanelli et al., 2012). Both networks had exactly 5,000 individuals. On average, networks generated using the Watts-Strogatz model had an average degree of 21.40 while the networks generated using the Erdos-Renyi model had an average degree of 21.51. The Watts-Strogatz model had a high clustering coefficient of 0.70, indicating the presence of communities, whereas the Erdos-Renyi model had a clustering coefficient of 0 indicating that individuals almost never form groups.

2.2.2. Decision-Making Equation at Baseline

In my ABM, each individual's decision-making was estimated using two probabilities: a daily probability of consuming fruit & vegetables (FV) and a weekly probability of consuming fast foods (FF). The US CDC has recommended a healthy diet by eating five servings of fruits and vegetables a day, but the population's daily serving of fruits and vegetables is mostly less than 5 (Blanck et al., 2008). Very low consumption of fruit and vegetables is highly associated with undesirable health outcomes such as ischemic stroke (Joshipura et al., 1999) and certain types of cancer (González et al., 2006). Studies have defined less than 2 servings of fruit and vegetable intake per day as an indicator for insufficient consumption of FV (Liu et al., 2000). In the model, the daily probability of consuming fruits and vegetables is defined as the probability of consuming at least 2 servings of FV a day, whereas the weekly probability of consuming fast foods is the probability of consuming at least one meal of fast food in a typical week. They were measured in the same way in both the FAB 2007 data that was used to estimate the weights, and in the Los Angeles County health survey 2007 (LACHS) which was used to validate the model (Los Angeles County Department of Public Health, 2007).

The essence of the model is that each individual agent has a vector of cognitive habits that includes taste preferences (T), health preferences (H), and price-sensitivity (PS). The preferences are both specific to the individual, and evolve over time. Price sensitivity is specific to the individual, but is exogenous and does not evolve over time. In addition, individuals are sensitive to the availability (A) of fruits and vegetables near where they live.

The model determines the probability of eating at least two servings of fruit & vegetables per day by the following equation:

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$$\Pr(FV > 1)_{i,t} = \beta_0 + \beta_1 * (T_{i,t}) + \beta_2 * (H_{i,t}) + \beta_3 * PS_i * (PI_{fv}) + \beta_4 * PS_i * (PI_{ff})$$

$$+ \beta_5 * (A_{FV_{i,t}}) + \beta_6 * (Age_i) + \beta_7 * (Gender_i) + \beta_8$$

$$* (Education_i) \qquad (1)$$

In this equation, the βs are the fixed weight parameters on each factor that determine all individuals' probabilities of frequently consuming fruits and vegetables at time t. The βs are model parameters to be estimated (in Chapter 3). Health beliefs - $H_{i,t}$, taste preference $T_{i,t}$, price sensitivity PS_i are individual i's cognitive habits. An individual's price sensitivity PS_i is related with the individual's socioeconomic status and assumed to remain constant throughout the simulation, whereas $H_{i,t}$ and $T_{i,t}$ are time-varying factors that can adapt to collective habits over time. PI_{fv} and PI_{ff} are food price indices for FV and FF respectively. They are global factors that apply to all individuals, in other words, the model assumes that all consumers face the same set of prices. To account for each individual's personal cognitive response to food prices, I multiply individual's price sensitivity by the price indices. β_3 and β_4 then represent the effect of price on each individual's food consumption decisions.

$A_{FV_{i,t}}$ represents accessibility to food outlets selling fruits and vegetables, assessed by each individual i at time t. When calculating the probability, each individual evaluates that if FV food outlets are accessible within walking distance (0.25 – 1 miles). Additionally, the decision-making equation also takes into account the impact of individual demographics (age, gender, level of educational attainment) on food consumption choices.

The probability of eating at least one meal from a fast-food restaurant per week is determined in a similar manner, as follows:

$$\Pr(FF > 1)_{i,t} = \delta_0 + \delta_1 * (T_{i,t}) + \delta_2 * (H_{i,t}) + \delta_3 * PS_i * (PI_{fv}) + \delta_4 * PS_i * (PI_{ff})$$
$$+ \delta_5 * (A_{FF_{i,t}}) + \delta_6 * (Age_i) + \delta_7 * (Gender_i) + \delta_8$$
$$* (Education_i) \qquad (2)$$

Here δs are the weights on each factor influencing an individual's decision of fast-food consumption. As described above, δs are fixed and common to all individuals. $T_{i,t}$, $H_{i,t}$, PS_i, PI_{fv}, PI_{ff} and $A_{FF_{i,t}}$ are all parameters to be estimated.

2.2.3 Updating Taste Preferences and Health Beliefs

The taste preferences and health beliefs of an individual *i* change over time, and their values at time *t* are denoted by $T_{i,t}$ and $H_{i,t}$ respectively. An individual's preferences and beliefs change in response to the taste preferences and health beliefs of friends in the social network, while retaining his/her own habits to a certain degree. Here habits represent an individual's own taste preference and health belief, which originate from his/her historic exposures and experiences.

The balance between one's own habits and the importance of peers' norms is denoted by $\alpha_i \in [0, 0.3]$, where larger values represent greater susceptibility to friends' influence. Susceptibility varies between individuals, thus the value of α depends on the individual *i*. This approach is based on Yang et al. (2011) who modeled the influence of friends on an individual's attitude towards leisure-time walking in their validated walking model (Yang, 2011). In the absence of any marketing strategy to promote either healthy

or unhealthy norms, each friend carries an equal influence and thus an individual's taste preference and health belief represent the balance between the average habits of friends and her own at t-1. Equations (3) and (4) describe the evolution of taste preferences and health beliefs without marketing:

$$T_{i,t} = (1 - \alpha_i)T_{i,t-1} + \alpha_i \frac{\sum_{j \in friends(i)} T_{j,t-1}}{\sum_{j \in friends(i)} 1} \qquad (3)$$

$$H_{i,t} = (1 - \alpha_i)H_{i,t-1} + \alpha_i \frac{\sum_{j \in friends(i)} H_{j,t-1}}{\sum_{j \in friends(i)} 1} \qquad (4)$$

Where α_i represents the extent to which individual i's cognitive habits are influenced by group habits in the social network. $\alpha_i = 0$ indicates no peer influence, whereas $\alpha_i > 0$ suggests an individual is susceptible to be influenced by friends' preferences and beliefs. $T_{i,t-1}$ and $H_{i,t-1}$ are individual's taste preference and health belief at time t-1. Individual j is in individual i's friends network, in the model, individual j has direct social connection with i. $\frac{\sum_{j \in friends(i)} T_{j,t-1}}{\sum_{j \in friends(i)} 1}$ and $\frac{\sum_{j \in friends(i)} H_{j,t-1}}{\sum_{j \in friends(i)} 1}$ then represent the average cognitive habits (taste preference and health belief) carried by the individual i's friends at time t-1. A sensitivity analysis is performed to test to what extent the level of α_i influence model outputs (See Chapter 3).

2.2.4 Mechanism of Food Marketing

Research has shown that marketing strategies can create an illusion of intimacy with the consumer, thereby biasing individual perceptions of social norms (Schor & Ford, 2007; Wiecha et al., 2006). This process has been exemplified in an experimental study regarding food marketing in children, which found that children who watched

advertisements for unhealthy foods were more likely to perceive that others like such foods as well (Dixon et al., 2007). Less is known regarding the effect of marketing for healthy foods, given that the vast majority of food advertising (81%) is for unhealthy foods (Batada et al., 2008; Larson & Story, 2008; McGinnis, Gootman et al., 2006; Wiecha et al., 2006).

Following the multi-level theory of decision-making, we assume that norms can evolve within a group in response to selective pressure (Zimmerman, 2013). In this study, we assume that marketing strategies can be designed to promote either unhealthy or healthy foods, where the marketing of healthy food represents one of the four interventions that we evaluate in order to address unhealthy dietary behaviors. It's less straightforward to quantify the effect of food marketing. But marketing strategy, if working effectively and persistently, may influence the values, perceptions and cognitive habits of the consumers.

To simplify this process, I denote the mechanism of marketing strategies by $\gamma \in (-1,1)$, following a uniform distribution, and its impact on individuals is viewed by the bias that it creates on the perception of peers. A positive γ represents advertisement for unhealthy foods, which increases the visibility of friends who have stronger taste preferences and decreases the visibility of friends who have stronger health concerns. Conversely, a negative γ represents advertisement for healthy foods, which decreases the visibility of friends who have stronger taste preferences and increases the visibility of friends who have stronger health concerns. This is formalized in equations (5) and (6):

$$T_{i,t} = (1 - \alpha_i)T_{i,t-1} + \alpha_i \frac{\sum_{\substack{j \in friends(i) \\ T_{j,t-1} > T_{i,t-1}}}(1 + \gamma)T_{j,t-1} + \sum_{\substack{j \in friends(i) \\ T_{j,t-1} \leq T_{i,t-1}}}(1 - \gamma)T_{j,t-1}}{\sum_{\substack{j \in friends(i) \\ T_{j,t-1} > T_{i,t-1}}}(1 + \gamma) + \sum_{\substack{j \in friends(i) \\ T_{j,t-1} \leq T_{i,t-1}}}(1 - \gamma)} \quad (5)$$

$$H_{i,t} = (1 - \alpha_i)H_{i,t-1} + \alpha_i \frac{\sum_{\substack{j \in friends(i) \\ H_{j,t-1} > H_{i,t-1}}}(1 - \gamma)H_{j,t-1} + \sum_{\substack{j \in friends(i) \\ H_{j,t-1} \leq H_{i,t-1}}}(1 + \gamma)H_{j,t-1}}{\sum_{\substack{j \in friends(i) \\ H_{j,t-1} > H_{i,t-1}}}(1 - \gamma) + \sum_{\substack{j \in friends(i) \\ T_{j,t-1} \leq T_{i,t-1}}}(1 + \gamma)} \quad (6)$$

where γ represents the bias created by food advertisement on the individual's perception of social norm. In equation (5), $\sum_{\substack{j \in friends(i) \\ T_{j,t-1} > T_{i,t-1}}}(1 + \gamma)T_{j,t-1}$ is the sum of taste preference values among friends who have stronger taste preference than the individual i, but is up-weighted in the context of marketing for unhealthy food. Similarly, $\sum_{\substack{j \in friends(i) \\ T_{j,t-1} \leq T_{i,t-1}}}(1 - \gamma)T_{j,t-1}$ is the down-weighted sum of values for friends who have smaller taste preference values. Therefore, $\frac{\sum_{\substack{j \in friends(i) \\ T_{j,t-1} > T_{i,t-1}}}(1+\gamma)T_{j,t-1} + \sum_{\substack{j \in friends(i) \\ T_{j,t-1} \leq T_{i,t-1}}}(1-\gamma)T_{j,t-1}}{\sum_{\substack{j \in friends(i) \\ T_{j,t-1} > T_{i,t-1}}}(1+\gamma) + \sum_{\substack{j \in friends(i) \\ T_{j,t-1} \leq T_{i,t-1}}}(1-\gamma)}$ represents the weighted average of friend's norm on taste preference. In equation (6),

$\frac{\sum_{\substack{j \in friends(i) \\ H_{j,t-1} > H_{i,t-1}}}(1-\gamma)H_{j,t-1} + \sum_{\substack{j \in friends(i) \\ H_{j,t-1} \leq H_{i,t-1}}}(1+\gamma)H_{j,t-1}}{\sum_{\substack{j \in friends(i) \\ H_{j,t-1} > H_{i,t-1}}}(1-\gamma) + \sum_{\substack{j \in friends(i) \\ T_{j,t-1} \leq T_{i,t-1}}}(1+\gamma)}$ is the weighted average of peers' health beliefs. α_i again is the extent to which an individual i is influenced by peers.

Consequently, the influence of friends is represented by a weighted average depending on the weight γ and their relative habits compared to that of the individual i. For example, if an individual i has four friends, two of them have stronger values in healthy eating than the individual i. Then healthy food marketing increases the visibility of the two peers who prefer healthier eating than the individual i, which affects the values of individual consumer through the influence of social network.

2.3 Model Settings

Among the 277 zip-code areas measured in the survey LACHS 2007, I randomly drew 5 zip-code regions that vary in geography, racial composition, and economic levels, making them representative of Los Angeles County. They are used as 5 different settings in the agent-based model (See Table 2.1). As show in Figure 2.1, all 5 areas are urban districts covering 1.3 – 5.8 square miles (U.S. Census Bureau; Census 2010). Each district is represented by a grid of 260 by 260 cells in the model. The environment is measured by the ratio of healthy to unhealthy food outlets in the district. Except for zip-code area 90011, all other areas have more unhealthy food stores than healthy food stores. In the area of 90011, there are more farmers' markets including WIC (Special Supplemental Nutrition Program for Women, Infants, and Children) markets and grocery stores selling fruits and vegetables than all other regions.

The model is first built on the setting of downtown Pasadena (zip-code: 91101). In 2010, there were 113 food outlets which can be categorized as FF venues (e.g., fast food chain/non-chain restaurants and ice cream stores) and 16 food outlets that can be categorized as FV venues (e.g., farmers' markets, supermarkets, WIC markets, and grocery stores selling fruits and vegetables) in that district (California Department of Public Health, 2008). Based on the food outlets data from California Department of Public Health, downtown Pasadena is not a food desert. Each outlet is randomly assigned to one cell (sensitivity analysis is later performed by assuming the outlets does not open in random locations). The 2010 census reported 17,698 residents aged 18 and over in downtown Pasadena, and those residents are assigned to unique locations chosen at random. Each resident is also assigned an age, a gender, and a level of educational

attainment. Based on these characteristics, residents are then assigned an initial taste preference, an initial health belief, and a price sensitivity (See Chapter 3).

Table 2. 1. Model Settings Using Statistics of Five Different Zip-Code Areas

Zip Codes	Age [a]		Gender [1, a]		Education [2, a]		Area [a] (sq. mi.)	No. FF outlets[b]	No. FV outlets[b]
91101	*18 – 34*	57%	*M*	48.07%	*LHS*	10.85%	1.3	116	13
	35 – 54	31.27%	*F*	51.93%	*HS*	16.27%			
	55 over	11.73%			*SC*	11.64%			
					C	61.24%			
90011	*18 – 34*	45.53%	*M*	50.78%	*LHS*	59.20%	4.3	47	64
	35 – 54	38.11%	*F*	49.22%	*HS*	22.87%			
	55 over	16.36%			*SC*	12.69%			
					C	5.24%			
90404	*18 – 34*	36.87%	*M*	47.63%	*LHS*	9.58%	2.0	65	7
	35 – 54	35.06%	*F*	52.37%	*HS*	15.16%			
	55 over	28.07%			*SC*	22.11%			
					C	53.16%			
90715	*18 – 34*	34.74%	*M*	47.86%	*LHS*	16.94%	1.7	10	6
	35 – 54	39.04%	*F*	52.14%	*HS*	23.92%			
	55 over	26.22%			*SC*	31.66%			
					C	27.48%			
90505	*18 – 34*	21.23%	*M*	47.38%	*LHS*	5.60%	5.8	164	24
	35 – 54	41.70%	*F*	52.62%	*HS*	17.29%			
	55 over	37.07%			*SC*	23.58%			
					C	53.53%			

1: M = Male; F= Female.
2: LHS: Less than high school; HS: Finished high school; SC: Some college; C: Finished college
a: Data from US Census 2010
b: Data from California Department of Public Health
c: Estimated from LACHS 2007

Selected Zipcode Areas
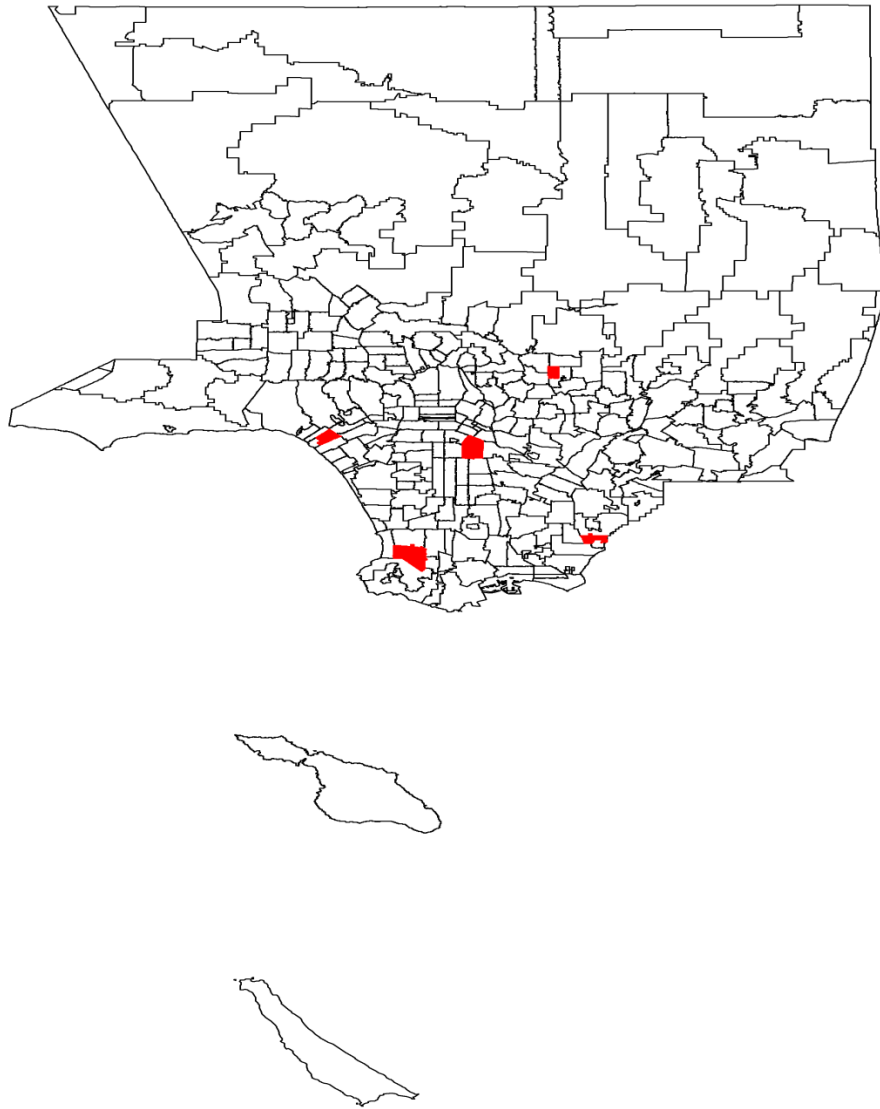
Figure 2. 1. All Five Zip-Code Areas Selected from Los Angeles County

CHAPTER 3. EMPIRICAL PARAMETERIZATION AND VALIDATION OF THE AGENT-BASED MODEL

Agent-based modelling holds the premise of integrating various sources of information and providing relevant evidence for policy-makers to support their decision-making processes. Fulfillment of this premise depends on the empirical parameterization of the models, which is also a fundamental process that defines the rigor of an agent-based model (Windrum, 2007).

Model validation assesses the robustness and uncertainty of the model parameters and outputs. The objective of model validation is to verify if the ABM is an acceptable representation of the actual system. Rand & Rust proposed four steps for model validation: (1) micro-face validation, (2) macro-face validation, (3) empirical input validation, and (4) empirical output validation (Rand & Rust, 2011).

Micro-face validation deals with the issue of whether the micro-level mechanism and properties of the model on the face of it corresponds to the real world. This validation process is to check conceptually if the model parameters (i.e., agents' attributes and behaviors) is reasonable and plausible (Klügl, 2008), and will answer questions like "Do agents in the model possess the same key attributes (i.e., preferences, attitudes) as individuals in real world?" or "Do the characteristics of agents seem conceptually realistic?" For example, if agents are modeled as hyper-rational, whereas individuals are known to be boundedly rational with adaptive expectations in certain circumstances, the agents in the model may not on face correspond to their real-world counterparts (Fagiolo et al., 2007).

Macro-face validation ensures that the aggregate output of the ABM on the face of it corresponds to the real-world macro-patterns. The process is to test whether model behaves the way that is not contradictory to the current understanding of the real-world system. Macro-face validation does not require the model to be fully empirical but can be an abstract reproduction of the real system. For example, Schelling's model reproduces a realistic residential segregation pattern based on interactions among agents following their simple behavioral rules – preference for living around people of the same race. Similar examples include models of human mate preferences in social psychology, where the model assumes that people either choose partners with relatively similar levels of attractiveness to their own or seek highly attractive partners (Smith & Conrey, 2007). The model is considered valid if the pattern that emerges from the simulation seems conceptually plausible.

In contrast to face validation, empirical input validation is a process to bring the model more closely in line with the empirical data and evidence. For example, in models of stock market, information on the agents' access to price and volume can be obtained from real-world market (Bonabeau, 2002). But assumptions are sometimes necessary if agents' behaviors are very complicated, for instance if reinforcement learning and neural networks are used to generate agents' learning strategies in financial models (Bonabeau, 2002). Sensitivity analysis is useful to test whether the model is sensitive to those assumptions and estimate the uncertainty of model predictions. Sensitivity analysis generally refers to an in-depth investigation of how the model outputs vary when one alters a particular set of model inputs, which usually includes sensitivity analysis on: (1)

micro- parameters (i.e. parameters in agents' behavioral rules), (2) macro- parameters (i.e. global/environmental parameters), and (3) initial conditions (Windrum, 2007).

Empirical output validation is to show that the output of the model corresponds to the real-world data. This process is to analyze if the empirical statistics/trend lie within the statistical distribution of model predictions. If the purpose of the model is to predict a potential outcome under certain scenarios (i.e., policy scenarios), model calibration is usually an important step, which involves systematic adjustment of model input parameters to produce model outputs that are more accurately fit empirical data at a baseline scenario. Model calibration is setting-specific, so parameter estimates can vary when setting changes. A detailed discussion of model calibration is presented in section 3.3 below.

This chapter presents an approach for the parameterization and validation of the agent-based model using empirical datasets. The Food Attitudes and Behaviors Survey is used to estimate the parameters in the food decision equations, US Census data are used to generate a synthetic population for modeling, and Los Angeles County Health Survey 2007 are used to empirically validate the model.

Chapter 3 is organized as follows. Section 3.1 introduces all model parameters and data sources. Section 3.2 presents the process to estimate the weights on each factor in the agent's decision-making equation. Section 3.3 introduces the procedure of model calibration. Section 3.4 performs a micro-face validation by showing the values and distributions of model parameters based on the setting of downtown Pasadena. Section 3.5 performs a macro face validation of the model by comparing the distribution of model

outputs with empirical distributions. Section 3.6 presents an empirical input validation that shows a sensitivity analysis on the parameter of social influence and a sensitivity analysis on the spatial distribution of food outlets. Section 3.7 performs an empirical output validation that tunes model parameters to fit the population-level empirical statistics under 5 different model settings. Section 3.8 summarizes this chapter.

3.1 Data Sources for Model Parameters

Figure 3.1 shows all model parameters and data sources used to estimate the parameters. Each dashed arrow represents the influence of a factor on another factor. An individual's demographic attributes are associated with cognitive habits such as taste preference (T), health belief (H) and price sensitivity (PS) in the individual's decision-making equation. As shown in the FAB survey, age, gender, and education are associated with health belief and price sensitivity, and age is also associated with taste preference. Accessibility (A_{fv} and A_{ff}) is evaluated by each individual based on his/her location and location of food outlets. Parameter α is the influence of peers, and γ is the effect of food marketing on individual's food decision. PI_{fv} and PI_{ff} are the price indices for fruit and vegetables and fast food, respectively. Food outlets evaluate their sales each quarter and decide whether to switch the type of food they sell. Parameter βs and δs are to be estimated in Section 3.2.

Prior information on the above parameters is obtained from data sources listed in the right column. In detail, most parameters βs and δs are estimated directly from the FAB survey. Agents' demographic characteristics are fitted with US census data. The number of food outlets in the district is obtained from California Department of Public Health. And several other parameters are obtained from the literature. For parameters

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with no empirical information, assumptions are made based on existing theories. For example, social network theories and marketing theories are used to model parameter α and γ.
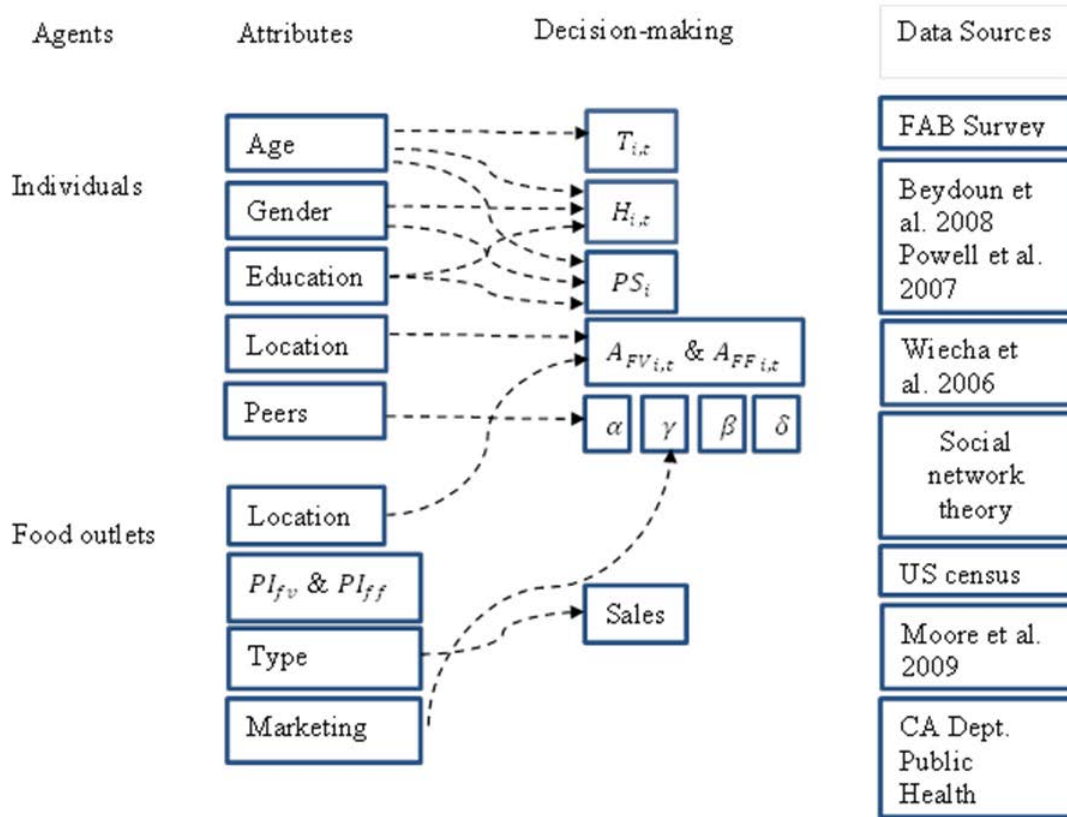
Figure 3. 1. Data Sources of Model Parameters

3.2 Estimation of Parameter βs and δs

A probit regression that employs a probit link function is applied to estimate the binary food consumption variable using the FAB dataset. The regression takes the following form, where Pr denotes probability and Φ is the cumulative distribution function of the standard normal distribution:

$$\Pr(Y = 1 | X) = \Phi(X'\beta)$$

I use the regression coefficients, estimated using the standard maximum likelihood from the regression, as parameter βs and δs in the agents' decision-making equations (In Chapter 2, Equation (1) and (2)). Among all the parameters, price indices and perceived accessibility to fast food are not measured in the FAB data. I obtain estimates from other empirical studies described below. As introduced in Chapter 2, parameter βs and δs represent the relative impact of each factor on the likelihood of consuming FV or FF, which are assumed to remain constant for the duration of the simulations.

The FAB Survey from 2007 comprises 3,397 adults, with an oversampling of African Americans. Sampling weights are provided using the 2000 US Census estimates to make the sample representative of the US population. The survey contains 65 questions in 8 sections, with its aim to evaluate various factors including attitudes and beliefs that are related to eating-behaviors among adults. A review shows that the factors selected in the survey predict nutrition behaviors well, in particular fruit and vegetable intake in adults (Shaikh et al., 2008).

Items in the FAB survey are put in relation with each factor of equation (1) and (2) in the following way. Taste preference is measured on a 5-point Likert scale as "I like sweet foods" and "I like salty foods" in the FAB survey. Health belief is also measured on a 5-point Likert scale as "I have a strong value for eating healthy". Price sensitivity is measured by "I don't eat fruits and vegetables as much as I like because they cost too much", and accessibility is defined as "It is hard for me to purchase fruits and vegetables in my neighborhood" and "When I eat out, it is easy for me to get fruits and vegetables". The questions are chosen in the survey based on associated references that have

demonstrated good reliability (National Cancer Institute, 2008). I rescaled all four variables to be bounded between 0 and 1 using the formula (X - Min) / Max, where X represents the original variable, Min is the minimum value of variable X and Max is the maximum value of variable X.

The FAB survey also queries the age, gender, educational attainment, and race/ethnicity of the respondents. It should be noted that income is not measured in the FAB survey; accordingly, educational attainment is used instead of income as a proxy measure for socioeconomic status in the model. This may be a reasonable approximation because educational attainment is related to income (Gregorio & Lee, 2002). Additionally, race is not included in the model since race is correlated with residential location, social networks, genetic predisposition as well as culture background (Gabriel & Rosenthal, 1989; McPherson et al., 2001), which would add too much complexity to the model and is therefore outside of the principal objective of the model at this point.

Table 3.1 presents the distribution of variables used to estimate βs and δs in the decision-making equation (1) and (2). Among the 3,397 respondents in the FAB Survey, 72% (N=2,448) of them ate at least 2 servings of fruits and vegetables per day, and 69% (N=2,338) consumed at least one meal from a fast food restaurant per week. About 40% of the respondents are about 35 – 54 years old, female, and have received a high school degree. Values for the psychosocial predictors range from 0 to 1, with higher values reflecting stronger taste preferences, stronger values for eating healthy, more sensitive to food prices, and easier access to FV outlets. The average taste preference, health belief and food accessibility are above 0.5, indicating that the respondents have relatively strong

taste, health value and easy access to FV stores. The mean value of price sensitivity is below 0.5, suggesting that the respondents are insensitive to FV prices.

The coefficients and confidence intervals of the variables for the two probit regressions are presented in Table 3.2. Taste preference and health belief significantly predict FV and FF consumption. The interpretation of coefficients in probit regression is not straightforward, so I take the derivatives and interpret the marginal effects of the regressors. In the probit regression on FV consumption, health belief has the largest impact on FV consumption. The marginal effect on taste preference means that for every increment of 0.1 points in the preference for sweetness and saltiness, the probability of eating at least two servings of FV per day decreases by 7.8 percentage points on average, keeping all else constant in the model. And the marginal effect on health belief indicates that the predicted probability of eating at least 2 servings of FV increases by 31.2 percentage points on average for every increment of 0.1 points in the respondents' health values. Price sensitivity for FV is also significantly associated with FV intake. Its marginal effect reflects that the expected probability of consuming FV decreases by 6.2 percentage points for each increase of 0.1 points in the respondents' sensitivity for FV price, keeping everything else constant in the model. Demographic variables including age, gender, and education are all significantly associated with FV intake. For example, the predicted probability of eating FV for a female respondent is 4.4 percentage points higher than a male respondent, adjusting for all other variables.

In the probit regression on FF consumption, the marginal effect on taste preference again indicates the marginal increase in the probability of consuming fast food once per week is about 14.3 percentage points on average for every increment of 0.1

points in the taste preference, and the marginal effects on health means the probability of eating fast food once per week reduces 16.3 percentage points for every increase of 0.1 points in the health belief, while keeping all else constant. Demographic characteristics also significantly predict FF consumption.

Table 3. 1. Distribution of Variables in the FAB Survey 2007 (N=3,397)

	Fruit and Vegetable Intake				Fast Food Consumption			
	Frequency (%) / Mean (SD)				Frequency (%) / Mean (SD)			
	>=2 servings/d N=2,448		<2 servings/d N=920		>=1 / wk N=2,338		<1/wk N=962	
Demographic Characteristics								
Age								
18 – 34 years	648	27.1	298	33.4	761	33.4	171	18.2
35 – 54 years	945	39.4	358	40.3	973	42.7	318	33.9
55 or older	803	33.5	235	26.4	546	24.0	450	47.9
Gender								
Male	882	36.9	408	45.7	947	41.6	326	34.8
Female	1507	63.1	485	54.3	1331	58.4	610	65.2
Education								
Less than high school	261	10.9	141	15.8	294	12.9	91	9.7
High school	700	29.3	302	33.9	715	31.4	261	27.7
Some college	735	30.7	250	28.1	698	30.7	269	28.6
College & Above	697	29.1	198	22.2	567	24.9	321	34.1
Psychosocial Predictors								
Taste preference	0.62	0.2	0.66	0.2	0.65	0.2	0.59	0.2
Health belief	0.66	0.3	0.49	0.3	0.58	0.3	0.67	0.3
Price sensitivity	0.39	0.4	0.45	0.4	(not available)			
Accessibility	0.69	0.2	0.65	0.2				

Table 3. 2. Predictors for Fruits and Vegetables Intake and Fast Food Consumption

(Coefficients and Confidence Intervals)

	Fruit and Vegetable Intake		Fast Food Consumption	
	Coef.	[95% Conf. Interval]	Coef.	[95% Conf. Interval]
Taste preference	-0.3	(-0.5, 0.0)*	0.5	(0.2, 0.7)***
Health belief	1.0	(0.9, 1.2)***	-0.5	(-0.7, -0.3)***
Price sensitivity	-0.2	(-0.4, -0.1)*		
Accessibility	0.2	(-0.1, 0.4)		
Age				
18 – 34 years	*Ref.*			
35 – 54 years	0.1	(0.0, 0.2)	-0.2	(-0.3, -0.1)***
55 or older	0.2	(0.1, 0.4)***	-0.7	(-0.9, -0.6)***
Gender				
Male	*Ref.*			
Female	0.1	(0.0, 0.2)**	-0.1	(-0.2, 0.0)***
Education				
Less than high school	*Ref.*			
High school	0.1	(-0.1, 0.3)	-0.1	(-0.2, 0.1)
Some college	0.3	(0.1, 0.4)***	-0.1	(-0.3, 0.0)
College & Above	0.3	(0.1, 0.5)***	-0.4	(-0.6, -0.2)***
_cons	-0.2	(-0.5, 0.1)	1.2	(0.9, 1.4)***
R-square		0.07		0.08

Since fast food price sensitivity and perceived accessibility to FF outlets are not measured in the FAB survey, and the impact of FF and FV price index on food intake are unknown, prior information from other studies is used to approximately infer parameter values in the model. A model calibration procedure is then conducted to bring the model

predictions more closely to the empirical statistics measured among the downtown Pasadena population.

Using logit regression analysis, Beydoun et al. (2008) reported the odds ratio of the 2007 FF price index on consuming fast food over the two 24-hour recall periods was 0.89 (95% CI: 0.78, 1.02). For low-income people seperately the odds ratio was 0.99 (95% CI: 0.74, 1.35), and for high-income people, the odds ratio was 0.87 (95% CI: 0.74, 1.02). The odds ratio of the 2007 FV price index on the binary outcome of fast food consumption was 0.95 (95% CI: 0.85, 1.07) on average, but for low-income and high-income population, the odds ratio was 0.79 (95% CI: 0.60, 1.02) and 0.94 (95% CI: 0.81, 1.08) respectively (Beydoun et al., 2008). Based upon those odds ratios, the coefficients of FF price index in the logit regression was about -0.12 (=Ln (0.89)) on average, varying from -0.01 (=Ln (0.99)) to -0.14 (=Ln (0.87)) by income levels; and the coefficient of FV price index was -0.05 (=Ln (0.95)), ranging from -0.24 (=Ln (0.79)) to -0.06 (=Ln (0.94)).

Powell et al. reported that the effect of the 2007 FF price index and the 2007 FV price index on frequent FV consumption was 0.073 (SD: 0.020) and -0.063 (SD: 0.031) respectively (Powell & Auld, 2007). In the probit model estimated using the FAB survey, the marginal effect of price sensitivity (the perception that FV costs too much) on frequent FV consumption was -0.0623 (SD: 0.023), very close to the marginal effect of FV price index in Powell's study.

Moore et al. estimated the odds ratio of self-reported exposure to fast foods within 1 mile of home on consuming fast food for more than once a week was 1.61 (coefficient = Ln(1.61) =0.48) (Moore et al., 2009).

3.3 Model Calibration

Calibration is a process to adjust model parameters until the model reproduces the empirically observed outcomes. The model needs to be calibrated when model parameters are adapted to fit a different setting or are estimated from heterogeneous populations. The calibration process is illustrated in Figure 3.2:
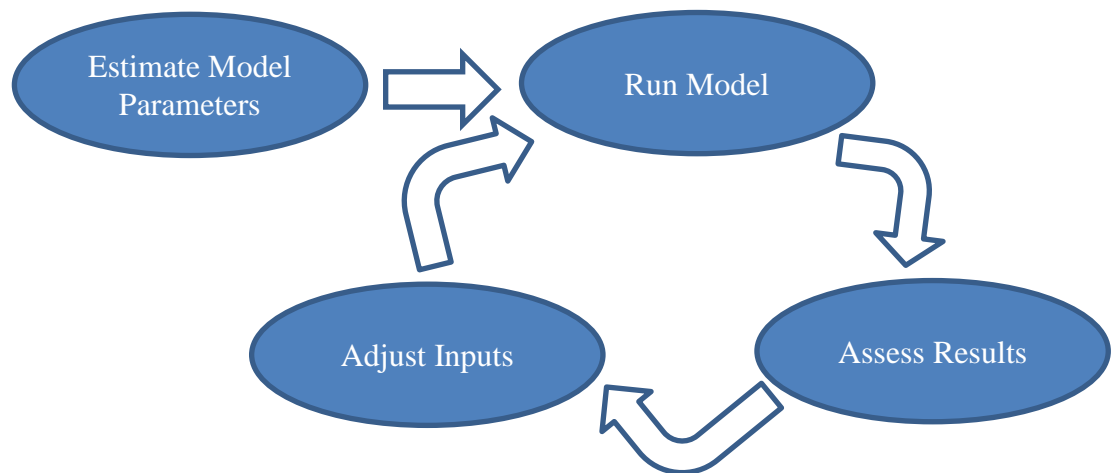
Figure 3. 2. Model Calibration Process, Adapted from (Taylor & Weinstein, 2012)

In Figure 3.2, the first step of model calibration is estimating model parameters from various possible sources, and then simulating the model based on these estimates. Next, model results are compared with empirical outcomes to assess how well the model outputs match the observed data. If the two differ substantially, parameters should be adjusted and the model should be run iteratively until model outputs fit the data. The acceptable criteria is that the empirical statistics should fall within the 95% confidence interval of the model outputs in a number of runs of simulation.

To calibrate the model, I fix the parameters that can be directly estimated from the FAB survey, and tune the values for the parameters that are not measured in the survey but have been assessed in other studies. The first model calibration is based on the setting

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of downtown Pasadena. The aforementioned studies did not directly estimate the coefficients on the product term of price indices and individual's price sensitivity, but I adjust model parameters β_0, β_4, δ_0, δ_3, δ_4 and δ_5 iteratively to fit the empirical outcomes measured in LACHS 2007.

Table 3.3 shows the paramter βs and δs (In Equation (1) and Equation (2)) in the calibrated model. Both means and standard deviations of the parameters are presented. Parameter β_1, β_2, β_3, β_5, β_6, β_7, β_8, δ_1, δ_2, δ_6, δ_7 and δ_8 are modeled the same as the coefficients estimated from the probit regressions. Parameter β_4 is varied between 0.1 and 0.2, given that the magnitude of coefficient of FF price index on Pr(FV) (0.073) is close to that of FV price index on Pr(FF) (-0.063) in Powell et al.'s study. I fix parameter δ_5 using the coefficient estimate in Moore's study, and adjust parameter δ_3 and δ_4. δ_3 and δ_4 are varied from -0.1 to -0.3 to reflect the sociodemographic differences in fast food price sensitivity. After fixing all other parameters, β_0 and δ_0 are adjusted accordingly by subtracting a fixed effect from the constant.

Table 3. 3. Estimation of Weights in the Decision-Making Equations

Weights	Definition	Values	
		Mean	Stand Deviation
β_0	Constant in equation (1)	-0.2	0.1
β_1 [a]	Relative impact of $T_{i,t}$ on $Pr(FV)_{i,t}$	-0.3	0.1
β_2 [a]	Relative impact of $H_{i,t}$ on $Pr(FV)_{i,t}$	1.0	0.1
β_3 [b]	Relative impact of *FV price* on $Pr(FV)_{i,t}$	-0.2	0.1

$\beta_4{}^b$	Relative impact of *FF price* on $Pr(FV)_{i,t}$	0.1	0.1
$\beta_5{}^a$	Relative impact of $A_{FVi,t}$ on $Pr(FV)_{i,t}$	0.2	0.1
$\beta_6{}^a$	Relative impact of Age_i on $Pr(FV)_{i,t}$	0 if $Age_i \in$ (18 - 34) 0.1 if $Age_i \in$ (35 - 54) 0.2 if $Age_i \in$ ($\geq$55)	
$\beta_7{}^a$	Relative impact of $Gender_i$ on $Pr(FV)_{i,t}$	0 if $Gender_i$ = Male 0.1 if $Gender_i$ = Female	
$\beta_8{}^a$	Relative impact of $Education_i$ on $Pr(FV)_{I,t}$	0 if $Education_i$ = less than high school 0.1 if $Education_i$ = high school 0.3 if $Education_i$ = some college 0.3 if $Education_i$ = college and above	
δ_0	Constant in equation (2)	0.8	0.1
$\delta_1{}^a$	Relative impact of $T_{i,t}$ on $Pr(FF)_{I,t}$	0.5	0.1
$\delta_2{}^a$	Relative impact of $H_{i,t}$ on $Pr(FF)_{I,t}$	-0.5	0.1
$\delta_3{}^c$	Relative impact of *FV price* on $Pr(FF)_{I,t}$	-0.3	0.1
$\delta_4{}^c$	Relative impact of *FF price* on $Pr(FF)_{I,t}$	-0.1	0.1
$\delta_5{}^d$	Relative impact of $A_{Ffi,t}$ on $Pr(FF)_{I,t}$	0.5	0.1
$\delta_6{}^a$	Relative impact of Age_i on $Pr(FF)_{I,t}$	0 if $Age_i \in$ (18 – 34) -0.2 if $Age_i \in$ (35 – 54) -0.7 if $Age_i \in$ ($\geq$55)	
$\delta_7{}^a$	Relative impact of $Gender_i$ on $Pr(FF)_{I,t}$	0 if $Gender_i$ = male -0.1 if $Gender_i$ = female	
$\delta_8{}^a$	Relative impact of $Education_i$	0 if $Education_i$ = less than high school	

on $Pr(FF)_{I,t}$	-0.1 if $Education_i$ = high school
	-0.1 if $Education_i$ = some college
	-0.4 if $Education_i$ = college and above

a. Using coefficient estimates by fitting a probit regression to the FAB data.
b. Based on information from Powell et al. and manually altering the parameter to fit the empirical outcome.
c. Based on information from Beydoun et al. and manually altering the parameter to fit the empirical outcome.
d. Based on information from Moore et al. and manually altering the parameter to fit the empirical outcome.

3.4 Micro-face Validation of Model Inputs

The model first simulates a synthetic population that matched the demographic distribution of adults in downtown Pasadena (Zip-code=91101). All variables except price indices depended on the individual i (See Table 3.4). Demographic variables including age, gender, and education are categorized into dummy groups and are assigned the value of 0 or 1. Values of all other individual attributes are bounded between 0 and 1. Price indices are modeled as exogenous variables and applied to the whole population. I used the FV and FF price indices in 2007 (Powell et al., 2007), which estimated the indices from the American Chamber of Commerce Researchers Association (ACCRA) Cost of Living Index reports 2007. The F&V price index was calculated based on prices collected in the following food categories: potatoes, bananas, lettuce, sweet peas, tomatoes, peaches, and frozen corn. Each price index was weighted based on expenditure shares provided by ACCRA derived from the BLS Consumer Expenditure Survey. The fast-food price index was based on the following three items included in the ACCRA data: a McDonald's Quarter Pounder with cheese, a thin crust regular cheese pizza at Pizza Hut and/or Pizza Inn, and fried chicken (thigh and drumstick) at Kentucky Fried Chicken

and/or Church's Fried Chicken. Since food is categorized as either FV or FF, there is no further breakdown per food item. Therefore, the present model does not account for the differences in taste and health benefits across different food items.

Accessibility is measured by whether individuals could walk to a given type of outlet within their buffer zone. The buffer zone commonly used for neighborhood walkability is a circle centered on each individual's home location with a 0.25 - 1 mile radius (Moore et al., 2009). Given that the space is discretized into square cells of 26.4 feet (0.005 mile), this buffer zone meant that an individual is aware of all locations reachable within 50 - 200 cells (0.25 mile/0.005 mile=50 and 1.0 mile/0.005 mile=200). Counting distances as cells (i.e., using a Manhattan distance) is a reasonable approximation for traveling in modern cities divided into blocks, such as the downtown of Pasadena, California (Eichler et al., 2012). All food outlets located within this buffer zone are given an accessibility of 1 (reachable), whereas outlets located outside have an accessibility of 0 (unreachable). $A_{FV_{i,t}}$ takes the values {0, 1}, if there are at least one FV food outlets within the buffer area, $A_{FV_{i,t}}$ equals to 1; otherwise, $A_{FV_{i,t}}$ equals to 0.

Table 3. 4. Description of Model Inputs for the Setting of Downtown Pasadena

Parameters	Definition and Values
Individual attributes	
Age $_i$ [a]	Age groups
	1. Ages 18 – 34 years: 57.00%;
	2. Ages 35 – 54 years: 31.27%;
	3. Ages 55 or above: 11.73%.

Gender $_i$ [a]   Gender

    1. Male: 48.07%;

    2. Female: 51.93%.

Education $_i$ [a]   Educational attainment

    1. Less than high school (LHS): 10.85%;

    2. Finished high school (HS): 16.27%;

    3. Some college (SC): 11.64%;

    4. Finished college (FC): 61.24%.

$T_{i,t}$ [b]   Taste preference at time t - The person prefers sweet and salty foods.

Age is negatively associated with taste preference

    1. Taste $\in$ (0.25-1) if Age = Ages 18-54;

    2. Taste $\in$ (0-0.75) if Age = Ages 55 or above.

$H_{i,t}$ [b]   Health belief at time t - The person has a strong value for eating

healthfully.

Age, being female and educational attainment are positively

associated with health belief

    1. Health $\in$ (0-0.75) if Age = Ages 18-54 & Gender = Male;

    2. Health $\in$ (0-0.75) if Age = Ages 55 or above & Gender = Male & Education <= HS;

    3. Health $\in$ (0-0.75) if Age = Ages 18-54 & Gender = Female & Education <= HS;

    4. Health $\in$ (0.25-1) if all other groups.

PS_i [b]   Price sensitivity - The person has a strong preference for cheaper

food.

Age and education level are negatively associated, and being female

is positively associated with price sensitivity

1. PS $\in$ (0-0.25) if Age = Ages 55 or above & Gender = Male & Education = FC;

2. PS $\in$ (0-1) if Age = Ages 18-54 & Gender = Female & Education = LHS;

3. PS $\in$ (0-0.5) if all other groups.

$A_{FV\,i,t}$ and $A_{FF\,i,t}$ Accessibility of fruit & vegetable outlets and Accessibility of fast food restaurants - The person is disinclined to purchase food sold outside of walking distance (0.25 – 1 mile).

1. Accessibility=1 if within walking distance
2. Accessibility=0 if outside of walking distance.

α The extent to which an individual is influenced by friends' social norms.

$\alpha \in [0, 0.3]$, uniform distribution.

Environmental attributes

$PI_{fv}{}^{c}$ FV price index - Weighted FV price index in 2007.

Set to 0.72 at baseline.

$PI_{ff}{}^{c}$ FF price index - Weighted FF price index in 2007.

Set to 2.71 at baseline.

γ Visibility weights on the social norm of friends. $\gamma \in (-1, 1)$, uniform distribution.

Set to 0 at baseline.

FF/FV [d]   Ratio of stores selling fast food versus fruits and vegetables.

Set to 7 at baseline.

Empirical Statistics

Pr(FV) [e]   The proportion of people who ate at least 2 servings of FV per day in

downtown Pasadena.

Pr(FV) = 0.81

Pr(FF) [e]   The proportion of people who ate at least 1 meal from a fast food

restaurant per week in downtown Pasadena.

Pr(FF) = 0.47

a. Age, gender and education are assumed the same distribution as in downtown Pasadena (zip = 91101) based on 2010 census.
b. Predicted using the FAB data.
c. Derived from Powell, L. M. (2007) that estimated the price indies from ACCRA.
d. Calculated from CDPH - Network for a Healthy California - GIS Map Viewer
e Estimated from LACHS2007, statistics in subpopulation of downtown Pasadena is adjusted using population weights.

To check the micro-face validity of the model, the simulated demographic

distribution is compared with the actual demographics in downtown Pasadena reported in

the US Census. This is accomplished by exporting the simulated data from the model into

an Excel file, and performing graphical and descriptive analysis in STATA 12.0

(StataCorp., 2011). The model runs only once, thus does not account for random

variation. Means and standard deviations (SD) are presented in the following tables. All

standard deviations indicate the distribution of model parameters across agents. As Table

3.5 shows, the simulated data and actual data have almost identical age, gender and

education distributions.

Table 3. 5. Comparison of Simulated and Actual Demographic Distributions

	Simulated Data	Actual Data

Gender		
Female	52.00%	51.93%
Male	48.00%	48.07%
Age Groups		
Ages 18 – 34 years	55.30%	57.00%
Ages 35 and above	44.70%	43.00%
Educational Attainment		
Less than high school	10.80%	10.85%
Finished high school	16.10%	16.27%
Some/ finished college	73.10%	72.88%

I then assess the model-simulated values and distributions of three key factors – Taste Preference, Health Belief and Price Sensitivity, and make a comparison with the empirical measures in the FAB survey. Because the demographics in the model and the FAB survey are very different, it is expected that values of the three factors would not be identical, but the distributions of the factors across socio-demographic groups should be similar.

As shown in Table 3.6, Taste Preference does not differ much between male and female, or across education levels. Young people prefer stronger taste than the middle-aged and the older people. But the taste difference between different age groups in the simulated data is larger than that in the actual data, which might be due to different

demographic distribution in the FAB data or due to random variation when the model runs.

Table 3. 6. Comparison of Taste Values in Simulated and Actual Data

	Taste Preferences			
	Simulated Data		**Actual Data**	
	Mean	**SD**	**Mean**	**SD**
Gender				
Female	0.51	0.25	0.62	0.24
Male	0.52	0.23	0.64	0.24
Age Groups				
Ages 18 – 34 years	0.62	0.22	0.66	0.23
Ages 35 and above	0.39	0.21	0.59	0.25
Educational Attainment				
Less than high school	0.55	0.25	0.63	0.26
Finished high school	0.51	0.24	0.63	0.24
Some/ finished college	0.51	0.24	0.63	0.24

Table 3.7 compares the baseline values of health beliefs in the model and in the FAB data. In both datasets, middle-aged and older population care more about healthy eating than the younger population, females care more about healthy eating than males, and people with higher education levels have stronger values in eating healthy than those with lower educational attainment.

Table 3. 7. Comparison of Values of Health Beliefs in Simulated and Actual Data

	Health Beliefs	
	Simulated Data	**Actual Data**

	Mean	SD	Mean	SD
Gender				
Female	0.62	0.23	0.65	0.24
Male	0.46	0.25	0.56	0.29
Age Groups				
Ages 18 – 34 years	0.49	0.26	0.59	0.30
Ages 35 and above	0.60	0.23	0.62	0.30
Educational Attainment				
Less than high school	0.44	0.24	0.58	0.32
Finished high school	0.50	0.26	0.59	0.31
Some/ finished college	0.56	0.25	0.63	0.28

Baseline values and distributions of price sensitivity are presented in Table 3.8. Younger people, females, and those who don't finish high school are more sensitive to food prices. The same pattern is observed in the FAB data.

Table 3. 8. Comparison of Values of Price Sensitivity in Simulated and Actual Data

	Price Sensitivity			
	Simulated Data		Actual Data	
	Mean	SD	Mean	SD
Gender				
Female	0.27	0.17	0.43	0.36
Male	0.21	0.14	0.38	0.33
Age Groups				
Ages 18 – 34 years	0.27	0.17	0.43	0.35
Ages 35 and above	0.20	0.14	0.40	0.35
Educational Attainment				
Less than high school	0.34	0.22	0.45	0.37
Finished high school	0.26	0.14	0.42	0.36

| Some/ finished college | 0.22 | 0.14 | 0.39 | 0.34 |

3.5 Macro-face Validation of Model Outputs

Figure 3.3 and 3.4 presents the comparison of model outputs with empirical statistics measured in the LACHS. Sampling weights are used to adjust the food consumption estimates for the population that are representative of adults in downtown Pasadena. The model predicts both probabilities of food intake and actual food consumption levels. I use the actual consumption levels, and compare the percentage of people who consume fast foods for more than once per week and percentage of people who eat more than two servings of fruits and vegetables each day with the same statistics in the LACHS 2007. As Figure 3.3 and 3.4 shows, the model outputs are very close to the empirical measurements.
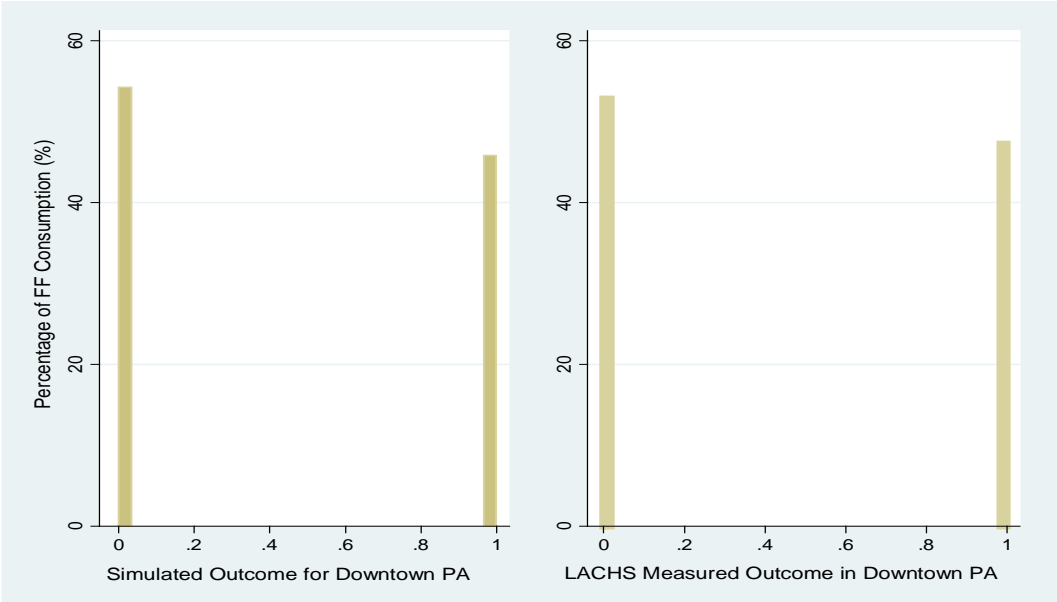
Figure 3. 3. Comparison of Model Output with Actual Data

(Weekly Consumption of Fast Foods)

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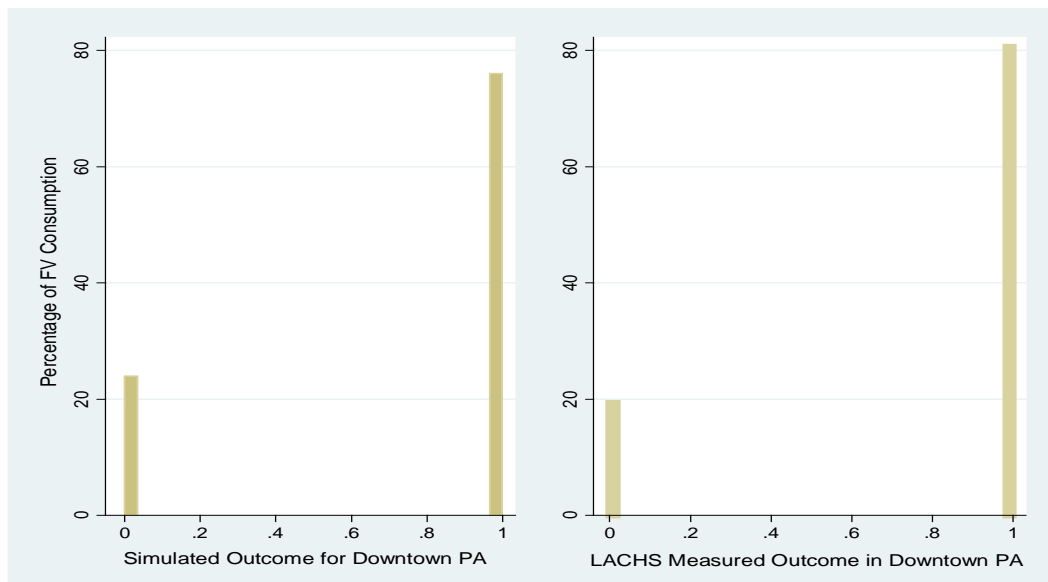
Figure 3. 4. Comparison of Model Output with Actual Data

(Daily Intake of Fruits and Vegetables)

The model assumes that individual's taste preference and health belief can be influenced by peers, but price sensitivity is assumed constant throughout model simulation. The parameters in the model-setup stage are compared with those at the end of the 1,095 periods in the simulation. As expected, the average values of taste preference and health belief update slightly after simulation (set $\alpha=0.3$). At the model setup stage, the average taste preference is 0.51, but it decreases to 0.48 to the end of the simulation. It suggests that people's habits in taste preference are slightly modified through the influence of social network. At the same time, the average health belief among all individual agents decreases from 0.54 to 0.52 after the simulation, which also reflects the influence of social network on this collective norm/habit in health belief. The average price sensitivity remains the same at the level of 0.24, since it is only associated with an

individual's own sociodemographic characteristics. The model-predicted average proportion of FV consumption is 0.47 (95% CI: 0.44, 0.49), identical to the empirical observed outcome of 0.47 in the population of downtown Pasadena. The model-simulated average FF intake is 0.80 (95% CI: 0.79, 0.81), similar to the actual measure of 0.81 in the population of interest (See Table 3.9).

Table 3. 9. Comparison of Parameter Values in Model Setup and After Simulation

	Model Setup		After Simulation		Actual Outcome[1]
	Mean	**[95% Conf. Interval]**	**Mean**	**[95% Conf. Interval]**	
Taste Preferences	0.51	(0.50, 0.53)	0.48	(0.48, 0.49)	
Health Beliefs	0.54	(0.53, 0.56)	0.52	(0.52,0.53)	
Price Sensitivity	0.24	(0.23, 0.25)	0.24	(0.23, 0.25)	
Pr(FF)			0.47	(0.44, 0.49)	0.47
Pr(FV)			0.80	(0.79, 0.81)	0.81

1. Estimated from the LACHS 2007.

Figure 3.5 and Figure 3.6 show how quickly the model converges to a steady-state, in which food choices, taste preference and health belief no longer change. Figure 3.5 suggests that food consumption probabilities converge at about 300-period of simulation. Figure 3.6 shows that taste preference and health belief converge at the time when the model runs for about 300 periods. Over time, with the influence of social network, an individual's cognitive habits become more similar to the collective habits, thus the average taste preference and health belief converge to a steady-state. Population-level food consumption also converges fast, even if adaptation of food outlets is accounted for.
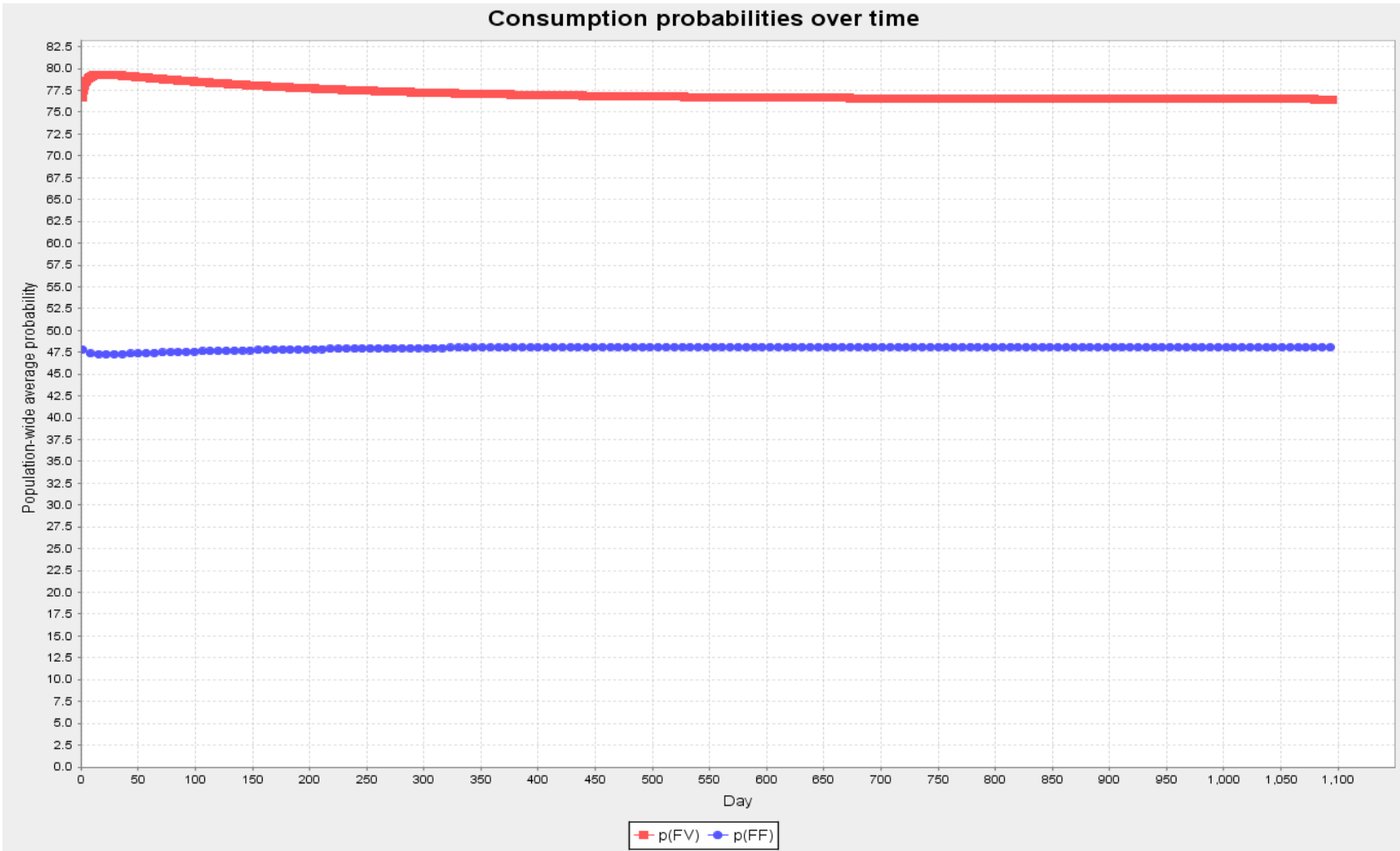
Figure 3. 5. Convergences of Food Consumption Probabilities
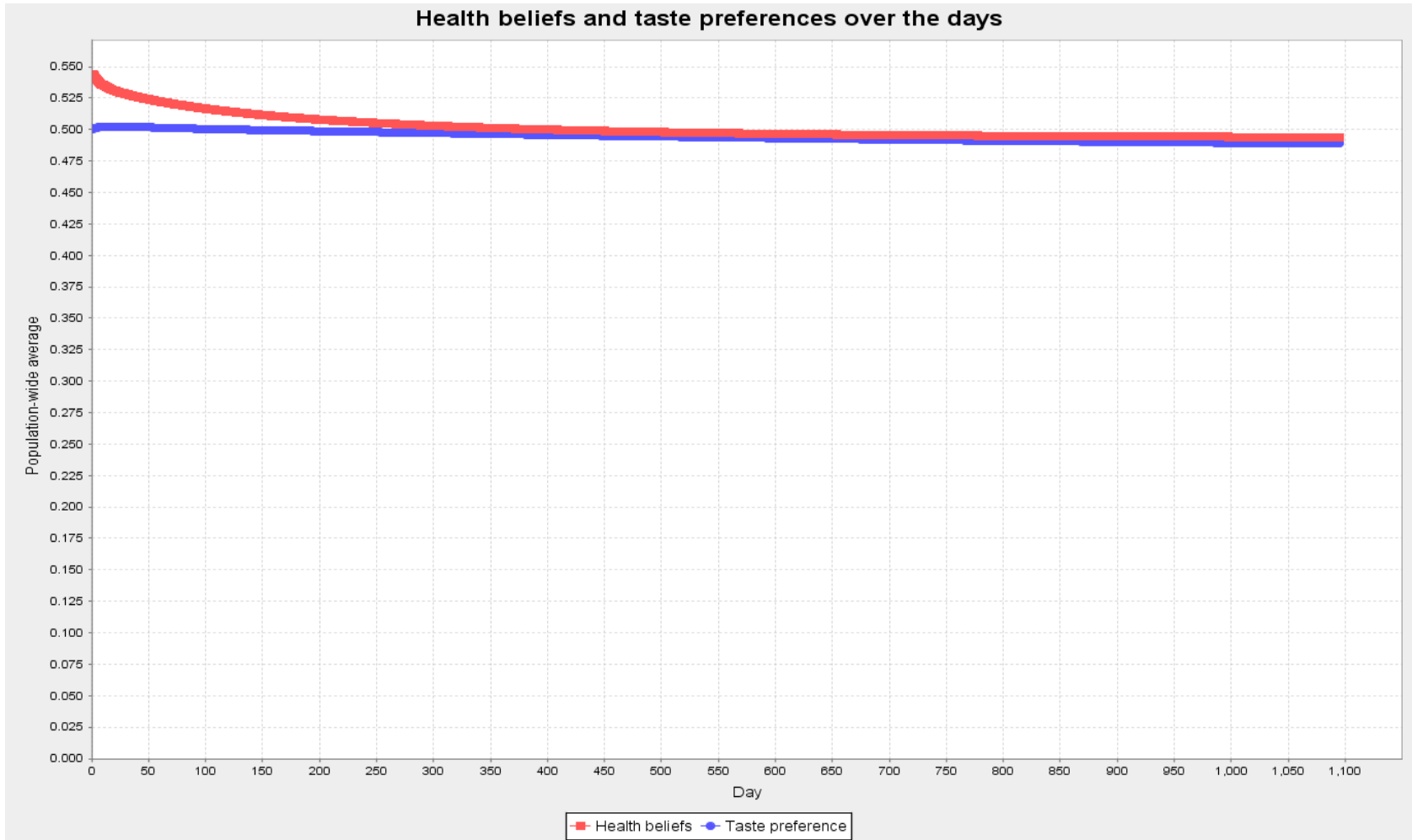
Figure 3. 6. Convergences of Health Beliefs and Taste Preferences

3.6 Empirical Input Validation

3.6.1 A Sensitivity Analysis on the Social Parameter α

One distinctive feature of the ABM is that it allows individual agents to influence and be influenced by other individuals. This feature is achieved by generating a social network to represent the social connection among the agents. Figure 3.7. presents the model-generated social network. It is a small-world social network. Among the 1000 individuals that are simulated in the model, 11222 social ties are generated in the computer. The average number of social ties (i.e. degree) is 21.45, including both close social ties and weak ties. In network analysis, a degree is defined as the number of direct connections an agent has, so a social tie can be counted twice when calculating average degree of a network. The clustering coefficient for this small-world network is 0.70.
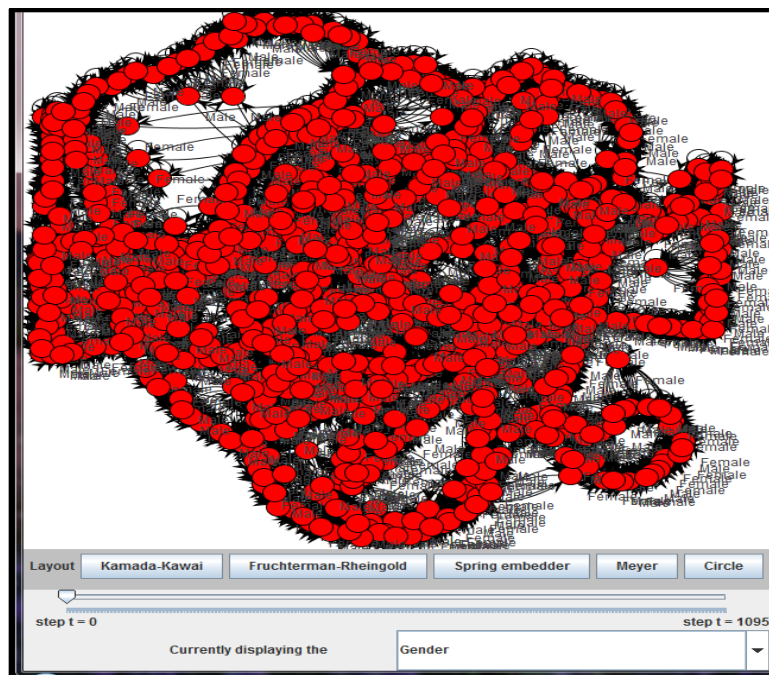
Figure 3. 7. A Model-Generated Social Network

The model uses parameter α to represent the extent to which a person's values (i.e. taste preference and health belief in food choices) influenced by group norms, whereas empirical value of this parameter is not clear. Christakis and Fowler found in their study that:

A person's chances of becoming obese increased by 57% (95% confidence interval [CI], 6 to 123) if he or she had a friend who became obese in a given interval. Among pairs of adult siblings, if one sibling became obese, the chance that the other would become obese increased by 40% (95% CI, 21 to 60). If one spouse became obese, the likelihood that the other spouse would become obese increased by 37% (95% CI, 7 to 73) (Christakis & Fowler, 2007).

Based on their study, I assume in the model that α be greater than 0, and less than 0.5, given that the network includes both strong and weak social ties that may have different impacts on an individual's values and behaviors. A sensitivity analysis is performed by varying the value of α between 0 and 0.5, keeping all else constant in the model. For each value of alpha, the simulation is run for 10 times to account for random variation.

Means and standard errors (SE) of model outputs are presented in Table 3.10. SE indicates the distribution of outcomes across runs of the model. In particular, the probability of consuming more than two servings of FV per day increases monotonically with an increase of α from 0 to 0.5, whereas the probability of weekly fast food intake does not change much when α is increased from 0 to 0.5. The reason might be that as in a concave function, the population-average FV consumption may be an increasing function

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of cognitive habits (taste preference and health belief), but it increases at a decreasing rate (i.e., diminishing marginal returns). Accordingly, as the influence of social network increases, each individual has a de facto habit that approaches the average taste preference and health belief in a population. In the limit, if everyone were in a single all-encompassing social network, eventfully each would converge to the same value. The average FV consumption probability will be higher with everyone at the average level than that with everyone having very different values. This emergence of concavity of the function does not work with population-average fast food intake, but seems to predict that more social influence increase people's FV consumption. Moreover, Table 3.10 also shows that the model outputs are closest to the actual statistics when α equals to 0.5.

Table 3. 10. A Sensitivity Analysis on the Social Parameter α

α	Pr(FF)		Pr(FV)	
	Mean	SE	Mean	SE
0	0.49	0.02	0.73	0.01
0.1	0.49	0.01	0.76	0.02
0.2	0.49	0.01	0.77	0.03
0.3	0.49	0.02	0.78	0.02
0.4	0.48	0.02	0.79	0.03
0.5	0.48	0.02	0.80	0.02

3.6.2 A Sensitivity Analysis on the Initial Condition

Food outlets are assumed to open in random locations, but this may be an oversimplification because food stores and restaurants often cluster within a region (Porter, 2000). For instance, the healthy food vendors in downtown Pasadena are mostly clustered to the left of the area (See Figure 3.8.), although the area is relatively small (1.3 square miles). I compare the model outputs under the random location condition with that under the unequal distribution condition. As seen in Table 3.11, there is no significant difference in the simulated probabilities of food intake between the two initial conditions, no matter what buffer is used as walking distance in the model. Generally, the model is not sensitive to the initial setup of food outlets, and random location of food outlets may be an appropriate assumption in this ABM.

Table 3. 11. A Sensitivity Analysis on the Initial Condition

Initial Conditions	Pr(FV)		Pr(FF)	
	Mean	SE	Mean	SE
Random Location – 1 mile buffer	0.78	0.02	0.50	0.02
Unequal Distribution – 1 mile buffer	0.79	0.02	0.49	0.01
Random Location – 0.5 mile buffer	0.78	0.03	0.49	0.02
Unequal Distribution – 0.5 mile buffer	0.75	0.03	0.48	0.02
Random Location – 0.25 mile buffer	0.72	0.03	0.48	0.02
Unequal Distribution – 0.25 mile buffer	0.71	0.02	0.48	0.02
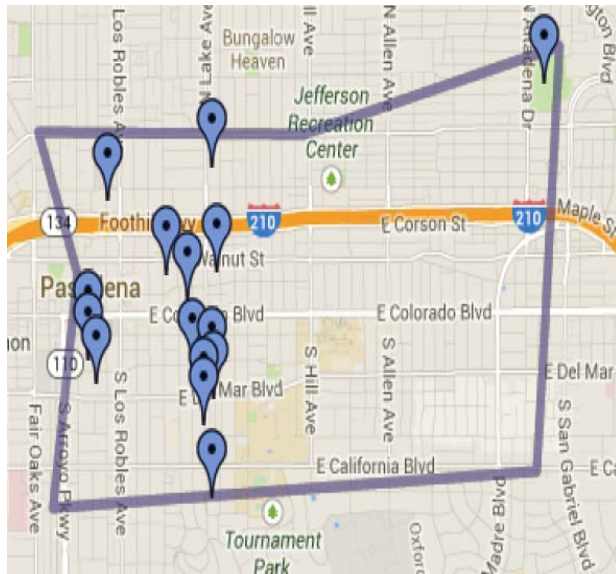
Figure 3. 8. Locations of Healthy Food Outlets

(Farmer's Market and Supermarkets) in Downtown Pasadena

I then explore the distribution of food outlets at the beginning and at the end of the simulation. In Figure 3.9 and 3.10, the red dots represent unhealthy food outlets and the green dots are healthy food outlets in the model. As expected, under both initial conditions, a number of food outlets switch the type of food they sell in response to the consumers' dietary choices during a three-year-period simulation (the circled dots).
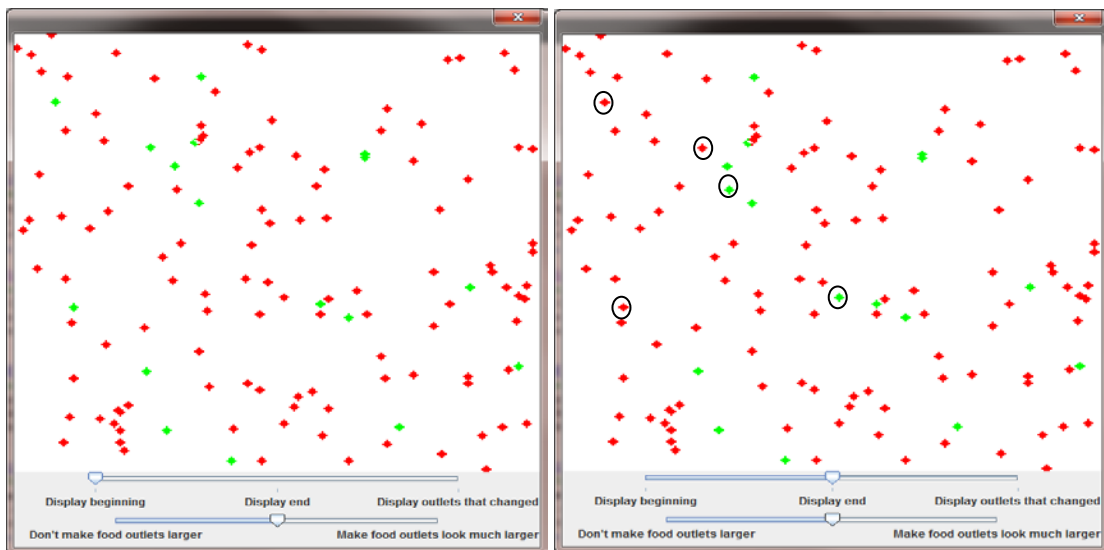
Figure 3. 9. Random Distribution of Food Outlets in the Model

(Beginning vs. End of Simulation)
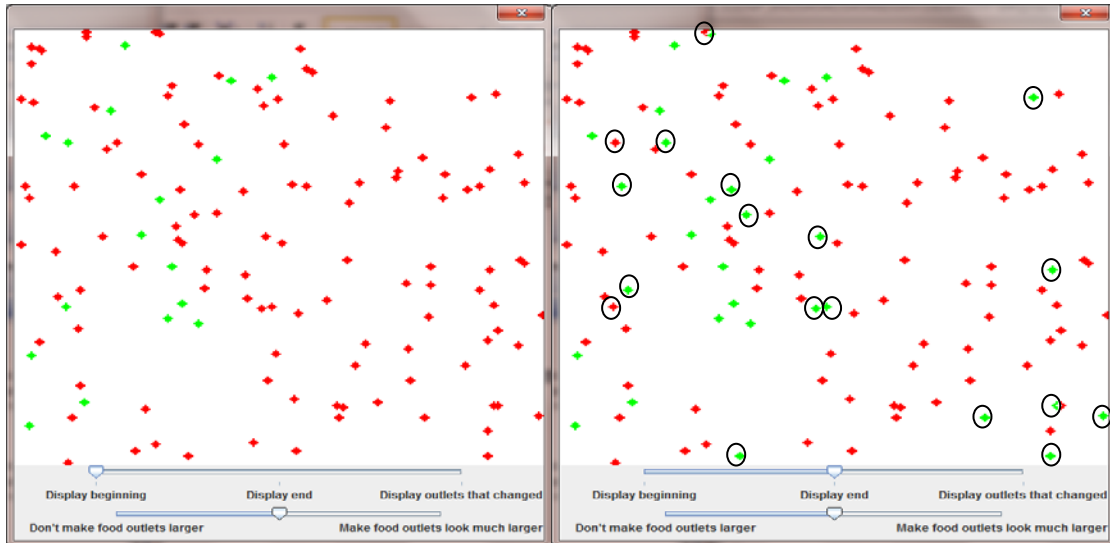
Figure 3. 10. Unequal Distribution of Food Outlets in the Model

(Beginning vs. End of Simulation)

3.7 Empirical Output Validation – Testing the Model Using Five Different Settings

Model parameters can vary based on specific settings and populations, but the variation should not be too large to make model prediction unreliable. Relying on the model for downtown Pasadena (Zip-code 91101), I tune 10 parameters with small variation (±0.2) such that model outputs match the empirical data. The model is simulated using a random sample of 1000 individuals, and are compared in the baseline case (i.e., without interventions) with FF and FV consumption proportions among the adult population in other four different regions estimated from the LACHS 2007 (See

Setting Selection in Chapter 2 Section 2.5). Each setting-specific model simulations are run 10 times to account for stochastic variation.

Table 3.12 presents values of the parameters and the simulated outcomes. All the empirical outcomes of the five regions fall within the 95% confidence intervals of model predictions. Compared to the zip-code area of 91101 that is accepted as a benchmark, in area 90011, when parameter β_1, β_2, β_3, β_4 and δ_2 vary within ± 0.2, the model predictions fit the actual data well. In 90404, model predictions fall within the acceptable region when parameter β_1, δ_1, δ_2, δ_3, δ_4 and δ_5 are adjusted by ± 0.1 or ± 0.2. In the area of 90715, only β_1 and β_2 are adjusted for the model to have an almost perfect fit with the empirical statistics. In 90505, β_1, β_2, β_5 and δ_4 are changed until the model outputs approximately match the actual outcomes.

Table 3. 12. Comparison of Simulated Results with Empirical Statistics

Zip Codes						Simulated Statistics		Empirical Statistics
						Mean	SE	
91101	β_1	0.5	δ_1	-0.3	**Pr(FV)**	0.79	0.036	0.81
	β_2	-0.5	δ_2	1.0	**Pr(FF)**	0.48	0.024	0.47
	β_3	-0.3	δ_3	-0.2				
	β_4	-0.1	δ_4	0.1				
	β_5	0.5	δ_5	0.2				
90011	β_1	0.3	δ_1	-0.3	**Pr(FV)**	0.70	0.031	0.71
	β_2	-0.7	δ_2	1.1	**Pr(FF)**	0.28	0.013	0.28
	β_3	-0.4	δ_3	-0.2				
	β_4	-0.3	δ_4	0.1				
	β_5	0.5	δ_5	0.2				
90404	β_1	0.6	δ_1	-0.4	**Pr(FV)**	0.69	0.026	0.71

	β_2	-0.5	δ_2	0.8	**Pr(FF)**	0.36	0.020	0.38
	β_3	-0.3	δ_3	-0.3				
	β_4	-0.1	δ_4	0.2				
	β_5	0.5	δ_5	0.1				
90715	β_1	0.6	δ_1	-0.3	**Pr(FV)**	0.83	0.025	0.83
	β_2	-0.4	δ_2	1.0	**Pr(FF)**	0.45	0.021	0.46
	β_3	-0.3	δ_3	-0.2				
	β_4	-0.1	δ_4	0.1				
	β_5	0.5	δ_5	0.2				
90505	β_1	0.6	δ_1	-0.3	**Pr(FV)**	0.87	0.016	0.87
	β_2	-0.4	δ_2	1.0	**Pr(FF)**	0.50	0.012	0.48
	β_3	-0.3	δ_3	-0.2				
	β_4	-0.1	δ_4	0.2				
	β_5	0.6	δ_5	0.2				

3.8 Summary

In recent decades, empirical parameterization of simulation models has become mainstream. Agent-based models integrate theories and empirical evidence from various sources and model agents' behaviors in the context of social interaction and external environment. In this chapter, I have applied a regression to estimate a number of the model parameters, and have adjusted parameters that are not available in the FAB data but based on information from other studies, providing an empirical basis for model prediction. Model validation is carried out by comparing model inputs/outputs with actual micro-level and macro-level data, and by a number of sensitivity analysis. The four main results are: (1) The model shows that fruit and vegetable consumption is a concave function of individual cognitive habits, that more social influence predicts more fruit and vegetable consumption at the population-level. (2) Model prediction is not sensitive to

the assumption on distribution of food outlets. Random distribution and unequal distribution of food outlets in the district generates almost identical model outputs. (3) The model converges quickly at about 300 periods of simulation. (4) Calibration is setting-specific. After calibrating the model to each of five zip-code level areas, the model fits the empirical statistics well.

CHAPTER 4. USING MODEL SIMULATION TO ASSESS THE IMPACT OF DIFFERENT INTERVENTIONS ON DIETARY CHOICES

This chapter concentrates on testing the potential impact of various policies on unhealthy eating behaviors using the calibrated ABM. Four different policies are assessed: (1) taxing unhealthy food ingredients; (2) providing subsidies for healthy foods; (3) zoning policies that limit the number of unhealthy food outlets; (4) promoting healthy eating norms through either community-based advocacy or a mass-media campaign. Policy simulations are conducted by manipulating relevant parameters in the model. Monte Carlo simulation is used based on the estimated or imputed distribution of model parameters to estimate the uncertainty of model predictions.

This chapter is organized as follows. Section 4.1 presents the impact of four policies on dietary choices measured by the two population-average probabilities of food consumption, applied in the setting of downtown Pasadena. Section 4.2 presents model predictions within four different settings and examines how much the policy impact varies by specific context. Section 4.3 estimates model robustness and uncertainty using Monte Carlo simulation.

4.1 Policy Simulations

Based on the calibrated model and assuming constant demographics, simulations are performed to answer the question of comparative statics - what would happen if a certain policy were applied in a population of interest. Policy simulations are conducted

by manipulating the model's four environmental parameters through the following policies:

- *Tax on unhealthy food.* The price index of fast food in the model is increased in increments by 1% up to 20% to reflect the effect of taxes on unhealthy food.

- *Subsidies for healthy food.* The price index of fruits and vegetables is lowered by 1% up to 20% to reflect the effect of increased agricultural subsidies.

- *Regulation of the local food environment.* Zoning regulations are modeled that would alter the ratio within a neighborhood of stores selling fast food to those selling fruits and vegetables (FF/FV, Table 3.4). The ratio is lowered from its baseline value of 7 to 4. Because lowering the ratio affects the relative availability of FF and FV, individuals will re-evaluate the access to FF or FV each period when they make food choices.

- *Promotion of healthy norms.* The impact of advertising healthy foods is examined by increasing the visibility (parameter γ, Table 3.4) given to healthy peers from 1% to 10% (This policy scenario is hypothetical, not based on implemented policy programs as those in the first three policies).

These policy experiments and their magnitudes are chosen so as to be similarly realistic policy options. For example, a soda tax or tax on sugar-sweetened beverages has been proposed in several states including the State of California (Connor, 2013), the State of Connecticut (CBSNewYork/AP, 2014) and the State of New York (Grynbaum, 2013). However, consensus has not been reached among the general public. New York City ban

on big sugary sodas was overturned last year (Aubrey, 2013). In Mississippi where one in three adults is obese, passing a regulation on soda tax was also very difficult (Hess, 2013). The model is simulated to show in downtown Pasadena whether and how much a tax on unhealthy food would make a difference on food consumption.

Zoning policies have been introduced in some regions particularly low-income communities. For example, South Los Angeles has banned new fast food establishments since 2008 (Medina, 2011). Other measures include efforts to attract farmers' markets in low-income neighborhoods (Spaces, 2013). The model simulates zoning policies by replacement of food outlets to show whether such measures would work in the population of interest.

The strategy of promoting healthy eating norm is perhaps the one that's most difficult to quantify. But the application of social norms and social networks to influence human behaviors is not uncommon. Solomon Asch (1955), in a well-known experiment, showed how people conformed to a dominant social norm. In his experiment, a group of 9 college male students were asked to answer a number of judgmental questions, and after a while, one individual found his answers did not match those of the others. He felt upset and changed his answers to conform to the group answers. However, all other 8 students were actually told by the experiment designer before the study to choose the incorrect answers (Asch, 1956). Asch's experiment influenced the field of social psychology, and some have applied this social norm theory to target risky behaviors by "debiasing" perception of social norms (Blanton et al., 2008; Feldman et al., 1997). For example, Feldman (1997) developed a value utilization/norm change (VUNC) model to alter the norms and core values of adolescents in Zambia that relates to risky sexual

behaviors within their social networks, which the authors claimed were the most effective approach to change the adolescents' unsafe sexual behaviors (Feldman et al., 1997).

In the literature of economics, drawing on social psychology, George Akerlof (2000) incorporated social identity and norms into a classic economic utility paradigm. He argues that individuals do not just respond to financial incentives and are not constrained only by asymmetric information, but also adhere to social norms for how people should behave in a social group and identities that are linked to "relevant others" in the social group (Akerlof & Kranton, 2000). Following his framework, others have modeled social norm as a parameter in an individual's utility function that influences the individual's decision-making (Clark, 2003). For example, Clark (2003) has identified that the well-being of an individual who was unemployed was strongly affected by the unemployment status in the reference group at the regional, partner or household level. He found that a rise of five percentage points in the regional unemployment rate reduced an unemployed's probability of in a good well-being status from 30% to around 20% (Clark, 2003).

Promotion of healthy social norms can work through healthy advertisements using mass media campaigns that change people's perception of an unhealthy norm or through community-based strategies that combine local leadership with policy actions (Wakefield et al, 2010). California's tobacco control campaign is one such example based on a mass media campaign to change norms around smoking. Based on longitudinal data from the California Adult Tobacco Survey (CATS), Zhang et al. (2010) found a significant link between the change of social norms and smoking-quitting behaviors (Odds Ratio: 1.7). They measured norms using social norm constructs based on measurements of

individuals' knowledge, attitudes and beliefs, and those constructs varied along with the change in population-average norm (Zhang et al, 2010).

Food marketing and newly-developed technologies in marketing have been widely studied in both public health and marketing literature (Cairns, 2013; Chandon, 2010; Improve, 2004; Luo, 2009), although most of them are for unhealthy food marketing. Strategies such as digital marketing, relational marketing, word-of-mouth marketing and marketing based on the collection of personal data have been very successful in facilitating consumer communications within the social network, biasing consumer's perception of norms, creating an illusion of intimacy with the consumers and enhancing consumer loyalty to the marketed products. But healthy food advertisement and social marketing are less studied. California's avocado campaign is an example of healthy food marketing. They used broadcast, social media and outdoor billboards to encourage consumers to purchase California's avocados. They also used online advertising on Facebook for targeted consumers who might share their menu ideas using avocados with friends (Commission, 2014).

In the current study, the impact of healthy food advertising is modeled as a positive bias (increasing visibility of norms shared by healthy peers) created on the social norm, so as to influence individual food intake through the social network. The "norm" is modeled as an individual's perception of the average habits in his or her peer group. Crucially, both in this model and in the real world, the perception of peer-average habits can differ from actual peer-average habits. Exogenous policy in this model works by manipulating this difference between perception and reality of peer-average habits. To illustrate this exogenously-induced bias, suppose an individual goes to a restaurant with a

group of ten friends. Half of them choose to eat healthy food. If the restaurant advertises the healthy food, it may increases the visibility of the healthy choice, so that the individual perceives 60% of his peer group as eating healthy food, when in reality only 50% do so. As a result, the individual is more likely to conform to the selected norm and chose to eat healthy food, just as in the Asch's experiment (Asch, 1956).

Each run of the simulation takes place over 1095 days (3 years) on a sample of 1,000 participants. For each set of variables, the simulation is run ten times to account for random variation.

Table 4.1 shows a part of results that contrasts simulated outcomes under the four different policy scenarios. Both means and 95% confidence intervals for mean outcomes across all the simulations are presented. The results show that price-based strategies (i.e., taxing unhealthy foods, subsidizing healthy foods) can lower the consumption of fast foods and increase the consumption of fruits and vegetables. However, improvements are small given the increases that are considered. A 10% increase in the price of fast foods results in a small decrease in FF consumption (1 percentage point on average) and a slight increase in the consumption of FV (2 percentage points on average), whereas a 20% increase in the price of fast foods yields a 2-percentage-point reduction in FF consumption and a 3-percentage-point increase in FV intake, on average. Results also show that reducing the price of fruits and vegetables have no considerable impact on FV consumption, but may potentially increase FF consumption, which may reflect an income effect, and be an unintended consequence.

Zoning policies aimed at improving the density of stores selling fruits and vegetables would increase the daily intake of FV by 3 percentage points on average, but have no impact on eating FF, assuming walking distance is 1 mile. Promoting healthy norms is the most impactful strategy among the four: a 5% improvement in the visibility of positive social norms yields a 6 percentage-point increase in FV consumption and a 2 percentage-point decrease in FF consumption, and a 10% improvement would have a 9-percentage-point impact on FV intake and at the same time reduce FF consumption by 5 percentage points on average, assuming a small-world network and α equal to 0.3.

Table 4. 1. Comparison of Impact of Different Interventions

on Food-Consumption Decisions (Mean/ 95% CI) [a]

	Baseline	Increasing taxes on FF [b]		Increasing subsidies on FV [c]		Zoning policy [d]		Promoting healthy norms [e]	
		10%	20%	10%	20%	6	4	5%	10%
Pr(FV)	0.79	0.81	0.82	0.80	0.78	0.81	0.82	0.85	0.88
	(0.77-0.81)	(0.80-0.82)	(0.81-0.84)	(0.78-0.81)	(0.77-0.79)	(0.79-0.83)	(0.80-0.83)	(0.84-0.86)	(0.86-0.89)
Pr(FF)	0.48	0.47	0.46	0.49	0.50	0.48	0.48	0.46	0.43
	(0.47-0.49)	(0.46-0.48)	(0.45-0.47)	(0.48-0.50)	(0.49-0.51)	(0.46-0.50)	(0.47-0.50)	(0.45-0.47)	(0.41-0.44)

a. In the parentheses: 95% confidence intervals
b. Increase the price index of fast food (P) in the model by 10% and 20%;
c. Decrease the price index of fruit and vegetables in the model by 10% and 20%;
d. Add fruit and vegetable outlets in the region so that the ratio of Fast-food to Fruit-and-Vegetable outlets falls from 7 to 6 (first column) or from 7 to 4 (second column).
e. Increase the visibility (parameter γ) given to healthy peers from 1% to 10%.

Figure 4.1 and 4.2 show the impact of various tax rates on individuals' food consumption. Means and 95% confidence intervals (i.e., the mean outcome across all the simulations) are plotted on both graphs. With tax rates increased from 0 to 20%, population-average FF consumption decreases and FV consumption increases, albeit by a small amount. Similarly, as shown in Figure 4.3 and Figure 4.4, subsidy on FV has relatively small impact on food consumption.
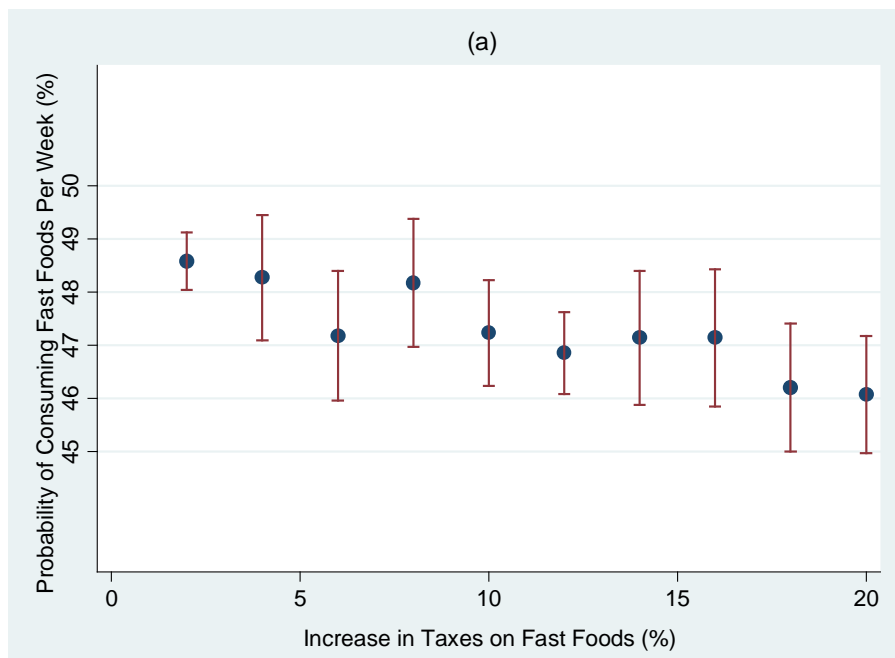
Figure 4. 1. The Impact of Taxes on the Consumption of Fast Foods, with 95% Confidence Bands

(b)
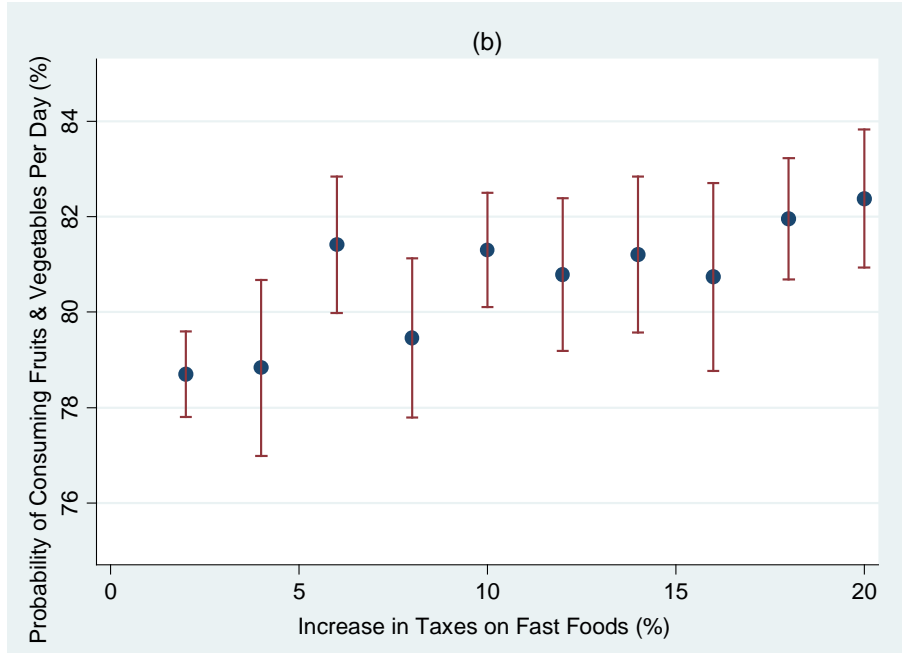
Figure 4. 2. The impact of Taxes on the Consumption of Fruits and Vegetables

(a)
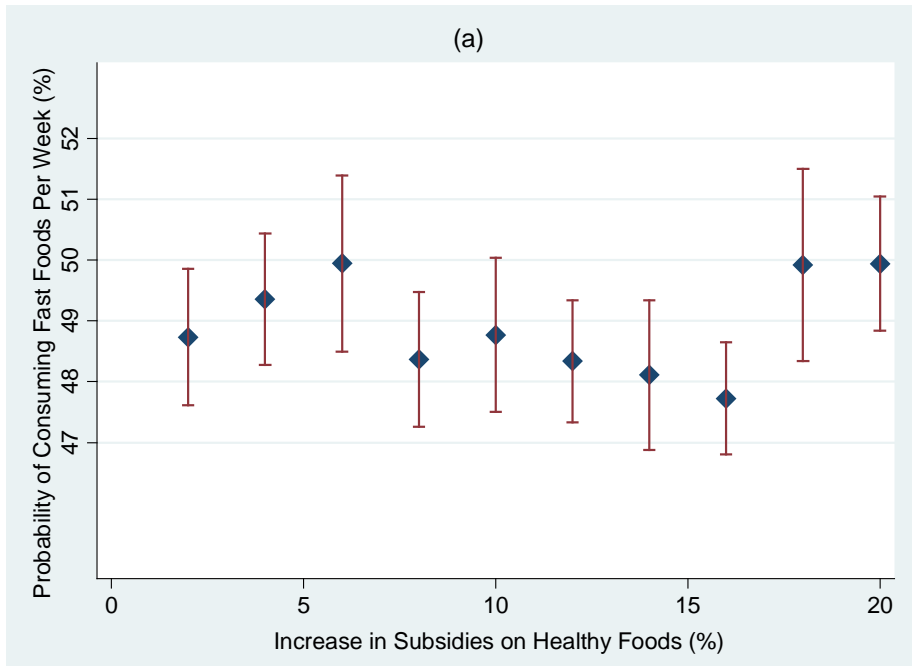
Figure 4. 3. The Impact of Healthy Food Subsidy on the

Consumption of Fast Foods

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(b)
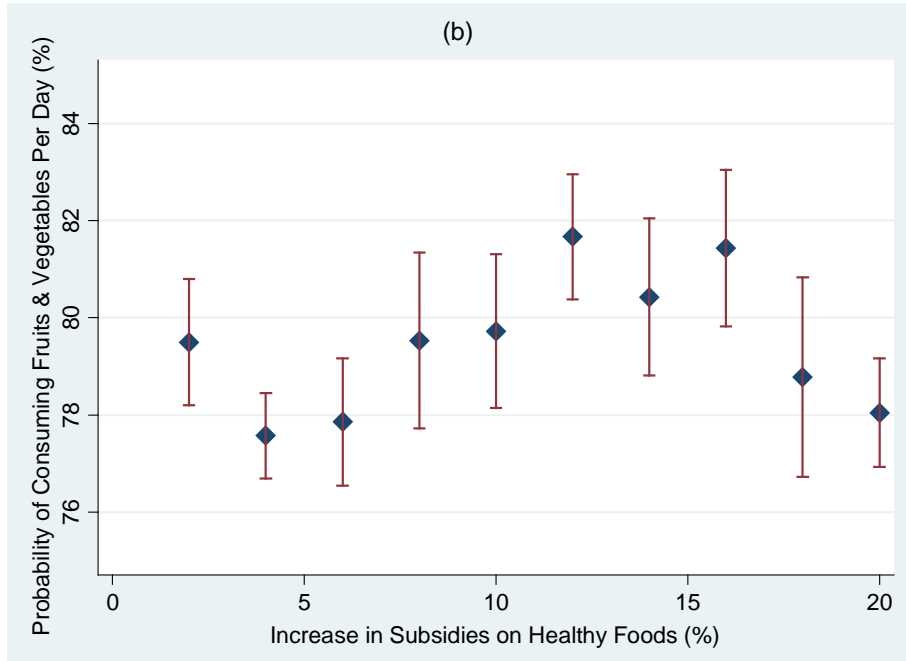
Figure 4. 4. The Impact of Healthy Food Subsidy on the

Consumption of Fruits & Vegetables

Figure 4.5 and Figure 4.6 show a zoning policy that changes the ratio of FF outlets to FV outlets from the baseline value of 7 to 4 has little impact on individuals' FF or FV consumption if individuals' walking distance is set to either one mile (squares) or half a mile (triangles). Even if individuals are to walk only 0.25 mile (circles), finding healthy stores would be harder but FV consumption would only be improved by 2 percentage points through extensive re-zoning to the permitting scheme that change the ratio of FF to FV outlets. However, one interesting result perceptible in Figure 4.6 is that expanding the buffer from 0.25 miles to 1 mile greatly increases fruits and vegetables consumption, suggesting that improving local transportation can be a more effective strategy than changing the mix of food outlets within an area.

This is driving by each individual's evaluation of food accessibility in the district. If they were only to walk 0.25 miles to purchase food, given that the region contains 7 to 4 times more unhealthy food stores than healthy food stores, there would be a high possibility that a healthy food store is out of their search scopes, bringing down the average fruit and vegetable consumption. Improving local transportation has the potential to largely increase individual's search scope for food-purchasing, however, car ownership and other convenience measures are not included in the model. If most people in downtown Pasadena drove a car and were likely to search food over a long distance, the implication that enhancing transportation network cannot be deduced from this model simulation.
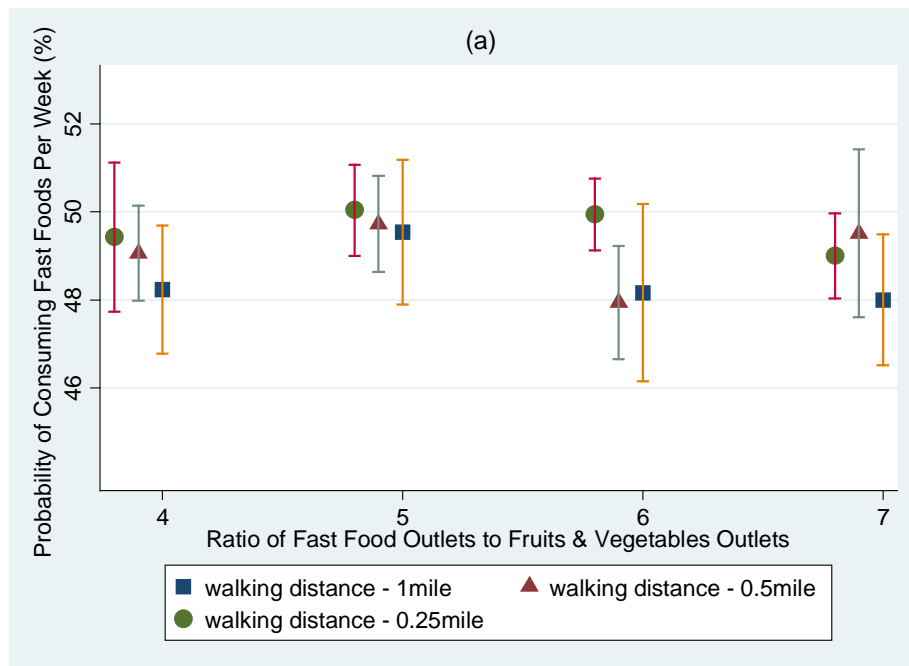
Figure 4. 5. The Impact of Zoning Policies (altering the ratio of stores selling fast food versus fruit & vegetables in the district) on the Consumption of Fruit &

Vegetables, Evaluated by Assuming Three Different Buffers for Food Accessibility:

1 mile (square), 0.5 mile (triangle), and 0.25 mile (circle)
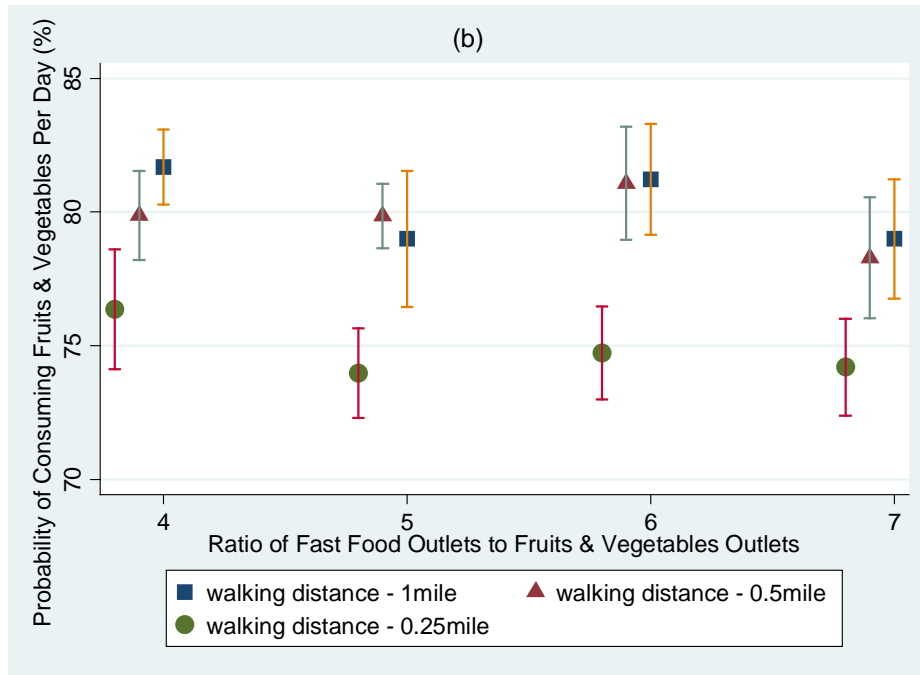
Figure 4. 6. The Impact of Zoning Policies (altering the ratio of stores selling fast food versus fruit & vegetables in the district) on the Consumption of Fast Foods

Furthermore, the promotion of healthy norms by enhancing the visibility to healthy eating norms from 1% to 10% continues to have strong impacts either in a small-world network (Figure 4.7 and Figure 4.8, first three bars) or in a random network (Figure 4.7 and Figure 4.8, fourth bar). There is a minimal difference in the predictions between a small-world network (i.e. community/cluster-based network) and a random network (i.e. media/internet-based network) when α (the importance of peers' influence) is set to 0.3. For each decrease of 10% in α, the impact of promoting healthy eating norms on FF consumption reduces slightly (Figure 4.7); a similar effect is witnessed regarding the impact on FV consumption (Figure 4.8).

(a)
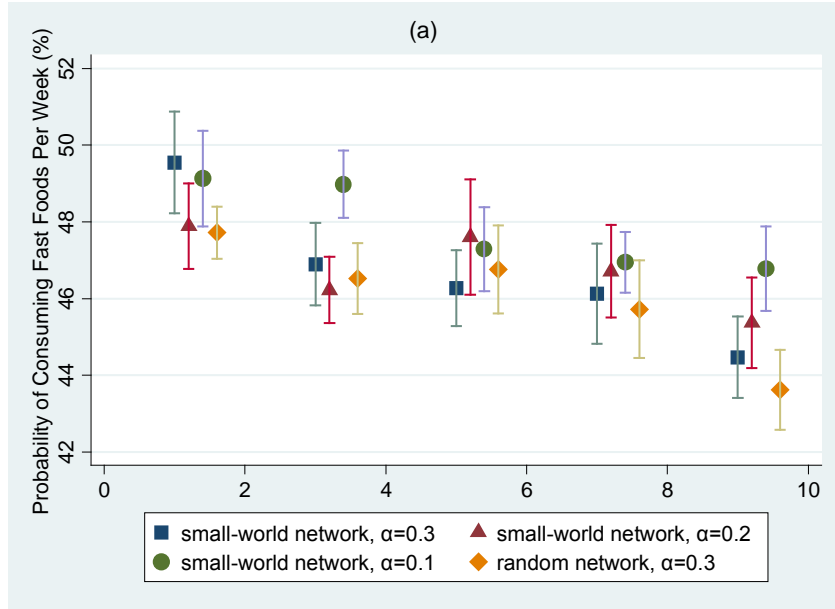
Figure 4. 7. The Impact of Promoting Healthy Norms on the Consumption of Fast Foods (4 scenarios are evaluated: The first three scenarios use a small-world network and varied the strength of the peers' influence α up to 0.3 (square), 0.2 (triangle), and 0.1 (circle). The fourth scenario uses a random network with α up to 0.3)

(b)
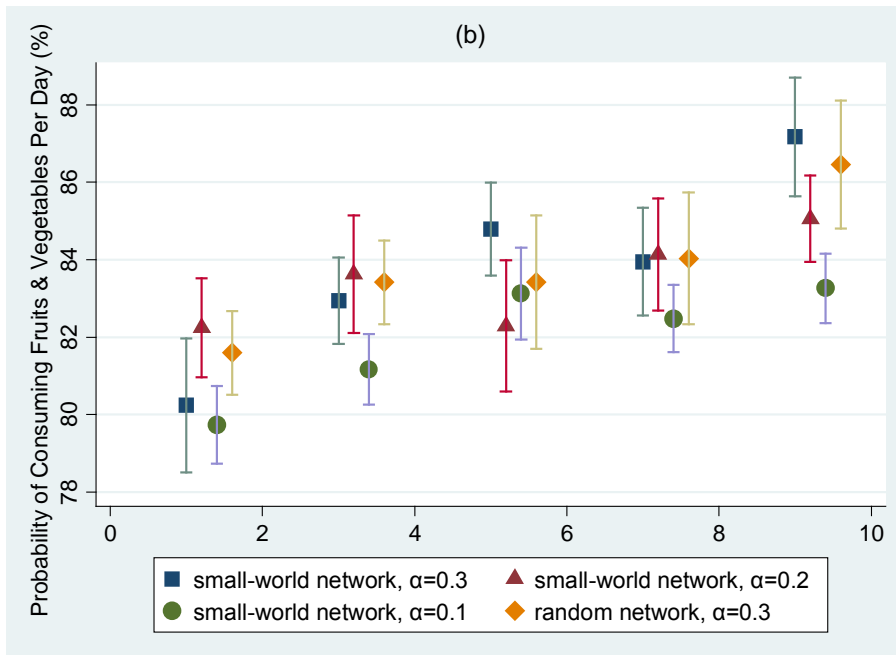
Figure 4. 8. The Impact of Promoting Healthy Norms on the Consumption of Fruits and Vegetables

4.2 Policy Impact in Different Context

Because the effects of policies may vary in different socio-economic contexts, the model is then run separately for different model environments. As shown in Table 4.2, except for the first setting (zip-code 90011), taxation has no considerable impact on both FF and FV consumption. In zip-code 90011, increasing taxes on fast foods reduces FF consumption by 2 percentage points on average. Subsidizing fruits and vegetables does not affect FV consumption, but in zip-code 90404, subsidy increases FF consumption, possibly because that reducing the price of FV makes FF more affordable for those who are price sensitive. Zoning policy significantly increases FV consumption and reduces FF consumption only in zip-code 90011, but has no impact in all other areas. However, promoting healthy norm is the most effective intervention if strength of the influence is strong. For example, a 10% increase in the visibility of healthy norm translates into a 10-percentage-point increase in FV intake and a 6-percentage-point decrease in FV consumption on average in zip-code 90011. The policy impacts in the four zip-code areas are not very different from those in the downtown Pasadena, thus do not vary much by specific neighborhood in Los Angeles County, partly because the sociodemographic distributions in those selected regions are not largely different from each other.

Table 4. 2. Predicted Impacts of Four Policies under Different Model Settings (Mean/ 95% CI) [a]

	Baseline	Increasing taxes on FF [b]	Increasing subsidies on FV [c]	Zoning policy [d]	Promoting healthy norms [e]

		10%	20%	10%	20%	6	4	5%	10%
Zip-code: 90011									
Pr(FV)	0.70	0.71	0.71	0.71	0.72	0.74	0.71	0.74	0.80
	(0.68-	(0.69-	(0.69-	(0.70-	(0.70-	(0.72-	(0.70-	(0.72-	(0.78-
	0.72)	0.73)	0.73)	0.72)	0.74)	0.76)	0.72)	0.76)	0.82)
Pr(FF)	0.28	0.26	0.26	0.28	0.28	0.25	0.26	0.26	0.22
	(0.27-	(0.25-	(0.25-	(0.27-	(0.27-	(0.23-	(0.25-	(0.25-	(0.21-
	0.29)	0.27)	0.27)	0.29)	0.29)	0.27)	0.27)	0.27)	0.23)
Zip-code: 90404									
Pr(FV)	0.69	0.69	0.69	0.68	0.69	0.68	0.68	0.71	0.75
	(0.66-	(0.67-	(0.68-	(0.67-	(0.68-	(0.67-	(0.66-	(0.69-	(0.74-
	0.72)	0.71)	0.70)	0.69)	0.70)	0.69)	0.70)	0.73)	0.76)
Pr(FF)	0.36	0.36	0.38	0.39	0.38	0.37	0.38	0.35	0.33
	(0.34-	(0.35-	(0.37-	(0.38-	(0.37-	(0.36-	(0.37-	(0.34-	(0.32-
	0.38)	0.37)	0.39)	0.40)	0.39)	0.38)	0.39)	0.36)	0.34)
Zip-code: 90715									
Pr(FV)	0.83	0.84	0.83	0.84	0.82	0.84	0.83	0.85	0.89
	(0.81-	(0.82-	(0.81-	(0.83-	(0.80-	(0.82-	(0.81-	(0.83-	(0.88-
	0.85)	0.86)	0.85)	0.85)	0.84)	0.86)	0.85)	0.87)	0.90)
Pr(FF)	0.45	0.44	0.45	0.46	0.47	0.45	0.44	0.43	0.41
	(0.44-	(0.42-	(0.44-	(0.45-	(0.45-	(0.44-	(0.43-	(0.41-	(0.39-
	0.46)	0.46)	0.46)	0.47)	0.49)	0.46)	0.45)	0.45)	0.43)
Zip-code: 90505									
Pr(FV)	0.87	0.87	0.88	0.88	0.87	0.87	0.89	0.88	0.92
	(0.86-	(0.86-	(0.87-	(0.87-	(0.85-	(0.86-	(0.87-	(0.87-	(0.91-
	0.88)	0.88)	0.89)	0.89)	0.89)	0.88)	0.91)	0.89)	0.93)
Pr(FF)	0.50	0.50	0.49	0.51	0.51	0.51	0.50	0.49	0.45

| (0.49- | (0.49- | (0.47- | (0.49- | (0.50- | (0.50- | (0.48- | (0.47- | (0.44- |
| 0.51) | 0.51) | 0.51) | 0.53) | 0.52) | 0.52) | 0.52) | 0.51) | 0.46) |

a. 95% confidence intervals in the parentheses.
b. Increase the price index of fast food (P) in the model by 10% and 20%;
c. Decrease the price index of fruit and vegetables in the model by 10% and 20%;
d. Add fruit and vegetable outlets in the region so that the ratio of Fast-food to Fruit-and-Vegetable outlets falls from 7 to 6 (first column) or from 7 to 4 (second column).
e. Increase the visibility (parameter γ) given to healthy peers from 1% to 10%.

4.3 Monte Carlo Sampling on Model Parameters

The model can be unreliable due to uncertainty in model parameters. The question is then if parameter uncertainty affects the model predictions. In the ABM, after calibrating the model outputs with empirical statistics, all parameters (i.e., betas and deltas) are assumed constant in the agent's decision-making equation. However, uncertainty remains, because the parameters are obtained from various data sources and based on different demographic distributions. Monte Carlo simulation is an approach that relies on repeated random sampling from distributions for modeling parameters, so as to provide an explicit description of model robustness (Steenland & Greenland, 2004).

Model robustness implies that a model is unbiased and reasonably efficient and that small deviations from the model assumptions will not impair the model performance substantially (Huber, 2011). To estimate robustness of the model, 100 randomly sampled parameter values are drawn from each of the (independent) distributions of the parameters, and policy impacts in the setting of downtown Pasadena are repeatedly estimated. I assess 8 parameters, which are most likely to affect the predictions of policy impacts. Recall that β_1, β_2, β_3 and β_5 measure the impacts of taste preference, health belief, FV price and accessibility to FV outlets on FV consumption, respectively. And δ_1, δ_2, δ_4 and δ_5 reflect the relative impact of taste, health, FF price and accessibility on FF

consumption. Values for each parameter are randomly sampled from a normal distribution with 0.1 as the standard deviations. Table 4.3 shows the distribution of the parameters in the Monte Carlo repeated samples.

Table 4. 3. Monte Carlo Sampling of Model Parameters (Betas and Deltas)

	N	Distributions	Mean	Std. Dev.	Minimum	Maximum
β_1	100	Normal	-0.3	0.1	-0.58	-0.04
β_2	100	Normal	1.0	0.1	0.74	1.28
β_3	100	Normal	-0.2	0.1	-0.48	0.10
β_5	100	Normal	0.2	0.1	-0.05	0.41
δ_1	100	Normal	0.5	0.1	0.23	0.73
δ_2	100	Normal	-0.5	0.1	-0.71	-0.26
δ_4	100	Normal	-0.1	0.1	-0.31	0.17
δ_5	100	Normal	0.5	0.1	0.25	0.77

I perform one-way sensitivity analysis by varying one parameter each time and plot the distribution of model predictions. A baseline scenario is compared with policy scenarios to assess whether the policy impacts are robust under the condition of parameter uncertainty. Table 4.4, Figure 4.9 and Figure 4.10 show that the extent to which policy impacts change when varying the values of parameters.

δ_4 measures the impact of FF price on FF consumption. Results show that at baseline, the weekly probability of FF consumption is about 0.49 on average (95% CI: 0.48 – 0.50) in response to the changes in δ_4, whereas under policy scenario (FF price increased by 20%), the FF probability is about 0.48 (95% CI: 0.47 – 0.49). The impact of taxation is relatively small even if uncertainty in parameter δ_4 is accounted for, as shown in the first graph of Figure 4.9. Parameter β_3 represents the influence of FV price on the

daily intake of FV. Compared with the baseline case scenario, the model-predicted probability of FV consumption is more sensitive to the changes in β_3 under the policy scenario, where Pr(FV) on average is 0.80 (95% CI: 0.79 – 0.81). But the average consumption level of FV is almost identical under both scenarios. Parameter δ_5 and β_5 measure the effect of accessibility on food consumption, as shown in Table 4.4 and Figure 4.9, model predictions are very close under both baseline and policy scenarios, suggesting that zoning policy has no considerable effect on the outcomes.

Table 4. 4. Model Predictions under Parameter Uncertainty

	Policy parameters [a]	Varying Parameters	Baseline Scenario			Policy Scenario		
			Mean	95% CI		Mean	95% CI	
Pr(FF)	PI_{ff}	δ_4	0.49	0.48	0.50	0.48	0.47	0.49
	FF/FV	δ_5	0.50	0.48	0.52	0.50	0.48	0.52
	γ	δ_1	0.48	0.47	0.49	0.43	0.42	0.44
	γ	δ_2	0.48	0.47	0.49	0.43	0.42	0.44
Pr(FV)	PI_{fv}	β_3	0.80	0.79	0.81	0.80	0.79	0.81
	FF/FV	β_5	0.79	0.77	0.81	0.79	0.77	0.81
	γ	β_1	0.79	0.78	0.80	0.86	0.85	0.87
	γ	β_2	0.80	0.79	0.81	0.86	0.85	0.87

a. The policy impact parameters altered under the policy scenario: PI_{ff} (Price index of fast food) increased by 20%; FF/FV (the ratio of fast food outlets to fruit and vegetable outlets) decrease to 4; γ (positive bias/visibility given to healthy norm) increased by 10%; PI_{fv} (Price index of fruit and vegetables) decreased by 20%.
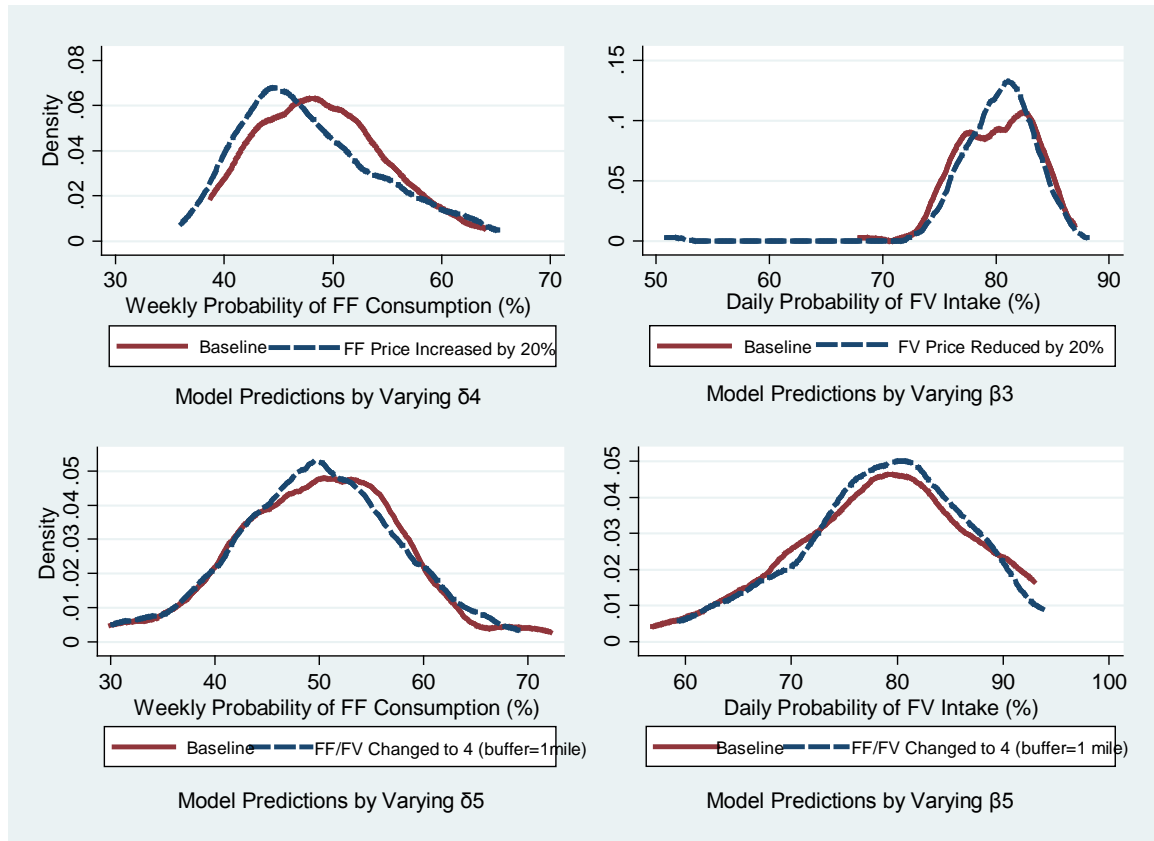
Figure 4. 9. Model Predictions by Varying the Parameters

δ_4 **(FF price impact on FF intake),** β_3 **(FV price impact on FV intake),** δ_5 **(FF accessibility on FF intake) and** β_5 **(FV accessibility on FV intake), respectively**

Parameter $\delta_1, \beta_1, \delta_2$ and β_2 are the impacts of cognitive habits on food consumption. With the changes in parameter values, the probabilities of FF and FV consumption differ systematically between the policy scenario (visibility given to the healthy norms increased by 10%) and the baseline scenario (See Figure 4.10 and Table 4.4).

In general, the model is robust as it is insensitive to small deviations from the distribution of parameters. Parameter uncertainty does not make model predictions diverge or cause the policy impacts unreliable.
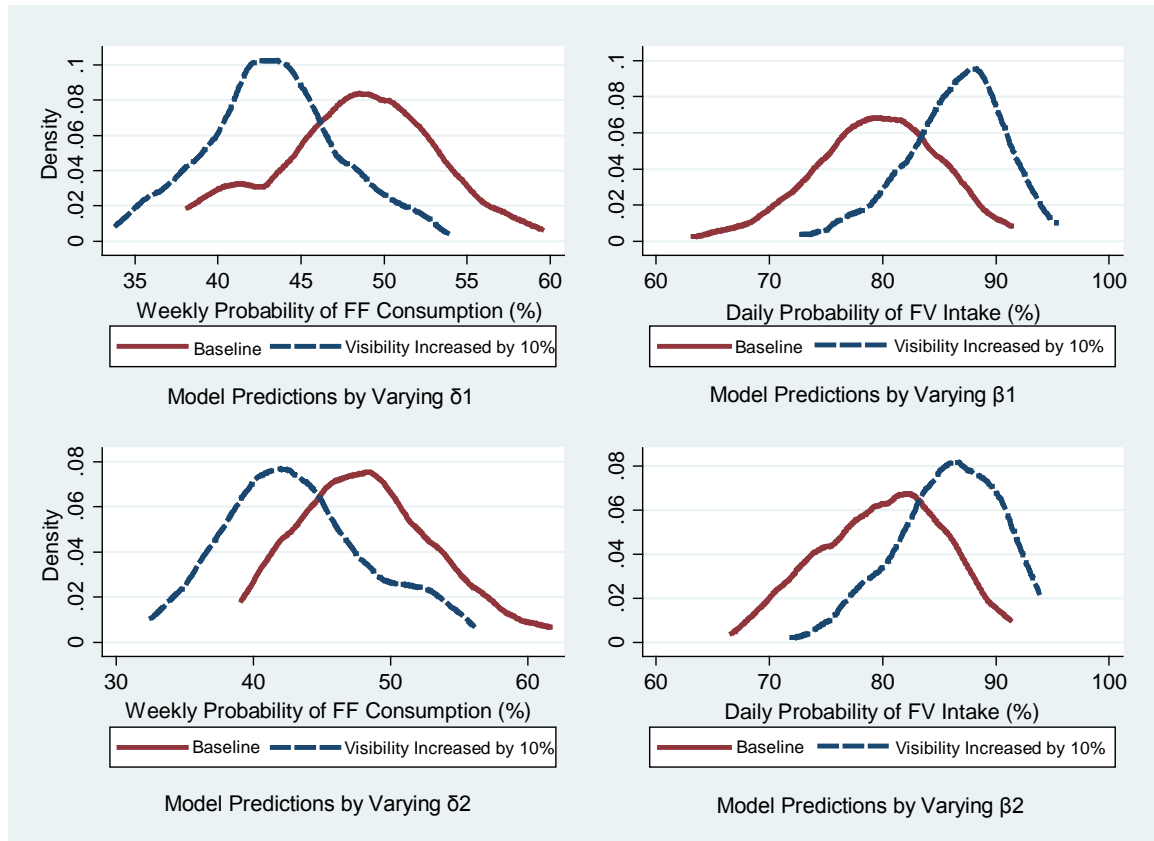
Figure 4. 10. Model Predictions by Varying the Parameters δ_1 (impact of taste preference on FF intake), β_1 (impact of taste preference on FV intake), δ_2 (impact of health belief on FF intake) and β_2 (impact of health belief on FV intake), respectively

CHAPTER 5. CONCLUSIONS

5.1 Summary of the Study

A typical unhealthy diet in America is comprised of too much high-calorie food and insufficient fruits and vegetables. The majority of behavioral theories and models focus exclusively on people as individuals, and interventions based on those strategies fail to create sustainable behavior change, nonetheless, this dynamic process is well-elucidated in the multi-level theory of population health, which emphasizes the social component in human cognitive habits and behaviors. Based on the multi-level theory of population health, this study develops an agent-based simulation model (ABM) to explicitly represent how an individual makes food choices in the context of social network and external food environment, so as to develop and test policy interventions that are most effective in influencing individual eating behaviors in Los Angeles County.

This ABM suggests that social networks have significant potential to influence dietary decisions. While the general point about social networks has been made before (Christakis & Fowler, 2007), the value of this simulation is to put this insight into comparative and quantitative perspective: not only do social networks affect dietary behavior, they may be the most significant modifiable contributor to it, and far stronger than other proposed interventions, such as strategies that change the relative prices and availabilities of healthy and unhealthy foods. Targeting food prices by introducing a tax on fat or sugar or by subsiding healthy foods may not change dietary behaviors to a great extent. Attracting more FV stores may not exert a powerful influence on behaviors in moderately dense urban areas like central Pasadena, given that people have easy access to both healthy and unhealthy foods nearby. But improving transportation networks may be

an alternative to improve accessibility to healthy food for cases when the areas that people perceive as being within walking distance are smaller.

Model validation is conducted in this study to examine whether the model is credible and an acceptable representation of a real-world food system. Various techniques are applied to ensure that both the model inputs and outputs are valid and match empirical data. The model has good face validity in that both the individuals' demographic distributions and the population-average food consumption are an approximate imitation of the real world. Model assumptions on social influence and food environment dynamics are considered reliable since the model outputs fit empirical statistics. Moreover, model outputs are further validated using 5 different model setups and are matched with statistics measured in empirical dataset. Monte Carlo sensitivity analyses show that the policy-impact predictions from the model are insensitive to moderate deviations from model parameters.

5.2 Policy Implications

This model simulation suggests that norm-based interventions may be more effective than tax-based policies as well as zoning policies. The benefits of reinforcing and reproducing healthy norms are obtained even if individuals do not form communities, suggesting that this strategy does not need to be community-based but can also be implemented for example via mass media.

The policies tested in this study have all been proposed as politically feasible interventions to curb the obesity epidemic (Finkelstein, 2004; Powell, 2009). The magnitude I find from the model simulation is similar to what might be expected from

some of results in the literature. A few states have imposed small taxes on carbonated beverages, and their experience has suggested that a tax on these products would have only a very small effect on obesity rates (Finkelstein, 2004). Studies using survey data found that demand for dairy products or salty snacks as well as frequent consumption of fruit and vegetable were price inelastic (Chou et al., 2004). Powell & Auld et al. estimated the own-price elasticity for fast food was about -0.03, and the cross-price elasticity for fruit and vegetables was 0.02, similar to what is predicted in this study (Powell & Auld, 2007). But evidence is mixed in the literature. Some studies predicted a larger impact of price on food consumption. For example, studies based on controlled laboratory experiments found youths were price elastic for both healthy and unhealthy food options (i.e., a 1-percent increase in food price is associated with greater than 1-percent reduction in food purchase) (Epstein & Jankowiak, 2012). There might be several explanations for the discrepancy of findings between those experimental studies and predictions from this model: (1) Studies have shown that there was a great sociodemographic difference in the fast food price sensitivity (Meyer & Guilkey, 2014), the experimental studies may only recruited a small sample who are young, low-income and price-sensitive. But according to data from the national representative FAB survey, the respondents are relatively insensitive to food prices (See Table 3.1). (2) The experimental studies may have manipulated quite a few of conditions and have limited external validity, whereas this model simulation is performed in specific settings, and are more relevant for the population of interest. (3) The substantial cost reduction for purchasing a calorie in recent decades may have some implications for the insensitivity of food price in general. The model suggests a 20% increase in fast food price index is not

enough to alter frequent consumption of fast food at the population -level, but demand may change if imposing a considerable increase in food price (i.e., 50% or 100% increase), that may not be feasible.

Alternatively, there has been an increasing adoption of social marketing in public health which has achieved important successes (Grier, S., & Bryant, 2005). For instance, the VERB$_{TM}$ program was an especially successful social marketing program that increased free-time physical activity among young people ages 9 – 13 by 34% after one year of intervention. The program is based on extensive marketing research that combines mass-media advertising, public relations, and interpersonal marketing. Another example was the TRUTH$_{TM}$ program, which used a community-based campaign to significantly predicted reduction of intention to smoke among teenagers (Odds Ratio = 3.54) (Grier, S., & Bryant, 2005). Notwithstanding its potential influence, social marketing has not yet been widely recognized and applied by public health professionals. On the contrary, traditional strategies such as pricing and environment regulation are more widely studied and advocated. This study suggests that strategies such as promoting healthy norms using social marketing may have a greater potential to produce sustainable behavior change.

However, the findings from model simulation should be understood in appropriate modeling context. The influence of healthy food advertisement or social marketing is modeled as a "positive bias" imposed on the peer's network. It can be difficult to estimate the actual, quantitative effect of such bias. In the model, this visibility / positive bias (parameter γ) is varied from 1% to 10%. Several studies used psychometric constructs to measure the change in perception of norm following peer education or mass media

campaign (Feldman et al., 1997; Zhang et al., 2010). To quantify the extent to which healthy food advertising can bias the norm of the social network, research will be needed to use appropriate psychometric instruments to measure the individual's perception of peer's norm before and after food marketing. Until such research is completed, it is difficult to know for certain whether the proposed healthy-norm intervention modeled here is within a realistic policy range.

5.3 Strengths and Limitations of the Agent-Based Model

The use of agent-based modeling to understand this public-health problem has certain important strengths. First, it provides a measure of the population-level impact of various policies. While previous research has carefully tested the significance of an effect of various determinants of dietary behavior within a hypothetical sample, the next step is to combine these insights into a single, population-based model. Agent-based modeling, of which the current analysis is only a small down-payment, may be a fruitful way forward in assessing the overall determinants of population-health outcomes. Second, unlike statistical models, ABM allows individuals to be connected and influenced by each other, which has considerable effects, as shown in this and other studies (Christakis & Fowler, 2007; Giabbanelli, 2012). The assumption of a stable unit-value treatment affect, on which nearly all statistical analyses depend, makes the statistical testing of social norms difficult (Manski, 1993), yet this difficulty should not be taken to imply that social norms are not important in determining behavior, or to ignore the fact that individual behaviors are rarely independent of each other.

Moreover, the ABM allows interactions between individuals and the external food environment, which itself can adapt to the individual's consumption. By relaxing those

assumptions, it is possible to observe the dynamic processes of this problem, beyond just explaining correlations between variables as statistical models typically do. Compared to other ABMs that have studied food systems (Giabbanelli et al., 2012; Hammond, R.A., 2012), this ABM is based on existing theories and empirical database. A thorough validation and Monte Carlo simulation are conducted to assess the model's robustness and reliability. Last but not least, the recognition that many public-health problems are indeed complex-systems problems makes multidisciplinary methods necessary to conduct public-health studies, and ABM is one such approach to synthesize evidence that aims at tackling the same health problem from various relevant sources.

Notwithstanding these advantages, this model also has important limitations. The first limitation is about the model itself. Model prediction is to some extent driven by the relationship between taste preference and health belief. Since the two are both modeled as cognitive habits, a simpler model would have just one parameter representing habits and keep the model simpler and easier to understand, but without detracting from the current implications of the model. Second, data is lacking regarding the extent to which a person is influenced by friends. A sensitivity analysis shows that the model outputs are identical to the empirical statistics when social influence on individual's cognitive habits is assumed to be 0.5 using setting of downtown Pasadena at baseline. This model uses a conservative value of 0-0.3. A small change in this value leads to a relatively large change on the outcome particularly for consumption of fruits and vegetables, suggesting the necessity of carefully parameterizing this factor in food-choice models. Also, fruits and vegetable consumption may be a concave function of health belief and taste preference, which are influenced most by the social referencing factor. Third, there is

little empirical information regarding how much an adult's perception of social norms can be biased by social marketing such as healthy food advertising. Both the mechanisms of how information of advertising passes and how it modifies perception remain unclear. More exploration on marketing theories and primary data are needed to quantifying the dynamics of norm change. Fourth, throughout the simulation, it is assumed that the population characteristics – the age, gender, and education distributions remain constant at 2010 values, and agents do not change locations. These assumptions may not hold in the presence of in- or out-migration, some of which might be endogenous as the food environment evolves. Fifth, only two stylized extreme options are used to measure individual's dietary choices, whereas dietary behaviors are far more complex than the model allows for. Finally, this study identifies that promoting healthy eating norms is the most effective intervention to curb the trend of obesogenic dietary behaviors, but the next step is to study what specific measures are most successful in delivering the message that changes the individual's perception of norms, such as story-telling techniques, mass media norm-reinforcement approach combined with policy actions, etc. (Yanovitzky & Stryker, 2001).

5.4 Future Work

Agent-based modeling is useful in studying complex health issues, as well as developing potential interventions for complex health problems. Development of future work would fall into three categories: (1) exploration of behavior theories to understand evolution of norms that govern individuals' and society's behaviors, (2) models from a static paradigm to a dynamic paradigm, and (3) applying a systems-science perspective and ABM approach to study and develop innovative and effective interventions.

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