

**A COMPARATIVE STUDY OF THE ETIOLOGY AND  
INTERVENTION OPTIONS OF CHILDHOOD OBESITY IN CHINA  
AND THE UNITED STATES USING SYSTEMS SCIENCE  
APPROACHES**

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## Abstract

**Objectives:** The overall goal of this research project is to study the etiology and intervention options of childhood obesity through comparative research between China and the US. Three specific aims are: 1) examine the relationship between Western fast food consumption (FFC) and childhood obesity; 2) examine the effects of social norms on school children's weight status and food behavior; 3) assess the effects of fiscal policies on children's beverage and energy intake.

**Methods:** The three aims are presented in three separate papers. In the first paper, using the nationwide China Health Nutrition Survey data, Heckman's two-stage selection model and quantile regression models were fitted. In the second paper, agent-based models (ABMs) were developed and linked with empirical longitudinal data collected in China and in the US. In the third paper, system dynamics models were built to assess the sugar-sweetened beverage (SSB) tax effects in China and the US.

**Results:** Household income was negatively associated with the likelihood of Western FFC decisions, while positively associated with Western FFC frequency in China. The ABM simulation study suggest that, in China, social norms may lead to a 0.05 ( $\text{kg}/\text{m}^2$ ) BMI increase for one unit of BMI below the social average, and a 0.045 ( $\text{kg}/\text{m}^2$ ) decrease for one unit of BMI above the social average. In the US, corresponding social norm effects were 0.025 ( $\text{kg}/\text{m}^2$ ) and 0.015 ( $\text{kg}/\text{m}^2$ ) respectively. The third essay indicates, in China, a 20% tax on SSB might cause an initial 11.5 kcal/d reduction in energy intake from beverage consumption; in a 10-year period, the net reduction of average daily energy intake compared to the level before taxing would decrease to 4 kcal/d. Similarly, in the US, there will be a net reduction of 36 kcal/d initially, with the

reduction decreasing to 10 kcal/d over a 10-year period. Subsidizing bottled water consumption could be more effective than SSB taxes.

**Conclusions:** China has its own unique patterns of childhood obesity, while sharing some features with the US. Policies that limit FFC, promote healthy social norms and subsidize bottled water consumption are needed in fighting childhood obesity.

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# **Chapter 1 Introduction and Specific Aims**

## **1.1 Introduction**

The prevalence of childhood obesity has been increasing worldwide over the past three decades. Both developed and developing countries have witnessed the fastest increasing rates. For instance, the rates of obesity have increased 2-3 folds in Australia, England, Germany, Iceland, Scotland, Chili, Japan and the US, and about 10 fold in China over the past 2-3 decades (Wang and Lobstein 2006). Although different measures and references were used to identify overweight and obesity in different countries, the substantial increasing trends within populations are consistent (Ebbeling, Pawlak et al. 2002, Wang and Lobstein 2006). Globally, it was estimated that the prevalence of childhood overweight and obesity increased from 4.2% in 1990 to 6.7% in 2010, and about 43 million children were overweight and obese in 2010.

Great concerns have been given to the increasing prevalence of childhood overweight and obesity due to the substantial negative health and economic impact of the epidemic. In China, fast economic development is associated with rapid growth in obesity. (Wang, Monteiro et al. 2002, Wang, Mi et al. 2006) Increased income seemed to have detrimental effects on health (Bell, Ge et al. 2002). High-income population groups are more likely to become overweight or obese (Jones-Smith, Gordon-Larsen et al. 2011). In contrast to developed countries, these patterns in China are unique and provide more unique research opportunities and possible solutions to obesity problems in developing and developed settings.

Examining the impacts of changing food environment is the key to understand the origin and development of childhood obesity in China. Rapid expansion of the fast-food

industry is one of the many notable changes occurring in the food sector in China. For example, KFC is the largest, fastest growing FF chain; opened its first restaurant in China in 1987; by early 2015, it has approximately 4,800 restaurants in over 850 cities throughout China. The volume of FF business in China has increased dramatically from 8.5 billion to 80.2 billion RMB from 2000 to 2013, by 9.5 times (Bureau 2001, Bureau 2014). Three major reforms have been conducted in agricultural sector in China which have promoted the growth of FF: (1) People's Commune System was reformed and replaced by the Household Responsibility System (in early 1980s); (2) marketing systems reforms for agricultural commodities and input factors (starting from the late 1980s); and (3) rural taxation system reform (starting from 2000). The agriculture tax was cancelled in 2005 and since summer 2007, the government has started to subsidize the production of hogs, dairy cattle, and edible oils. China joined the World Trade Organization (WTO) in December 2001. As part of its WTO commitments, China was expected to reduce overall average agricultural tariffs from 22% to 17% by 2004. China agreed to reduce tariffs on U.S. priority agriculture products from 31% to 14% by 2005. For example, the tariff on beef should be reduced from 45% to 12%, and poultry from 20% to 10% (House 2000).

These policy changes have led to the liberalization of domestic markets and international trade, narrowed the domestic-international price gaps, stimulated the domestic production and promoted imports, and facilitated the vertical integration of the FF industry and helped largely reduce FF ingredient costs. As a consequence, increased FF consumption has become a public health concern giving its adverse health effects. However, different from the U.S., where most of FF is consumed by low SES people, in

China, most FF was consumed by higher SES groups and in urbanized areas compared to lower-SES and rural groups. A working paper by our team found a significant inverse association between Engel coefficient and FF growth, indicating that, as consumers become wealthier in China, the demand for FF is also increasing. However, the health impact of FF industry expansion and FF consumption in China remain understudied.

Social norm and peer influence is another important environmental factor. Studies have shown that children would choose healthier snacks when an unfamiliar accompanying peer choosing these snacks (Salvy, Kieffer et al. 2008). Moreover, children would eat more cookies if accompanied by sibling, than if accompanied by a strange child or if eating alone (Salvy, Vartanian et al. 2008). The EAT Project in Minnesota also revealed that both the school-wide normative intention to lose weight and friends' dieting practices associated with girls' unhealthy weight-control behaviors (Eisenberg, Neumark-Sztainer et al. 2005). The pressures from peers' preference and teasing on body images are associated with those risky practices for weight-loss (Field, Javaras et al. 2008). As a country with long and rich history which values collectivism, the role that social norm may have played in the growth of childhood obesity is a largely ignored and under-investigated area.

The three essays in this thesis tried to fill the research gaps and examined these risk factors of childhood obesity and the potential policy options to prevent childhood obesity using a combination of advanced traditional methods and systems models. Obesity is a complex system problem. Individuals' energy-balance-related behaviors occur not in isolation but as a function of the interactions between individual level factors and their broader context, which requires researchers to simultaneously consider,

examine, and address the whole, wide range of biological and socio-environmental drivers of the target outcomes in order to fully understand the underlying mechanisms and causes and to develop effective and sustainable interventions (Butland, Jebb et al. 2007, Huang and Glass 2008, Trogon, Nonnemaker et al. 2008, Wang, Xue et al. 2015). The complex causal loops and feedback relationships between exposure and outcomes (including desired and unexpected ones) and interpersonal influences/ interactions that are relevant to childhood obesity cannot be well demonstrated using conventional statistical models (Wang, Xue et al. 2014, Wang, Xue et al. 2015). A number of related challenges have demonstrated that traditional analytic approaches are inadequate to address the obesity problem, while systems approaches offer new insights and unique opportunities.

## **1.2 Specific aims and hypotheses**

The overall object of this study is to investigate the drivers and potential mechanisms underlying the development of childhood obesity in China and conducted comparative research between China and the US. This study has three specific aims which were studies and presented in Chapters 3-5, i.e., my three research essays, respectively.

**Aim 1:** Using advanced statistical methods to: a) examine the temporal trends in fast food consumption, b) test the association between fast food consumption and weight status among children in China using nationwide longitudinal data, and c) compare results with findings in the US.

**Hypothesis 1a:** Fast food consumption has been increasing in Chinese children over the past three decades.



**Hypothesis 1b:** The increase in fast food consumption was positively associated with the increase in obesity in Chinese children.

**Aim 2:** Using innovative systems science methods (i.e. simulation systems modelling, in particular agent-based models): a) examine the effects of social norm on school children's BMI growth and fruit and vegetable (FV) consumption in China and in the US, and b) compare the difference of social norm effects in different social settings.

**Hypothesis 2a:** Social norm influences children's BMI growth and FV consumption in China and in the US.

**Hypothesis 2b:** The impact of social norm is greater in China than in the US in terms of influencing children's BMI and FV consumption.

**Aim 3:** To develop a systems model based platform: a) examine the interactions and dynamics in the demand-supply system regarding sugar sweetened beverage consumption, and b) assess the tax effects on children's beverage and energy intakes in the short- and long-run among children in China and in the US, and c) explore potential effective alternative policy/intervention options for childhood obesity prevention.

**Hypothesis 3a:** Supply response has significant impact on the effects of sugar sweetened beverage (SSB) taxes through nonlinear feedback loops in the supply-demand system.

**Hypothesis 3b:** The SSB tax effect will diminish in the long run.

**Hypothesis 3c:** Subsidizing healthy beverage will be more effective than taxing SSBs in terms of reducing energy intake in children.

The related background and methods to study these aims are introduced in the next chapter.

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# **Chapter 2 Background, Conceptual Framework, and Research Methods**

## **2.1 Background and significance**

The prevalence of childhood obesity has been increasing in almost all the countries in the world over the past three decades. Developed countries and developing countries undergoing nutrition transitions have witnessed the fastest increasing rates. For instance, the rates of obesity have increased 2-3 folds in Australia, England, Germany, Iceland, Scotland, Chili, Japan and the U.S., and about 10 fold in China over the past 2-3 decades (Wang and Lobstein 2006). Although different measures and references were used to identify overweight and obesity in different countries, the substantial increasing trends within populations are consistent (Ebbeling, Pawlak et al. 2002, Wang and Lobstein 2006).

### **2.1.1 Childhood obesity worldwide and in the US and China**

Globally, it was estimated that the prevalence of childhood overweight and obesity has reached an alarming level in both the developing and the developed countries: in 2013, 12.9% of boys and 13.4% of girls in the developing countries and 23.8% of boys and 22.6% of girls in the developed countries were either overweight or obese. (M. Ng et al., 2014) The dramatic increase in the obese population will have substantial adverse health and social effects especially in populations with lower socioeconomic status. (Organization 2016) How to halt the epidemic is a global public health challenge.

In the U.S., overweight in children and adolescents (aged 2–19 years) is defined as a BMI at or above the 85th percentile and lower than the 95th percentile, and obesity is defined as a BMI at or above the 95th percentile for children of the same age and sex, using the Centers for Disease Control and Prevention (CDC) growth charts. In general, prevalence of obesity in children and adolescents (2-19 y) has been increasing constantly over the past three decades in the US. According to 2009-2010 National Health and Nutrition Examination Survey (NHANES), 32% of children and adolescents ages 2-19 years are overweight, and 17% of them are obese.

Recent data suggests this rising trend may be stabilizing in recent years (Jeffery 2004, Ogden, Carroll et al. 2012). Note that, however, there were remarkable disparities across gender-race/ethnicity. Between 1999-2002 and 2009-2010, there was a significant increasing trend in African-American and white boys ( $P=.009$ ) while the obesity rates in girls remained relatively stable throughout all racial/ethnic groups (Ogden, Carroll et al. 2012). Comparisons across gender-race/ethnicity showed that Mexican American boys had highest absolute prevalence compared to African-American and white boys, although there was a converging trend between Mexican-American and African-American boys towards 2009-2010. For girls, highest prevalence was found in African-American girls and the ethnic disparities were greater in girls than in boys. Different patterns were also evident across gender-age groups. From 1988-1994 to 2007-2008, the prevalence of obesity of all age groups in both genders increased from 16% to 17%. However, the trends were not consistent for all gender-age groups. Between 2003-2004 and 2007-2008, the prevalence of obesity among children aged 2–5 years started to drop, decreasing from 15% to 10%

for boys and 13% to 11% for girls, despite the increasing trends in other gender-age groups (Wang and Beydoun 2007, Ogden, Carroll et al. 2012).

To gain more insights, we can examine other four measures: BMI-z, waist circumference (WC), and triceps skinfold thickness (TST). Between 1999 and 2008, NHANSE suggested that children aged 6-19 y had higher mean BMI-z than younger children aged 2-5 y. Males aged 6-11 y and females aged 12-19 were the groups with the highest mean BMI-Z compared to other age groups of the same gender. Since 2003-2004, there was a decreasing trend overall and the BMI-z in males aged 2-5 y dropped faster than others. Comparing the trend among racial/ethnic groups, there was an increase in African-American boys since 2003-2004 while the BMI-z in other race/ethnic groups decreased or remained relatively constant.

Trends in waist circumference (WC) in US children and adolescents also showed significant differences across gender, age, and ethnicity groups. Between 1999-2000 and 2007-2008, NHANSE indicated that mean WC was stable for all the age groups (2-5 y, 6-11 y, and 12-19 y) in boys and girls. However, breaking down the trends by race/ethnicity, white children showed a significant increase in mean WC. Consequently, over the 10-year period, there was a faster increase of prevalence of WC $\geq$ 90th percentile in white boys and girls compared to other racial/ethnic groups. NHANES 1988-1994 and 1999-2004 suggested that BMI, WC, and triceps skinfold thickness (TST) all increased for children at different percentiles of the respective distributions of these measures. However, annual changes were faster in obese groups and the changes in WC were greater than the other two measures, indicating greater health risks. (Wang 2011)

In developing world such as China, due to fast economic growth, obesity and related non-communicable diseases have also emerged and posed new challenges to public health professionals. In China, increasing disposable per capita income associated with decreasing food prices have caused shifts in traditional diet towards western diet characterized by high intakes of animal-source food, oils, and added-sugar. As a result, the prevalence of obesity has increased almost 10 fold over the past two decades. A large national survey on school children suggested that approximately 15% boys and 9% girls were either overweight or obese in 2005, as compared to 1-2% in 1985. (Ji & Cheng, 2009) In major cities, approximately 50% of adults and 20% of the children are overweight or obese.

Childhood obesity has become a major public health problem because of its serious adverse physiological and psychological consequences in both childhood and adulthood. Evidence on the association between childhood obesity and hypertension, dyslipidemia, hyperinsulinaemia, and vascular abnormalities has been well-documented (Freedman, Dietz et al. 1999, Tounian, Aggoun et al. 2001, Sinha, Fisch et al. 2002, Weiss, Dziura et al. 2004). Findings from a large cohort study of 276,835 children suggested that higher childhood BMI values are associated with increased risk of CHD in adulthood (Baker, Olsen et al. 2007). Overweight and obesity have also been identified as important risk factors for the development of type 2 diabetes in youth (Meyre, Bouatia-Naji et al. 2005). Children with type 2 diabetes may experience microvascular and macrovascular complications at younger ages (Hannon, Rao et al. 2005). Moreover, psychological well-being of children is largely affected by their weight status. Studies have found that obese children may be more likely to

have serious emotional problems and more likely to report a suicide attempt (Falkner, Neumark-Sztainer et al. 2001). Depression, sadness, loneliness, and nervousness associated with decreasing levels of self-esteem among obese children compared with their nonobese counterparts were widely observed (Strauss, Smith et al. 1985, Strauss 2000). Self-esteem is crucial in the cognitive development. Poor cognitive development will have long-term adverse effect on education, future employment and other aspects of adult life (Tershakovec, Weller et al. 1994, Laitnien, Power et al. 2002, Tunceli, Li et al. 2006).

Paralleling the increasing prevalence of childhood obesity is the rise of obesity-associated medical cost. In the US, annual costs of obesity-associated hospitalizations for children and youth ages 6–17 increased from \$35 million in 1979–1981 to \$127 million in 1997–1999 (Wang and Dietz 2002). From 2001 to 2005, the total obesity-associated hospitalization cost for children and youth ages 2–19 increased from \$125.9 million to \$237.6 million in 2005 (Trasande, Liu et al. 2009). A recent study estimated that, from 2020-2050, adolescent overweight will cause annual undiscounted attributable direct medical costs to increase from approximately \$130 million to \$10 billion, with additional indirect costs from lost productivity of \$942 million in 2020 to \$36 billion in 2050 (Lightwood, Bibbins-Domingo et al. 2009). In China, obesity related non-communicable diseases, such as diabetes, hypertension, cardiovascular diseases (CVD) are also causing substantial health and economic burden on individuals and the county's health care system. A study using 2003 national data estimated that the direct cost of non-communicable diseases attributable to overweight and obesity was about 2.8 billion, accounting for



4% of National Total Medical Expenditure (Zhao, Zhai et al. 2008). If the trend continues, the indirect costs of obesity and obesity-related dietary and physical activity patterns will reach a level of 8.73% of gross national product (GNP) in 2025 (Popkin, Kim et al. 2006).

### **2.1.2 Unique characteristics of China and research opportunities**

China offers an unprecedented opportunity for systems-oriented pediatric obesity research considering its large population size, area and regional contextual variation; the rapid economic growth and many social- environmental transformations over the past 2-3 decades including dramatic changes in its food systems and steep growth of fast food industry. In contrast to the findings in developed countries, existing studies showed that the family wealth and parental education were positively associated with adolescent overweight and obesity in China. (Hsu, 2011; (Li, Dibley et al. 2007)

The large variance and change in macro-level contextual variables and development of the obesity epidemic in China over time and across geographic regions can help advance understanding of disparities in the U.S. through comparative studies. This will broaden the range of potential environmental and policy intervention options to be tested. Findings will have many important policy implications for the U.S. and other countries, eg, in assisting them to reexamine their national food policies and programs and the potential future options to fight the obesity and chronic disease epidemic.

### **2.1.3 Changing food landscape in China**

Economic growth has been profoundly altering the food system in China since its market-oriented reform in early 1980s. As Chinese consumers become wealthier, consumption of meat, fats and oils, and sugar and sweeteners have been growing rapidly. (Ng, Zhai et al. 2008, Gong and Wu 2009, Ortega, Wang et al. 2009) The fast changing food environment makes China an interesting case to study the shifts in dietary behavior and the consequent effects on childhood obesity intrinsically embedded in policy, economic, environmental, social and cultural context.

### **2.1.4 Changes in food production**

There have been three major reforms in agricultural sector in China: (1) People's Commune System was reformed and replaced by the Household Responsibility System (early 1980s), (2) marketing systems reforms for agricultural commodities and input factors (starting from late 1980s), and (3) rural taxation system reform (starting from 2000). The agriculture tax was canceled in 2005 and since summer 2007, the government started to subsidize the production of hogs, dairy cattle, and edible oils. The subsidies will be kept as a standard system in long run. Prices of the agricultural commodities fluctuated but showed upward trending during such process. Before middle 1990s, China's domestic food prices were far below international prices due to protective international trade and domestic marketing policies. The price distortion held the domestic food prices low compared to the world and prevented food commodities being imported from international market. During this stage, production was significantly affected by procurement policies

including subsidies and taxations. The liberalization of domestic markets and international trade in the mid-1990s and accelerated by China's access to WTO has been narrowing the domestic-international price gaps, which stimulated the domestic production and promoted imports. All these policy shocks have had dramatic impacts on the food production but their nutritional implications are still understudied.

### **2.1.5 Changes in food processing**

Growing food industry has been playing a key role helping shape the food system in China. Increasing number of the food processing enterprises and intensifying competition made possible the greater availability and affordability of diverse food products. In 1991, annual sales of food and beverage business were less than 5 billion (yuan). In 2010, the output reached over 130 billion (yuan). Currently, there are about 26,000 large scale food companies taking 72% of the total market share. Processed food can be classified as 525 kinds in 28 categories. Food abundance is well supported by a booming retail sector which increases by 7% a year. The emergence of hypermarkets and supermarkets largely brought down the retail price of unhealthy high-energy-density foods and sugar-sweetened beverages. Several studies have examined the changes in the aggregate dietary intakes such as oil, fat, and sugar. However, little is known about the impacts of these changes on the risk of obesity for children from different SES strata.

### **2.1.6 Changes in Food Consumption**

Since late 1980s, market have gradually become the major force that determines the price of meat commodities. The real meat prices have increased

significantly over the last two decades. (Huang et al. 2007) During the same period, meat consumption has been consistently showing an upward trend. Income may be the key variable that affects consumption choice. If income continues to increase, the increasing in meat consumption is inevitable. Studies on the China case would help resolve the debate of using fiscal approaches to change dietary behavior. Pork is the primary meat consumed in China and accounts for about 66% of total meat consumption. (FAO 2006) However, household pig farming is rapidly declining in rural China (Lixing 2006; Wang 2009) and the trend is predicted to continue by the Chinese Ministry of Agriculture. (Wang 2010) Market, policy, and socioeconomic factors may all contribute to the declines. In such context, we will be able to assess the impact of food system response to policy/environment changes and consequently the health effects.

### **2.1.7 Rapid growth of fast food industry**

Expansion of the fast-food industry is one of the many changes occurring in the food sector in China, which offers unique opportunity to observe the multifaceted social, economic, cultural, and environmental impacts on changing dietary behavior and health consequences. For example, as a milestone in the fast food industry in China, KFC opened its first store in China in 1987. In 2012, the numbers reached over 4000. Foreign fast food consumption accounts for large portion of food-away-from-home. Furthermore, western fast food consumption has become status seeking behavior especially among children and youth. Mapping these system changes in food environment, societal, cultural, and economic context to the individual dietary

behaviors will help identify multi-level drivers that contribute to the rising childhood/adult obesity rates in domestic and global settings. The fast-food industry has been developing most rapidly in more economically advanced areas, while relatively slower in less developed cities. I will be able to examine the differential effects of fast-food density and consumption patterns on calorie intake, and in turn the obesity risk at aggregate and individual levels.

## **2.2 Conceptual framework**

### **2.2.1 Environmental impacts on energy-balance related behaviors**

Energy balance is the central concept to understand obesity. In an oversimplified fashion, obesity can arise when energy intake chronically exceeds energy expenditure, causing the storage of energy as triglyceride in adipose tissue and changing body weight and composition. From the first law of thermodynamics, internal energy in a closed system always equals the energy input. Energy stores are thus only determined by the energy expenditure in the form of physical activity, basal metabolism, and thermogenesis. However, energy imbalance is not a result of individual choices, but largely determined by the interactions between individual energy-balance related behaviors and the environment.

The ANGELO (Analysis Grid for Environments Linked to Obesity) is a well-known model conceptualizing environment. Under the model framework, an environment can be described by a 2 X 4 matrix. The environmental size is on one axis with two levels: microenvironment and macroenvironment. Microenvironments include settings, such as homes, neighborhoods, schools; macroenvironments provide supporting environments for Microenvironments, such as industry sectors, transport,

health care system. The other axis categorizes an environment into four types: physical, economic, political, and socio-cultural (Swinburn, Egger et al. 1999). This framework can be used to help identify problems and prioritize possible interventions.

The EnRG (Environmental Research framework for weight Gain prevention) is another highly cited framework which provides an integrated view to understand and explain the causal relationships between environmental influences and behavior (Kremers, de Bruijn et al. 2006). The model adopts an dual process view in which behavior could be a result from direct response to environment without cognitive effort; and on the other hand, behavior could be conscious acts based on beliefs and decisions. Based on the ANGELO framework, causal mechanisms between environment and behavior are introduced in the model. The indirect causal mechanisms describe mediating influence of behavior-specific factors on behaviors. These factors include cognitive mediators and other person and behavior-related factors.

Some studies treat the environment as the causes of the certain health outcomes. In such models, environment, such as food availability, affects purchasing, consumption and subsequent health outcomes. For example, Lytle (2009) showed the direct causal relationship between the availability of low-fat and high-fat milk and fat intake related diseases.

### **2.2.2 Social norm and peer influence**

Peer influence is another important environmental factor. Children would choose healthier snacks when an unfamiliar accompanying peer choosing these

snacks (Salvy, Kieffer et al. 2008). Moreover, children would eat more cookies if accompanied by sibling, than if accompanied by a strange child or if eating alone (Salvy, Vartanian et al. 2008). Another experiment by the same research group, following children's PA and the social context for 7 consecutive days, found that more intense PA was reported happened in the context of being with peers or close friends (Salvy, Bowker et al. 2008).

A study measured 10-13 year-old UK children's PA and dietary intake by a 3-day pedometer record and a 3-day food diary, and found peer effect on PA, but not dietary intake (Finnerty, Reeves et al. 2009). The EAT Project in Minnesota also revealed that both the school-wide normative intention to lose weight (proxy for the norm) and friends' dieting practices (proxy for the peer influence) associated with girls' unhealthy weight-control behaviors (Eisenberg, Neumark-Sztainer et al. 2005). The pressures from peers' preference and teasing on body images are associated with those risky practices for weight-loss (Field, Javaras et al. 2008). In addition, stigma on receiving school meals for free or reduced price may also direct children to less healthy foods in school (Mirtcheva and Powell 2009).

Social network analysis of students' nomination of friends showed that adolescents tended to nominate those who had similar weight status as friends (Valente, Fujimoto et al. 2009). The National Longitudinal Study of Adolescent Health (Add Health) further showed adolescent's BMI was correlated with their friends' after controlling the shared environmental effect and individual characteristics (Renna, Grafova et al. 2008, Trogdon, Nonnemaker et al. 2008). Adolescents whose friends' mean BMI was 1 unit higher at baseline would in average

gain 0.04 unit of BMI during follow-up (Halliday and Kwak 2009). While these studies applied different ways to adjust for the collinear issue between “endogenous (or ‘social effect’)”, “exogenous (or ‘shared environment’)”, and “correlated (or ‘homiphily’)” explanations on the observed concomitant behaviors in groups, these cross-sectional findings echoed to the prominent research using prospective data from the Framingham Study (Christakis and Fowler 2007, Fowler and Christakis 2008). Our preliminary study on the US children also showed evident social norm impact (Wang, Xue et al. 2014).

Based on these observations, I developed a conceptual framework presented below.

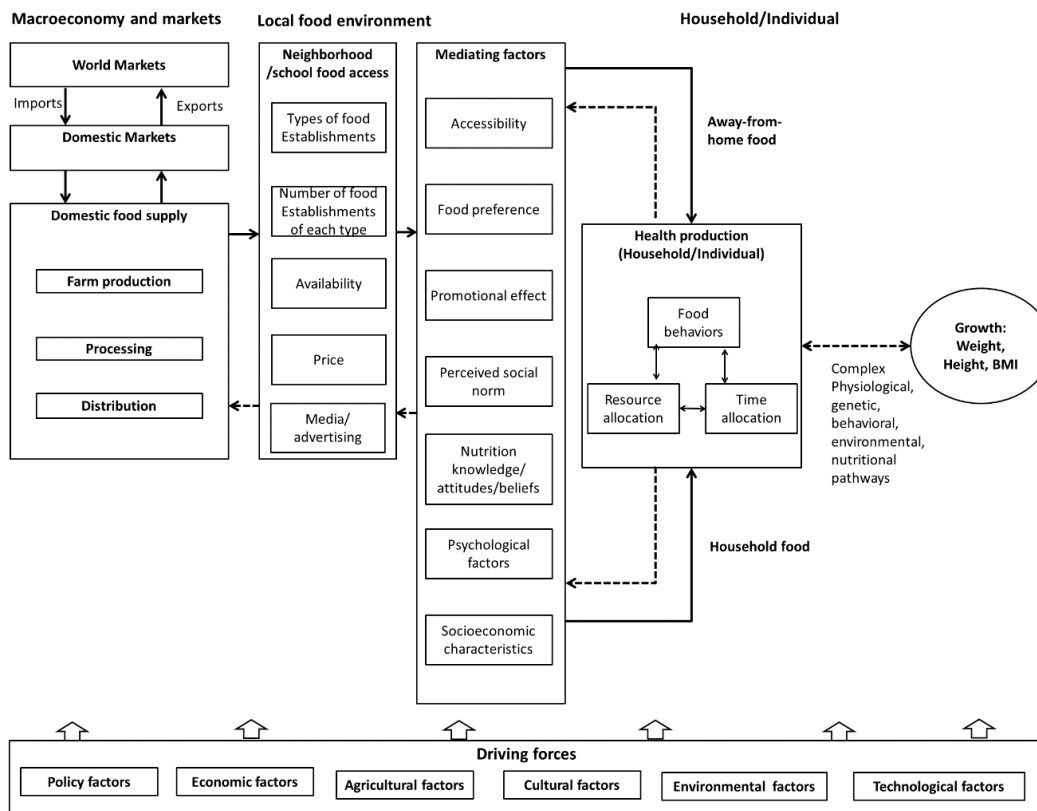
### **2.2.3 An integrated conceptual framework**

My conceptual framework incorporates individual, family, neighborhood, and policy, economic, social factors. It provides a broad framework to explain the complex relationships between and across multilevel factors that may determine obesity risk and the related disparities. Fast changing macroeconomic and local food environment significantly impact dietary patterns via numerous mediating factors, contributing to energy imbalance and parents’ and children’s health production activities. Policy, economic, agricultural, cultural, environmental, and technical drivers exert their influences at higher contextual levels and along the whole health production process. There are also feedback loops among the actors/players in the systems. For example, macroeconomic environment could affect local food price and availability, while local food demand and supply also influence domestic and



international markets. At the household level, parenting practices may affect children's weight status and children's weight status will affect parenting style and may have an impact on household food environment. Family SES plays a key role determining what communities the children live and what schools they attend. Macroeconomic environment and food policies determine the food availability, food prices, and density of food stores and restaurants and other establishments in communities which would affect the family's and child's food choices, while the family recourses and parents' and child's education, nutrition/health related knowledge/perceptions could affect how they may respond to the environmental factors. However, this conceptual framework is not comprehensive and does not intend to include and demonstrate all the factors and pathways (eg, the other factors included in the UK Foresight Project on obesity). From the multilevel perspective, there five levels in the framework: societal, neighborhood, school, family, and individual. There are feedback loops between and across neighboring levels, as well as within each level, which jointly influence the EBRB, i.e. food intake and PA, and consequently determine energy balance and weight outcome.

Figure 2-1: Conceptual Framework - Health Production and Obesity



## 2.3 Research Methods

The three aims were studied in three separate essays. For aim 1, traditional Heckman’s two-stage selection model were fitted to examine potential factors influencing fast food consumption (FFC) decision among Chinese children and quantile regression models were fitted to assess the differential effects of FFC on children’s weight outcomes across BMI distributions. To study aims 2-3, systems modeling method were used. Specially, Agent-based models (ABMs) in a utility maximization framework were developed and linked with empirical longitudinal data collected in the Childhood Obesity Prevention through Physical Activity Promotion project in Nanjing, China; and in the US, the Early Childhood

Longitudinal Study – Kindergarten Cohort (ECLS-K). System dynamics models were built to simulate the dynamic interactions in the supply-demand system and assess the sugar sweetened beverage (SSB) tax effects and explore the potential alternative policy options in China and the US.

### 2.3.1 Traditional Statistical Analysis

Heckman’s two-stage model (Heckman 1979) was used to examine children’s fast food consumption decision and the level of consumption. The first stage is to estimate an equation that determines the probability for the decision. The second stage estimates the participation magnitude, i.e. the factors that affect the frequency for a child to consume FF in a given week. The model can be set up as the following:

The fast food consumption frequency model:

$$y_1 = x_1\beta_1 + \varepsilon_1$$

where  $x_1$  is a vector of independent variables,  $y$  is the FF consumption frequency. The selection is determined by

$$y_2 = \begin{cases} 1, & \text{if } x_2\delta_2 + \varepsilon_2 > 0 \\ 0, & \text{otherwise} \end{cases}$$

The selection equation was estimated at the first stage by maximum likelihood as a probit model to estimate the effects of the independent variables on the probability of choosing to consume FF or not from the whole sample of FF consumers and non-consumers. Then a vector of inverse Mills ratios was generated from the parameter estimates. The level of FF consumption was then regressed on the

explanatory variables,  $x$ , and the vector of inverse Mills ratios from the selection equation.

Quantile regression models. Moreover, as we know, linear models provide information on conditional means. However, conditional mean regressions are not informative enough in revealing the effects of risk factors for obesity along a weight distribution. For example, it is possible that the relationship between fast food consumption and body weight may vary at different points of the distribution. Quantile regressions were thus estimated to at different percentiles. Quantile regression can be understood in a relatively simple setup as below:

A linear regression of BMI could be specified as:

$$y_i = \beta_0 + \beta_1 x_{i,1} + \dots + \beta_p x_{i,p} + \varepsilon_i$$

$y_i$  is the BMI of individual  $i$ .  $x_{i,p}$  is a scalar representing covariates in the model of individual  $i$ . This model estimates how the changes of  $x_{i,p}$  affects the change of conditional mean of  $y_i$ , i.e. the marginal effect of  $x_p$  on  $y_i$ . However, by only looking at the changes of conditional mean  $E[y|\mathbf{X}]$ , important information is missing for other locations across the whole distribution. This is not trivial in this study given that knowing the differential relationship across the conditional distribution of the outcome variable  $y$  is of critical importance for interventions and policies. Therefore, we conduct quantile regressions to examine the impact of exposures on weight outcome across its distribution. The general framework of the quantile regression can be understood as the following (Koenker and Bassett 1978): assume the cumulative distribution of  $y$  as  $F$ , then for a given quantile  $q \in (0,1)$

$$F(y_q) = q, \text{ and } y_q = F^{-1}(q)$$

Hence,

$$y_q = F^{-1}(p) = \mathbf{x}'_i \boldsymbol{\beta}_q + \varepsilon_i$$

To obtain the estimate of vector  $\boldsymbol{\beta}_q$ , we can minimize

$$\min_{\boldsymbol{\beta}} \sum_{i: y_i \geq \mathbf{x}'_i \boldsymbol{\beta}_q} q |y_i - \mathbf{x}'_i \boldsymbol{\beta}_q| + \sum_{i: y_i < \mathbf{x}'_i \boldsymbol{\beta}_q} (1-q) |y_i - \mathbf{x}'_i \boldsymbol{\beta}_q|$$

The meaning of  $\beta_{jq}$  is the marginal change in the quantile  $q$  due to a marginal change in the  $j$ th element of  $\mathbf{x}$ . Practically, we use bootstrap to obtain the standard errors of the estimates.

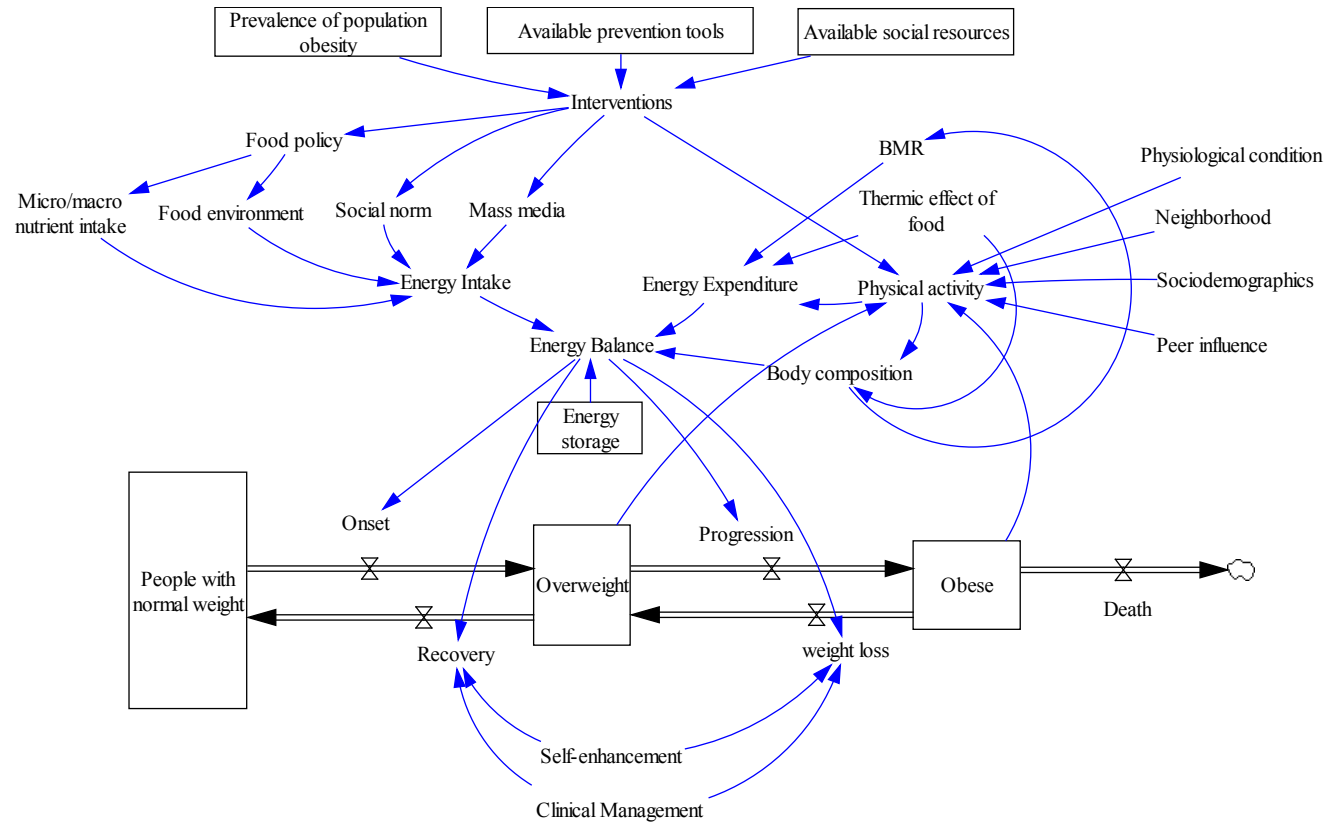
### 2.3.1 Systems science approaches

For Aim 2 and & 3, systems science approaches were the primary analysis approaches. As illustrated in above sections, the causes of the growing obesity epidemic are complex, involving the complex interactions of social, economic, cultural, environmental, and biological factors. Obesity fits to be conceptualized as a complicated and complex system problem. First, it involves multidimensional and complicated components. Second, all these components interact with one another and could interplay in various fashions among heterogeneous subpopulations. Third, the system may not respond to the input (interventions) linearly and proportionally. Statistics-based epistemology is insufficient to disentangle the complex nature of the obesity epidemics at large, although it helps unravel the independent associations between these obesity-causing factors and the obesity epidemics. Moreover,

traditional randomized controlled trials (RCTs) may be costly, time consuming, inappropriate or infeasible for evaluating policy interventions.

Systems science approaches are powerful and innovative approaches to study complex obesity problems. Systems science approaches are based on systems models for quantitative analysis of the research object using computational/mathematical modeling, such as agent-based modeling, system dynamics modeling, and network analysis (Epstein, 2006; O'Connor & McDermott, 1997). Systems models focus on the dynamic and nonlinear interactions among agents, environments, systems components, and subs systems at different levels in a complex system. Systems models acknowledge that a change in one area of a system can adversely affect another area of the system, and thus promote organizational communication at all levels. Figure 2-5 provides an example of the complexity of obesity in a systems dynamic framework. It depicts the complicated mechanisms implicated in the obesity epidemic, such as the roles of food prices, social networks, genetics, neurobiology, environment, and social norms towards eating, physical activity (PA) and obesity (Wang, Xue et al. 2015).

Figure 2-2: Complexity of obesity in a system dynamics framework



Note: The rectangles represent the stocks or states of the variables; the arrows indicate potential casual relationships; the pipes represent the flows in and out of the stocks; the valves represent the flow rates; the cloud represents the destination of the flow.

General systems theory was founded by Ludwig von Bertalanffy as an interdisciplinary practice applied to open system such as growing organisms. This system fills the void that classical laws of thermodynamics cannot elucidate because they only work for closed systems (Von Bertalanffy 1956). Along with his contribution to theoretical biology, Bertalanffy pioneered the development of modern systems bioscience (Von Bertalanffy 1956). Kamada put forward a theory and practice of systems biomedicine in 1992 (Kamada 1992). Thereafter, Zieglgänsberger and Tölle proposed the concept of systems biology (Zieglgänsberger and Toile 1993). In 1994, Zeng developed the concepts of systems bioengineering and systems genetics (Zeng 1994). The application of systems science in biomedical research dates back to the 1960s with the development of computing capacity and the necessary simulation software. Research has been initiated and bolstered by using SS tools in modeling systems from the micro, cellular level through the macro, socioeconomic level and the impacts of these various systems on population health and health disparities.

The reductionist paradigm has dominated the obesity and public health field for decades. It has identified been used to identify and target specific causes and risk factors for infectious diseases and non-communicable chronic diseases. Research findings based on this approach have been translated into public health policies and campaigns. Nevertheless, the traditional reductionist approach when dealing with the obesity epidemic has many limitations, for example: 1) the reductionist approach does not consider the complicated and complex nature of the system. Actors/factors that affect obesity risk such as consumers, food industry, families, schools, retailers, government agencies, policymakers, trade associations, NGOs, public health agencies, the media, and



healthcare providers, have different goals, motivations, modes of decision-making, and forms of connection to other actors and levels above and below them in the hierarchy of levels. Policy shifts or other interventions will affect each differently, and each has a different sphere of potential influence as an agent of change. Without taking into account the diversity of these actors, policies cannot leverage potential synergies, and run the risk that successful interventions in one area may be counteracted by responses elsewhere in the system. Policies that do not take into account the full set of actors and their responses can even backfire dramatically. 2) Complicated mechanisms implicated in the obesity epidemic such as the roles of genetics, neurobiology, environment, and social norms towards eating, PA and obesity, through the linkages and feedback between these mechanisms are not and cannot be well studied or well understood using traditional approaches. 3) linear thinking in traditional approaches. As the built environment has been acknowledged as critical to human behaviors and public health, it is always assumed as one-way direction that the environment affects individuals. Nevertheless, the built environment should be a result of the population's characteristics. Landscape of local food market would change and evolve in response to the local population's health conditions and concerns. However, there was no appropriate reductionist approach to study how the shifts in built environment (macro-level) emerge from the bottom (micro-level). Systems simulation may realize this bottom-up process of environment dynamics (Auchincloss 2011).

Compared to traditional approaches, systems approaches are capable of unfolding the underlying mechanisms, modeling non-linear and circular causality, studying the whole obesogenic environment instead of focusing on some selected factors based on

theories and evidence, which enable researchers and policy makers to observe the leaves of a tree (analytical approach) as well as whole forest (system thinking) (Wang, Xue et al. 2014, Wang, Xue et al. 2015) system dynamics model and agent-based model are the two main systems modeling approaches used in this thesis study.

### **2.3.2 System Dynamics Model (SDM)**

SDM is a modeling and simulation tool to investigate complex dynamic problems by incorporating non-linear relationships such as stock and flow, feedback loop, time lag, threshold of effect. The behaviors of the system (research object) and related factors are of interest at the system level, so SDMs are usually using variable-based equations to capture the relationships among the factors at the same level. For example, SDM can model the flows between susceptible pool and prevalence pool in a population during an epidemic episode. SDM enables researchers to incorporate multiple subsystems into consideration at a time, each of which may include a number of interrelated factors in a complex system. Based on the systems understanding, the researchers can represent and project the systems behaviors for the future under the specific initial settings in the models.

The following key elements are the building blocks of a SDM:

**Level:** stock, accumulation, or state variable. It changes continuously over time.

**Rate:** flow, movement. It changes the levels.

**Auxiliary:** intermediate variables

**Source:** systems of levels and rates outside the boundary of the model

**Sink:** where flows terminate outside the system

**Feedback loops:** information from an action travels through a system and returns its point of origin, reinforcing/balancing initial action.

### **2.3.3 Agent-Based Model (ABM)**

Different to SDM, ABM takes a bottom-up view of studying the systems. ABM re-creates and predicts the complex phenomena of group/system by simulating the agents' actions and interactions, which are the building blocks of the group/system. The process is one of emergence from the lower (micro) level of systems to a higher (macro) level (Wang, Xue et al. 2015). The individual agents are presumed to be acting in what they perceive as their own interests (e.g., health, economic benefit, or social status). The agents may experience learning, adaptation, and reproduction. In an ABM, every individual actor's (or "agent's") behaviors are determined by decision rules as computer codes.

An essential distinction between ABM and SDM is that the former can realize space into the computation model: physical space (distance), social space (social network), or information space (i.e., internet network). Agents are placed in a spatial context with specified starting conditions, and interact with each other and with their environment given a set of behavior rules. Agents can be heterogeneous and different from one another in numerous ways relevant to obesity, e.g., gender, age, race, SES, environment, social network. In this way, the computer simulation "grows" macro-level patterns and trends from the micro-level (e.g., Epstein, 2006).

ABM is not an event-oriented modeling technique, i.e. exploring the cause of a phenomenon not from an event-based perspective but focusing on revealing of the

underlying process. In most cases, the process is the reason of a social phenomenon but not certain triggering event (e.g., Schelling 1969; Schelling 1971; Kalick and Hamilton 1986). This feature gives the ABM possibility to model non-equilibrium dynamics. The key attributes of an ABM include: 1) Agents are placed in a spatial context with specified starting conditions, and given a set of adaptive rules for interaction with each other and with their environment. 2) Agents can be highly heterogeneous and differ from one another in numerous ways relevant to obesity. 3) The agents' decision processes and their interactions produce the output for agents themselves and for the systems as a whole. As our recent published study showed, ABM can provide unique insights in childhood obesity prevention /intervention design (Chen, Xue et al. 2016).

The Essay 2 mainly used the ABM to examine social norm effects and Essay 3 used SDM to test policy effects as shown in the following chapters.

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## Chapter 3 – Western Fast Food Consumption and Childhood

### Obesity in China

#### Abstract

**Objective:** To study the trends in Western fast food consumption (FFC) among school-age children in China and examine the association between Western FFC and obesity using nationwide survey data

**Methods:** Longitudinal data from the China Health and Nutrition Survey 2004-2009 (N = 2656) were used. ANOVA were conducted to examine the temporal trends of FFC among Chinese school children (aged 6-18 years). Heckman's two-stage selection model was fitted to examine potential factors influencing Western FFC decisions, and quantile regression models were fitted to assess the differential effects of Western FFC on children's weight outcomes across BMI distributions. Estimates from traditional mean regression models were also obtained for comparison purposes.

**Results:** FFC (reported as having consumed Western fast food in the past three months) increased dramatically between 2004 and 2009, from 18.5% to 23.9% in those aged 6-18, and the increase was greater in boys (16.3% to 21.1%,  $P < 0.001$ ) than in girls (23.6% to 24.4%,  $P < 0.001$ ). The increase was also more pronounced in the low- and median-income groups than in high-income groups, where there was a slight decrease in high-income group (10.3% to 19.2% in low-income households; 11.2% to 18.5% in medium-income households; 36.2% to 35.1% in high-income households,  $P < 0.01$ ). Our two-stage model estimates suggest that household income was negatively associated with the likelihood of Western FFC consumption decisions, while positively associated with FFC levels, with a every 20,000RMB increase in annual per capita income leading to one

more consumption in three months. However, our quantile regression estimates did not find a significant association between FFC and children's BMI z-scores and weight status (overweight or obesity). This result is in line with the findings in the US.

**Conclusions:** FFC increased substantially in Chinese children, especially in older children, boys, and those from low- and medium-income families, rural areas, and East China, compared to their counterparts. Policies and interventions to promote healthy eating among school children in China are urgently needed to prevent adverse health effects of FFC in the near future, especially in low- and mid-income groups.

**Key words:** child, Western fast food, obesity, overweight, body mass index, China

### **3.1 Introduction**

The last three decades have seen a growing global obesity epidemic, with overweight and obesity rates among children increasing in many countries, including China (Wang and Lobstein 2006, Wang, Mi et al. 2007, de Onis, Blossner et al. 2010). In the U.S., the prevalence of childhood overweight and obesity has tripled since the 1970s (Ogden, Carroll et al. 2012). In China, overweight and obesity prevalence has increased rapidly in children, from less than 3% overall in 1985 to approximately 10% in girls and 20% in boys in 2010, and the overall rate in major cities like Beijing is over 20% (Wang, Mi et al. 2007, Shan, Xi et al. 2010).

There has been a strong interest in developing effective childhood obesity prevention programs (Wang, Wu et al. 2013). Along with the increasing obesity prevalence, research suggests that rapid economic development, urbanization, globalization and changes in government policies followed by China's entry into the World Trade Organization (WTO) have led to emerging Western fast food outlets and dietary shifts among the Chinese population (Popkin 1999, Pingali 2007), which may have fueled the growing obesity epidemic. For example, since the first American fast food chain, Kentucky Fried Chicken (KFC), opened its first restaurant in China in 1987, the number of KFC restaurants had increased to over 4,200 in more than 800 cities and towns by 2012 (KFC 2012). McDonald's added 200 restaurants in 2011 and grew to over 2,000 restaurants within three decades in China (McDonald's 2014). In 2002, the fast food industry yielded 200 billion Chinese Yuan in annual sales (approximately US\$24 billion), accounting for 2/5 of China's food and beverage sales (Vertinsky 2002).



The relationship between Western fast food consumption (FFC) and weight status remains ambiguous in the existing literature. Some research suggests a positive association while others do not (Rosenheck 2008, Shan, Xi et al. 2010). Moreover, only a few cohort studies have tested the influence of FFC on obesity (Pereira, Kartashov et al. 2005, Duffey, Gordon-Larsen et al. 2007). Very limited longitudinal studies have been conducted to examine the effect of FFC on weight status in children, and no study has been conducted in Chinese children (Rosenheck 2008).

This study examined the changes over time in FFC and tested the association between FFC and obesity (including overweight) among children in China using nationwide longitudinal data. We hypothesized that FFC had increased over time in China and that FFC increased obesity risk in children.

### **3.2 Methods**

#### *Study design*

We conducted both cross-sectional and longitudinal analyses using longitudinal survey data collected in the 2004 and 2009 China Health and Nutrition Survey (CHNS), which covered nine provinces throughout China (Wang, Xue et al. 2014)(Wang, Xue et al. 2014)(Wang, Xue et al. 2014)(Wang, Xue et al. 2014)(Wang, Xue et al. 2014)(Falkner, Neumark-Sztainer et al. 2001). Figure 3-1 shows the map of the CHNS coverage for these two waves.

< Figure 3-1 about here >

CHNS is a large-scale, household-based open cohort which includes about 4,400 households and 26,000 individuals in nine provinces, namely, Heilongjiang, Liaoning, Shandong, Henan, Jiangsu, Hubei, Hunan, Guizhou, and Guangxi. CHNS used a multi-stage, random cluster sampling scheme to collect nationally representative data that covered key public health risk factors and health outcomes, demographic, social and economic factors at the individual, household and community levels (Zhang, Zhai et al. 2014). At the individual level, detailed health-related data were measured, including dietary intake, physical activity, smoking and drinking behaviors, anthropometrics, blood pressure and limited clinical data (Zhang, Zhai et al. 2014).

### *Study Sample*

Our study sample was from the 2004 and 2009 CHNS because FFC data were not available before 2004. The question on FFC was only asked among those aged 6 years or older. Thus, we included children aged 6 to 17. These who were 13-17 years old in the wave of 2004 were not in the cohort in 2009 as they became 18 years old and above. A total of 293 observations were missing for BMI. By removing the observations with missing BMI, we obtained a final sample of 2,656 observations, with 1,542 children in 2004 and 1,114 children in 2009; among them, 376 individuals had complete data in both waves. Children included in the analytic sample were similar to those in the non-analytic sample.

### *Key Study Variables and Data Collection*

BMI and obesity status: BMI was calculated as measured weight in kilograms divided by height in meters-squared. During the survey, weight and height data were collected by trained health workers from the individual's comprehensive physical exam at the local clinic or at the respondent's home during each visit (Ng, Norton et al. 2012). Height was measured without shoes to the nearest 0.2 cm using a portable stadiometer, and weight was measured without shoes and in light clothing to the nearest 0.1 kg on a calibrated beam scale (Seca North America, Chino, CA, USA).

Overweight and obesity in children were defined based on the International Obesity Task Force's (IOTF's) gender- and age-specific BMI cut-off points for children aged 2-18 years old, which correspond to an adult BMI of 25 kg/m<sup>2</sup> (overweight) or 30 kg/m<sup>2</sup> (obesity) (Cole, Bellizzi et al. 2000). Children's BMI varies with age and gender; thus, we calculated BMI z-scores adjusting for age and sex.

FFC: Western FFC, excluding Chinese fast food. This definition is used throughout the entire article. Data for FFC were obtained from self-reports on this question in CHNS, "During the past 3 months, how many times have you eaten at a Western fast food restaurant, such as McDonald's or Kentucky Fried Chicken?" Responses to this question were dichotomized into 1: consumed at least once; or 0, not consumed at all, to calculate the percentage of Western fast food consumers.

#### *Other Covariates*

Urbanicity: Classification as urban or rural residents depended on the administrative definitions of the communities in which the participants lived.

Ethnicity: Ethnic groups were dichotomized into Han and other, as Han is the majority (>90%) ethnic group in China.

Family income: Income groups were categorized based on annual per capita household income tertiles in that wave. Annual per capita household income was adjusted to 2011 yuan currency values.

Physical activity: We looked at specific metabolic equivalent time (MET) intensity values, including in-school and before- or after-school physical activity, transportation to/from school, and sedentary activities, which were retrieved from children's self-reports. Based on the Compendium of Physical Activities, one unit of MET is defined as the ratio of a person's working metabolic rate relative to his/her resting (basal) metabolic rate, and the final unit for physical activity variables is MET in kcal/(kg\*h) (Ainsworth, Haskell et al. 2000). We aggregated children's in-school and after-school physical activities, transportation to/from schools and sedentary behaviors to obtain the total MET.

Other dietary intake variables: The data utilized the 2002 version of the Food Composition Table (FCT) to calculate macronutrient intake values for the dietary data. Caloric, fat and carbohydrate intake were obtained from 3-day 24-hour recalls reported by the children's parents. We dichotomized caloric, fat and carbohydrate intake based on data distribution as well as dietary recommendations (Macronutrients and Intakes 2005). However, we did not include dietary intakes in our regression analyses due to their strong associations with FFC; instead, we looked into their relationships with FFC patterns.

Geographical region: East China, Northeast, South China, Central China and Southwest. Northeast includes Liaoning and Heilongjiang provinces; East China includes

Jiangsu and Shandong; Central China includes Henan, Hubei, and Hunan; South China includes Guangxi, and Southwest includes Guizhou.

### *Statistical Analysis*

First, we examined FFC patterns among children who participated in both waves (in 2004 and 2009), and looked at children of the same age range in both waves. We used McNemar test to test the difference in the prevalence of FFC for dependent samples (same cohort) and Chi-squared test to test the difference in the prevalence of FFC for independent samples, respectively, to determine whether there were any significant differences in terms of the percentage of fast food consumers over time.

We employed the Heckman's two-stage model to examine the factors that may influence FFC (Heckman 1979). The first stage is to estimate an equation that determines the probability for children to decide whether to consume FF. The second stage estimates the participation magnitude, i.e., the factors that affect the frequency of a child consuming FF in a given week. The model can be set up as the following:

The FF consumption frequency model is:

$$y_1 = x_1\beta_1 + \varepsilon_1$$

where  $x_1$  is a vector of independent variables,  $y$  is the FF consumption frequency. The selection is determined by

$$y_2 = \begin{cases} 1, & \text{if } x_2\delta_2 + \varepsilon_2 > 0 \\ 0, & \text{otherwise} \end{cases}$$

The selection equation was estimated at the first stage by maximum likelihood as a probit model to estimate the effects of the independent variables on the probability of

choosing to consume FF or not from the whole sample of FF consumers and non-consumers. Then a vector of inverse Mills ratios was generated from the parameter estimates. The level (i.e. frequency) of FF consumption was then regressed on the explanatory variables,  $x$ , and the vector of inverse Mills ratios from the selection equation. Panel Heckman model is not available yet in the literature. So I pooled the 2004 and 2009 data to obtain more efficient estimates. Cluster robust standard errors were used to handle the correlation between two repeated measures for some subjects. Indeed, this is similar to use mixed effect model to handle longitudinal data. For example, STATA used similar routines to create clustered robust standard errors as for mixed effect models. Since our data have large number of zeros in FFC, one may propose to use the zero-inflated-Poisson (ZIP) model. However, ZIP models allow the zeros in both the decision and consumption level stages, which is not suitable for our analysis.

Next, we examined the associations between FFC and BMI z-score and weight status in children. As we know, linear models provide information on conditional means. However, conditional mean regressions are not informative enough in revealing the effects of risk factors for obesity along a weight distribution. It is possible that the relationship between FF consumption and body weight may vary at different points along the distribution. Quantile regressions were thus estimated at percentiles 25%, 50%, 85% and 95%. Quantile regression can be understood in a relatively simple setup as below. A linear regression of BMI could be specified as:

$$y_i = \beta_0 + \beta_1 x_{i,1} + \dots + \beta_p x_{i,p} + \varepsilon_i$$

where  $y_i$  is the BMI of individual  $i$ .  $x_{i,p}$  is a scalar representing covariates in the model of individual  $i$ . This model estimates how the changes of  $x_{i,p}$  affect the change of the

conditional mean of  $y_i$ , i.e., the marginal effect of  $x_p$  on  $y_i$ . However, by only looking at the changes of the conditional mean  $E[y|\mathbf{X}]$ , important information is missing for other locations across the whole distribution. This is not trivial in this study, given that knowing the differential relationship across the conditional distribution of the outcome variable  $y$  is of critical importance for interventions and policies. Therefore, we conduct quantile regressions to examine the impact of exposures on weight outcome across its distribution. The general framework of the quantile regression can be understood as the following (Koenker and Bassett 1978):

Assume the cumulative distribution of  $y$  as  $F$ , then for a given quantile  $q \in (0,1)$

$$F(y_q) = q, \text{ and } y_q = F^{-1}(q)$$

Hence,

$$y_q = F^{-1}(q) = X_i' \beta_q + \varepsilon_i$$

To obtain the estimate of vector  $\beta_q$ , we can minimize

$$\min_{\beta} \sum_{i: y_i \geq x_i' \beta_q} q |y_i - x_i' \beta_q| + \sum_{i: y_i < x_i' \beta_q} (1-q) |y_i - x_i' \beta_q|$$

The meaning of  $\beta_{jq}$  is the marginal change in the quantile  $q$  due to a marginal change in the  $j$ th element of  $\mathbf{x}$ . We conducted both cross-sectional and longitudinal analysis. In longitudinal analysis, to establish temporality, we estimated the effect of FFC at baseline on BMI z-score and log odds of being overweight or obese during follow-up.

Analysis was conducted using Stata (Version 11.1, StataCorp).

### 3.3 Results

#### *Study Sample Characteristics*

Table 3-1 shows the subjects' socio-demographic characteristics. On average, children in wave 2009 were slightly younger than those in 2004, had higher family incomes, with more residing in South China and fewer in the Northeast region, consumed fewer daily calories, had lower physical activity levels, and had higher average BMI z-scores. Other characteristics were comparable in 2004 and 2009.

<Table 3-1 about here>

#### *Trends in Fast Food Consumption*

Table 3-2 presents the time trends in the proportion of fast food consumers by socio-demographics, lifestyles and weight status for the same cohort aged 6-12.99 years in 2004 (thus aged 11-17.99 years in 2009). The proportion of fast food consumers rose from 18.5% in 2004 to 23.9% in 2009 ( $P < 0.001$ ). The increase was greater in boys (16.3% to 21.1%,  $P < 0.001$ ) than in girls (23.6% to 24.4%,  $P < 0.001$ ). The prevalence of FFC remained relatively low. The figure in minority ethnic groups almost tripled over time ( $P < 0.001$ ), far faster than that in the Han majority.

<Table 3-2 about here>

The rise in the percentage of fast food consumers was most pronounced in the low- and median-income groups (10.3% to 19.2% in low-income households; 11.2% to



18.5% in medium- income households, both  $P < 0.001$ ). It decreased significantly in the high-income group (36.2% to 35.1%,  $P < 0.01$ ).

The same trends existed among the urban and rural residents. The percentage increased dramatically in both urban (38.0% to 43.3%,  $P < 0.05$ ) and rural residents (11.0% to 15.9%,  $P < 0.001$ ).

While the percentage consumed increased dramatically in the Northeast (17.5% to 29.0%,  $P < 0.001$ ), South (5.7% to 13.4%,  $P < 0.001$ ) and Southwest regions (5.8% to 15.7%,  $P < 0.001$ ), it decreased slightly in the remaining regions.

In terms of dietary intakes, the percentage of fast food consumers increased significantly (20% to 25.2%,  $P < 0.001$ ) among those who consumed 1,200 kcal or more per day. The percentage of fast food consumers increased in all fat and carbohydrate intake subgroups.

Compared to 2004, more children with a low physical activity level (MET in kcal/[kg\*h]  $\leq 5,000$ ) consumed fast food in 2009 (16.9% in 2004 to 23.7% in 2009,  $P < 0.001$ ), while fewer children with a high physical activity level (MET in kcal/[kg\*h]  $> 5,000$ ) consumed fast food (26.2% in 2004 to 24.7% in 2009,  $P < 0.001$ ). Among children with different weight status, more underweight or normal weight children consumed fast food in 2009 (19.7% in 2004 to 25.1% in 2009,  $P < 0.001$ ), compared to those who were overweight (22.9% in 2004 to 18.8% in 2009,  $P < 0.001$ ).

Table 3-3 shows the trends in the percentage of fast food consumers by socio-demographics, lifestyles and weight status characteristics for participants in the same age range in 2004 vs. those in 2009, i.e., to examine the time trends controlling for age. From 2004 to 2009, more adolescents aged 13-17 reported consuming fast food, while it did not

change much in children aged 6-10. For children aged 13-17, there was a dramatic increase (17.9% to 26.3%,  $P < 0.01$ ). Among children aged 6-10, it did not change much, but it more than tripled among ethnic minorities (5.2% to 16.9%,  $P < 0.05$ ), while it decreased in East China (where the proportion was high in 2004) over time (43.3% to 32.1%,  $P < 0.01$ ).

<Table 3-3 about here>

FFC rates increased significantly more in the medium-income group (13.7% to 22.2%,  $P < 0.05$ ), among rural residents (10.3% to 20.6%,  $P < 0.001$ ), among those who consumed 12,000 kcal or more per day (18.3% to 26.7%,  $P < 0.01$ ), among those who consumed more fat (23.2% to 36.8%,  $P < 0.05$ ), and among those who were underweight or normal weight (17.4% to 26.2%,  $P < 0.001$ ). The consumption rate was higher in all carbohydrate intake and physical activity level subgroups. The consumption rate was mostly stable in other groups.

#### *Factors associated with Fast Food Consumption*

Table 3-4 presents the estimates from the Heckman two-stage models. Household income was a key factor that significantly influenced children's choice of FF consumption as well as the level of consumption. As the results indicate, an increase in the per capita household income would decrease the probability for a child to consume FF. However, in probit estimation, the magnitude of the change in the probability depends on the comparison base of the household income and the values of other

independent variables. As the second stage estimation results indicate, once the decision of consuming FF or not was made, the level of consumption was positively associated with per capita household income, though the effect is small, with a 20,000 RMB increase leading to about 1 more time FFC in 3 months.

<Table 3-4 about here>

#### *Association between Fast Food Consumption and Children's Weight Status*

Table 3-5 presents the estimates from quantile regression models. FFC was the main exposure and age, ethnicity, household income, urbanicity, geographical region and physical activity levels were controlled. The relationship between FFC and children's BMI z-scores did differ across the BMI distribution, as indicated by the difference of coefficients at different percentiles. The effects of FFC on weight outcomes could be higher on the upper tail of BMI distributions. However, the estimates of FFC on weight outcomes were not statistically significant.

<Table 3-5 about here>

For comparison, we also estimated the association using regular linear and logistic regression models. As presented in Table 1-6, the associations between FFC and BMI-z score were not significant.

### **3.4 Discussion**

Our analysis of the nationwide survey data shows that FFC (excluding Chinese fast food) increased significantly among Chinese school-age children during 2004-2009, and the increase was especially rapid among some groups, such as older children, boys, those from low- and medium-income families, and those from rural areas and East China, compared to their counterparts. During this period, FFC decreased in children who were from high-income families and those who were overweight. In almost all socio-demographic subgroups, as children aged, they reported having consumed fast food in the past three months. This finding was likely to be fueled by the increased accessibility of Western fast food restaurants and children's increased pocket money and independence. The trend was different by age group. The FFC rate in children was relatively stable, while it increased rapidly in adolescents, from 17.9% to 26.3%. For adolescents, the increasing trend was prominent in boys, those of Han ethnicity, from medium-income families, rural residents, from East China, of under/normal weight, or those with a diet high in calories or fat. These findings are likely due to their increased independence and peer influence.

The Western fast food industry has been growing rapidly in China since the late 1980s, especially over the past two decades. Compared to two decades ago, nowadays children have better access to fast food, and the food has become more affordable. Moreover, FFC is viewed favorably among children. A cross-cultural study on brand identity reported that Chinese children had more favorable impressions of KFC than did their US counterparts (Witkowski, Ma et al. 2003). Despite these changes in the food

environment in China, our findings indicate some large spatial-temporal disparities and time trends in FFC in adolescents between urban and rural regions: urban adolescents had more FFC. However, during 2004-2009, FFC increased in rural areas, but decreased in urban areas. Such spatial-temporal differential patterns mirror the inequalities of regional economic development and reflect the nonlinear effect of income rise on food-away-from-home (FAFH) consumption. It is known that an increase in income generates a greater increase in FAFH expenditure in high-income households than in low-income households in China (Ma, Huang et al. 2006). On one hand, as an important component of FAFH, FFC increased dramatically in rural areas with an increase in rural household income. On the other hand, the effect of increasing household income in urban areas on FAFH was more pronounced for other foods. In high-income urban households, more awareness of health, media influence, and increased demand for high quality food in recent years may have resulted in a decrease in FFC, as it may be increasingly viewed as unhealthy for children.

By separating the age and period effects, we found different patterns. In general, as age increased, more children had consumed Western fast food, while the consumption prevalence in young children did not change much. This finding is likely because adolescents who had entered middle and high schools had more autonomy and pocket money and were more likely to be under peer influence than younger kids (Houldcroft, Haycraft et al. 2014, Verstraeten, Van Royen et al. 2014). Therefore, older children had more freedom and opportunities to consume Western fast food.

Interestingly, the FFC rate decreased in the children from high-income families, but those from low- and medium-income families increased their FFC. This result is

consistent with the shifted nutrition transition and findings that the burden of obesity and metabolic risk has started to move from the better-off to the poorer population groups in some developing countries (Popkin 2014).

Moreover, our results suggest household income may have a differential impact on FFC in terms of the choice to consume and the level of consumption. Consistent with the general trends in FFC, our two-stage model estimates suggest that children from higher income families were less likely to consume fast food. However, once a child determined to consume fast food, household income was positively associated with the level of FFC.

We did not find a meaningful association between western FFC and children's weight status. Our analysis using quantile regression techniques further suggest a non-significant association between FFC and children's weight outcomes across the BMI distributions. These results are in line with the findings of previous studies. For example, a study using the CHNS data also showed that overweight and obesity were not associated with fast food preference in adults, and food environment might play a smaller role than nutritional knowledge in influencing consumers' consumption choices (Zhang, van der Lans et al. 2012). One plausible explanation of these findings could be that, although FFC generally increased, western FFC was still not a large contributor of children's daily energy intake in China.

Some empirical and review studies have examined the associations between FFC, increased fat and calorie intakes and childhood obesity (Rosenheck 2008, Fraser, Clarke et al. 2012). However, most of these findings were based on studies conducted in high-income countries such as the United States. To our knowledge, thus far, Rosenheck's

(2008) review is the most comprehensive in its review of 16 studies (6 cross sectional, 7 prospective cohort, 3 experimental studies). It concluded that the association between FFC and weight gain was not clear, but sufficient evidence exists for public health recommendations to limit FFC and facilitate healthier menu selection. Of the 7 prospective cohort studies, 4 were conducted among children and adolescents, 6 found a positive association between more frequent FFC and an increase in total caloric intake or BMI. All 3 studies conducted among young adults reported an association between FFC and increased BMI. Our study helps fill two main gaps in this literature: Only a small number of studies have tested the association between FFC and overweight/obesity in developing countries, and very few previous studies have used longitudinal data. Two large cross-sectional studies have examined the association in China, but provided conflicting findings. Our previous cross-sectional study among 21,198 children in Beijing reported a positive association between FFC and overweight/obesity (Shan, Xi et al. 2010), but another study among 9,023 adolescents from seven large cities in China reported a negative association (Hsu, Johnson et al. 2011). We are also aware that the validity of these findings are subject to appropriateness of analysis approaches these studies employed.

However, although our results do not suggest a significant association between FFC and children's weight outcomes in China, FFC may affect overweight/obesity indirectly. For example, FFC may have promoted western food culture among Chinese children, which may influence their other food intake and cause a shift to high-energy-density food and drinks at home or away from home. In the long run, adverse health

effects will be inevitable if the trends of FFC in China continue without effective interventions.

The study also has limitations. First, only 376 children had complete follow-up data. The low follow-up rate was mainly because children were not at home during the follow-up data collection, and some families had moved out of the previous community. Second, the definition of fast food was not clearly specified in the survey questionnaire. The survey question asked about the number of times children visited fast food restaurants like McDonald's. In this case, other Western fast food restaurants may have not been taken into account.

In conclusion, more Chinese children have consumed Western fast food over time. The increase is dramatic and is more rapid in some groups, such as among adolescents (vs. younger children), boys (vs. girls), children of non-Han ethnicity, those from low- and medium-income families (vs. high-income groups), and those from rural areas or East China (vs. other areas), although their absolute FFC level may still be lower than that of their counterparts. More efforts are needed to study the impact of FFC on health outcomes, as well as policy and interventions to promote healthy eating among children in China.



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Table 3-1: Socio-demographic characteristics of children aged 6-17 years in nine provinces in China: China Health and Nutrition Survey 2004 and 2009

	Year 2004 (n=1542)	Year 2009 (n=1114)	With data in both waves (n=376)
Age (years), mean (SD)	12.4 (3.3)	11.6 (3.2)	9.0 (1.8)
Girls, n (%)	723 (46.9)	493 (44.3)	166 (44.2)
Han Ethnicity, n (%)	1,303 (84.8)	919 (83.1)	303 (80.1)
Income/capita(RMB, yuan) <sup>†,‡</sup> , mean (SD)			
Low	1,445.8 (800.3)	2,370.0 (1474.2)	1431.1 (776.6)
Medium	4,378.6 (942.7)	6,772.1 (1,426.1)	4526.9 (927.4)
High	11,556.8 (6,279.4)	19,112.2 (14,723.4)	11421.6 (4729.0)
Urban residents, n (%)	447 (29.0)	305 (27.4)	105 (27.9)
Region <sup>§</sup> , n (%)			
Northeast	350 (22.7)	166 (14.9)	81 (21.5)
East China	255 (16.5)	200 (18.0)	62 (16.5)
Central China	492 (31.9)	337 (30.3)	86 (22.9)
South China	220 (14.3)	212 (19.0)	72 (19.2)
Southwest	225 (14.6)	199 (17.9)	75 (20.0)
Caloric intake (kcal) <sup>l</sup> , mean (SD)	1,909.5 (679.5)	1,715.6 (622.1)	1636.1 (590.2)

Fat intake (% kcal) <sup>†</sup> ,			
mean (SD)	28.8 (10.7)	29.2 (11.0)	28.9 (10.7)
Carbohydrate intake			
(% kcal) <sup>†</sup> , mean (SD)	59.1 (10.9)	57.9 (11.1)	59.1 (11.0)
Physical activity level			
(MET in kcal/(kg*h)) <sup>‡</sup> ,			
mean (SD)	4,426.0 (4,651.7)	3,949.0 (3,410.4)	3666.1 (3377.7)
BMI z-score <sup>¶</sup>	-0.01 (0.9)	0.02 (1.1)	0.01 (1.0)

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Note: SD, standard deviation. MET, metabolic equivalent of task. BMI, body mass index.

<sup>†</sup> Annual per capita household income inflated to year 2011 currency values.

<sup>‡</sup> Income groups were categorized based on annual per capita household income tertiles in that wave. In year 2004, low income ranged from -1,206.0 to 2,797.2 yuan, medium income ranged from 2,803.7 to 6,190.3 yuan, high income ranged from 6,196.2 to 60,557.5 yuan. In year 2009, low income ranged from -10,347.3 to 4,483.4 yuan, medium income ranged from 4,501.2 to 9,562.9 yuan, high income ranged from 9,578.8 to 168,998.9 yuan.

<sup>§</sup> Regions include: Northeast (Liaoning, Heilongjiang), East China (Jiangsu, Shandong), Central China (Henan, Hubei, Hunan), South China (Guangxi), Southwest China (Guizhou).

<sup>†</sup> Caloric, fat and carbohydrate intakes were obtained from 3-day 24-hour recalls.

<sup>‡</sup> MET was obtained by aggregating children's in-school and after school physical activities, transportations to/from schools and sedentary behaviors.

<sup>¶</sup> Weight and height was measured by trained clinical staffs. BMI was calculated from weight (kg) divided by height (meter) squared. BMI z-scores were calculated based on children's age and gender groups within this sample.

Table 3-2: Longitudinal analysis: Trends in the percentage (%) of Western fast food consumers among Chinese school-age children followed up from 2004 to 2009 (the same cohort, n=376), by socio-demographics, lifestyles and weight status: China Health and Nutrition

	Year 2004	Year 2009	p <sup>§</sup>	Trend ¶¶
	% <sup>‡</sup>	% <sup>‡</sup>		
All <sup>l</sup>	18.5	23.9	.000	↑
Gender				
Boy	16.3	21.1	.000	↑
Girl	23.6	24.4	.000	↑
Ethnicity				
Han	21.0	26.0	.000	↑
Not Han (minorities)	6.0	15.9	.000	↑
Household income (per capita) <sup>l</sup>				
Low	10.3	19.2	.000	↑
Medium	11.2	18.5	.000	↑
High	36.2	35.1	.002	↓
Residence				
Urban	38.0	43.3	.10	↑
Rural	11.0	15.9	.000	↑
Region <sup>¶</sup>				
Northeast	17.5	29.0	.000	↑
East China	45.2	44.3	.37	↓
Central China	20.7	19.8	.000	↓



South China	5.7	13.4	.000	↑
Southwest	5.8	15.7	.000	↑
Dietary intake				
Caloric intake (kcal) <sup>††</sup>				
<1,200	13.9	13.9	.000	↓
≥1,200	20.0	25.2	.000	↑
Fat intake (as % of total energy intake) <sup>††</sup>				
≤35	15.7	18.6	.000	↑
>35	26.6	41.0	.001	↑
Carbohydrate intake ( as % of total energy intake) <sup>††</sup>				
≤50	34.3	47.8	.07	↑
>50	14.5	18.3	.000	↑
Physical activity level (MET in kcal/(kg*h)) <sup>‡‡</sup>				
Less active ≤5,000	16.9	23.7	.000	↑
Active >5,000	26.2	24.7	.000	↓
Weight Status (based on BMI) <sup>§§</sup>				
Under/normal weight	17.5	24.3	.000	↑
Overweight	22.9	18.8	.18	↓
Obese	42.9	50.0	.000	↑

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Note: MET, metabolic equivalent of task. Results came from a sample of children who participated in both waves 2004 and 2009. Imputation treated any missing responses or those answered “unknown” as “0” when there was no fast food restaurant in the respondent's community.

† Age is not listed here as children in waves 2004 and 2009 belong to different age groups.

‡ % represents the % of consumers among that specific sample.

§ *P*-value for McNemar tests to examine if there was any significant difference between the percentage of fast food consumers in wave 2004 and that in wave 2009.

¶ Questions on FFC frequency: “During the past 3 months, how many times have you eaten at a Western fast food restaurant, such as McDonald’s or Kentucky Fried Chicken?” Responses to this question were dichotomized into 1: consumed at least once or 0: not consumed or unknown to calculate the percentage of fast food consumers.

∣ Annual per capita household income inflated to year 2011 yuan currency values.

¶ Regions include: Northeast (Liaoning, Heilongjiang), East China (Jiangsu, Shandong), Central China (Henan, Hubei, Hunan), South China (Guangxi), Southwest China (Guizhou).

†† Caloric, fat and carbohydrate intake were obtained from 3-day 24-hour recalls. They were dichotomized based on data distribution as well as dietary recommendations.

‡‡ MET was aggregated from children’s in-school and after school physical activities, transportations to/from schools and sedentary behaviors.

§§ Weight and height was measured by trained clinical staffs. BMI was calculated as weight (kg) divided by height (meter) squared. Weight status was determined based on the International Obesity Task Force (IOTF) gender- and age-specific BMI cut-offs.

¶¶ ↑: increase; ↓: decrease; →: no change from 2004 to 2009.

Table 3-3: Time trends in the percentage (%) of Western fast food consumers among Chinese children of the same age range between 2004 and 2009

	Children aged 6-10 in 2004 or 2009				Children aged 13-17 in 2004 or 2009			
	(N=1534)				(N=362)			
	Year 2004	Year 2009	Sig. <sup>†</sup>	Trend <sup>¶¶</sup>	Year 2004	Year 2009	Sig. <sup>†</sup>	Trend <sup>¶¶</sup>
	%	%			%	%		
Among all <sup>‡,§</sup>	18.1	18.3		→	<b>17.9</b>	<b>26.3</b>	***	↑
Age (years) <sup>l</sup>								
6-8 or 13-15	18.2	17.1		→	16.2	24.3		↑
9-10 or 16-17	18.1	19.9		→	21.3	31.7		↑
Gender								
Boys	15.3	18.7		→	<b>15.0</b>	<b>25.0</b>	**	↑
Girls	21.2	17.7		→	21.3	27.8		↑
Ethnicity								
Han	21.1	18.5		→	<b>19.1</b>	<b>27.6</b>	**	↑

Not Han (minorities)	<b>5.2</b>	<b>16.9</b>	*	↑	9.5	19.0		↑
Household income/capita (yuan) <sup>l</sup>								
Low	7	9.2		→	13.3	17.7		↑
Medium	9.9	14.8		→	<b>13.7</b>	<b>22.2</b>	*	↑
High	39.3	32.0		→	26.9	36.2		↑
Urbanicity								
Urban	42.1	42.3		→	34.3	38.8		→
Rural	9.7	9.8		→	<b>10.3</b>	<b>20.6</b>	***	↑
Region <sup>l</sup>								
Northeast	23.6	28.1		→	19.3	29.7		↑
East China	<b>43.3</b>	<b>34.1</b>	**	↓	<b>23.4</b>	<b>41.2</b>	**	↑
Central China	13.4	15.4		→	15.7	24.2		↑
South China	6.8	6.0		→	15.4	15.2		→
Southwest	5.3	13.3		→	15.0	21.2		↑

Weight Status<sup>\$\$</sup>

Under/normal weight	16.5	17.5	→	<b>17.4</b>	<b>26.2</b>	***	↑
Overweight	27.3	26.7	→	30.3	26.5		→
Obese	33.3	16.7	→	0.0	33.3		↑

*Dietary intakes*

Caloric intake (kcal)<sup>††</sup>

<1,200	14.9	12.3	→	22.9	21.2		→
≥1,200	19.6	20.1	→	<b>18.3</b>	<b>26.7</b>	**	↑

Fat intake ( as % of total energy intake)<sup>††</sup>

≤35	14.7	14.4	→	16.8	22.4		↑
>35	28.5	25.9	→	<b>23.2</b>	<b>36.8</b>	*	↑

Carbohydrate intake ( as % of total energy intake)<sup>††</sup>

≤50	36.1	25.6	→	<b>26.2</b>	<b>41.3</b>	*	↑
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>50	13.6	15.3	→	<b>16.6</b>	<b>22.2</b>	*	↑
Physical activity level (MET in kcal/(kg*h)) <sup>‡‡</sup>							
≤5,000	16.6	16.8	→	<b>16.5</b>	<b>24.4</b>	**	↑
>5,000	26.6	24.2	→	<b>20.7</b>	<b>30.8</b>	*	↑

Note: MET, metabolic equivalent of task. Results came from two samples of children who aged 6-10.99 years in waves 2004 and of the same age in 2009, or children who aged 13- 17.99 years in waves 2004 and of the same age in 2009. Imputation treated any missing responses or those answered “unknown” as “0” when there was no fast food restaurant in the respondent's community.

<sup>1</sup> Age group 6-8.99 for children aged 6-10.99, and age group 13-15.99 for children aged 13-17.99. Age group 9-10.99 for children aged 6-10.99, and age group 16-17.99 for children aged 13-17.99. The age range of 6-10.99 and 13-17.99 were chosen so that there were no overlaps between children of the same age range in wave 2004 and 2009.

<sup>†</sup> \*  $P < .05$ ; \*\*  $P < .01$ ; \*\*\*  $P < .001$  for Chi-squared tests to examine if there was any significant difference between the percentage of fast food consumers in wave 2004 and that in wave 2009.

§ Questions on FFC frequency: “During the past 3 months, how many times have you eaten at a Western fast food restaurant, such as McDonald’s or Kentucky Fried Chicken?” Responses to this question were dichotomized into 1: consumed at least once or 0: not consumed or unknown to calculate the percentage of fast food consumers.

| Annual per capita household income inflated to year 2011 yuan currency values.

¶ Regions include: Northeast (Liaoning, Heilongjiang), East China (Jiangsu, Shandong), Central China (Henan, Hubei, Hunan), South China (Guangxi), Southwest China (Guizhou).

†† Caloric, fat and carbohydrate intake were obtained from 3-day 24-hour recalls. They were dichotomized based on data distribution as well as dietary recommendations.

‡‡ MET was aggregated from children’s in-school and after school physical activities, transportations to/from schools and sedentary behaviors.

§§ Weight and height was measured by trained clinical staffs. BMI was calculated from weight (kg) divided by height (meter) squared. Weight status was determined based on the International Obesity Task Force (IOTF)’s gender- and age-specific BMI cut-offs.

¶¶ ↑: increase; ↓: decrease; →: no change from 2004 to 2009.

Table 3-4: Two-stage Heckman model estimates of factors associated with fast food consumption in Chinese children: China Health and Nutrition Survey 2004-2009<sup>^</sup>

First stage estimation:			
Probit model estimates of the likelihood of FF consumption (decision of consuming: yes/no, as outcome variable) <sup>1</sup>			
Independent variables	Coefficient	95% CI	p-value
BMI-z score	-0.06	(-0.23, 0.09)	
Per capita income (in 10000 RMB)	-0.2	(-0.22, -0.16)	***
Gender	0.28	(0.23, 0.34)	***
Age	0.002	(-.0771, 0.079)	
Ethnicity	0.28	(-0.26, 0.82)	
Urban region	-0.11	(-0.10, 0.88)	
Second stage estimation:			
Factors influencing FF consumption frequency (times in the past three months as outcome variable)			
BMI-z score	-0.01	(-0.18, 0.16)	
Per capita income (in 10000 RMB)	0.2	(0.11, 0.21)	***
Gender	0.3	(0.28, 0.33)	***
Age	0.03	(-0.05, 0.10)	
Ethnicity	0.33	(0.11, 0.56)	
Urban region	1.47	(1.40, 1.54)	***

Note. \*  $P < .05$ ; \*\*  $P < .01$ ; \*\*\*  $P < .001$

^2004 and 2009 data were pooled for analysis and cluster roused standard errors were used to tackle correlations between repeated measures.

<sup>1</sup>Questions on FFC frequency: “During the past 3 months, how many times have you eaten at a Western fast food restaurant, such as McDonald’s or Kentucky Fried Chicken?” Responses to this question were dichotomized into 1: consumed at least once or 0: not consumed or unknown to calculate the percentage of fast food consumers.



Table 3-5: Quantile regression estimates of the associations between Chinese children's Western fast food consumption and their BMI z-scores: China Health and Nutrition Survey 2004-2009

		Outcome: BMI z-score <sup>†,‡</sup>			
Exposure: Consumed fast food vs. not (ref.) <sup>l</sup>	Coefficient $\beta$ at 4 percentile				
	25 <sup>th</sup> (95% CI)	50 <sup>th</sup> (95% CI)	85 <sup>th</sup> (95% CI)	95 <sup>th</sup> (95% CI)	
<b><i>Cross-sectional</i></b>					
1) For wave=2004					
Boys (n=794)	-0.02 (-0.16, 0.12)	0.06 (-0.05, 0.18)	0.007 (-0.19, 0.21)	0.13 (-0.09, 0.34)	
Girls (n=703)	0.003 (-0.02, 0.03)	.008 (-0.03, 0.05)	0.0002 (0.09, 0.09)	-.01 (-0.16, 0.13)	
2) For wave=2009					
Boys (n=612)	0.03 (-.02, 0.07)	0.02 (-0.09, 0.13)	-0.05 (-0.14, 0.05)	-0.08 (-0.28, 0.12)	
Girls (n=480)	-0.01 (-0.08, 0.06)	-0.03 (-0.13, 0.06)	0.02 (-0.07, 0.11)	-0.05 (-0.19, 0.10)	
<b><i>Longitudinal</i></b>					
Boys (n=210)	0.06 (-0.11, 0.20)	0.04 (-0.16, 0.24)	0.10 (-0.08, 0.30)	0.01 (-0.19, 0.21)	
Girls (n=166)	0.009 (-0.03, 0.05)	0.004 (-0.05, 0.06)	-0.004 (-0.07, 0.06)	-0.01 (-0.24, 0.22)	

Note. \*  $P < .05$ ; \*\*  $P < .01$ ; \*\*\*  $P < .001$

<sup>†</sup> Weight and height was measured by trained clinical staffs. BMI was calculated from weight (kg) divided by height (meter) squared. BMI z-scores were calculated based on children's age and gender groups within this sample.

<sup>‡</sup> Quantile regression model estimates: BMI z-scores in year 2004/2009 regressed on FFC in the same year stratified by gender, controlling for age, ethnicity, household income, urbanicity, geographical region and physical activity levels; in longitudinal analysis, FFC from last wave is the independent variable controlling for age, ethnicity, household income, urbanicity, geographical region and physical activity levels

<sup>l</sup> Questions on FFC frequency: "During the past 3 months, how many times have you eaten at a Western fast food restaurant, such as McDonald's or Kentucky Fried Chicken?" Responses to this question were dichotomized into 1: consumed at least once or 0: not consumed or unknown to calculate the percentage of fast food consumers.

Table 3-6: Mean regression model based estimates of associations between Chinese children's Western fast food consumption: China Health and Nutrition Survey 2004 and 2009

Exposure: Consumed fast food vs. not (ref.) <sup>  </sup>	Outcome: BMI z-score <sup>†,‡</sup>		Outcome: Overweight or Obese <sup>§, 1</sup>	
	$\beta$	(95% CI)	OR	(95% CI) <sup>¶¶</sup>
<b><i>Cross-sectional</i></b>				
1) For wave=2004				
Boys (n=794)	0.13	(-0.16, 0.42)	1.62	(0.52, 5.12)
Girls (n=703)	0.00	(-0.40, 0.40)	0.92	(0.26, 3.27)
2) For wave=2009				
Boys (n=612)	0.41**	(0.04, 0.78)	2.79	(0.87, 8.97)
Girls (n=480)	0.09	(-0.31, 0.49)	0.94	(0.25, 3.52)
<b><i>Longitudinal</i></b>				
Boys (n=210)	0.02	(-0.71, 0.75)	0.71	(0.38, 1.32)
Girls (n=166)	-0.14	(-1.03, 0.75)	NA <sup>J</sup>	NA <sup>J</sup>

Note. \*  $P < .05$ ; \*\*  $P < .01$ ; \*\*\*  $P < .001$

OR= Odds Ratio, CI= Confidence Interval. NA, not applicable.

<sup>†</sup> Weight and height was measured by trained clinical staffs. BMI was calculated from weight (kg) divided by height (meter) squared. BMI z-scores were calculated based on children's age and gender groups within sample.

<sup>‡</sup> Linear regression models: For cross-sectional data analyses, BMI z-scores in year 2004/2009 regressed on FFC in the same year stratified by gender, after controlling for age, ethnicity, household income, urbanicity, geographical region and physical activity levels. For longitudinal data analyses, BMI z-scores in year 2009 regressed on baseline FFC stratified by gender, after controlling for baseline age, ethnicity, household income, urbanicity, geographical region and physical activity levels.

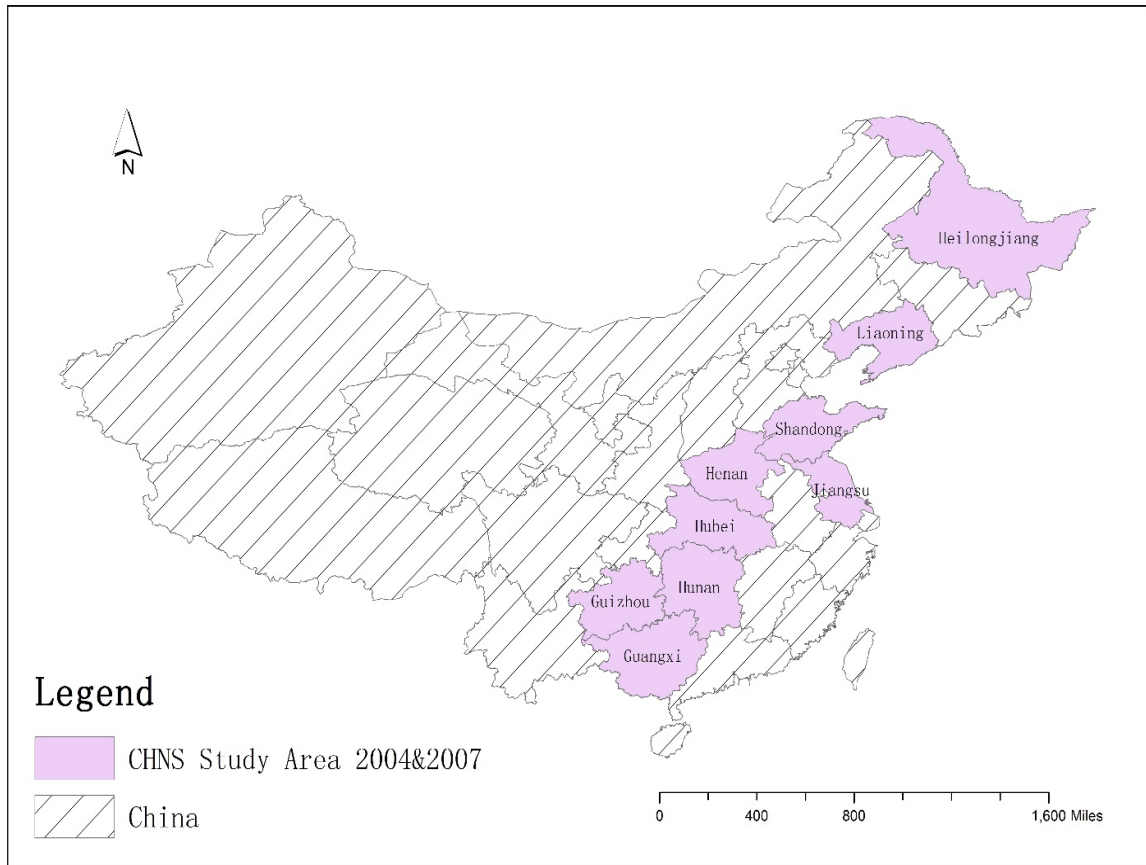
<sup>1</sup> Logistic regression models: For cross-sectional data analyses, the log odds of being overweight or obese in year 2004/2009 regressed on FFC in the same year stratified by gender, after controlling for age, ethnicity, household income, urbanicity, geographical region and physical activity levels. For longitudinal data analyses, the log odds of being overweight or obese in year 2009 or not regressed on baseline FFC stratified by gender, after controlling for baseline age, ethnicity, household income, urbanicity, geographical region and physical activity levels.

<sup>||</sup> Questions on FFC frequency: "During the past 3 months, how many times have you eaten at a Western fast food restaurant, such as McDonald's or Kentucky Fried Chicken?" Responses to this question were

dichotomized into 1: consumed at least once or 0: not consumed or unknown to calculate the percentage of fast food consumers.

<sup>J</sup>The sample size was too small to obtain 95% CI in logistic regression.

Figure 3-1: Map of the China Health and Nutrition Survey (CHNS) coverage 2004-2009



# **Chapter 4 – Agent-based Modeling of Social Norm Impacts on Obesity and Eating Behaviors among School Children in China and the United States**

## **Abstract**

**Objectives:** Although the importance of social norms in affecting health behaviors has been increasingly recognized, the current understanding of social norm effects on obesity is limited due to data and methodology limitations. This study aims to use nontraditional innovative systems science methods to examine: a) the effects of social norms on school children’s BMI growth and fruit and vegetable (FV) consumption in China and in the US, and b) compare the difference in social norm effects in different social settings.

**Methods:** We built an agent-based model (ABM) in a utility maximization framework and parameterized the model based on empirical longitudinal data collected in Nanjing, China, in the Childhood Obesity Prevention through Physical Activity Promotion in China study and in the US in the Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K) to test the follow-the-average social norm affecting children’s BMI growth and FV consumption.

**Results:** The correlation between observed and ABM-predicted BMI was about 0.9, indicating the satisfactory performance of our ABMs. Our simulations suggested the

follow-the-average social norm acts as an endogenous stabilizer, which automatically adjusts positive and negative deviance of an individual's BMI from the group mean of a social network. In China, our simulation analysis suggests that social norms may lead to a 0.05 (kg/m<sup>2</sup>) BMI increase for those with one unit of BMI below the average, and a 0.045 (kg/m<sup>2</sup>) decrease for those with one unit of BMI above the average. In the US, corresponding social norm effects were much smaller than those in China, being 0.025 (kg/m<sup>2</sup>) and 0.015 (kg/m<sup>2</sup>) per BMI unit differences above or below the social average, respectively. Our simulation also showed that misperception of the social norm would push up the mean BMI and cause the distribution to be more skewed to the left. Our simulation results did not provide strong support for the role of social norms on FV consumption.

**Conclusions:** Social norms influence children's BMI growth in China and the US, with greater effects in Chinese children. High obesity prevalence will lead to a continuous increase in children's BMI due to increased socially acceptable mean BMI. Interventions promoting healthy body image and desirable socially acceptable BMI should be implemented to control the childhood obesity epidemic.

**Keywords:** systems models, agent-based model, body mass index, child, obesity, overweight, social norms, networks

## 4.1 Introduction

The causes of the growing obesity epidemic are complex, involving the complex interactions of social, economic, cultural, environmental and biological factors. Although the importance of social norms in affecting health behaviors is widely recognized, the current understanding of social norm effects on obesity is limited. The dynamic interplay between individuals, groups, and environments pose challenges to traditional methods of deriving a holistic view of “contagious” obesity (Christakis and Fowler 2007, Cohen-Cole and Fletcher 2008).

There have been efforts to identify pathways and mechanisms in social norm influences. Eisenberg et al. measured social norm effects by asking respondents whether they had friends who dieted to lose or keep from gaining weight (Eisenberg and Neumark-Sztainer 2010); Thompson et al. (2006) used multifaceted scales to measure peer influence (Thompson, Shroff et al. 2007), such as the degree of teasing that respondents received from friends about weight and appearance, and their friends’ influence on their ideas of body image and weight-control strategies; Shomaker and Furman (2008) measured the social reinforcement of thinness from close social group members (e.g., mother, close friends and romantic partners) (Shomaker and Furman 2009); Christakis and Fowler (2007) examined obesity spreading through social networks using the Offspring Cohort from the Framingham Heart Study (Christakis and Fowler 2007). However, traditional analytical approaches have led to mixed empirical findings in the literature. Leahey et al. (2011) showed social norms for obesity did not differ between normal and overweight or obese groups (Leahey, LaRose et al. 2011). The influence of a social network might disappear once other social and contextual factors were considered



in the analytical models (Cohen-Cole and Fletcher 2008). These different results came from the alternate foci and hypotheses based on a reductionist point of view.

Obesity problems need to be conceptualized as complicated and complex system problems (Wang, Xue et al. 2015). They involve multidimensional and complicated components, and all these components interact with one another and could interplay in various fashions among heterogeneous subpopulations. Statistics-based epidemiology is insufficient to disentangle the complex nature of the obesity epidemic at large, although it helps unravel the independent associations between these obesity-causing factors and the obesity epidemic (Epstein 2006; O'Connor & McDermott, 1997). Systems methods attempt to examine the research question as a whole. Agent-based models (ABM), as a major application of systems methods, simulate agent behaviors at the micro level and can generate macro-level emergent patterns from the bottom up (Epstein 2006, Wang, Xue et al. 2014, Wang, Xue et al. 2015). As our recent study showed, ABM can provide unique insights in childhood obesity research (Chen, Xue et al. 2016).

This study is part of the big NIH U54 (U54 HD070725) project. The U54 Request for Application (RFA) requires the research to include these features: 1) framing obesity as a complex systems problem, 2) setting cross-disciplinary, cross-level hypotheses at the outset of research, 3) testing and evaluating structural interventions at the environmental and policy levels, 4) capacity building including systems training, 5) developing and applying systems methodologies, and 6) maintaining a global perspective. With the aid of ABM, this study aimed to examine the role that the follow-the-average (FTA) social norm may play in the spread of childhood obesity. FTA is a popular hypothesized mechanism that how social norms may affect behavior but has not been well tested using empirical data (Hammond and Epstein 2007). Following FTA, individuals evaluate their status and adjust to engage

in socially acceptable behaviors. The rule has its theoretical and empirical foundation (Cialdini and Trost 1998, Ariely 2001, Chong and Treisman 2005, Burke, Heiland et al. 2010). In this study, we specifically examined how FTA as one type of social norm may influence children's body mass indices (BMI) and their consumption of fruits and vegetables (FV). We tested how misperception of the FTA may affect children's BMI growth. Based on rationality and the assumption of utility maximization, a group of schoolchildren's BMI and FV intake within social networks (schools) were simulated. Since social influence on individuals' BMI is usually masked and mixed with food and built environment effects, there has been considerable debate about whether obesity is contagious. The results from our ABM simulations intend to answer this question from a generative standpoint.

## **4.2 Methods**

### ***Overview of study design***

We developed an ABM linked with longitudinal empirical data collected from the Childhood Obesity Prevention through Physical Activity Promotion in China project and a US nationally representative study, the Early Childhood Longitudinal Study – Kindergarten Cohort (ECLS-K). We conducted simulation analysis using the ABM. ABM is a type of computational model suitable to simulate micro-level behaviors and the dynamic interplays among agents (Epstein 2006, Auchincloss and Roux 2008). Although there are some applications of ABMs in topics such as substance abuse, influenza epidemics and hospital networks (Andre, Ijaz et al. 2007, Cobb, Graham et al. 2010,

Mabry, Marcus et al. 2010, Gwizdala, Miller et al. 2011, Lee, Ye et al. 2012), the applications of ABMs on public health, including obesity research, remain limited.

***Agent-based model, a systems model***

We built an ABM to examine and test the possible mechanisms of social norm effect on children's BMI and fruit and vegetable consumption behavior. ABM is suitable for this study for a number of reasons: It can incorporate space into the computation model, including physical space (distance) and social space (social networks); agents can be placed in a spatial/social context with specified starting conditions and interact with each other and with their environment, given a set of behavior rules. Agents can be heterogeneous and different from one another in numerous ways relevant to obesity, e.g., gender, age, race, SES, environment, social network. In our model, the agents are children. The children interact with each other in a given social network, which is the school they attend, as suggested by existing studies (Urberg, Değirmencioğlu et al. 1995). The objective of each child is to maximize his/her utility. All the children observe the socially acceptable body image (quantified by BMI in the model) and the consumption behavior in their network. Under the social norm influence, deviation from the socially acceptable body image and consumption behavior causes disutility. These are the rules that govern how these children interact with each other and how the interaction leads to the self-adjustment of the children's BMI and FV consumption. Figure 4-1 describes the structure of our ABM.

<Figure 4-1 about here>

### ***Behavioral rules for the ABM***

The key task of our ABM is to assess the social norm effect. There is no common definition of social norms. In a general sense, social norms are rules that guide individual behavior in interactions with others. Group pressure ensures the avoidance of deviant acts in group members' behavioral decision-making process. The norms and how individuals communicate the norms play a central role in the process. In our model, the social norm effect was modeled through the behavior rule that governed children's interactions, i.e., the FTA rule (Hammond and Epstein 2007). This rule defines how individuals communicate with the social environment. Individuals evaluate their status and adjust to engage in socially acceptable behaviors. The rule has its theoretical and empirical foundation (Cialdini and Trost 1998, Ariely 2001, Chong and Treisman 2005, Burke, Heiland et al. 2010). The reference group from which the normative information is derived is a determinant of the communication and interaction patterns as well. The following sections explain how the behavior rule was defined in the ABM to capture the social norm effect.

***1) The effect of a social norm on children's BMI:*** Each agent (child) exists within a social network (i.e., a school) and is subject to equal peer influence within that network. Agents interact with each other, obeying the follow-the-average rule in which agents adjust their BMI to match the mean BMI in their social network. Thus, within a social network, everyone contributes to the construct of the social norm and is influenced by it. The boundary of the social network in this study was assumed not to extend beyond the school that the agent attended, i.e., there was no communication or spill-over effect

between schools. At baseline, each agent was assigned an initial BMI according to the empirical data.

Under the FTA rule, the BMI for agent  $i$  at time  $t$  can be expressed in a simple form:

$$(1) \quad BMI_{it} = BMI_{it-1} + \alpha_t * \delta * DIF_{it-1} + E$$

where DIF is the difference between the individual BMI and the social mean BMI at the beginning of the last time interval,  $E$  captures the average growth trend as children age, as determined by genetic and biological factors and shared environmental factors.  $\alpha$  is the average net effect of the social norm on BMI change. Heterogeneity was explicitly introduced by  $\delta$ , a random shock drawn from the uniform distribution in the range between 0 and 1. This shock modified the average net social norm effect across individuals and was used to represent an individual's capability to adjust to a socially acceptable BMI level given restrictions imposed by physical, psychological, environmental and other contextual factors.

**2) The effect of social norms on children's FV consumption:** Similarly, agents' FV consumption behavior was defined as:

$$(2) \quad FV_{it} = FV_{it-1} + \beta_t * \delta * DIFV_{it-1}$$

where DIFV is the difference between the individual FV consumption and the social mean FV consumption at the beginning of the last time interval,  $FV_{it-1}$  is the FV

consumption index of agent  $i$  at time  $t-1$ ,  $FV_{it}$  is the FV consumption index of agent  $i$  at time  $t$ ,  $\beta$  is the average propensity for agents to adjust their FV consumption to fill the gap, and  $\delta$  is a random draw from a standard unit normal random variable, representing the individual heterogeneity due to environmental, physiological, psychological and other unobservable factors.

**3) Hypothetical scenarios of misperception of the social norm:** In our model, we assumed that children can perfectly observe the social mean BMI and fruit and vegetable consumption behavior of their social network. However, in reality, imperfect observation may occur, which leads to misperception of the social norm, as some studies suggest (Maximova, McGrath et al. 2008, Duncan, Wolin et al. 2011). Based on the learned parameters in the previous model settings, we examined the impact of misperceptions on children's BMI changes. We constructed three hypothetical scenarios in which follow-the-average remains as the governing rule, but children with a BMI above social average may wrongly perceive the real situation:

Scenario 1. Qualitative deviance misperception, i.e., children with a BMI above the real social average perceive their BMI as under the average and make BMI adjustments opposite to what the FTA rule would suggest.

Scenario 2. Consensus misperception, i.e., children with a BMI above the real social average perceive that others have a similar BMI and make no attempt to make changes.

Scenario 3. Probabilistic quantitative misperception, i.e., children with a BMI above the social average correctly observe the real social average BMI within a range of

probabilities. For illustration purpose, we assumed 50% of these children are able to make the expected changes, while the remaining 50% follow Scenario 1.

### ***Calibration and validation of ABM generated findings***

**1) Model calibration and validation:** From the generative perspective, the validity of an ABM crucially depends on how well the model-generated data can reproduce the observed data. To our knowledge, there is no established algorithm available in the literature to guide numerical parameter calibration for ABMs. We used empirical longitudinal data to calibrate and validate our model. First, we initialized the model by assigning baseline attributes to each agent. These attributes included gender, age, race/ethnicity, baseline BMI and FV consumption, as well as the social network in which the agent resided. The social networks had no spatial relationship, as we did not examine the spillover effect. The parameters to be estimated were  $\alpha$  and  $\beta$ , defined in the behavioral rules as described in the previous section. Then the model searched for the numeric values of  $\alpha$  and  $\beta$  until the model-generated data matched the empirical data to the greatest extent possible.

The criterion we used in our calibration was the Mean Squared Error (MSE), and we also checked the distribution between the observed and the model-generated data distributions, i.e., deciles, the means and the standard deviations. We compared the agreement between the observed and the ABM-generated data using moments, correlation coefficients and distributional characteristics.

Our ABMs were designed using NetLogo 5.2 (Wilensky 1999). Other statistical analyses were conducted using SAS 9.2 and STATA 11.

*2) Data from the Childhood Obesity Prevention through Physical Activity Promotion in China Project:*

The Childhood Obesity Prevention through Physical Activity Promotion in China project was initiated and conducted by the Nanjing Municipal Center for Disease Control & Prevention. There were 32 primary and 16 junior high schools randomly selected from 8 districts in Nanjing, China. The 4th and 7th graders were recruited. Baseline data were collected in September 2013; follow-up data were collected in May 2014. Participants' ages ranged from 9 to 14 years old, with most of them being 9 (grade 4 in the primary schools, n = 32) and 14 (grade 7 in the junior high schools, n = 16). Routine health-related education was provided to all study schools, while a specially developed 1-year multi-component PA promotion program was implemented in intervention schools. PA was assessed with a validated questionnaire. This self-administered instrument was used to collect information on students' demography, their knowledge, attitudes and practices (KAP) about obesity, the status of their physical activity and their diet in the previous week. Body height, weight and blood pressure were measured by trained hospital doctors.

We used the Childhood Obesity Working Group of the International Obesity Taskforce (IOTF) Reference to categorize the Chinese children in the study as normal weight, overweight, or obese based on age, gender and BMI (Cole et al. 2000). The IOTF BMI references were developed based on nationally representative cross-sectional datasets from six countries: Brazil, Great Britain, Hong Kong, the Netherlands, Singapore, and the United States. The age-gender specific cutoff points for children correspond to adult BMI cutoff points as defined by the World Health Organization:



BMI < 25 kg/m<sup>2</sup> for normal weight, BMI 25–29.99 kg/m<sup>2</sup> for overweight, and BMI ≥ 30 kg/m<sup>2</sup> for obesity.

Fruit and vegetable consumption was measured by asking the participants how many times they consumed vegetables (excluding potatoes) and fruits in the past week. Table 1 presents the characteristics of the participants in the China data.

*3) Empirical data (Early Childhood Longitudinal Study – Kindergarten Cohort, ECLS-K):*

The ECLS-K is a study following a nationally representative sample of children recruited from 1280 schools across the US in 1998-1999 up to the 8<sup>th</sup> grade (in 2007). Schools were the sites for sampling and recruitment. Since food consumption frequencies were collected only at the follow-ups in the 5<sup>th</sup> and 8<sup>th</sup> grades, we utilized data from these two waves of follow-up for the current model: the 5<sup>th</sup> grade as baseline and the 8<sup>th</sup> grade as follow-up.

In this study, we selected children who stayed at the same school from 5<sup>th</sup> to 8<sup>th</sup> grade. We excluded those who transferred to another school so as to prevent the contamination of different schools and therefore different social networks in the model. Schools with 10 or more student participants in the 5<sup>th</sup> grade were included in the analysis.

Table 4-1 presents the summary characteristics of the children in the data.

< Table 4-1 about here >

The 2000 CDC Growth Chart was used to convert children's BMI into sex-age specific Z scores and percentiles. The age-sex-specific percentiles of  $\geq 85^{\text{th}}$  and  $\geq 95^{\text{th}}$  were used to define overweight/obesity and obesity status, respectively (Kuczmarski, Ogden et al. 2002). To generate mutually exclusive weight status groups when examining the agreement between observed data and the ABM-simulated data, we defined the non-overweight group as sex-specific percentiles  $< 85^{\text{th}}$  or  $\geq 95^{\text{th}}$  and the non-obese group as sex-specific percentiles  $< 95^{\text{th}}$ .

The ECLS-K assessed children's food consumption in the 5th and 8th grades. The FV index is a compound index constructed from children's self-report consumption frequencies in the previous week (7 days). Children reported their consumption of fruits and vegetables as zero, 1-3 times in the last week, 4 to 6 times in the last week, 1 time per day, 2 times per day, 3 times per day, and 4 or more times per day. We constructed a FV index score, a continuous variable, by adding up the separate consumption frequencies. We also categorized FV consumption as  $< 3$  vs.  $\geq 3$  times per day.

## **Results**

### ***ABM simulation findings on the effect of social norm on children's BMI***

After a thorough calibration and validation process, as described in the previous section, we obtained the  $\alpha$  for those whose BMI was below the social average, which was 0.025 ( $\text{kg}/\text{m}^2$  /year), while the  $\alpha$  for those whose BMI was above the social average was 0.015. The general BMI growth trend,  $E$ , was found to be 0.65  $\text{kg}/\text{m}^2$  /year in the US model. The  $\alpha$  in the ABM for Chinese children was 0.05 ( $\text{kg}/\text{m}^2$ ) for those whose BMI was below the social average and 0.045 for those above the social average, with the

general trend being 0.28 kg/m<sup>2</sup> /year. Table 4-2 reports the descriptive statistic comparisons for both the US and Chinese models. It is evident that the ABM-simulated BMI distribution “mimics” well the observed BMI distribution. The correlations between simulated BMI and observed BMI were as high as 0.87 and 0.9 for the US and Chinese data, respectively.

We conducted a sensitivity analysis to check for the existence of the proposed social norm mechanism. In the US ABM, the mean squared error (MSE) between the simulation and the observation for BMI was 4.86<sup>2</sup>. After we silenced the social norm effect with the growth trend unchanged, the MSE increased to 4.92<sup>2</sup>, indicating the existence of social norm effects and the validity of the model, though the magnitude is small.

As Table 4-3 shows, we further categorized the children as normal, overweight, and obese based on the IOTF international reference for Chinese children and the CDC 2000 growth chart for the US children. Kappa statistics suggested a high agreement between the observed and ABM-predicted weight status. These results suggest the validity of our hypothesized mechanism of the social norm effect on children’s BMI changes.

We stratified our models by gender and by grade (in the Chinese model only). However, significant differences were not suggested by these simulation results. The social norm was shown to have similar impact on boys and girls.

< Table 4-3 about here >

### ***ABM simulation findings on the effect of social norms on children's FV consumption***

In the Chinese children, the parameter for the social norm effect was calibrated to be 0.2, while for children who consumed FV above the average level, the coefficient of the social norm was calibrated to be 0.09. In contrast, for the US model the social norm effect was 0.14 for those who consumed FV above the average level, while the coefficient was to 0.05 for those who consumed FV below the average. Table 4-2 reports the summary statistics of the observed and simulated FV consumption distributions, showing that the ABM-predicted FV consumption under social norm influence was close to the observed, especially around the median.

Nevertheless, a comparison of the correlation coefficients between the observed and ABM-predicted FV intakes indicates that social norms might explain less FV consumption variance in our ABM in both countries. As Table 4-2 and Table 4-3 suggest, however, FTA did not perform well in explaining FV consumption variations, as evidenced by low Kappa statistics. This finding indicates that social norms may play a less influential role in children's FV consumption.

### ***Simulation evidence on personal misperception and social consequences***

According to the general model mentioned above, we compared the children's BMI changes with and without the presence of misperceptions. Using the US data as an example, Table 4-4 reports the mean BMI changes from 5<sup>th</sup> grade to 8<sup>th</sup> grade under the influence of misperceptions. It shows that individuals' misperceptions of normative BMI would lead to an increase of overall mean BMI at the group level. Among the three

scenarios, the mean qualitative misperception would cause the largest mean BMI increase. ABM simulations showed similar patterns when using the Chinese data.

<Table 4-4 about here>

## **Discussion**

Using ABM and empirical data, this study demonstrated the effects of social norms on Chinese and US children's BMI growth and FV consumption, i.e., a follow-the-average social interaction rule. Our analysis showed a good agreement between observed and ABM-predicted BMI, e.g., the Pearson's correlation coefficients were high, indicating the validity of our ABM and the existence of the follow-the-average social norm effect. Furthermore, country differences were apparent. The social norm was shown to have a higher impact on children's BMI growth in China than in the US.

*Social Norms and Children's BMI Changes:* As the simulation results suggest, the influence of the social norm on children's BMI adjustment is asymmetric, though the deviation from social average BMI could trigger the adjustment process in either direction. It is more difficult for children to lower BMI growth than to gain BMI in order to meet the social norm. This result is in line with the finding of Bernier et al. that children in the lowest BMI percentile have a greater desire for change in body shape (Bernier, Kozyrskyj et al. 2010). Moreover, the results suggest that for children whose BMIs were at the upper tail of the BMI distribution, their BMI adjustment behaviors become more heterogeneous and the social norm contributes little in explaining their BMI changes. This phenomenon could be due to various endogenous and exogenous factors, which cause higher heterogeneous behavior among these children, for example,

differences in energy metabolism and appetite control and the influence of environment. Under-average children had a clear aim to attain growth above the average rate, while the over-average children faced the conflicting aims of fulfilling linear growth potential and preventing overweight/obesity. This dilemma adds to the complexity and heterogeneity of weight/BMI-change among the heavier children.

Cross-country differences were evident. Our models suggested apparent differences in the social norm effect between China and the US. The magnitude of the social norm impact on children's BMI change was about 2-3 times higher in Chinese children than in the US children. Such difference has cultural roots. Originating in its rich cultural traditions, Chinese society values collectivism (Earley 1989). Children are taught to follow the norm of social groups for the benefit of individuals and the whole society. Research has shown that Chinese are more group oriented than Americans (Earley 1989). Moreover, empirical findings suggested that Chinese tend to be more homogenous compared to other national groups (Triandis, McCusker et al. 1990). Therefore, maintaining a socially acceptable and desirable body image could be a more important factor influencing Chinese children's weight outcomes.

*The Social Norm and FV Consumption:* Asymmetric social norm influence was evident in FV consumption as well. The ABM simulation suggests that on the one hand, children with low FV consumption may be influenced by the perceived social norm to increase their FV consumption, while those with high FV consumption may be less influenced by others in the same social network. Our findings indicate that the attributes of the FV themselves, such as visual cues and palatability, may be more important than social norms when children are making food decisions, especially when their

consumption reaches a threshold level (Pliner and Mann 2004). Nutrition education about the health benefits of FV thus should intervene to facilitate desirable behavior changes. These results suggest the importance of nutrition education and the power of good role-models in initiating and maintaining high FV consumption.

The impact of the social norm on FV consumption was less evident than that on BMI adjustment. This is likely to be because low/high FV consumption may not cause immediate consequences in social binding and thus leads to fewer behavioral changes. In contrast, body image can be directly observed and may incur negative psychological effects, such as suicidal attempts, lower self-esteem and depression (Strauss, Smith et al. 1985, Strauss 2000). Therefore, we may expect to observe much stronger social norm effects on children's BMI than on their FV consumption behavior because of the difference in the seriousness of the consequences.

The weaker predicted or observed social norm impact on FV intake could also be affected by intra-individual variation in weekly food consumption. Moreover, FV consumption in our data was measured in frequency, rather than amount. Although children consume a greater quantity of foods when growing up, the FV consumption pattern (frequency) may be established at earlier life stages. Hence, children's real FV consumption frequency might not change much with the FTA rule. Food environment and household dietary habits may have a greater influence on children's food choices than peer influence.

*Strengths and Limitations:* This study is the first cross-country ABM-based study examining the effects of social norms on childhood obesity. For the first time in the field, we tested social norm impacts on BMI adjustment behavior and FV intake among

children using large, empirical, longitudinal data sets in different cultural settings. Our model focused on the "individual-level effect" rather than solely examining the weight distribution transitions. Furthermore, we added the time dimension in the analysis of the adjustment process. As an improvement to existing models, our model explicitly accounted for the heterogeneity of individuals and gender differences and showed asymmetric social influence on children's BMI. Burke and Heiland (2007) used NHANES data to calibrate their model, but the data was too limited to identify social networks and analyze agent behavior within these networks (Burke and Heiland 2007). The data we used provided natural, well-defined social networks—the children's schools—which largely enhanced the ability of our model to simulate real-world social norm effects.

Compared to the existing studies on the contagious nature of obesity among family members and friends, the ABM of this study overcomes the intrinsic limitations and gaps embedded in the traditional methods, such as the confounding effects of homophily and shared environment, mis-specified regression models and sensitive estimation approaches. Hypothetical mechanisms are explicitly simulated and tested through ABM, generating concrete evidence that allows us to make causal inferences about the effect of social norms on BMI distribution among children.

The study has a few limitations: First, the BMI model did not incorporate the child's behavioral approaches to adjusting their BMI under the influence of social norms. Changing energy intake and physical activity both can lead to BMI changes. We did not model specific behavioral changes during the BMI adjustment process. Second, due to the scope of this study, the model did not test the effectiveness of potential intervention



options to promote desirable social norm effects and to inhibit negative impacts, simultaneously. Third, the model cannot distinguish pure social norm effects from the influence of other factors, such as the influence of the media and food environment at national and local levels, which could reinforce the social norm effect. Fourth, boys and girls may perceive differently regarding body image and thus may follow different social norms. The current study did not test the potential differences. However, these limitations do not weaken the current study, but warrant more future research.

In conclusion, our agent-based model simulation analysis calibrated with empirical data demonstrated the possible effects of social norms on children's BMI growth in China and the US as well as the considerable differences in the effects between these two countries, which supports our hypothesis as well. The follow-the-average social interaction rule could be one of the mechanisms that influence children's BMI growth, although it was not helpful in explaining fruit and vegetable consumption to a substantial extent. These results indicate that health education and promotion of obesity awareness, which may influence socially acceptable and unacceptable body weight, are important to prevent excessive weight gain in school children. Moreover, the influence of social norms could be more prevalent and robust in China than in the US due to cultural differences. Hence, tailored strategies in different populations should be developed to improve social intervention-based childhood obesity prevention programs and policies. Agent-based models can be useful to help explore social network factors affecting childhood obesity and eating behaviors.

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Table 4-1: Distribution of the BMI and fruit and vegetable (FV) consumption of Chinese children (9-13 yrs, CHNS) and US children (10-14 yrs, ECLS-K)

Variables	Baseline						Follow-up				
	US children										
	Number of schools <sup>1</sup>		Observations <sup>1</sup>	Mean	SD	Min	Max	Mean	SD	Min	Max
BMI (kg/m <sup>2</sup> )	60		740	20.2	4.5	12.2	57.5	22.4	4.8	14.7	46.3
FV consumption (times/week)	60		740	18.6	17.2	0.0	115.5	19.2	14.0	0.0	86.0
	Chinese children										
BMI (kg/m <sup>2</sup> )	48		9860	19.3	3.7	9.7	36.9	19.6	3.8	10.1	45.1
FV consumption (times/week)	48		9860	7.8	5	0.0	80	8	4.8	0.0	60

Note:

<sup>1</sup>Number of US schools have been rounded for confidentiality purposes.

Table 4-2: Observed and Agent based model (ABM) predicted BMI (kg/m<sup>2</sup>) and fruits and vegetables (FV) intake (times/week) distributions at follow-up

a: Comparison between Observed and ABM-Predicted data for Chinese children

	Mean	SD	Percentiles									Correlation coefficient <sup>1</sup>
			10	20	30	40	50	60	70	80	90	
<b>BMI (kg/m<sup>2</sup>) distribution at</b>												
<b>Follow-up</b>												
Boys and girls												
Observed	19.6	3.8	15.3	16.4	17.2	18.0	18.9	19.8	20.9	22.4	24.5	
ABM-predicted	19.6	3.6	15.5	16.5	17.3	18.1	19.0	19.9	21.0	22.4	24.5	
												0.9
Boys												
Observed	20.1	4.0	15.8	16.8	17.6	18.4	19.4	20.44	21.64	23.3	25.6	
ABM-predicted	20.2	3.8	15.9	16.9	17.8	18.7	19.7	20.7	21.8	23.4	25.5	
												0.9



Girls

Observed 19.0 3.4 15.1 16.1 17.0 17.8 18.6 19.4 20.4 21.6 23.5

ABM-predicted 18.9 3.2 15.2 16.1 16.9 17.6 18.4 19.2 20.1 21.3 23.2

0.9

**FV consumption (times/week)**

**distribution at follow-up**

Observed 19.2 14.0 8.0 10.0 11.0 13.0 14.0 14.0 14.0 15.0 26.0

ABM-predicted 19.7 14.8 7.0 9.3 11.0 13.0 14.0 14.0 14.0 16.9 24.5

0.2

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Note:

<sup>1</sup> Correlation coefficient between observed and ABM -predicted values for BMI or FV.

b: Comparison between Observed and ABM-Predicted data for US children

	Mean	SD	Percentiles									Correlation coefficient <sup>1</sup>
			10	20	30	40	50	60	70	80	90	
<b>BMI (kg/m<sup>2</sup>) distribution at</b>												
<b>follow-up</b>												
Boys and girls												
Observed	22.4	4.8	17.8	18.7	19.6	20.4	21.3	22.1	23.4	25.2	28.9	0.9
ABM-predicted	22.2	4.4	17.9	18.7	19.4	20.2	21.1	22.2	23.6	25.3	27.8	
Boys												
Observed	22.3	4.5	17.6	18.6	19.4	20.3	21.4	22.3	23.6	25.9	28.9	0.9
ABM-predicted	22.2	4.1	17.7	18.5	19.3	20.1	21.4	22.7	24.1	25.8	28.2	
Girls												

Observed	22.4	5.0	17.9	18.9	19.8	20.4	21.1	22.0	23.1	24.8	28.9	
ABM-predicted	22.2	4.7	18.0	18.9	19.5	20.4	20.9	21.9	23.3	24.6	27.2	0.9

**FV consumption (times/week)**

**distribution at follow-up**

Observed	19.2	14.0	6	8	10	12.5	14.5	18	23	28.5	39	
ABM-predicted	19.7	14.8	8.0	10.0	11.3	12.8	14.4	17.5	21.0	26.9	37.7	0.3

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Note:

<sup>1</sup> Correlation coefficient between observed and ABM -predicted values for BMI or FV.

Table 4-3: Agreement between observed and ABM-Predicted weight status and fruits and vegetables (FV) consumption ...Chinese and US children

Observed at follow-up	ABM-predicted at follow-up		Kappa <sup>1</sup>
	N	N	
<b>Chinese children</b>			
<b>Weight status</b>			
	Normal	Overweight/obese	
Normal	5866	475	
Overweight/obese	424	3093	0.80
	non-obese	obese	
non-obese	8640	149	
obese	243	826	0.79
<b>FV consumption</b>			
	< 3 times per day	>=3 times per day	
< 3 times per day	7419	991	
>=3 times per day	1071	377	0.15
<b>US children</b>			
<b>Weight status</b>			
	Normal	Overweight/obese	
Normal	452	49	
Overweight/obese	40	195	0.72

	Non-overweight	Overweight	
Non-overweight	538	73	
Overweight	55	70	0.42
	non-obese	obese	
non-obese	605	21	
obese	30	80	0.72
<b>FV consumption</b>	< 3 times per day	>=3 times per day	
< 3 times per day	378	102	
>=3 times per day	138	118	0.26

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Note:

<sup>1</sup>Kappa measures the agreement of between the observed and ABM -predicted values for BMI or FV.

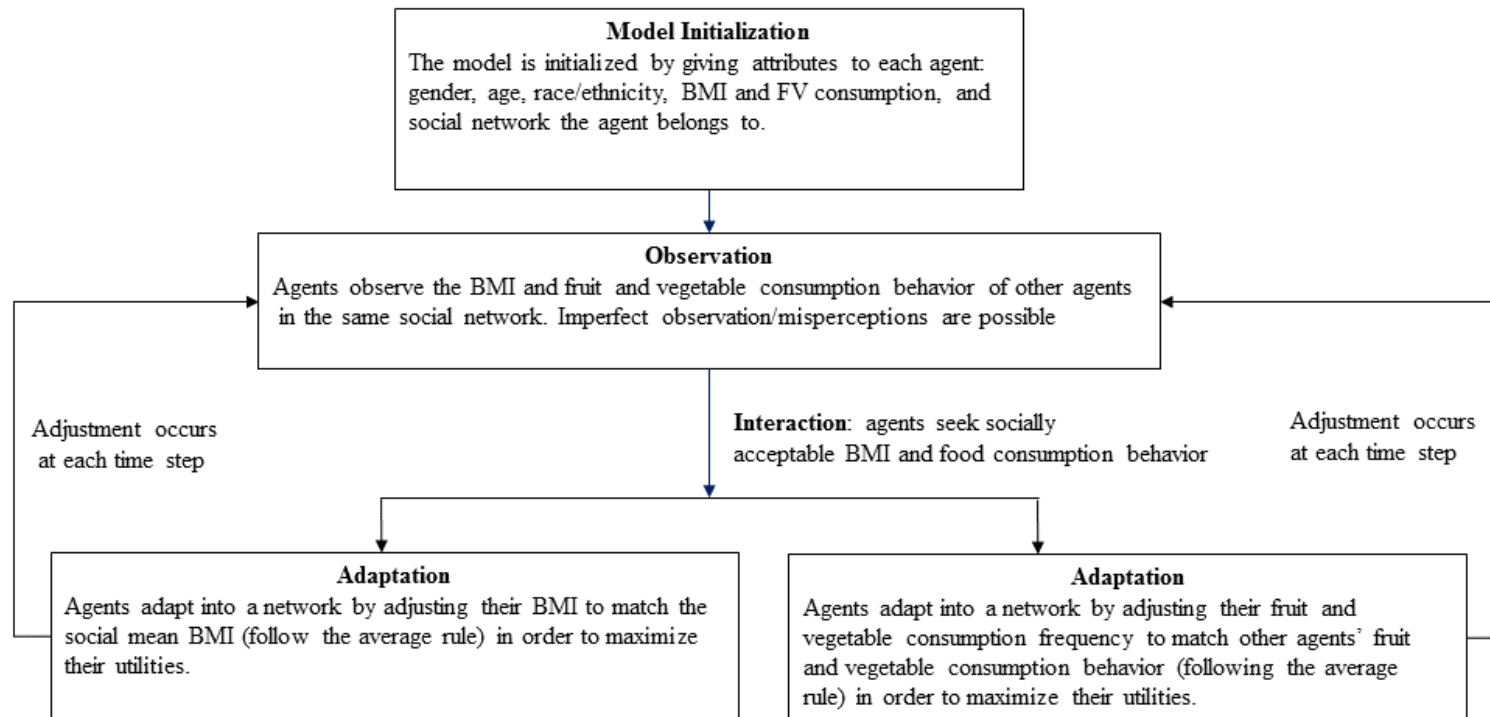
Table 4-4: ABM simulation testing impact of misperception of social norm on social mean BMI changes- four scenarios using US data <sup>1</sup>

		Scenario 1	Scenario 2	Scenario 3
Baseline scenario		Qualitative deviance misperception	Consensus misperception	Probabilistic quantitative misperception
Grade	Mean	Mean	Mean	Mean
5th	20.15	20.15	20.15	20.15
6th	20.85	20.91	20.86	20.86
7th	21.52	21.64	21.55	21.54
8th	22.18	22.37	22.22	22.21

Note:

<sup>1</sup> Baseline scenario-- Individual children correctly perceive the social mean BMI and adjust accordingly. Scenario 1. Qualitative deviance misperception, i.e. children with a BMI above real social average perceived their BMI as under the average and make opposite BMI adjustments; Scenario 2. Consensus misperception, i.e. children with a BMI above real social average perceived others are having similar BMI and make no attempt to make changes; and Scenario 3. Probabilistic quantitative misperception, i.e. children with a BMI above social average correctly observed the real social average BMI with a range of probability and 50% of these children are able to make the expected changes while the remaining 50% follow Scenario 1.

Figure 4-1: An agent-based model (ABM) of social influence on children’s BMI change and fruit and vegetable consumption



## Appendix: Model Documentation

### Purpose

Social norm theory suggests that the behavior of individuals embedded in a social network is influenced by their perceptions of how other members believe and behave within that social system. Individual behavior is purposively rationalized to avoid disapproval of other group members. This model aims to examine: a) the effects of social norms on students' BMI growth and their fruits and vegetables (FV) consumption; and b) the effects of misperceptions of social norms on US children's BMI growth.

### State Variables and Scales

Children are the agents that belong to a specific social network, defined as schools.

Variable name	Brief description
BMI	Children's body mass index
FV	Children's weekly fruit and vegetable consumption frequency
Coordinates	X and Y coordinates of the schools representing the locations and boundaries of the social networks

We do not include spillover effects across social networks, so any relationship between schools is not modeled. The system reaches an equilibrium when all the sub-networks reach their equilibria.

### Process Overview and Scheduling



The model assumes rationality and utility maximization of agents. Deviation from socially determined mean body weight and eating behavior leads to disutility. An agent observes body images and eating decisions of other agents and adjusts his/her own body weight and food intake to gain social acceptance and thus achieve their goals of utility maximization.

All of the agents have identical behavior rules. The adjustments are made at each time step. The updating occurs simultaneously for all the agents.

### **Design Concepts**

#### *Emergence*

The model explores the emergent phenomena of the patterns of fruit and vegetable consumption, BMI trajectory of the whole population, and trends in the prevalence of agents with BMI  $\geq$  85th and  $\geq$  95th percentiles of the CDC growth chart. These are the results that emerge from individual decisions of the agents and interactions between the agents.

#### *Adaption*

Agents in the system are allowed to learn, adjust and update. They aim to adapt into a network by following the social mean behavior and weight status in order to maximize their utility.

#### *Interaction*

Agents interact at a local level. Agents interacted with each other by obeying the follow-the-average rule in which agents adjust their food intake and weight to match the mean

BMI and fruit and vegetable consumption in their social network. Thus, within a social network, everyone contributed to the construct of the social norm and was influenced by it. The boundary of a social network was assumed not to extend beyond the school that an agent attends, i.e., there was no communication or spill-over effect between schools.

### *Sensing*

Agents perfectly observe the BMI and fruit and vegetable consumption behavior of others in the same social network. Misperception scenarios in which information was not perfect were also examined.

### *Stochasticity*

The heterogeneity of the agents' ability to self-adjust was reflected by random draws from a uniform distribution.

### *Observation*

Observations include BMI and fruit and vegetable consumption distributions and temporal trends.

### **Initialization**

The model is initialized by setting the attributes of the agents, including gender, age, race/ethnicity, and BMI and FV consumption at baseline and by assigning agents to specific social networks (schools) based on empirical data.

### **Input**

Further inputs are not required once the model is initialized.

### **Sub-models**

Agents adjust their BMI to match the social mean BMI to maximize utility. The interaction rule that governs BMI change for an agent  $i$  at time  $t$  can be expressed in a simple form:

$$BMI_{it} = BMI_{it-1} + \alpha U(0,1) DIF_{it-1} + E$$

where DIF is the difference between the individual BMI and the social mean BMI at the beginning of the last time interval,  $E$  captures the average growth trend as children age, as determined by genetic and biological factors, and shared environmental factors.  $\alpha$  is the average net effect of social norms on BMI change. Heterogeneity was explicitly introduced by a random shock drawn from the uniform distribution in the range between 0 and 1. This shock modified the average net social norm effect across individuals and was used to represent an individual's capability to adjust to a socially acceptable BMI level given restrictions imposed by physical, psychological, environmental and other contextual factors.

Similarly, the interaction rule that governed agents' FV consumption behavior was defined as:

$$FV_{it} = FV_{it-1} + \beta_t * \delta * DIFV_{it-1}$$

where DIFV is the difference between the individual FV consumption and the social mean FV consumption at the beginning of the last time interval,  $FV_{it-1}$  is the FV consumption index of agent  $i$  at time  $t-1$ ,  $FV_{it}$  is the FV consumption index of agent  $i$  at time  $t$ ,  $\beta$  is the average propensity for agents to adjust their FV consumption to fill the gap, and  $\delta$  is a random draw from a standard unit normal random variable, representing

the individual heterogeneity due to environmental, physiological and psychological factors.

# **Chapter 5 To Tax or Not to Tax – Systems Dynamics Modeling to Explore Potential Strategies to Reduce Sugar-Sweetened Beverage Consumption among Chinese and US Children**

## **Abstract**

**Objectives:** Using fiscal policies to influence unhealthy diet behavior, including sugar sweetened beverage (SSB) consumption, has becoming increasingly popular. However, the effectiveness and unintended consequences remain understudied. This study examined: 1) the interactions and dynamics in the SSB supply-demand system; 2) tax effects on beverage and energy intakes in the short and long run in Chinese and US children; and 3) option of subsidizing bottled water consumption and compared the effects with SSB taxes.

**Methods:** We developed a system dynamics model (SDM) and simulated the dynamics of SSB and its substitute consumption in response to an excise SSB tax in China and the US based on the data from Childhood Obesity Study in China Mega-cities and the US National Health and Nutrition Examination Survey (NHANES), and explored the effects of bottled water subsidies.

**Results:** Our model projected that in both countries, a tax-induced SSB price increase would initially result in reduced SSB consumption. However, the dynamics in the demand system and supply response could offset the reduction over time. In China, a

20% tax on SSB would cause an 11.5 kcal/d reduction in energy intake from beverage consumption, however, over a 10-year period, the net reduction of average daily energy intake compared to the level before taxing would decrease to 4 kcal/d. In the US, a 20% tax might result a net reduction of 36 kcal/d initially, and the reduction would decrease to 10 kcal/d in a 10-year period, i.e., the initial effect decreases from approximately 1.5 cans less consumption of regular soda per week to about half a can per week in 10 years. Our simulations suggest that subsidizing bottled water price could be more effective in reducing SSB consumption and promoting bottled water consumption in both the short and long run, as compared to SSB taxes.

**Conclusions:** Our systems models based simulation analysis indicates that supply response and the dynamics in demand are important when assessing potential tax effects on SSB consumption. Subsidizing bottled water prices should be implemented together with SSB taxes and might be more effective and generate less controversy as a policy-based intervention to promote healthy beverage consumption.

**Keywords:** sugar-sweetened beverage, tax, systems models, system dynamics model, obesity

## 5.1 Introduction

Childhood obesity has become a serious public health threat in China and in the United States (Wang and Beydoun 2007, Flegal, Carroll et al. 2010, Ogden, Carroll et al. 2012). The underlying causes of the obesity epidemic are complex. The complications and dynamic correlations in the obesity system make the effect of interventions targeting a single risk factor highly unpredictable and may lead to unintended consequences, because the system may react differently than expected. For example, New York City's calorie-labeling policy was associated with a null effect or even unfavorable food consumption or purchasing behaviors (Elbel, Kersh et al. 2009, Vadiveloo, Dixon et al. 2011). As for banning fast food advertisements, it was argued that the saved cost from marketing could be transferred to a lower retail price, which might increase consumption (Kuchler, Golan et al. 2005). Traditional reductivist approaches have successfully revealed behavioral rules that govern persons, groups, organizations and even societies or markets. Nevertheless, innovative methods are needed to incorporate these pieces of knowledge and envision how the whole system would work when important players' behavioral or decision rules are considered as a whole, as well as how the system may respond to any attempt or action to change it. Systems science provides an opportunity to do this.

Sugar-sweetened beverage (SSB) consumption is associated with obesity risk (Ludwig, Peterson et al. 2001, Schulze, Manson et al. 2004, Ebbeling, Feldman et al. 2006, Malik, Schulze et al. 2006, Vartanian, Schwartz et al. 2007, Mozaffarian, Hao et al. 2011). SSBs usually include soda, fruit drinks, sports and energy drinks, sweetened coffee and tea, and other sweetened beverages. A recent study in China suggests that in

large cities, 34% of children aged 3-7 consumed SSBs at least once per week, and there was a statistically significant association between increased SSB intake and higher BMI-for-age Z-scores and increased risk of being overweight or obese (Yu, Chen et al. 2016). In the US, excess energy intake from SSB consumption, particularly among youth, has become a major public health concern. Although recent nationally representative data showed a decreasing trend of SSBs consumption among children (2-19 y) and adults ( $\geq$  20 y), the energy intake from SSBs is still high, with a daily average of 155 kcal/d and 151 kcal/d, which equals one can of regular soda, in 2009-2010 for children and adults, respectively (Kit, Fakhouri et al. 2013).

Taxation on SSBs has become an increasingly popular strategy to help reduce consumption. Some studies have suggested that increasing SSB prices by imposing taxes would help reduce SSB consumption and generate revenues (Brownell, Farley et al. 2009, Andreyeva, Chaloupka et al. 2011). For example, a simulation study reported that a penny-per-ounce excise tax would reduce SSB consumption by 33.1 kcal/day and 54.2 kcal/day for children ages 6-11 years and 12-19 years, respectively (Levy and Friend 2013). Another study projected that a nationwide penny-per-ounce tax on SSBs could generate new tax revenue of \$79 billion over 2010-2015 (Andreyeva, Chaloupka et al. 2011). It was also suggested that a nationwide penny-per-ounce excise tax would prevent cardiovascular diseases and diabetes, reduce medical costs by more than \$17 billion, and generate \$13 billion revenue during 2010-2020 (Wang, Coxson et al. 2012). As of 2009, 33 states in the US had levied a sales tax on soft drinks at an average rate of 5% (Brownell, Farley et al. 2009). However, these taxes have shown little effect, as the tax



may be too small to influence SSB consumption (Chriqui, Eidson et al. 2008, Fletcher, Frisvold et al. 2010, Sturm, Powell et al. 2010).

Price elasticity of demand, defined as the ratio of the percentage change in demand to the percentage change in price, is the key concept used in existing studies estimating potential tax effects. Price elasticity of demand measures the responsiveness of consumers reacting to price changes. Suppose we have soda and orange juice in the demand system. If the soda's price increases by 10%, and thus the quantity demanded of soda decreases by 10%, then the own price elasticity of soda is -1; conversely, if a 10% increase in soda's price leads to a 10% increase in the quantity demanded for orange juice, then the cross-price elasticity of soda and orange juice is 1. Though useful, price elasticity is often used in an isolated and simplified way, in the case of beverage tax effects. Thus far only a few studies on SSBs have examined substitution effects by considering both the own price and cross-price elasticities (Fletcher, Frisvold et al. 2010, Smith, Lin et al. 2010, Zhen, Wohlgenant et al. 2011, Dharmasena and Capps 2012). These studies provided a more comprehensive economic grounding to estimate the potential tax effects.

A thorough understanding of the market system dynamics is needed to avoid unintended consequences and to develop sustainably effective policies. Our review of the existing literature revealed that all the estimates of price elasticities took a static view and implicitly assumed a one-stage game setting. Tax-induced price changes were treated as if they would have an immediate, once-and-for-all effect on SSB. However, changes in the demand for the substitutes will lead to changes in their own prices, which will further affect SSB consumption. This process can continue until the system reaches a new

equilibrium. Much of the existing literature does not consider dynamics in the demand system and differentiate between immediate-term, short-term, and long-term effects as a system. Some marketing research (Jedidi, Mela et al. 1999, Kopalle, Mela et al. 1999) has shown that reducing prices through promotions could have positive short-term effects on sales, while the long-term effects could be negative. These findings suggest that tax effects should be estimated with a time scale corresponding to the length of time required to reach the new balance point.

Moreover, despite the large body of literature on SSB taxes, the existing studies are largely focused on the consumers. The role that the supply side may play is ignored and unexplored, which may have substantial implications for the tax effects. In addition, tax effects have been primarily statistical models-based. For example, the recent study on Mexico claimed that the SSB tax in Mexico was associated with SSB consumption reduction (Colchero, Popkin et al. 2016). The causal inference cannot be made, and the pre- and post-comparison largely depends on the validity of the statistical model specification, which is hard to test. More solid evidence based on sound methods and data is thus needed before conclusions can be drawn.

The present study proposed two important factors to consider in a tax effect analysis: interdependence and reciprocal effects between the demand for SSBs and their substitutes, and feedbacks between supply and demand. We built a system dynamics model (SDM) to assess the potential effect of an excise SSBs tax on beverage consumption and energy intake from beverages in China and in the US. SDMs have been used previously to address dietary, physiological and demographic effects of obesity (Abdel-Hamid 2003, Homer, Milstein et al. 2006), but market effects on consumption

and weight outcomes remains an under-studied area. This study represents an initial effort to formulate and explore the implications of a SDM of the markets for SSBs and their substitutes. We explored: 1) the interactions and dynamics in the demand system; 2) SSB tax effects on beverage and energy intakes in the short and long run; and 3) other market means other than taxing SSBs.

## **5.2 Methods**

### ***Why system dynamics modeling?***

System dynamics is a modeling and simulation tool to investigate complex dynamic problems in terms of their stocks and flows and nonlinear feedback loops (Sterman 2000). Stocks, sometimes referred to as levels or states, are defined as materials or information that accumulates in the system. Materials or information flows in and out of the stocks. Feedbacks are the transmission and return of materials or information in the system. Positive feedback loops reinforce the system behavior, while negative loops tend to offset changes and maintain the equilibrium of the system. SDM was originally proposed by Forrester (1957) as a method for building computer simulation models of problematic behavior in industrial processes. It provides a useful tool to address many public health issues (Homer and Hirsch 2006, Sterman 2006). For example, we can project the effect of potential interventions without relying on randomized trials, which may be either costly in many ways or impossible to conduct in the real world (Hirsch, Homer et al. 2010). In the case of SSB taxes, the market dynamics due to a number of factors involved in demand and supply, such as dynamic firm pricing decisions, response

to market conditions, information lags, changes in consumer preference, etc., make SDM a suitable platform to examine tax effects.

### ***Data***

The data used in the simulations to estimate possible empirical policy effects in China were obtained from the Childhood Obesity Study in China Mega-cities (COCM) that was collected in October 2015. COCM sampled 1,648 students from 16 schools in four Chinese mega-cities: Beijing (China's capital city, North China), Shanghai (the largest city in China, East China), Nanjing (China's capital city before 1949, East China), and Xi'an (the largest city in West China). In each city, two primary schools and two middle schools were selected. In each school, one class was randomly selected from the 3rd to the 9th grade. All students in the selected classes and their mothers (or other primary caregivers, if mothers were absent) were interviewed. Data collected included child growth and health, family characteristics, home/community/school environment, beverage consumption, and energy-balance related behaviors. The study was approved by the Ethical Committee of The State University of New York at Buffalo and related collaboration institutes in China. Written informed consent was obtained from parents or children.

The data for the estimates in the US were mainly from the NHANES data that were used in the USDA Economic Research Service report to estimate price elasticity and potential reduction in beverage consumption and energy intake.

### ***Economic rationale and model setup***

Our SDM is based on existing studies predicting the tax impact on SSB consumption. To make the model tractable, we began with simple rules within the system

dynamics paradigm. Alternative formulations (or “competing models”) are possible and, indeed, may better represent the dynamics of supply and demand in the beverages industry. However, our purpose here is to illustrate potentially important economic concepts and the modeling approach, not to make definitive conclusions.

Econometric estimates from existing literature provide empirical parameter values for the model. We made the following necessary assumptions: 1) all SSBs, including soda, fruit drinks, sports and energy drinks, sweetened coffee and tea, and other sweetened beverages, were treated as a single homogenous composite product; 2) the supply and demand responses to price changes were modeled at market level; and 3) the market under study does not affect the prices of other goods and factors for SSB production. These simplifications enable us to avoid consideration of the complexities surrounding differentiated products, supply and demand changes in other goods and factor markets, and the interactions between these markets.

Figure 5-1 presents the SDM, including the demand and supply factors and their relationships. The demand of SSBs is determined by its own price and the prices of other substitutes. Assuming there is no change in disposable income, when the price of SSBs increases, the demand for SSBs decreases. In contrast, when the prices of other substitute beverages (e.g., milk and juice) increases, the demand for those beverages will decrease, but the purchase of SSBs will increase. Price elasticity is defined as:

$$e_{i,j} = \frac{\partial q_i}{\partial p_j} \frac{p_j}{q_i}$$

Where  $q_i$  is the quantity demanded for commodity  $i$ ,  $p_j$  is the price of commodity  $j$ . The price elasticity measures the percentage change in the quantity of beverage  $i$  demanded as a result of a one percent change in the price of beverage  $j$ .

<Figure 5-1 about here>

Consistent with existing literature, we assume that price elasticities are constant, indicating an implicit assumption of an exponential form of demand functions.

The quantities and prices are specific to a certain time period  $t$ . Currently, there is no consensus on what constitutes a plausible substitute set. Without losing generalizability, we only considered four representative beverages in the demand system: SSBs, whole milk, low fat milk, and 100% juices. The price increase in SSBs also causes an increase in the consumption of the substitutes. Increased consumption will likely lead to an increase in the prices of the substitutes, which could reversely affect the demand for SSBs, the magnitude of the changes being dependent on the cross-price elasticities between SSBs and the substitutes. The current SSB consumption level was based on the COCM and NHANSE data.

One important feedback loop in the system models is the dynamic interactions between SSBs supply and demand. A decrease in demand will affect suppliers' revenue and increase their costs due to factors such as adjustment of production and maintenance of inventory. SSB suppliers will respond by manipulating the price to help increase demand and maximize profits. We used supply response coefficients to indicate the magnitude of the responses, which ranges from 0-100% of the change in consumption

and reflects the beverage industry's capability of attenuating the price to mitigate consumption changes and associated costs. We set the coefficients by assuming a response scenario that corresponds to the tax passing rate of 90% in the second year and decreases linearly with time. As Cawley et al (2016) found that less than half the SSB tax at Berkley was passed to consumers.

We also examined the potential tax effects under different levels of excise taxes. By hypothetically increasing the current penny-per-ounce tax (equivalent to increase current SSB price by about 20%) to 35% and 50%, we assessed the nonlinear relationship between tax effects and the magnitude of taxes.

All the simulations were conducted using Vensim 5.10c (Ventana Systems, Inc). The details model setup and parameter values are described in the Appendix.

### **5.3 Results**

The following results are presented to illustrate the conceptual possibilities and capabilities of a SDM of the beverage industry, in particular what might be learned from simulating the impact of a tax on beverage consumption. However, , we do not represent these results as definitive conclusions.

#### ***Potential tax effects on beverages and energy intake with supply-demand feedbacks***

As a prominent proposal in the literature (Brownell and Frieden 2009, Wang, Coxson et al. 2012), we used a penny-per-ounce excise tax (equivalent to 20% tax rate on current price) on SSBs to assess tax effects. Figure 5-2 presents the changes in SSB consumption due to the tax shock over a 10-year period of time. In this case, the 20% tax

was assumed to take full effect in one year. To avoid unnecessary complexity and to make the cases comparable, we assumed similar supply and demand responses in China and in the US. SSB consumption was predicted to decrease by 24% in one year, assuming a -1.2 own-price elasticity (Smith, Lin et al. 2010). By adding only a low SSB supply response, it is evident that after a drop in the first year, the consumption of SSBs will reverse the downward trend and gradually bounce back. Meanwhile, consumption of the substitutes, i.e., 100% juices, whole milk, and low fat milk, stays at a level higher than the year before the tax over time. However, the consumption of these substitutes tends to stabilize at the original consumption level, in concordance with the SSB consumption. The price of SSBs changed in the opposite direction of the SSB consumption (Figure 5-2).

<Figure 5-2 about here>

Table 5-1 presents the results of a long-term tax effect on average daily caloric intake for adults and children. Energy intake reduction due to the decrease in SSB consumption will occur initially, but then consumption will rise in the following periods. The offsetting effects from substitutes will also decrease over time. Based on the COCM data, a 20% tax on SSBs will initially cause an 11.5 kcal/d reduction in energy intake from beverage consumption, however, in a 10-year period, the net reduction of average daily energy intake compared to the level before taxing decreases to 4 kcal/d. Similarly, based on estimates of caloric intake from Smith et al. (2010), a 20% tax on SSBs in the US will cause a net reduction of 36 kcal/d initially, but the reduction will decrease to 10



kcal/d in a 10-year period, i.e., the initial effect decreases from approximately 1.5 cans less consumption of regular soda per week to about half a can per week in 10 years.

<Table 5-1 about to be here>

### ***Tax effects on energy intake under different tax rates***

Table 5-2 reports the estimates under these three scenarios. The net tax effects decay quickly with time. During a 10-year period, only about 25% of the initial energy reduction would remain from a 20% SSB tax, i.e., a 4 kcal/d and 10 kcal/d reduction for Chinese children and US children, respectively, at the 10<sup>th</sup> year. Higher taxes do not necessarily improve this outcome in the long run. When the tax was increased to 35%, the energy reduction at the 10<sup>th</sup> year was 8.6 kcal/d and 12.4 kcal/d in China and the US, respectively. When a 50% tax was applied, the improvement was still not substantial over a 10-year period.

<Table 5-2 about here>

### ***Which strategy is more effective – taxing or subsidizing?***

Based on the demand system estimates from the USDA ERS, we further explored the potential effects of subsidizing bottled water consumption as an alternative option (Figure 5-3). As Figure 5-4 shows, a 20% subsidy on bottled water would initially lead to a reduction of about 15% in SSB consumption, while causing about a 5% and 9% increase in 100% juice and low-fat milk consumption, respectively, in the first year.

<Figure 5-4 about here>

If we assume similar supply responses as in the SSB tax scenario, to make it comparable, then as Figure 5-4 suggests, the consumption of bottled water will remain at a higher level compared to the pre-subsidy state during the initial 10-year period, while SSB consumption will constantly decrease due to the initial subsidy for bottled water and the endogenous dynamics between supply and demand in the system.

## **5.4 Discussion**

Policy impact is often difficult to test using traditional research design because policies act in a complex world. This study demonstrated the necessity and applicability of using SDM to study policies and interventions related to complex obesity problems. SDM simulations provided insights to predict and assess the effectiveness of fiscal pricing policies aiming at changing beverage consumption to curb the obesity epidemic. Though a promising strategy to address the obesity epidemic, the effectiveness of fiscal policy instruments such as SSB taxation in altering food consumption behaviors and their influence on energy intake and body weight remains unproven. Realizing that markets are complex systems, this study adds two additional dimensions to assess the potential tax effects on beverage consumption: dynamic supply responses and SSB-substitute interactions and feedbacks.

The three main contributions of the present study are the following, considering the current literature. First, we suggested two important conceptual possibilities when considering SSB tax effects: the potential supplier response and reciprocal relationships between SSBs and their substitutes (other beverages), i.e., a price increase of SSBs may

impact the price and consumption of its substitutes, which would in turn affect the price and consumption of SSBs. These two concepts have not drawn much attention in related research and discussions. Second, we built a SDM and applied it to show the potential responses (and interactions) of the SSB suppliers and consumers, which is a methodology contribution and provides numerical examples. Third, based on parameters from real world data, our results suggest subsidizing bottled water consumption is a more effective option than taxing SSBs to reduce SSB intake and reduce energy intake in children in the long run. However, future empirical studies are needed to help refine the model assumptions so that they better mimic the real world and provide more precise estimates and predictions.

Our SDM simulation results suggest that it is important to consider the multiple players in the system and the time scale in the estimation. The main distinction we draw is between short- and long-term effects, which hold the key to a better understanding of the potential tax impact. As our simulation analysis indicates, a 20% tax-induced price increase could lead to about a 24% reduction in SSB consumption initially. However, the effect may be temporary. A recent study examining the tax effects in Berkley, CA suggests that the SSB tax may have caused a 21% decrease in SSB consumption (Falbe, Thompson et al. 2016). However, the consumption data were reported and not from sales data. Moreover, long term effects need to be examined. Suppliers would respond to the decrease in sales in a variety of ways, such as price reductions and product promotions. As Cawley et al (2016) found that the tax pass through rate may be less than 50% at the end (Cawley and Frisvold 2015). By incorporating such mechanisms into our model, even a low level of supply response would lead to an overall energy reduction of only

25% of the initial decrease in a 10-year period of time. These results are dependent on the model assumptions regarding market structure and conditions. However, the simulations demonstrate the conceptual possibilities and suggest that knowing the potential offsetting impact of supply response is of critical importance to assess the potential tax effects.

Some studies have argued that existing SSB taxes were too small to alter consumption (Chriqui, Eidson et al. 2008, Fletcher, Frisvold et al. 2010, Sturm, Powell et al. 2010). An experimental study also suggested that SSB tax may not have impact on consumption. The study showed that a 10% tax only resulted in a short-term (1-month) decrease in soft drink purchases, but had no effect over a 3-month or 6-month period (Wansink, Hanks et al. 2012). Understanding the relationship between tax magnitude and effect on consumption will have substantive policy implications. However, this is very costly, if not impossible, to test using intervention trials. In this study, as an example application of SDM, we explored various tax rate options to identify potential effectiveness through simulations. Our simulations suggest solely increasing the tax rates would not be effective to improve the long-term effect. Subsidizing bottled water consumption could be used in combination with SSB taxes as a policy package to promote healthy beverage consumption.

This study has some limitations. First, the supply response considered in the model is at aggregate level based on a set of assumptions. Market structure and an individual firm's strategic behaviors were not incorporated. Empirical findings about industry behaviors in response to taxes are needed for a more realistic model specification. Second, we did not differentiate the price elasticities across SES, racial/ethnic, age and gender groups, which could help add more information regarding

the differential tax effects across subpopulations. Nevertheless, we demonstrate that systems models can serve as a useful tool to simulate the potential effects of policy intervention options and the various responses and interactions among the related stakeholders (e.g., SSB suppliers and consumers and policy makers), which will help guide actual field studies and policy development.

In conclusion, our SDM simulation results suggest that an SSB tax could increase SSB price initially, but over time, SSB producers may share the tax burden by reducing the price so as to increase sales. Supply response and the dynamics in demand are important when assessing tax effects. As the research on the tobacco industry suggests, suppliers could develop “defense plans” to offset short-run price increases resulting from tax increases through marketing means such as couponing and multi-pack promotions (Chaloupka, Cummings et al. 2002). Taxing SSB and subsidizing bottled water consumption could be both implemented and will be more effective and generate less controversy as a policy tool to promote healthy beverage consumption.

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Table 5-1: System dynamics model simulated potential effect of a 20% excise tax on sugar sweetened beverages (SSB) on daily energy intake (kcal/day) from different beverages among children in China and the U.S. over a period of 10 years

<b>Overall change of calorie intake compared to base year (prior to the introduction of the tax)</b>										
<b>Years</b>										
<b>Beverages</b>	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<b>Chinese children ( Kcal/d) †</b>										
SSBs	-19.7	-19.1	-18.1	-16.6	-14.7	-12.5	-10.2	-8.0	-5.9	-4.1
Fruit										
juices	3.9	3.7	3.4	3.0	2.5	1.9	1.3	0.8	0.4	0.0
Milk*	4.4	4.2	3.9	3.4	2.9	2.3	1.7	1.1	0.6	0.2
Net										
change <sup>§</sup>	-11.5	-11.2	-10.8	-10.1	-9.3	-8.3	-7.2	-6.0	-4.9	-4.0
<b>US children (Kcal/d) ‡</b>										
SSBs	-46.3	-45.1	-42.6	-39.0	-34.5	-29.4	-24.0	-18.7	-13.9	-9.7
100% fruit										
juices	6.6	6.3	5.8	5.1	4.2	3.3	2.3	1.4	0.6	0.0
Whole										
milk	2.3	2.2	2.0	1.8	1.5	1.2	0.9	0.6	0.3	0.1
Low fat										
milk	1.5	1.5	1.4	1.2	1.0	0.8	0.6	0.4	0.2	0.1

Net

change<sup>§</sup>    -35.9   -35.1   -33.4   -30.9   -27.8   -24.1   -20.2   -16.3   -12.7   -9.6

---

**Note:**

† For Chinese children, base year calorie intake estimates based on the COCM data. Price elasticities were specified in the appendix similar to the US children for demonstration purpose.

‡ For the US children, calorie intake and price elasticity estimates from the of Smith, Lin et al. (2010) were used in the calculations.

\*Any kind of milk.

§ Net energy intake changes from consuming all beverages.

Table 5-2: Simulated effect of different tax rates on net energy intake reduction from sugar-sweetened beverages during a period of 10 years

<b>^ Net daily calorie intake changes compared to base year (Kcal/d) over</b>										
<b>time</b>										
<b>Year</b>										
	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>
<b>Tax rate</b>	<b>Chinese children *</b>									
20%	-11.5	-11.2	-10.8	-10.1	-9.3	-8.3	-7.2	-6.0	-4.9	-4.0
35%	-20.0	-19.9	-19.5	-18.8	-17.7	-16.3	-14.4	-12.3	-10.3	-8.6
50%	-28.6	-29.0	-29.5	-29.7	-29.2	-27.5	-24.5	-20.9	-17.6	-15.4
	<b>US Children*</b>									
<b>Tax rate</b>										
20%	-35.9	-35.1	-33.4	-30.9	-27.8	-24.1	-20.2	-16.3	-12.7	-9.6
35%	-62.9	-61.6	-59.1	-55.2	-50.0	-43.6	-36.3	-28.9	-22.0	-16.4
50%	-89.8	-88.7	-86.4	-82.0	-74.9	-64.9	-52.5	-39.8	-29.1	-22.3

**Note:**

^ Net energy intake changes from consuming all beverages.

Figure 5-1: A system dynamics model of tax effects on beverage consumption and supply

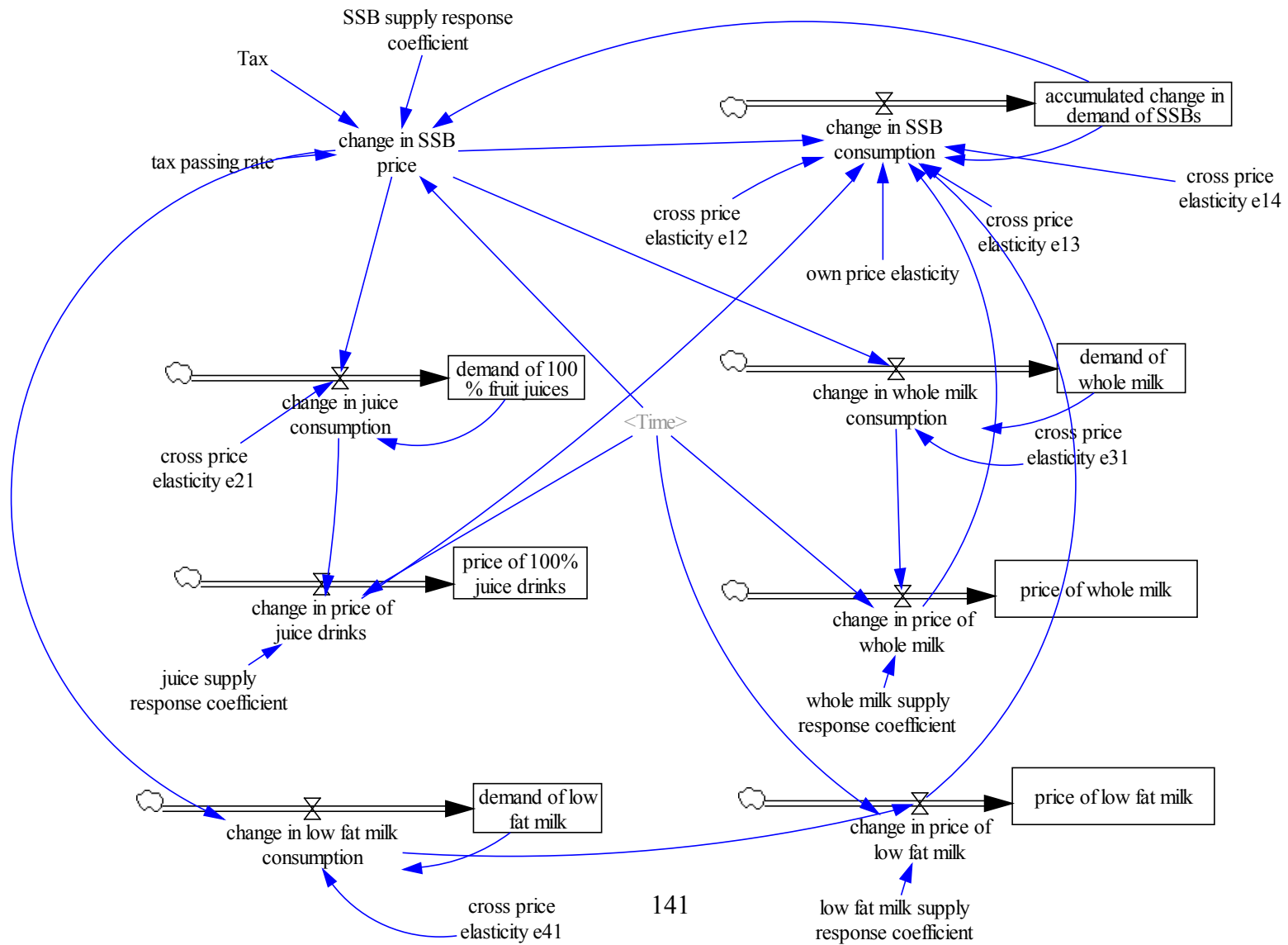
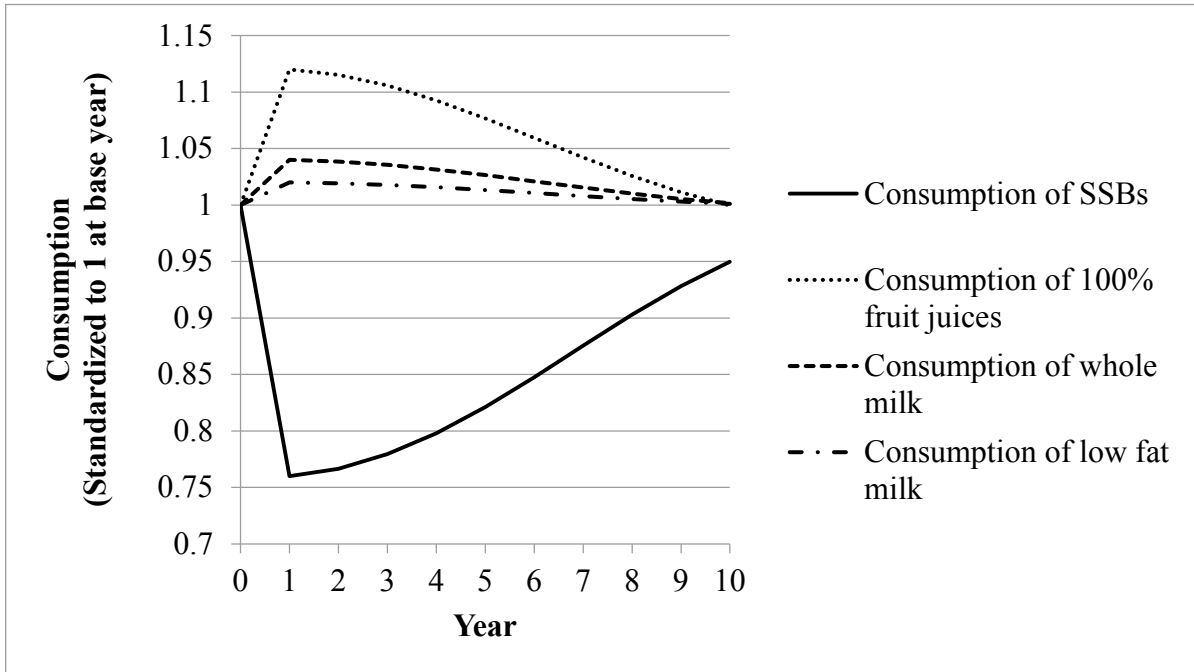


Figure 5-2: Tax effect on the consumption of various beverages (sugar sweetened beverages, 100% fruit juices, whole milk, and low fat milk) and price of SSBs with low SSB supply response over 10 years: findings based on system dynamics models

(a). Consumption of beverages relative to base year



(b) Price of sugar sweetened beverages relative to base year

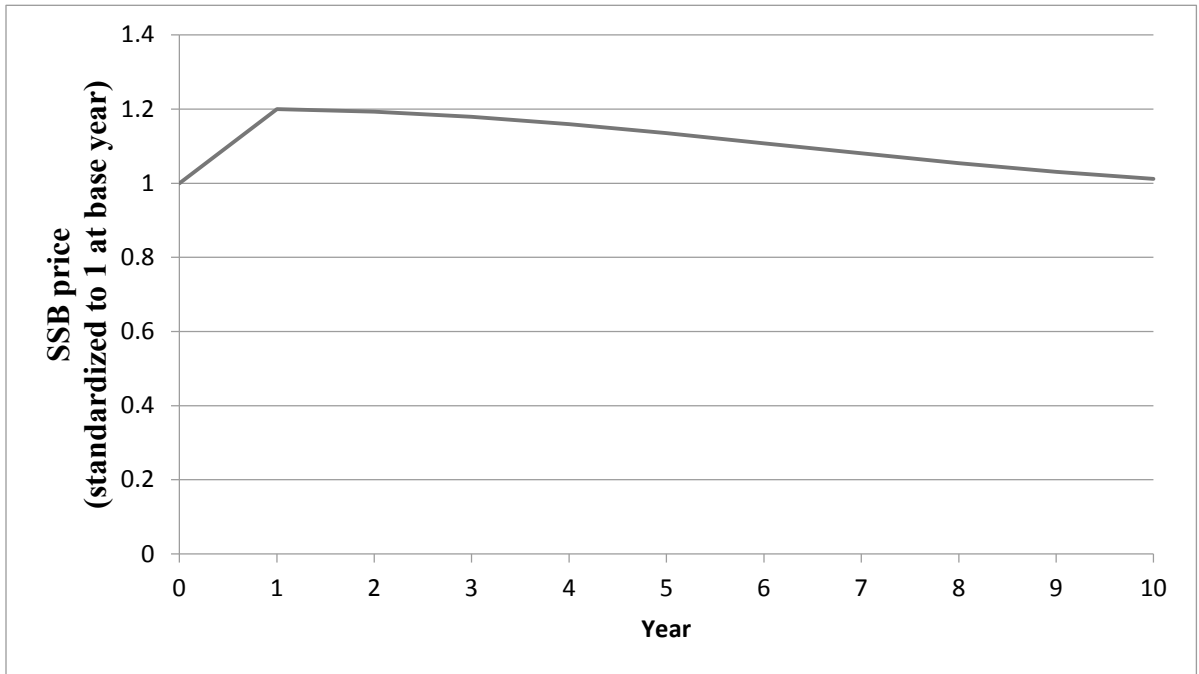




Figure 5-3: A system dynamics model to explore bottled water subsidy effects on beverage consumption and supply

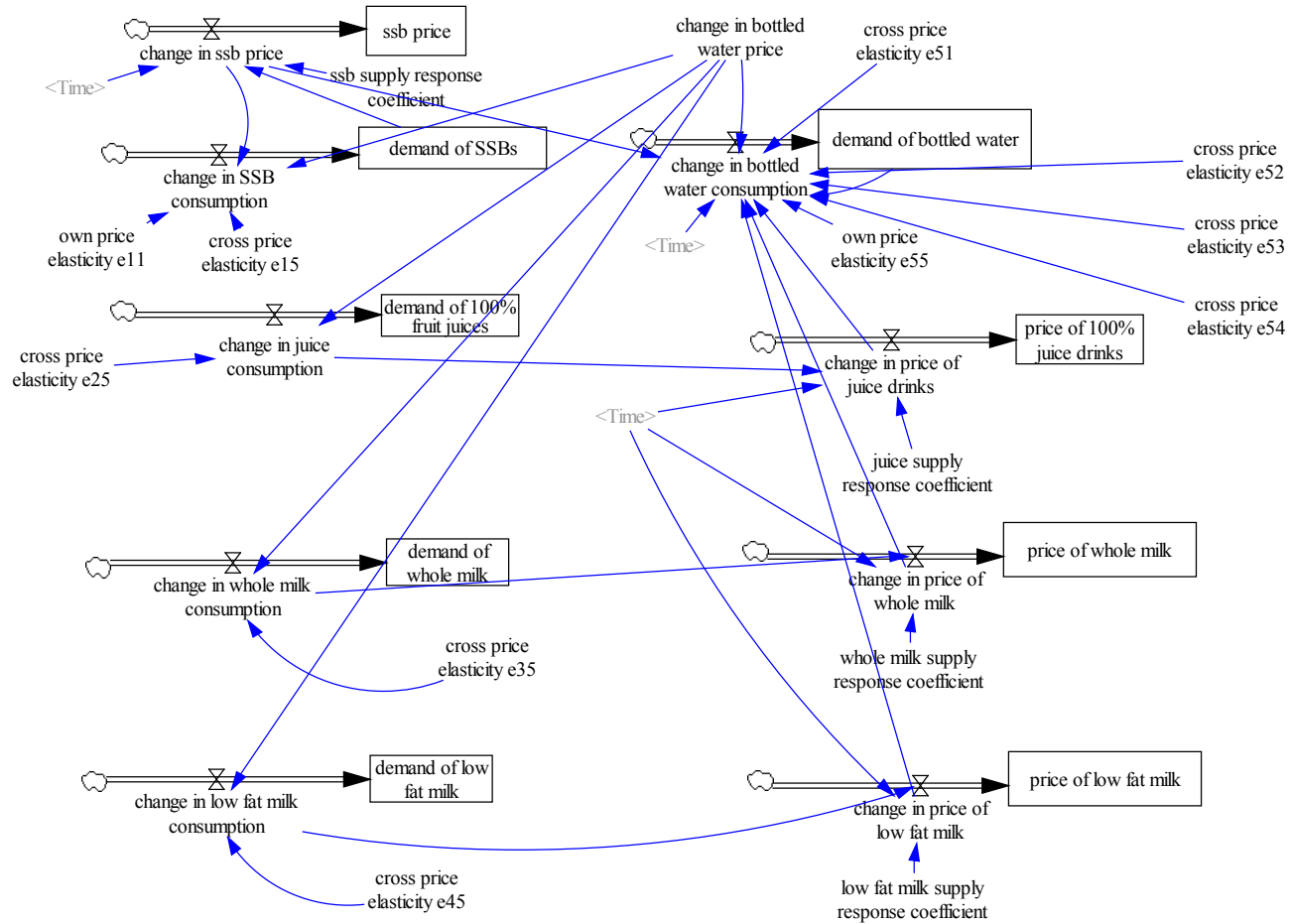
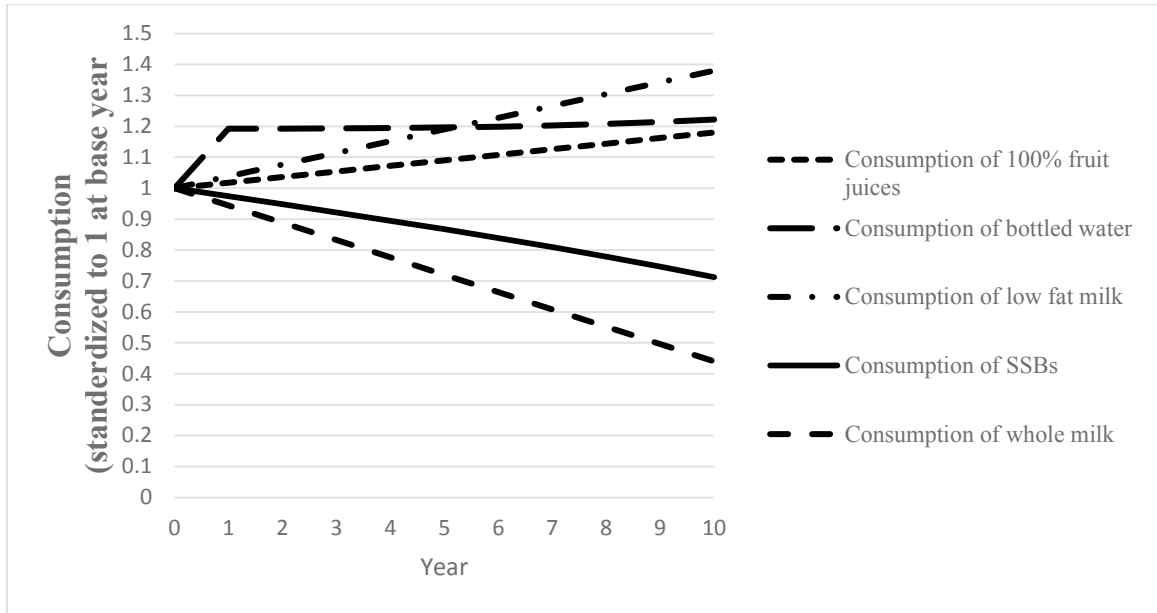


Figure 5-4:10 year subsidy effect on the consumption of various beverages (bottled water, sugar sweetened beverages, 100% fruit juices, whole milk, and low fat milk) based on US price elasticities estimates



## Appendix: System dynamics model document

### I. SSB market structure assumption

To examine the important features without mathematic complications, we assume an oligopolistic SSB market, but firms jointly behave as monopoly. With constant price elasticity of demand, the tax effect on price derived based on profit maximization is:

$$\frac{dP}{dt} = \left( \frac{1}{1 + \frac{1}{\varepsilon}} \right) \left( \frac{dMC}{dy} \frac{dy}{dt} + 1 \right). P \text{ is SSB price, } t \text{ is tax, } \varepsilon \text{ is price elasticity of demand, MC is}$$

marginal cost that SSB firms are facing,  $y$  is SSB demand.  $\frac{dMC}{dy} \frac{dy}{dt}$  is negative. The

nonlinear relationship between MC and  $y$  over time will affect the tax effect on price.

### II. Model setup

#### INITIAL AND START TIMES:

- (1) INITIAL TIME = 0
- (2) FINAL TIME = 10

#### STOCK AND FLOW RELATIONS FOR EACH OF THE 7 STOCKS

##### DEMAND

- (3)  $d(\text{demand of SSBs})/dt$   
 $= (\varepsilon_{11} * \Delta \text{ price of SSBs} + \varepsilon_{12} * \Delta \text{ price of juice drinks} + \varepsilon_{13} * \Delta \text{ price of whole milk} + \varepsilon_{14} * \Delta \text{ price of low fat milk}) * \text{demand of SSBs}$
- (4)  $d(\text{demand of 100\% fruit juices})/dt$   
 $= \varepsilon_{21} * \Delta \text{ SSB price} * \text{demand of 100\% fruit juices}$
- (5)  $d(\text{demand of whole milk})/dt$   
 $= \varepsilon_{31} * \Delta \text{ SSB price} * \text{demand of whole milk}$

$$(6) \quad d(\text{demand of low fat milk})/dt \\ = \epsilon_{41} * \Delta \text{SSB price} * \text{demand of low fat milk}$$

#### CHANGES IN PRICES DURING THE INITIAL YEAR

$$(7) \quad \Delta \text{ price of 100\% juices} = \\ \Upsilon_2 * \epsilon_{21} * \Delta \text{SSB price}$$

$$(8) \quad \Delta \text{ price of whole milk} = \\ \Upsilon_3 * \epsilon_{31} * \Delta \text{SSB price}$$

$$(9) \quad \Delta \text{ price of low fat milk} = \\ \Upsilon_4 * \epsilon_{41} * \Delta \text{SSB price}$$

$$(10) \quad \Delta \text{ price of SSB} = \\ \text{Tax} * \alpha$$

#### CHANGES IN PRICES FOR YEARS 2-10

$$(11) \quad \Delta \text{ price of 100\% juices} = \\ \text{MIN}(\Upsilon_2 * \epsilon_{21} * \Delta \text{SSB price} * \text{demand of 100\% fruit juices} * T, 0.1)$$

$$(12) \quad \Delta \text{ price of whole milk} = \\ \text{MIN}(\Upsilon_3 * \epsilon_{31} * \Delta \text{SSB price} * \text{demand of low fat milk} * T, 0.02)$$

$$(13) \quad \Delta \text{ price of low fat milk} = \\ \text{MIN}(\Upsilon_4 * \epsilon_{41} * \Delta \text{SSB price} * \text{demand of low fat milk} * T, 0.05)$$

$$(14) \quad \Delta \text{ SSB price} = \\ \text{MAX}(\Upsilon_1 * \text{demand of SSBs} * T, -0.3)$$

### III. System dynamics model of tax effects on beverage consumption -model parameters

Parameter	Definition	value	Reference
T	tax rate	20%	(Brownell, Farley et al. 2009, Fletcher, Frisvold et al. 2010, Andreyeva, Chaloupka et al. 2011, Levy, Friend et al. 2011) (Andreyeva, Long et al. 2010, Smith, Lin et al. 2010, Dharmasena and Capps 2012)
$\epsilon_{11}$	SSB own price elasticity (assumed similar for US and Chinese children for comparison purpose)	-1.2	(Smith, Lin et al. 2010, Dharmasena and Capps 2012)
$\epsilon_{22}$	100% juice own-price elasticity	-1	2012)

			(Smith, Lin et al. 2010, Dharmasena and Capps 2012)
ε33	whole milk own-price elasticity	-1	(Smith, Lin et al. 2010, Dharmasena and Capps 2012)
ε44	low fat milk own-price elasticity	-0.7	(Smith, Lin et al. 2010, Dharmasena and Capps 2012)
€55	Bottled water own price elasticity	-1	(Smith, Lin et al. 2010)
	percentage change in 100% juice consumption as result of the		(Smith, Lin et al. 2010, Dharmasena and Capps 2012)
ε21	percentage change in SSB price	0.6	(Smith, Lin et al. 2010, Dharmasena and Capps 2012)
	percentage change in whole milk consumption as result of the		(Smith, Lin et al. 2010, Dharmasena and Capps 2012)
ε31	percentage change in SSB price	0.2	(Smith, Lin et al. 2010, Dharmasena and Capps 2012)

			(Smith, Lin et al. 2010,
	percentage change in low fat milk consumption as result		Dharmasena and Capps
€41	of the percentage change in SSB price	0.1	2012)
			(Smith, Lin et al. 2010,
	percentage change in bottled water consumption as result		Dharmasena and Capps
€51	of the percentage change in SSB price	0.75	2012)
	percentage change in 100% juice consumption as result		(Smith, Lin et al. 2010,
	of the		Dharmasena and Capps
€25	percentage change in bottled water price	-0.09	2012)
	percentage change in whole milk consumption as result		(Smith, Lin et al. 2010,
	of the		Dharmasena and Capps
€35	percentage change in bottled water price	0.28	2012)
			(Smith, Lin et al. 2010,
	percentage change in low fat milk consumption as result		Dharmasena and Capps
€45	of the percentage change in bottled water price	-0.19	2012)

	percentage change in SSB consumption as result of the		(Smith, Lin et al. 2010,
ε12	percentage change in 100% juice price	0.2	Dharmasena and Capps 2012)
	percentage change in SSB consumption as result of the		(Smith, Lin et al. 2010,
ε13	percentage change in whole milk price	0.03	Dharmasena and Capps 2012)
	percentage change in SSB consumption as result of the		(Smith, Lin et al. 2010,
ε14	percentage change in low fat milk price	0.02	Dharmasena and Capps 2012)
	percentage change in SSB consumption as result of the		(Smith, Lin et al. 2010,
ε15	percentage change in bottled water price	0.1	Dharmasena and Capps 2012)
	percentage change in bottled water consumption as result		(Smith, Lin et al. 2010,
ε52	of the percentage change in 100% juice price	-0.1	Dharmasena and Capps 2012)



			(Smith, Lin et al. 2010,
	percentage change in bottled water consumption as result		Dharmasena and Capps
ε53	of the percentage change in whole milk price	0.28	2012)
			(Smith, Lin et al. 2010,
	percentage change in bottled water consumption as result		Dharmasena and Capps
ε54	of the percentage change in low fat milk price	-0.5	2012)
			(Brownell, Farley et al. 2009,
			Smith, Lin et al. 2010,
			Andreyeva, Chaloupka et al.
			2011, Dharmasena and
α	tax passing rate	100%	Capps 2012)
		equivalent to an ability of	
		increasing 10% of the	
		sales: 0.03 under 20% tax	
Υ1	Supply response coefficient of SSB suppliers	rate, 0.04 under 35% tax	Assumed

		rate, 0.06 under 50% tax rate	
		0.01, equivalent to an ability of increasing 10%	
Y2	Supply response coefficient of 100% juice suppliers	of the sales	Assumed
		0.005, equivalent to a ability of increasing 10%	
Y3	Supply response coefficient of whole milk suppliers	of the sales	Assumed
		0.002, equivalent to a ability of increasing 10%	
Y4	Supply response coefficient of low fat milk suppliers	of the sales	Assumed

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## **Chapter 6 – Implications and Conclusions**

### **6.1 Fast Food Consumption and Childhood Obesity in China**

Here u may continue to use FFC to replace ‘fast food consumption’ as you did in other chapters.

Our analysis of the nationwide survey data shows that Western FFC increased significantly among Chinese school-age children during 2004-2009, and the increase was especially rapid among those from low- and medium-income families and those from East China, compared to their counterparts.

The increase in FFC was fueled primarily by disposable income growth. The per capita disposable income increased by 11 times after accounting for inflation between 1978 and 2012, increasing from about 340 RMB to 24,500 RMB. The income increase has induced a significant increase in the consumption of food-away-from-home (FAFH), including FFC (Insik, Cheng et al. 2004, Ma, Huang et al. 2006). In the mid-1990s, urban household average per capita annual FAFH expenditure was < 200 RMB, while it increased to about 1000 RMB in 2010 (Liu, Wahl et al. 2012).

However, we did observe differences in FFC changes in subgroups. During 2004-2009, FFC increased in rural areas but decreased in urban areas. Moreover, interestingly, FFC prevalence decreased in children from high-income families but increased in those from low- and medium-income families. This result is consistent with a shifted nutrition transition and findings that the burden of obesity and metabolic risk has started to move from the better-off to the poorer population groups in some developing countries (Popkin 2014). Such differential patterns mirror the inequalities of regional economic

development and reflect the nonlinear effect of income increases on food-away-from-home (FAFH) consumption. It is known that an increase in income generates a greater increase in FAFH expenditure in high-income households than in low-income households in China (Ma, Huang et al. 2006). On the one hand, as an important component of FAFH, FFC increased dramatically in rural areas with an increase in rural household income. On the other hand, the effect of increasing household income on FAFH in urban areas more pronounced for other foods. In high-income urban households, more awareness of health, media influence, and increased demand for high quality food in recent years may have resulted in a decrease in FFC, as fast food may be increasingly viewed as unhealthy for children.

From the supply side, the fast expansion of the Western fast food industry was a major driver. Thanks to China's economic reforms and its access to WTO, the liberalization of domestic markets and international trade narrowed domestic-international price gaps, stimulated domestic production and promoted imports, all of which facilitated the vertical integration of the FF industry and helped fuel its growth. In addition, China's transformation from a rural agricultural economy to an industrialized economy has provided the FF industry with a vast, cheap labor supply to help it expand. As a result, compared to a decade ago children in today's China have much easier access to fast food and it has become more affordable. Moreover, FFC is viewed favorably among Chinese children. A cross-cultural study on brand identity reported that Chinese children had more favorable impressions of KFC than did their US counterparts (Witkowski, Ma et al. 2003).

To our surprise, our results do not suggest a significant association between Western FFC and obesity among Chinese children. This is consistent with some of the findings in the US. This could potentially be due to FFC accounting for only a small proportion of Chinese children's daily total energy intake, as well as due to measurement errors in people's dietary intakes. Nevertheless, if the increasing trends continue, the adverse health effects of fast consumption could be expected in the near future in China. National and regional policies and programs that guide the growth and operation of the fast food industry and promote healthy eating are urgently needed.

## **6.2 Potential Social Norm Effects on Child Food Consumption and Obesity Risks in China and the US**

Using ABM and empirical data, I have demonstrated the effects of social norms on Chinese and US children's BMI growth and FV consumption, i.e., a follow-the-average social interaction rule. As the simulation results suggest, the influence of the social norm on children's BMI adjustment is asymmetric, though the deviation from social average BMI could trigger the adjustment process in either direction. It is more difficult for children to lower BMI growth than to gain BMI in order to meet the social norm. This result is in line with the finding of Bernier et al. that children in the lowest BMI percentile have a greater desire for change in body shape (Bernier, Kozyrskyj et al. 2010). Moreover, the results suggest that for children whose BMIs were at the upper tail of the BMI distribution, their BMI adjustment behaviors become more heterogeneous, and the social norm contributes little in explaining their BMI changes. This phenomenon could be due to various endogenous and exogenous factors, which cause higher levels of

heterogeneous behavior among these children, for example, differences in energy metabolism and appetite control and the influence of the environment. Under-average children had a clear goal to attain growth above the average rate, while the over-average children faced the conflicting aims of fulfilling their linear growth potential but preventing overweight/obesity. This dilemma adds to the complexity and heterogeneity of weight/BMI-change among the heavier children.

Cross-country difference was evident. My models suggested apparent differences in the social norm effect between China and the US. The magnitude of the social norm impact on children's BMI change was about 2-3 times higher in Chinese children than in the US children. Such difference has its roots in culture. Based in its rich cultural traditions, Chinese society values collectivism. Children are taught to follow the norm of social groups for the benefit of individuals and the whole society. Research has shown that Chinese are more group-oriented than Americans (Earley 1989). Moreover, empirical findings have suggested that Chinese tended to be more homogenous compared to other national groups (Triandis, McCusker et al. 1990). Therefore, maintaining a socially acceptable and desirable body image could be a more important factor influencing Chinese children's weight outcomes.

The impact of the social norm on FV consumption was less evident than that on BMI adjustment. This is likely to be because low/high FV consumption may not cause immediate consequences in social binding and thus leads to fewer behavioral changes. In contrast, body image can be directly observed and may incur negative psychological effects, such as suicidal attempts, lower self-esteem and depression (Strauss, Smith et al. 1985, Strauss 2000). Moreover, the findings indicate that the attributes of FVs, such as

visual cues and palatability, may be more important than the social norm when children are making food decisions, especially when their consumption reaches a threshold level (Pliner and Mann 2004). Nutrition education about the health benefits of FV thus should intervene to facilitate desirable behavior changes.

Given that this was my first time in the field, I tested the social norm impact on BMI adjustment behavior and FV intake among children using large, empirical, longitudinal data sets from different cultural settings. My model focused on the "individual-level effect" rather than solely examining weight distribution transitions. Furthermore, I added the time dimension in the analysis of the adjustment process. As an improvement to existing models, my model explicitly accounted for the heterogeneity of individuals and gender differences and showed asymmetric social influence on children's BMI. Compared to the existing studies on the contagious nature of obesity among family members and friends, the ABM of this study overcomes the intrinsic limitations and gaps embedded in the traditional methods, such as the confounding effects of homophily and shared environment, mis-specified regression models and sensitive estimation approaches. Hypothetical mechanisms are explicitly simulated and tested through ABM, generating concrete evidence for us to make causal inference about the effect of social norms on the BMI distribution among children.

In conclusion, the follow-the-average social interaction rule ("social norms") could be one of the mechanisms that influence children's BMI growth, although it was not helpful in explaining fruit and vegetable consumption to a substantial extent in our study populations in China and the US. These results indicate that health education and the promotion of obesity awareness, which may influence socially acceptable and

unacceptable body weight, are important to prevent excessive weight gain in school children. Moreover, the influence of social norms could be more prevalent and robust in China than in the US due to cultural differences. Hence, tailored intervention strategies in different populations should be developed to improve social norm-based childhood obesity prevention programs and policies. Systems science models like the agent-based model can be useful to help explore social network factors affecting childhood obesity and eating behaviors or other health outcomes.

### **6.3 Potential Fiscal Policy Options to Prevent Childhood Obesity – System Dynamics Modeling Simulation Results for China and the US**

The effectiveness of fiscal policy instruments such as SSB taxation in altering food consumption behaviors and the influence of such measures on energy intake and body weight remains unproven, despite some recent studies showing that SSB tax may be associated with SSB consumption reduction under certain conditions and model specifications (Colchero, Popkin et al. 2016). Policy impact is often difficult to test using traditional research design. My study demonstrated the necessity and applicability of using SDM to study policies and interventions related to complex obesity problems. SDM simulations provided insights to predict and assess the effectiveness of fiscal pricing policies aimed at changing beverage consumption so as to curb the obesity epidemic.

Our SDM simulation results suggest that it is important to consider the multiple players in the system and the time scale in the estimation. The main distinction we draw is between short- and long-term effects which hold the key to a better understanding of



the potential tax impact. As our simulation analysis indicates, a 20% tax-induced price increase could lead to about a 24% reduction in SSB consumption initially. However, the effect is temporary. Suppliers would likely respond to the decrease in sales in a variety of ways, such as price reductions and product promotions. By incorporating such mechanisms in our model, even a low level of supply response would lead to the overall energy intake reduction being only 25% of the initial decrease in a 10-year period of time. These results are dependent on the model assumptions regarding market structure and conditions. However, the simulations demonstrate the conceptual possibilities and suggest that knowing the potential offsetting impact of supply response is of critical importance to assess the potential tax effects.

In contrast to the conventional belief as widely adopted in the related literature, that as long as consumers are responsive to price changes and do not substitute non-taxed high-energy-containing beverages, taxing SSBs can alter consumption and reduce energy intake and body weight, we argue, as illustrated in our SDM simulations, that solely imposing taxes on SSB may not be as effective as many expected. Subsidizing consumption of more healthy beverages is a more effective and sustainable option. As our results indicate, subsidizing bottled water consumption can help reduce SSB consumption substantially in both the short and the long run.

The SDM simulation results in this study suggest that an SSB tax could increase SSB prices initially, but over time, SSB producers may share the tax burden and reduce their prices so as to increase sales. Supply response and the dynamics of demand are important when assessing tax effects. As the research on the tobacco industry suggests, suppliers could develop “defense plans” to offset short-run price increases resulting from

tax increases, using marketing means such as couponing and multi-pack promotions (Chaloupka, Cummings et al. 2002). Subsidizing bottled water consumption in China and the US could be more effective and generate less controversy as a policy tool to promote healthy beverage consumption.

#### **6.4 Overall conclusions**

China has its own unique patterns of childhood obesity, while also sharing some common features with the US. FFC has been increasing in China, both in adults and children, over the past three decades. This could lead to many serious health, financial and social consequences in the future. Policies and population-based programs that regulate the growth and operation of the fast food industry and promote healthy eating are urgently needed in China. Social norms play a significant role in influencing people's health behaviors and body weight, especially young people's, in both China and the US. Due to its long history and cultural roots, social norm effects are more pronounced in China. Social interventions aiming at prompting healthy energy-balance-related behaviors could be effective in China and in the US. Given the growing use and impact of social media, this could provide a promising intervention venue. Tax on SSBs may not be as effective as many people have believed or hoped if supply responses are considered in the complex, dynamic, supply-demand system. Subsidizing bottled water consumption could be more effective and generate more desirable effects in the long run in terms of reducing SSB consumption and energy intake, and thus help fight the obesity epidemic.



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## CURRICULUM VITAE

HONG XUE, PhD, MS

Place and Date of Birth: Chengdu, China, 11/30/1979

### Office:

Systems-Oriented Global Childhood Obesity Intervention Program

Department of Epidemiology and Environmental Health      Tel: 716-829-5346, Fax: 716-829-2979  
Email: hongxue@buffalo.edu

School of Public Health and Health Professions

University at Buffalo, State University of New

York

Kimball Tower, Room 801, 3435 Main St,

Buffalo, NY 14214

### A. EDUCATION

2010 - **Ph.D. candidate** in Nutritional Epidemiology (Degree expected October, 2016)  
Department of International Health, Bloomberg School of Public Health, Johns Hopkins  
University, Baltimore, MD

PhD Dissertation Title: A comparative study of the drivers of childhood obesity epidemic  
in China and the United States using systems approaches

2010 **Doctorate of Philosophy, Economics – Specialty: Health Economics**

Virginia Polytechnic Institute and State University, Blacksburg, VA

PhD Dissertation Title: Three Essays on Consumer Behavior and Health Outcomes: An  
Economic Analysis of the Influence of Nutrition Information and Knowledge on Food  
Purchasing Behavior and the Impacts of Primary Care Givers' Parenting on Childhood  
Obesity

2005 **Master of Science, Economics – Specialty: Health Economics**

North Carolina A&T State University, Greensboro, NC

Thesis Title: Consumers' Food Thermometer Use and Foodborne Illness Behavior

2001 **Bachelor of Science, Economics,**

Southwest University of Finance and Economics (SWUFE), China



## B. APPOINTMENTS

- 2014 – Research Assistant Professor, Project Director, Systems-oriented Global Childhood Obesity Intervention Program, Department of Epidemiology and Environmental Health, School of Public Health and Health Professions, University at Buffalo, State University of New York (SUNY)
- 2014 – Project Manager, NIH U54 Center grant, "Multilevel Systems-oriented Childhood Obesity Study in China" (one of the three key research projects in the NIH U54 Center grant), Department of Epidemiology and Environmental Health, School of Public Health and Health Professions, University at Buffalo, State University of New York (SUNY)
- 2014 – Project Manager, NIH R01 project, "Causes and Interventions for Childhood Obesity: Innovative Systems Analysis", Department of Epidemiology and Environmental Health, School of Public Health and Health Professions, University at Buffalo, State University of New York (SUNY)
- 2011 –2013 Project Manager, Johns Hopkins Global Center on Childhood Obesity (funded by a \$16 million NIH U54 center grant), Johns Hopkins University, Baltimore, MD
- 2011 – 2013 Project Manager, NIH R01 project, "Causes and Interventions for Childhood Obesity: Innovative Systems Analysis", Department of International Health, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD

## C. RESEARCH GRANT PARTICIPATION

### Pending grants (selected)

**Title:** Promoting Research and Innovation in Methodologies for Evaluation (PRIME): Developing a Benchmark System for Evaluating Interventions of First-year STEM Gatekeeper Courses

**Funding:** National Science Foundation, \$2.9 million, 7/1/2016 – 6/30/2021

**Objectives:** 1) To design and use a comprehensive data system to capture many variables that potentially impact students' retention and degree completion in STEM disciplines; 2) to develop and validate systems models that dynamically monitor and predict students' performances in and satisfactions with undergraduate learning in STEM disciplines with the ultimate goal of completing degrees within four years; and 3) to develop a theory of institutional curriculum and pedagogical transformation for student retention and degree completion in STEM disciplines.

**Role:** Co-Investigator

**Title:** An Automated Web-based Archive System for Local School Wellness Policies

**Funding:** National Institutes of Health (NIH, R15 grant), 07/01/2016-06/30/2018, \$484,141

**Objectives:** To use the latest machine learning to develop an automatic surveillance system of school wellness policy

**Role:** Co-Investigator of subcontract with UB (PI: Qi Zhang)

**Title:** Smartphone app usage, redemption, and nutritional outcomes of WIC participants

**Funding:** National Institutes of Health (NIH, R15 grant), 09/01/2015-08/30/2017, \$470,694

**Objectives:** To use the latest artificial intelligence technology to develop an automatic surveillance system of school wellness policy

**Role:** Co-Investigator of subcontract with UB (PI: Qi Zhang)

**Title:** Trajectories, dynamics, and between-group disparities in obesity health outcomes from infancy through adulthood in the U.S.

**Funding:** National Institutes of Health (NIH, R21 grant), 07/01/2015-06/30/2018, \$422,632

**Objectives:** To study the key multilevel risk factors in timing events and transitions in the development of obesity from infancy through adulthood.

**Role:** Co-Investigator of subcontract with UB (PI: Liang Wang)

### Active grants

**Title:** Systems-Oriented Pediatric Obesity Research and Training Center Grant

**Funding:** NIH/NICHD (U54 HD070725-01, U54 Center grant total \$16.1 million, 9/2011 - 12/2016).

**Objectives:** Using integrated conceptual framework, innovative analysis approaches, and rich data 1). To study how complex factors may affect childhood obesity and, 2). To test potential intervention options in the US

**Role:** Co-I (PI: Youfa Wang)

**Title:** Multilevel Systems-oriented Childhood Obesity Study In China (one of the three key projects in the NIH U54 Center grant)

**Funding:** NIH/NICHD (U54 HD070725-01, \$2.1 million, 9/2011/9 - 12/2016)

**Objectives:** Using a systems-oriented approach, 1). To study multilevel complex factors and their changes on children and their families' decisions, eating, physical activity, and adiposity outcomes and 2). To study the differential responses and dynamic feedbacks between individuals and families and the environments

**Role:** Co-I (PI: Youfa Wang)

#### **D. PROFESSIONAL COMMUNITY INVOLVEMENT**

2010 - , Member of American Society for Nutrition (ASN)  
2007 - , Member of American Economic Association (AEA)  
2005 - , Member of Agricultural & Applied Economics Association (AAEA)

#### **E. PROFESSIONAL AND ACADEMIC HONORS AND AWARDS (selected)**

- 1) The Obesity Society Pat Simons Travel Award – 2015
- 2) Young Professional and Graduate Student Travel Grants, Agricultural and Applied Economics Association – 2009
- 3) Member of Gamma Sigma Delta since 2005
- 4) Academic Excellence, North Carolina A&T State University, 2005

#### **F. EDITORIAL ACTIVITIES**

##### **Manuscript Reviewer (selected):**

American Journal of Public Health  
Health Education & Behavior  
International Journal of Obesity  
PLOS ONE

#### **G. TEACHING EXPERIENCE**

2015 & 2016	Invited lectures on Economics and Obesity in the Obesity Epidemiology class, University at Buffalo, SUNY.
2011 & 2012 Fall	Teaching Assistant, Johns Hopkins Bloomberg School of Public Health, Baltimore, MD. Course name: Advanced Nutritional Epidemiology. Taught all the lab sessions and provided a lecture each year.
2008 summer	Lecturer, Department of Agricultural and Applied Economics, Virginia Polytechnic Institute and State University, Blacksburg, VA. Course name: Advanced Mathematics in Economics. Taught and gave all the summer lectures in advanced math for first year PhD students in economics, finance, and accounting.
08/2006–10/2006 &	

08/2007–10/2007: Instructor, Department of Agricultural and Applied Economics, Virginia Polytechnic Institute and State University, Blacksburg, VA.  
Course name: Qualifying Exam Review. Taught the second year PhD students for qualifying exams in advanced Microeconomics, Macroeconomics, and Econometrics.

### **Student Advisees at SUNY Buffalo**

(Since 2014, served on their thesis committees and as their RAship project co-supervisor)

Xi Cheng, 2014-, PhD student, research assistant

Wudeneh Mulugeta, MD, MPH, 2014-2015, MS student (also Internal Medicine & Preventive Medicine Chief Medical Resident at UB), thesis topic: Overtime shifts in diseases patterns among refugees in Buffalo

Vivian Wang, 2014-2015, MS student, thesis topic: Gender difference in obesity and overweight rate among children in China and the reasons

Huiru Chang, 2015- MS student, thesis topic: Longitudinal changes in students' eating behaviors, physical activity and obesity risk in China

Zhengqi Tan, MD, 2014- MPH student, thesis topic: parenting influence on childhood obesity in China

Kelsey Smith, 2014-, MPH student, thesis topic: A website- and family-based childhood obesity prevention study (as part of our collaboration with NASA)

## **H. COMPUTER PROGRAMING PROFICIENCY**

### **Statistical packages:**

Guass, SAS, Stata,

### **Scientific computing:**

Matlab

### **General programing and complex systems analysis & simulation:**

Python, Vensim, Netlogo

### **Website development and programming:**

HTML, CSS

## **I. LICENSE & CERTIFICATE**

Completion of the Complex System Analysis Training - New England Complex System Institute 2013, covered essential concepts and applications of complex systems and mathematical methods and simulation strategies.

## **J. PUBLICATIONS (Selected)**

### **1. Selected papers published in peer-reviewed journals**

- (1). **Xue H**, Mainville D, Wen You W, Nayga R. “Nutrition Knowledge, Sensory Evaluation and Consumers’ Willingness to Pay for Nutritionally Differentiated Grass-Fed Beef,” *Food Quality and Preference*, 2010, 21(7): 857-866.
- (2). Fallah-Fini S, Rahmandad H, Chen HJ, **Xue H**, Wang Y. Connecting Micro Dynamics and Population Distributions in System Dynamics Models. *System Dynamics Review*, 2013, 29(4):197-215.
- (3). Wang Y, **Xue H**, Esposito L, Joyner MJ, Bar-Yam Y, Huang T-T. Applications of Complex Systems Science in Obesity and Non-Communicable Chronic Disease Research. *Advances in Nutrition*, 2014, 5(5), 574-577.
- (4). Wang Y, **Xue H**, Chen HJ, Igusa T. Examining Social Norm Impacts on Obesity and Eating Behaviors among US School Children Based on Agent-based Model. *BMC Public Health*, 2014, 14(1):923.
- (5). Lim HJ, **Xue H**, and Wang Y. Association between obesity and metabolic co-morbidities among children and adolescents in South Korea: the 2007-2008 Korea National Health and Nutrition Examination Surveys. *BMC Public Health*, 2014, 14: 279.
- (6). Zhang Q, Liu SY, Liu R, **Xue H**, and Wang Y. Food Policy Approaches to Obesity Prevention: An International Perspective. *Current Obesity Reports*, 2014: 1-12.
- (7). Wang Y, **Xue H**, Liu SY. Applications of Systems Science in Biomedical Research Regarding Obesity and Non-communicable Chronic Diseases -- Opportunities, Promise and Challenges. *Advances in Nutrition*, 2015, 6(1), 88-95.
- (8). Zhang JG, Wang HJ, Wang Y, **Xue H**, Wang ZH, Du W, Su C, Zhang J, Jiang HR, Zhai FY and Zhang B. Dietary patterns and their associations with childhood obesity in China. *British Journal of Nutrition*, 2015: 1-7
- (9). Liu SY, Osgood N, **Xue H**, Wang Y. Systems Simulation Model for Assessing the Sustainability and Synergistic Impacts of Sugar-sweetened Beverages Tax and Revenue Recycling on Childhood Obesity Prevention . *Journal of the Operational Research Society*. 2015 Dec 9.
- (10). **Xue H**, Wu Y, Wang X, Wang Y. Time Trends in Fast Food Consumption and Its Association with Obesity among Children in China. *PLOS One*. 11.3 (2016): e0151141..
- (11). Zhang J, **Xue H**, Cheng X , Wang ZH, Zhai FY , Wang Y, Wang HJ. Influence of Proximities to Food Establishments on Body Mass Index

- among Children in China. *Asia Pacific Journal of Clinical Nutrition*. 2016 Jan 21;25(1):134-41
- (12). Chen H, **Xue H**, Kumanyika S, Wang Y. School Beverage Environment and Children's Energy Expenditure Associated with Physical Education Class: An Agent-based Model Simulation. *Pediatric Obesity*. 20 APR 2016 DOI: 10.1111/ijpo.12126
  - (13). Li M, **Xue H**, Wen M, Wang W, Wang Y. Nutrition and physical activity related school environment/policy factors and child obesity in China: a nationally representative study of 8573 students in 110 middle schools. *Pediatric Obesity*. 2016 July.
  - (14). Wu Y, **Xue H**, Wang H, Su C, Du S, Wang Y. The Impact of Urbanization on Community Food Environment in China. *Asian Pacific Journal of Clinic Nutrition*. In press.

2. **Selected working papers** (some are under review, some will be submitted soon in spring 2016)

Under review by peer-reviewed journals

- (1). Xue H, Cheng X, Jia P, Wang Y. Community walkability and childhood obesity - A US national longitudinal study (2007-2014).
- (2). Chen HJ, Xue H, Liu, TTK Huang, Wang C, Wang Y. Obesity in the United States and economic intervention options: A study linking ecological epidemiology and system dynamics modeling.
- (3). Jia P, Cheng X, Xue H, Wang Y. Applications of geographic information systems related data and methods in obesity-related public health research.
- (4). Jia P, Li M, Xue H, Lu L, Xu F, Wang Y. School environment and policies and associations with child eating behavior and overweight/obesity in urban China: The Childhood Obesity Study in China Mega-cities.
- (5). Jia P, Wang M, Li Y, Xue H, Wang Y. The application of spatial approaches in obesity research.
- (6). Jia P, Xue H, Zhang J, Wang H, Wang Y. Time trends in demographic and geographical differences in childhood obesity in China – evidence from twenty years' longitudinal data.
- (7). Li M, Xue H, Wang W, Wang Y. Parental Expectation and Children's Screen-based and Academic-related Sedentary Behaviors in China: A Nationally Representative Study.
- (8). Min JW, Xue H, Wang HC, Li M, Wang Y. Are single children more likely to be overweight or obese than those with siblings? - The influence of China's one-child policy on childhood obesity.
- (9). Wang HC, Min JW, Xue H, Du SF, Xu F, Wang HJ, Wang Y. Factors contributing to sex differences in childhood obesity prevalence in China.
- (10). Yang Y, Xue H, Wang, Y. Active Travel to and from school among school age children during 1997-2011 and associated factors in China.
- (11). Liu S, Li Y, Xue H, Osgood N, Wang Y. Investigating diffusion of simulation approaches capturing heterogeneity and homogeneity in population health and health care research: Agent-based model and system dynamics model.

- (12). Liu S, Triantis KP, Zhang L, Xue H, Wang Y. Capturing Multi-Stage Fuzzy Uncertainties in Big Data Simulation Using Hybrid System Dynamics and Agent-Based Models for Enhancing Policy Implementation.
- (13). Li M, Xue H, Wang WD, Wen M, Wang Y. The impact one the one-child policy in China on the childhood obesity epidemic: findings from a large national study.
- (14). Li M, Xue H, Wang WD, Wang Y. Parental Expectations and Children's Screen-based and Academic-related Sedentary Behaviors in China: A Nationally Representative Study.
- (15). Li M, Xue H, Jia P, Wang Y. Pocket Money, Eating Behaviors, and Weight Status for Children in Four Chinese Mega-cities
- (16). Li M, Xue H, Wang W, Wen M, Wang Y. Increased obesity risks for being an only child in China: findings from a nationally representative study of 19,487 children.
- (17). Li M, Fu R, Xue H, Wang Y. Maternal Obesity and Child Peer Victimization: Intergenerational Impact of Weight Stigma in the United States.
- (18). Xu C, Liu S, Liu G, Bishai D, Xue H, Wang Y. An Economic Analysis of Adherence with Medications for Diabetes Patients Based on System Dynamics Modeling.
- (19). Yang Y, Xue H, Liu S, Wang, Y. System dynamics modeling of Active Travel to School patterns and determinants among children in China.

To be submitted soon

- (1). **Xue H**, Liu S, Wang Y. Exploring intervention options to prevent childhood obesity in China: A Systems Simulation Study
- (2). **Xue H**, Chen H, Hobbs B, Igusa T, Levy D, Wang C, Frick F, Wang Y. Simulating tax effects on sugar-sweetened beverage (SSB) consumption and childhood obesity, under review.
- (3). Wang Y, **Xue H**, Liu S. New opportunities offered by “big data” for public health research and promotion
- (4). **Xue H**, Nayga R, Jr., You W, Mainville D. Endogenous Influence of Nutrition Knowledge on Consumer's Willingness to Pay for Healthy Food
- (5). Jia P, **Xue H**, Wang H, Wang Y. Spatial analysis of childhood obesity and local food environment inequalities in China
- (6). Wang L, **Xue H**, Wang Y. Multilevel factors of food intake decisions of children and families in China
- (7). Wang L, **Xue H**, Wang Y. Exploring different responses of Chinese children and families to their food environment
- (8). Wang Y, Wang L, Xue H, Qu W. Fast food industry, consumption and association with obesity in China
- (9). Du W, Wang H, **Xue H**, Wang Y, Zhang B. The Impact of Processed/Packaged and Restaurant Food Consumption on Eating Behaviors and Weight Status in Chinese Children

### **3. Presentations in international conferences (selected)**

- (1). **Hong Xue**, Jun Zhang, Youfa Wang. A China-USA comparative study of peer influence on childhood obesity and eating behavior: Social Network Analysis and Agent Based Modeling (ABM). Experimental Biology, San Diego, CA, Apr 2 - 6, 2016
- (2). **Hong Xue**, Peng Jia, Wang H, Wang Y. Spatial analysis of childhood obesity and local food environment inequalities in China. The Obesity Week, Los Angeles, CA, Nov 2 - 7, 2015
- (3). **Hong Xue**, Xi Cheng, Peng Jia<sup>1</sup>, Youfa Wang. Community walkability and childhood obesity - A US national longitudinal study (2007-2014). The Obesity Week, Los Angeles, CA, Nov 2 - 7, 2015
- (4). **Hong Xue**, Huijun Wang and Youfa Wang. Effects of Neighborhood Social Norms on Children's Diets and Weight Outcome in China. Experimental Biology, Boston, Mar 28- Apr 1, 2015
- (5). **Hong Xue**, Yang Wu, and Youfa Wang. "A counterfactual analysis of changing economic context and its impact on dietary intakes in Chinese children", Experimental Biology, San Diego, CA, April 26 - 30, 2014
- (6). **Hong Xue**, Qi Zhang, Hsin-Jen Chen, Yang Wu, Shiyong Liu, Youfa Wang. "When Do Sugar-sweetened Beverage Taxes Reduce Consumption? - A Dynamic Approach to Understanding Supply-side Determinants", the 12th International Congress on Obesity, Kuala Lumpur, Malaysia, Mar 17 - 20, 2014

### **K. MAIN RESEARCH INTERESTS**

Health Economics, Nutrition, Epidemiology, Systems Science, Obesity, big data. I am particularly interested in systems approach oriented economic and nutritional epidemiological research on obesity and non-communicable disease (NCD) prevention and control in domestic and international settings.