FOOD CHOICE, NUTRITION AND HEALTH

by

YU CHEN

(Under the Direction of Chen Zhen)

ABSTRACT

The objective of this dissertation is to quantify associations and potential causal relations between food policies and consumer decisions in the United States and China.

Chapter 2 estimates the impact of sodium reduction on the demand for instant noodle in China. Although there has been talk of voluntary sodium reduction among major Chinese food manufactures, it is not clear how unilateral or coordinated sodium reductions would affect companies' market shares. To answer this question, in this chapter, we simulated several sodium reduction scenarios to look at the demand changes under different scenarios. We estimated a random-coefficient logit demand model which includes all major instant noodle brands and varieties.

Chapter 3 examines the association between the US Supplemental Nutrition Assistance Program (SNAP) and the nutritional quality of participants' food-at-home (FAH) purchases. Using the detailed food purchase data from the US Department of Agriculture (USDA) National Household Food Acquisition and Purchase Survey (FoodAPS), we investigate the potential heterogeneity in the association between SNAP and diet quality among consumers with different levels of nutrition attitude.

Chapter 4 estimates the effects of SNAP and price on low-income households' food spending, based on which we discuss food tax and subsidy strategies to improve households' nutritional status. We use the FoodAPS data combined with a two-part model to estimate the food group-specific marginal propensity to spend out of SNAP benefits and price elasticities of demand for eighteen food groups. Considering low-income households with worse food hardship are more likely to self-select into SNAP, we use state-level variation in SNAP enrollment policies and eligibility requirements and respondent-level variation in driving distance to the nearest SNAP office as instrumental variables to identify the causal effect of SNAP on food spending.

INDEX WORDS: Sodium reduction strategy, Random-coefficients logit model, Chinese scanner data, SNAP participation, Nutritional quality, Low-income households, Marginal propensity to spend, Two-part model, FoodAPS

FOOD CHOICE, NUTRITION AND HEALTH

by

YU CHEN

B.S., Finance, China Agricultural University, 2013

M.S., Statistics, University of Georgia, 2018

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2019

FOOD CHOICE, NUTRITION AND HEALTH

by

YU CHEN

Major Professor: Chen Zhen

Committee: Travis A. Smith
Gregory J. Colson

Electronic Version Approved:

Suzanne Barbour
Dean of the Graduate School
The University of Georgia
August 2019

DEDICATION

To my loving family, friends, and colleagues

ACKNOWLEDGEMENTS

I am heartily grateful to my advisor, Dr. Chen Zhen, whose efforts and support made this dissertation possible. Dr. Zhen provided me with endless encouragement and excellent guidance throughout my graduate studies. He spent countless hours discussing my research and proofreading my papers, and patiently guided me to the best solution on many problems. He supported me in every facet of my professional career and continued to push me to be the best version of myself. It has been such an honor to have worked with him and I am very proud to be his student.

I also deeply appreciate my committee members, Dr. Travis A. Smith and Dr. Gregory J. Colson, who provided many valuable comments that improved the contents of this dissertation. They have offered valuable assistance to me from the time I enrolled in their classes. I thank them for always being there to help me and I sincerely appreciate it. I would also like to thank Dr. Jeffrey H. Dorfman, with whom I enjoyed working on a research paper which has provided me an impetus towards future research.

I will forever be thankful to my former research advisor in China, Dr. Xiangming Fang, who offered me this precious chance to pursue my Ph.D. in the U.S. Thank you for your endless support and encouragement for my desire to study here.

The life at the UGA is a priceless treasure to me forever, and I want to thank all my friends and colleagues. Thanks to Akash Issar and I-Chieh Lee for their valuable advices on my research, for being so supportive, for always listening, and for helping me reach further. Thanks to Jiahui Ying, Wenying Li, Yunhan Li, and Mengyao Li for their continuous support and generous help in the past 4 years. I will always remember the precious days of our lives: the discussion of difficult problems, the selfless sharing of ideas, the smiles in our gathering and the thoughts of our lives and future. Also, I would like to thank the other faculty and staff in the Department of Agricultural and Applied Economics.

Finally, I would like to give my most sincere gratitude to my parents for their unconditional love and unwavering support of my academic pursuit. Thank you for believing in me. None of this would be possible without you being by my side.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

CHAPTER 1

INTRODUCTION

Food choice is a major factor for healthy living. The palatability and enjoyment of food are often tied to the fat, salt and sugar content - three key ingredients that make the food have an undeniable sensory appeal and difficult to resist (Bolhuis, Costanzo, Newman, & Keast, 2015; Leshem, 2009). Nevertheless, over-consumption of food high in fat, salt, and sugar is the cause of at least 14 million deaths or 40% of all deaths every year from non-communicable diseases (NCDs) globally (Beaglehole et al., 2011).

Reducing the amount of salt has been identified as a priority and the most cost-effective intervention to NCDs, by lowering blood pressure, and thereby reducing the risk of cardiovascular disease deaths (Sookram, Munodawafa, Phori, Varenne, & Alisalad, 2015; Webb et al., 2017). The Institute of Medicine (IOM) in the U.S. recommended several strategies for reducing sodium daily intake (Boon, Taylor, & Henney, 2010). The primary strategy is to set mandatory national standards for the sodium content of foods. In the interim, the strategy has been to encourage the food industry to voluntarily reduce the sodium content of foods. Therefore, in the first chapter, we discussed the feasibility of voluntary and mandatory sodium reduction strategies through estimating the impacts of reducing sodium content from a leading brand and further from all brands on the demand for instant noodle products in the China market.

There is evidence that low-income populations are more likely, than their higher-income counterparts, to purchase and consume foods of lower nutritional quality (Darmon & Drewnowski, 2008). In the United States, the Supplemental Nutrition Assistance Program (SNAP, formerly the

Food Stamp Program) is the largest domestic hunger safety net program, serving 40.4 million low-income Americans in fiscal year 2018 at a cost of $60.9 billion in food benefit. The SNAP provides recipient households monthly benefits to support their food purchases at authorized retailers. We would hope that dietary quality would be better among program participants because of receiving additional benefits. However, prior studies suggest that SNAP participation is associated with suboptimal dietary patterns and even lower diet quality than their income-eligible nonparticipating counterparts (Andreyeva et al., 2015; Nguyen et al., 2014), and has led researchers to study how SNAP benefits are spent.

In the second chapter, we estimate the SNAP-diet relationship among low-income households. This paper contributes to investigate the potential heterogeneity in this association among consumers with different levels of nutrition attitude. Addressing this will inform the debate on potential restructuring of SNAP. This analysis uses detailed food purchase data from the US Department of Agriculture (USDA) National Household Food Acquisition and Purchase Survey (FoodAPS). The nutritional quality of each food item is measured by the nutrient profiling algorithm of the Guiding Stars program, as well as using the Healthy Eating Index-2010 as an alternative measure.

To explore how the SNAP benefits are spent, a strand of literature focuses on estimating the marginal propensity to spend (MPS) on food out of SNAP benefits, which measures how much food expenditures rise in response to a $1 increase in SNAP benefits. In the third chapter, I provide new evidence on estimating the food group-specific marginal propensity to spend (MPS) out of SNAP benefits. The paper includes 9 unique food groups and each group is further classified as a starred and no-star subgroups, thus giving us 18 food groups in total (the star level of food is identified by the Guiding stars program). Our estimates shed light on the food spending differences between healthy and unhealthy food, which contribute to designing targeted strategies to improve dietary quality of SNAP households.

Aside from SNAP participation, we also take food prices into consideration. Price is one of the most important determinants of food choice (Lusk and Briggeman, 2009). Changes in food prices create incentives for low-income households to alter their eating pattern. For example, subsidies could be provided to healthier foods (e.g., fruit and vegetables) and less healthy foods could be taxed (e.g., sugar-sweetened beverages (SSB) and salty snacks) (Andreyeva et al., 2011; Dong and Lin, 2009). Therefore, in this chapter, I first estimate the price elasticities on food subgroups differentiated by food type and healthfulness, then I simulate low-income households' likely responses to a tax on no-star meat and beans, no-star beverage and no-star snacks and a subsidy on starred vegetables and starred whole fruits.

References

Andreyeva T, Chaloupka FJ, Brownell KD. Estimating the potential of taxes on sugar-sweetened beverages to reduce consumption and generate revenue. *Preventive Medicine* 2011;52; 413-416.

Andreyeva, T., Tripp, A. S., & Schwartz, M. B. (2015). Dietary Quality of Americans by Supplemental Nutrition Assistance Program Participation Status: A Systematic Review. *American Journal of Preventive Medicine, 49*(4), 594-604. doi:**https://doi.org/10.1016/j.amepre.2015.04.035**

Beaglehole, R., Bonita, R., Horton, R., Adams, C., Alleyne, G., Asaria, P., . . . Watt, J. (2011). Priority actions for the non-communicable disease crisis. The Lancet, 377(9775), 1438-1447. doi:https://doi.org/10.1016/S0140-6736(11)60393-0

Bolhuis, D. P., Costanzo, A., Newman, L. P., & Keast, R. S. (2015). Salt Promotes Passive Overconsumption of Dietary Fat in Humans–3. The Journal of nutrition, 146(4), 838-845.

Boon, C. S., Taylor, C. L., & Henney, J. E. (2010). Strategies to reduce sodium intake in the United States: National Academies Press.

Darmon, N., & Drewnowski, A. (2008). Does social class predict diet quality? *The American Journal of Clinical Nutrition, 87*(5), 1107-1117. doi:10.1093/ajcn/87.5.1107

Dong D, Lin B-H. 2009. Fruit and Vegetable Consumption by Low-Income Americans: Would a Price Reduction Make a Difference? (Ed)^(Eds). 2009.

Leshem, M. (2009). Biobehavior of the human love of salt. Neuroscience & Biobehavioral Reviews, 33(1), 1-17.

Lusk JL, Briggeman BC. Food Values. American Journal of Agricultural Economics 2009;91; 184-196.

Nguyen, B. T., Shuval, K., Njike, V. Y., & Katz, D. L. (2014). The Supplemental Nutrition Assistance Program and Dietary Quality Among US Adults: Findings From a Nationally Representative Survey. *Mayo Clinic Proceedings, 89*(9), 1211-1219. doi:**https://doi.org/10.1016/j.mayocp.2014.05.010**

Sookram, C., Munodawafa, D., Phori, P. M., Varenne, B., & Alisalad, A. (2015). WHO's supported interventions on salt intake reduction in the sub-Saharan Africa region. Cardiovascular Diagnosis and Therapy, 5(3), 186-190. doi:10.3978/j.issn.2223-3652.2015.04.04

Webb, M., Fahimi, S., Singh, G. M., Khatibzadeh, S., Micha, R., Powles, J., & Mozaffarian, D. (2017). Cost effectiveness of a government supported policy strategy to decrease sodium intake: global analysis across 183 nations. Bmj, 356, i6699. doi:10.1136/bmj.i6699

CHAPTER 2

TASTE OR HEALTH? A PRODUCT-LEVEL DEMAND ANALYSIS IN THE INSTANT NOODLE MARKET*

* Yu Chen and Chen Zhen. To be submitted to *Health Economics.*

2.1. Abstract

Although there has been talk of voluntary sodium reduction among major Chinese food manufactures, it is not clear how unilateral or coordinated sodium reductions would affect companies' market shares. To answer this question, we estimate the impact of sodium reduction on the demand for instant noodle in China, using a random-coefficient logit demand model including all major instant noodle brands and varieties. Results suggest that demand is positively associated with both sodium and saturated fat levels. This implies that if a company unilaterally lowers sodium amounts across its product line, it will lose market share to its competitors. The positive valuation of saturated fat by consumers suggests that if a mandated sodium reduction is implemented through regulation, manufacturers could compensate the negative impact on sales by reformulating their products to contain higher levels of saturated fat, which would offset the health benefits gained from a reduction in sodium.

Key words: Sodium reduction strategy, Random-coefficients logit model, Chinese scanner data

2.2 Introduction

Food choice is a major factor for healthy living. The taste of food is always rated as the most important driver in food consumption and repeated food purchases (Lusk & Briggeman, 2009; Stanton, 2013). The palatability and enjoyment of food are often tied to the fat, salt and sugar content - three key ingredients that make the food have an undeniable sensory appeal and difficult to resist (Bolhuis, Costanzo, Newman, & Keast, 2015; Leshem, 2009). Nevertheless, over-consumption of food high in fat, salt, and sugar is the cause of at least 14 million deaths or 40% of all deaths every year from non-communicable diseases (NCDs) globally (Beaglehole et al., 2011).

Excessive sodium intake is common and linked to cardiovascular disease in most countries. In 2010, 99.2% of the global adult population have mean sodium intakes exceeding the World Health Organization (WHO) recommended maximum of 2 g per day, and an estimated 1.65 million annual deaths from cardiovascular diseases worldwide were attributable to excess dietary sodium (Mozaffarian et al., 2014; Powles et al., 2013). Reducing the amount of salt has been identified as a priority and the most cost-effective intervention to NCDs, by lowering blood pressure, and thereby reducing the risk of cardiovascular disease deaths (Sookram, Munodawafa, Phori, Varenne, & Alisalad, 2015; Webb et al., 2017). Additionally, WHO Member States have agreed to a global target of a 30% reduction in salt intake by 2025 (WHO, 2013).

National and international organizations are developing programs to reduce sodium consumption through educational and labeling activities (Dötsch et al., 2009). For example, initiatives on salt reduction labelling include traffic lights (UK), warnings (Finland), and logos (e.g., Canada) (Webster, Dunford, Hawkes, & Neal, 2011). However, a key factor limiting the success of efforts for the sodium reduction goal is that salt, the primary source of sodium in the diet, is used to enhance the flavor of foods, and in some products is needed also for preservation and processing (Bolhuis et al., 2015; Leshem, 2009). The Institute of Medicine (IOM) in the U.S. recommended several strategies for reducing sodium daily intake (Boon, Taylor, & Henney, 2010). The primary strategy is to set mandatory national standards for the sodium content of foods. In the interim, the strategy has been to encourage the food industry to voluntarily reduce the sodium content of foods.

Prior studies discussed the feasibility of voluntary and mandatory sodium reduction strategies from the perspective of their cost-effectiveness. For example, Pearson-Stuttard et al. (2018) suggested that the proposed US Food and Drug Administration voluntary sodium reformulation policy could generate substantial health gains and net cost savings if the reformulation targets can be achieved. Webb et al. (2017) concluded that a government regulation strategy combining industry agreement and public education to reduce dietary sodium was highly cost-effective worldwide, even without taking account of healthcare savings. Nevertheless, it is not clear how consumers and food companies respond to sodium reduction strategy. Intuitively, if reducing sodium content results in less palatable products, it will lower consumers' demand and they could purchase other alternative foods instead, resulting in food companies' market share decreased. While as Moss (2013) suggested that food companies always adjust the mix of fat, sodium, and sugar in their products to achieve the so-called taste "bliss point" for consumers. Therefore, food companies could compensate the decreased sales through food reformulation which may cause some unintended consequences. These are all key factors that affect the success of the implementation of salt reduction initiatives and need to be identified and addressed from the outset.

In this paper, we fill this gap through estimating the impacts of reducing sodium content from a leading brand and further from all brands on the demand for instant noodle products in the China market– a typical convenient food market and an important source of sodium intake. Our empirical estimation uses the random-coefficients logit model that accounts for the heterogeneity in consumers' preferences with respect to different products. The results suggest that if a company with a large share in the market unilaterally lowers sodium amounts across its product line, it will lose its market share to its competitors. This indicates that voluntary standards will not be enough to provide sustainability of sodium reductions. Hence, if there is an industry-wide sodium reduction mandate through regulation, sales of all companies will decline. As a result, instant noodle companies may shift their attention to other ingredients to compensate for the taste of products. For example, food companies could compensate the negative impact on sales by reformulating their products to contain higher levels of fat - which may cause over-consumption of fat, this is an unintended consequence that offsets the health benefits gained from a reduction in sodium. It is thus challenging to achieve the goal of reducing sodium content to the safe levels that is in line with the public health recommendation, the strategies must be supported by policy makers and ensure coordination with food industry.

This paper makes two main contributions. First, our analysis contributes to a strand of literature that focuses on estimating the price elasticity of demand for a particular type of food, we fill the gap by providing the first estimates of demand for instant noodle products in China and shed light on how product market shares are associated with nutrients content. Second, our analysis examines the feasibility of voluntary and mandated sodium reduction strategies through providing evidence on the demand changes of instant noodle products caused by sodium reduction. We contribute by providing evidence from a market viewpoint to guide policy makers about designing optimal sodium reduction program.

The rest of the paper is organized as follows. The next section explains the characteristics of the Chinese instant noodle market. Section 3 presents the construction of our data set. Section 4 introduces the demand model that generates price elasticities and that helps in conducting the counterfactual simulation of the demand change. Section 5 provides the results of instant noodle demand and sodium reduction simulation. The last section presents the conclusion.

2.3. The Chinese instant noodle market

Instant noodle is one of the first ready-to-eat foods launched widely in the global food industry. The demand for instant noodle products is driven by their convenience, low cost, and product diversity. Chinese instant noodle market is the largest instant noodle market in the world. In 2015, the World Instant Noodles Association reported that 52 countries consumed 97.7 billion servings, out of which Chinese instant noodle demand accounted for nearly half, with sales topping 40 billion packets annually (Zhu, 2015). Large consumption usually occurs among college students, migrant workers and during train journeys (Atkinson, 2017; Kynge, 2013; Sun, Yin, Yang, Gong, & Xiao, 2015). Besides, the Chinese instant noodle market is a matured market with a large number of products, making it a typical market when estimating the instant noodle demand.

Particularly, it is a market that usually at the heart of policy debates, concerns regarding to its nutritional content have pushed instant noodles under scrutiny of public opinions. Instant noodle is high in sodium, Park, Lee, Jang, Chung, & Kim (2011) estimated that the average daily sodium intake of instant noodle consumers was more than 6.4 g, of which one pack of instant noodle can contribute over 30%, nearly reach the recommended sodium daily value[1] (2.4 g). Besides, prior studies have found that instant noodle is associated with a higher risk for gastric cancer compared with that of plain noodles, and eating instant noodles more than twice a week is associated with a higher prevalence of metabolic syndrome (Shin et al., 2014; Youm & Kim, 1998). Therefore, instant noodle products are often criticized as unhealthy or as a type of "junk" food because of its excessive sodium content and lack of nutrition. This has drawn the attention of regulatory agencies on the production practices in this market.

2.4. Data

We use a unique barcode-level scanner dataset, known as Kantar Worldpanel[2], which has a 40,000-household consumer panel in China. The data is stratified by province/municipality, household's monthly income, and the barcode of products. We use the dataset that tracks the four-week instant noodle purchase of urban households from 20 provinces and 4 municipalities in 2011 and 2012. The consumer purchasing information includes total purchase volume and expenditure, and we also augment this data with additional products' nutrient information which is collected from food companies' websites.

"A market" in this paper is defined as combination of province/municipality and time period (year and quad-week (four weeks)). For example, the purchase occurred in BeiJing and during the first quad-week of year 2011 (BeiJing-2011-quad-week1) is "a market". Therefore, there are 624 markets and 18,208 observations in total based on 24 provinces/municipalities and 13 four-week each year in 2011 and 2012. From prior studies, market size can be set equal to the

---

[1] Sources: Food and Drug Administration:
http://google2.fda.gov/search?q=vitamin&client=FDAgov&site=FDAgov&lr=&proxystylesheet=FDAgov&requiredfields=-archive%3AYes&output=xml_no_dtd&getfields=*
Vitamin and minerals:
http://www.accessdata.fda.gov/scripts/InteractiveNutritionFactsLabel/vitamins-and-minerals.html

[2] Kantar Worldpanel is an international company dealing in consumer knowledge and insights based on continuous consumer panel.

number of households in the economy (e.g., S. Berry, Levinsohn, and Pakes (1995)), or parameterized using market-level data characteristics (such as population) that vary across markets (e.g., S. T. Berry (1990)). In this paper, we set the market size as an estimate of the total instant noodle purchases of each market, that is, we multiply an estimate of four-week per capita instant noodle purchase (34 packs3) by the number of total population in this market (NBS, 2018).

Each market comprises a large number of instant noodle products that individually account for small shares of the market. To limit the number of products in the demand model and to preserve as much of the product differentiation as possible, we first select nine top instant noodle brands in terms of their relative large market shares in the data (given in the Table 2.1). Second, we create unique products by aggregating similar items based on brand, flavor and package shape. Specifically, we classify instant noodle products into four common flavors: beef, pork, chicken, and seafood. We also classify the products into two packages: "bag" and "other packages" such as barrel, box, and cup, etc. For example, we define MasterKong brand with beef flavor and bag packaging (MasterKong-Beef-Bag with product number 111) as a unique product. The market share of each unique product is calculated as dividing its purchase volume by the market size. The market share of the outside good is defined as the difference between one and the sum of all unique products' market shares.

The observed characteristics of instant noodles include price, serving size (weight per pack) and nutrient content, i.e., sodium, fat, energy, protein, and carbohydrate. Table 2.1 lists the summary statistics of 9 instant noodle brands. Selected instant noodle brands on average account

[3] Sources: China tops world in instant noodle consumption: report(2014). *Global Times*. Retrieved from http://www.globaltimes.cn/content/897921.shtml

for 34.15% of the market. The prices of instant noodle are about 2 RMB per 100 g, except that Nissin brand is more than twice as expensive. A 100-gram instant noodle product, on average, contains sodium 1.89 g (varies from 0.96 to 2.42 g), equivalent to 4.73 g or about 1 teaspoon salt. This almost reaches the existing maximum sodium intake level (2,300 mg/d sodium or 5.8 g/d salt) established by the 2005 Dietary Guidelines for Americans. Besides, a 100-gram instant noodle product contains fat 20.51 g (varies from 7.35 to 23.37 g) and energy 1,890 KJ (varies from 1,620 KJ to 2,035 KJ). Therefore, based on a 2,000 kcal/day diet (i.e., 8,368KJ/day), this provides about one-third of the fat requirement (65g) and 23% of daily energy requirement (FDA, 2018).

2.4.1. Price Index Construction and Instrumental Variables

Price is potentially endogenous which may be caused by omitted variables from unobserved characteristics. For example, when consumers value quantity over quality, they would prefer to purchase relative cheaper products, then omitted variable bias may occur. Zhen, Finkelstein, Nonnemaker, Karns, and Todd (2014) proved that using Fisher ideal price indices can partly account for this quantity-quality trade-off within a food category. Therefore, we construct the Fisher ideal price index for each aggregated unique instant noodle product. For the unique product j, the Fisher ideal price index is calculated as:

$$p_{jht} = \sqrt{\frac{\sum p_{mht} q_{m0}}{\sum p_{m0} q_{m0}} \frac{\sum p_{mht} q_{mht}}{\sum p_{m0} q_{mht}}} \tag{1}$$

Where p_{mht} and q_{mht} are the price and purchase quantity of original product *m* for household *h* in market *t*, and p_{m0} and q_{m0} are the base price and base quantity of product *m* which are set at their national means.

Besides, we also construct the instrument variable for the price index to reduce bias, using an approach similar to that of Hausman (1996). It is calculated as the weighted average of the price indices of the same product from all other provinces in the same time period. The weight is the inverse of the distance between the capital cities of the target province and other provinces. This type of price instrument is assumed that after controlling for mean household evaluations of instant noodle products and household demographic effects, prices that faced by households from different provinces are not affected by common demand shocks. Using prices of other locations to instrument endogenous prices is also useful in overcoming endogeneity bias because of lack of supply-side factors (Nevo, 2000; Zhen et al., 2014). Besides, we also use interactions of price instrument with nutritional attributes as additional instruments for price to help increase estimation efficiency.

Product's characteristics, i.e., nutritional attributes of instant noodle, are considered exogenous in this paper. First, nutrients are assumed to be determined at their optimal level to produce the best flavor. Papers that treat product's characteristics as endogenous have different assumptions. For example, Fan (2013) analyzes the effects of ownership consolidation on the US daily newspaper market, assuming that product characteristics will be affected by the mergers. The author makes the adjustments in newspaper characteristics using the demographics in nonoverlapping markets of a newspaper's competitors as instruments. Second, the concept of Fan (2013)'s instruments construction for product characteristics is not appropriate for this paper. Fan (2013) can solve the endogenous problem of newspaper's characteristics based on a key feature that the circulation area of a newspaper partially overlaps with other newspapers' circulation areas. In our analysis, the selected instant noodle products are the most popular ones that account for large market share of each market, and most of their circulation areas are over all the provinces/municipalities.

2.5. Methodology

2.5.1. Demand

The random-coefficients logit model which was proposed by Berry, Levinsohn, and Pakes (1995), referred below as the BLP model, is widely used to estimate demand for a large number of differentiated products with various attributes. BLP model was originally applied to automobiles and has been widely applied to estimate food products such as breakfast cereals (Chidmi & Lopez, 2007; Nevo, 2001), frozen foods (Mojduszka, Caswell, & Harris, 2001) and ketchup (Rennhoff, 2008). BLP model can reduce the number of parameters to be estimated by projecting the products on a space of characteristics, in addition, it incorporates random coefficients for product characteristics which creates flexible substitution patterns and takes into account the heterogeneity in consumers' preferences. In this paper, we apply the BLP model to estimate the demand for instant noodle market using a barcode-level scanner dataset, allowing us to look more closely at the nature of consumer choices in this market.

In the model, a consumer is assumed to choose an instant noodle product to maximize his/her utility, driven by the product characteristics as well as consumer's preferences. The indirect utility of consumer i from consuming a unique instant noodle product j in market t is represented by equation (2).

$$u_{ijt} = -\alpha_i p_{jt} + \boldsymbol{\beta} \boldsymbol{x_{jt}} + \xi_{jt} + \varepsilon_{ijt} \quad i = 1, \ldots, I_t,\ t = 1, \ldots, T,\ j = 1, \ldots, J \qquad (2)$$

Where p_{jt} is the price of instant noodle product *j* in market *t*, $\boldsymbol{x_{jt}}$ is a vector of attributes of product *j*, including sodium, fat, energy, protein, carbohydrate content, quadratic terms of sodium and fat, and an interaction term of sodium and fat. ξ_{jt} is the unobserved product characteristics for product *j* in market *t*, and ε_{ijt} is the error term.

We include instant noodle brand, province/municipality, and quad-week dummy variables in the model to capture some unobserved characteristics. Brand-specific dummy variables help to capture some brand characteristics that do not vary by market. Province/municipality and quad-week dummy variables are market-specific variables that contribute to identify the variation of the preferences for instant noodle products by province and time periods.

Consumer *i* can choose to purchase none of the instant noodle products that we considered. Therefore, we include an outside good which allows for substitution between the selected instant noodle products and a substitute, and the indirect utility of the outside good is $u_{i0t} = \varepsilon_{i0t}$.

Following equation (2), α_i is modeled as follows:

$$\alpha_i = \alpha + \sigma_\alpha \nu_i \qquad\qquad \nu_i \sim P_\nu(\nu) \tag{3}$$

Where ν_i captures the unobserved consumers' characteristics (e.g. valuation of product's taste). We assume that $P_\nu(\nu)$ follows a normal distribution. Thus, we have,

$$\begin{gathered} u_{ijt} = \delta_{jt}\left(x_{jt}, \xi_{jt}, p_{jt}; \alpha\right) + \mu_{ijt}\left(p_{jt}, \nu_i; \sigma_\alpha\right) + \varepsilon_{ijt} \\ \delta_{jt} = -\alpha p_{jt} + \boldsymbol{\beta x_{jt}} + \xi_{jt} \qquad \mu_{ijt} = -\, p_{jt}\sigma_\alpha \nu_i \end{gathered} \tag{4}$$

where δ_{jt} is mean utility which is common to all consumers, and $\mu_{ijt} + \varepsilon_{ijt}$ represents a mean-zero heteroskedastic deviation from the mean utility which captures the effects of random coefficients.

Let A_{jt} defines all the individuals who choose product *j* in market *t*, where $A_{jt} = \{(\nu_i, \varepsilon_{i0t}, \ldots, \varepsilon_{iJt}) | u_{ijt} \geq u_{ilt} \quad \forall l = 0,1,\ldots,J\}$, $l = 0$ denotes the outside good.

Assume that ε_{ijt} is a mean-zero stochastic term distributed independently and identically as Type I extreme value distribution, the market share of the product j in market t is an integral over the consumers in the region A_{jt}, given by:

$$s_{jt} = \int_{A_{jt}} dP(\nu, \varepsilon) = \int_{A_{jt}} dP_{\varepsilon}(\varepsilon)\, dP_{\nu}(\nu) \tag{5}$$

$$s_{jt} = \int_{A_{jt}} \left(\frac{\exp(\delta_{jt}+u_{ijt})}{1+\sum_{k=1}^{J_t}\exp(\delta_{kt}+u_{ikt})}\right) dP_{\nu}(\nu) \tag{6}$$

where $P_{\varepsilon}(\varepsilon)$ and $P_{\nu}(\nu)$ are population distribution functions and are assumed to be independent of each other.

The price elasticities of the market share are given by:

$$\eta_{jkt} = \frac{\partial s_{jt}}{\partial p_{kt}} \cdot \frac{p_{kt}}{s_{jt}} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \int \alpha_i s_{ijt}(1-s_{ijt}) dP_{\nu}(\nu) & if \quad j = k, \\ \frac{p_{kt}}{s_{jt}} \int \alpha_i s_{ijt} s_{ikt} dP_{\nu}(\nu) & if \quad otherwise \end{cases} \tag{7}$$

where $s_{ijt} = \frac{\exp(\delta_{jt}+u_{ijt})}{1+\sum_{k=1}^{J_t}\exp(\delta_{kt}+u_{ikt})}$ (8)

The price sensitivity now is a probability-weighted average and can differ over products that allows for flexible patterns of substitution (Vincent, 2015).

2.5.2 Market share simulation

With the estimates from the BLP model, we simulate the changes of products' market shares under three sodium reduction scenarios, and the simulated market share for product *j* in market *t* is obtained by using equation (9).

$$s_{jt} = \frac{1}{R}\sum_{i=1}^{R} \frac{\exp\{\delta_{jt} - p_{jt}\sigma_{\alpha}v_r^{\alpha}\}}{1+\sum_{m=1}^{J}\exp\{\delta_{jt} - p_{jt}\sigma_{\alpha}v_r^{\alpha}\}} \tag{9}$$

Where R (we set R=500) is the number of random draws of distribution $P_{\nu}(\nu)$, v_r^{α} is the *r*th draws of the normal distribution $P_{\nu}(\nu)$.

In the simulation, we assume price is the same as original price since instant noodle products are cheap and the cost of sodium and fat[4] are low, changing sodium and fat content will not significantly change the price. After obtaining the estimates of simulated market shares under different scenarios, we can further calculate the new price elasticities using equation (7).

2.6. Results

2.6.1 Demand results

Table 2.2 shows the estimates of the BLP model. Consumers have a negative and strong valuation of price, on average, the effect of price on consumer's utility is -2.507, with the standard deviation of 1.192 reflecting the price variation effect. Sodium and fat are the main ingredients which contribute to the taste of instant noodle product, as expected, results show that consumers have significant valuation of sodium and there is inverse "U-shaped" relationship between consumers' utility and sodium level while keeping other product attributes fixed, the similar result is shown for fat content. The negative coefficient of the interaction term of fat and sodium implies that increasing fat level will decrease the marginal effect of sodium on the consumers' mean utility.

Additionally, results of brand fixed effects show that compared with MasterKong brand, consumers on average have a preference on HuaFeng, Nissin and WuGuDaoChang while lower valuation for other brands. Other fixed effects show that the preferences for instant noodle vary by province and time, for example, compared with the first four-week of the year, consumers are more likely to purchase instant noodles in the second and third four-week periods, while less likely to purchase instant noodles from the fifth to the eighth four-week periods.

[4] Fat in the instant noodle products comes from the palm oil, which accounts for 18% of the cost of instant noodle products.

Our analysis includes 9 top instant noodle brands and in total 51 products based on their large market shares in our data. The results show that all own-price elasticities are negative and cross-price elasticities are positive. All of the instant noodle products are own-price elastic, indicating that intake of instant noodle product is responsive to its own price changes. The magnitude of the own-price elasticities ranges from -1.487 for MasterKong-Beef-Bag product to -1.862 for HuaLong-Seafood-Bag product. There are no prior studies as the reference for the price elasticities of instant noodles, but we find that the magnitudes of the own-price elasticities are close to previously estimated elasticities of cakes and cookies[5] demand (Zhen et al., 2014). The full table of price elasticity of instant noodle products is shown in the Appendix Table A.1a - Table A.1h.

Table 2.3a and 2.3b show the price elasticities of demand for instant noodle products of the top four brands that occupy the instant noodle market, and among which have the strongest competition, i.e., MasterKong, JinMaiLang, Uni-President, and BaiXiang. MasterKong is the leading brand, when we fix the flavor and package shape, the own-price elasticities of MasterKong products are smaller than other three brands, showing consumers' preference on it. For example, when the flavor is beef and the package shape is bag, the own-price elasticity of MasterKong is -1.487, less elastic than JinMaiLang, Uni-President, and BaiXiang (with the own-price elasticity of -1.649, -1.616 and -1.719, respectively[6]). Using the same comparison method, results show that beef flavor has less elastic own-price elasticities than other flavors.

Cross-price elasticity estimates are consistent with a priori expectation. For example, the average cross-price elasticitity is 0.229 between MasterKong-Beef-Bag product and other

---

[5] The own price elasticity is -1.697 for cakes and cookies in Zhen et al. (2014) .

[6] That is, compare the own-price elasticity of products with product number of 111, 211, 311, and 411 from Table 2.3a and 2.3b.

products, meaning product choices are more responsive to changes in the price of the products with MasterKong brand, beef flavor, and bag package. Similarly, product choices are responsive to the changes in the price of the Uni-President-Beef-Bag, JinMaiLang-Beef-Bag, and MasterKong-Beef-Nonbag products. Moreover, product choices are more responsive to changes in the price of products with bag than other packages. That is, when we fix the instant noodle brand and flavor, compare the products with different package shapes, the magnitude of cross-price elasticity of bag packaged product is always bigger than products with other packaging. It is plausible given that bag package is more common than other packages, more varieties exist, causing stronger substitution of the bag packaged products.

2.6.2. Counterfactual simulation

Excess sodium intake is a risk factor for hypertension and cardiovascular disease (Beaglehole et al., 2011; Mancia et al., 2017). The Institute of Medicine (IOM) in the U.S. recommends strategies for reducing sodium intake to no more than 2,300 mg per day for persons two or more years of age. As its primary strategy for sodium reduction, the IOM committee recommends setting mandatory standards for the sodium level in foods. In advancing the implementation of mandatory standards, an interim strategy is to encourage food industry to voluntarily act to reduce the sodium content of foods. In line with the strategies, we therefore simulate three sodium reduction scenarios for instant noodle products to explore the corresponding change in their market shares: (1) MasterKong brand (a leading brand that accounts for the largest market share) voluntarily reduces sodium content from its products by 10%, while keeping other demand shifters (i.e., price and other nutrients) fixed; (2) all of the instant noodle brands are mandated to reduce the sodium content by 10%; and (3) all of the brands reduce sodium by 10% while increasing fat[7] by 6%.

Under the simulated scenarios, the demand for instant noodle products changes. Table 2.4 compares the market shares under different scenarios. First, a decrease in the sodium content of products from MasterKong brand leads to a decrease of 5.56 percentage points in the market share of MasterKong. This is due to substitution with products from other brands (whose market shares increase in total by 1.78 percentage points) as well as with the outside option (whose market share increases by 3.78 percentage points). Second, when sodium content is mandated to reduce by 10 percent from all brands, the market share drops to 28.40%, a 5.75 percentage points decrease from the original market share (34.15%). Besides, changes in market share are heterogeneous across brands. Master Kong, Uni-President and WuGuDaoChang have larger percentage points decrease. It is interesting to note that when we reduce the sodium content, brands with the highest original sodium content (BaiXiang and HuaLong) experience an increase in their market shares. Third, when instant noodle products from all brands reduce the sodium content by 10% as well as increasing 6% fat content, compared to the mandated sodium reduction scenario, except that WuGuDaoChang maintains its market share, the market shares from all other brands increase, as a result, the overall market share rises back to 33.88%, approaching to the original market share.

Besides, the own-price elasticity estimates of instant noodle products change under different scenarios (as seen in Table 2.5). In the baseline scenario, the own-price elasticity varies from -1.862 to -1.487, with the median value being -1.703. When products of MasterKong brand reduce their sodium content by 10%, the median value of own-price elasticity becomes -1.650.

[7] Fat increases by 1 gram, another nutrient, energy will increase 37 KJ accordingly.

Furthermore, when all the brands reduce sodium content by 10%, the median value of own-price elasticity becomes -1.627. The results show that both voluntary and mandated sodium reduction would decrease the magnitudes of the own-price elasticities.

Sodium affects the taste and consumers are keen on foods that are salty (Moss, 2013). Voluntary reduction in the sodium content unilaterally from MasterKong brand results in a decrease of its market share. This highlights the difficulty in marketing lower-salt instant noodle products when competitors' products that are not lower in salt are preferred by consumers. Furthermore, if all brands reduce sodium content from the products, many consumers will purchase other food to substitute instant noodles. The remaining consumers are the ones that have relative stronger preference for the instant noodle products or have fewer food choices to substitute instant noodles with. This can be confirmed by our results that when the sodium content decreases, the magnitudes of own-price elasticity decrease, meaning that the demand for instant noodle become less elastic than before. Another compelling finding is that reformulation of sodium and fat content could maintain the products' market shares, or in other words, catering to consumers' taste in the instant noodle market.

2.7. Conclusion

The global high prevalence of cardiovascular diseases has raised concerns regarding the sodium content of the foods that we consume. Two main sodium reduction strategies are widely discussed in prior studies, one is to call for efforts by the food industry to voluntarily reduce sodium in their products and the other is to set mandatory standards for the sodium content of foods. To assess the feasibility of these two strategies from a consumer demand angle, we focus our analysis on the Chinese instant noodle market that is frequently criticized for containing high amounts of sodium, and we simulate the impact of each sodium reduction strategy on the demand for instant noodles using the random-coefficients logit model formulated by Berry, Levinsohn & Pakes (1995).

We find that if the sodium content is reduced voluntarily by 10 percent from MasterKong brand (a leading instant noodle brand), the market share of its products will decrease by 5.56 percentage points, and other brands in total will increase market share by 1.78 percentage points. This implies that if a company unilaterally lowers sodium amounts across its product line, it will lose market share to its competitors. This provides the evidence on the challenges that voluntary sodium reduction strategy faces.

Compared with the voluntary sodium reduction strategy, it has been suggested that an industry-wide mandated sodium reduction strategy can be more effective since the changes to the food environment makes it easy for the population to consume less salt (Dötsch et al., 2009). Our analysis shows that when the sodium content is reduced by 10 percent from all brands, sales of all companies decline and the whole market share decreases by 5.75 percentage points. However, increasing fat content would offset the demand effect of sodium reduction. This empirical finding reveals the potential of food reformulation toward reducing populations' salt intake, that is, food companies could produce palatable products with less sodium content by means of ingredient reformulation.

It should be noted that food reformulation may cause unintended consequences. As our analysis shows, food companies could compensate the negative impact on sales by reformulating their products to contain higher levels of fat, this may result in fat over-consumption and offset the health gains from sodium reduction. As we know, fat over-consumption can increase the risk of illnesses, such as obesity (Stewart, Newman, & Keast, 2011; Swinburn et al., 2011), heart diseases (De Souza et al., 2015; Praagman et al., 2016) and diabetes (Ravussin & Smith, 2002).

Although food reformulation has been recommended as an effective way toward reducing populations' salt intake in prior studies (e.g., Kloss, Meyer, Graeve, and Vetter (2015); Regan et al. (2017)), we suggest that it is critical to monitor changes in the food supply side to avoid the unintended consequences and to ensure that new formulations are truly healthier.

To summarize, efforts to reduce population sodium intake is underway, as part of an overall strategy to support healthy diets. Sodium reduction strategies needs to be designed to help achieve the safe levels of sodium in consumers' diet without loss of consumers' acceptance of foods and to avoid the unintended consequences. To this end, the sodium reduction strategies must be supported by policy makers and ensure coordination with food industry.

2.8. References

Allais, O., Bertail, P., & Nichèle, V. (2010). The Effects of a Fat Tax on French Households' Purchases: A Nutritional Approach. *American Journal of Agricultural Economics, 92*(1), 228-245. doi:10.1093/ajae/aap004

Atkinson, S. (2017). Why are China instant noodle sales going off the boil? Retrieved from https://www.bbc.com/news/business-42390058

Beaglehole, R., Bonita, R., Horton, R., Adams, C., Alleyne, G., Asaria, P., . . . Watt, J. (2011). Priority actions for the non-communicable disease crisis. *The Lancet, 377*(9775), 1438-1447. doi:https://doi.org/10.1016/S0140-6736(11)60393-0

Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, 841-890.

Berry, S. T. (1990). Airport presence as product differentiation. *The American Economic Review, 80*(2), 394-399.

Bolhuis, D. P., Costanzo, A., Newman, L. P., & Keast, R. S. (2015). Salt Promotes Passive Overconsumption of Dietary Fat in Humans–3. *The Journal of nutrition, 146*(4), 838-845.

Boon, C. S., Taylor, C. L., & Henney, J. E. (2010). *Strategies to reduce sodium intake in the United States*: National Academies Press.

Chidmi, B., & Lopez, R. A. (2007). Brand-Supermarket Demand for Breakfast Cereals and Retail Competition. *American Journal of Agricultural Economics*, *89*(2), 324-337.

De Souza, R. J., Mente, A., Maroleanu, A., Cozma, A. I., Ha, V., Kishibe, T., . . . Beyene, J. (2015). Intake of saturated and trans unsaturated fatty acids and risk of all cause mortality, cardiovascular disease, and type 2 diabetes: systematic review and meta-analysis of observational studies. *Bmj*, *351*, h3978.

Dötsch, M., Busch, J., Batenburg, M., Liem, G., Tareilus, E., Mueller, R., & Meijer, G. (2009). Strategies to Reduce Sodium Consumption: A Food Industry Perspective. *Critical Reviews in Food Science and Nutrition, 49*(10), 841-851. doi:10.1080/10408390903044297

Fan, Y. (2013). Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market. *American Economic Review, 103*(5), 1598-1628. doi:doi: 10.1257/aer.103.5.1598

FDA, U. S. F. a. D. A. (2018). Daily Values of Nutrients. Retrieved from https://www.accessdata.fda.gov/scripts/InteractiveNutritionFactsLabel/sodium.html

Hausman, J. A. (1996). Valuation of new goods under perfect and imperfect competition. In *The economics of new goods* (pp. 207-248): University of Chicago Press.

Kloss, L., Meyer, J. D., Graeve, L., & Vetter, W. (2015). Sodium intake and its reduction by food reformulation in the European Union — A review. *NFS Journal, 1*, 9-19. doi:https://doi.org/10.1016/j.nfs.2015.03.001

Kynge, J. (2013). Migrant workers shape China's future.

Leshem, M. (2009). Biobehavior of the human love of salt. *Neuroscience & Biobehavioral Reviews, 33*(1), 1-17.

Lusk, J. L., & Briggeman, B. C. (2009). Food Values. *American Journal of Agricultural Economics, 91*(1), 184-196. doi:10.1111/j.1467-8276.2008.01175.x

Mancia, G., Oparil, S., Whelton, P. K., McKee, M., Dominiczak, A., Luft, F. C., . . . Narula, J. (2017). The technical report on sodium intake and cardiovascular disease in low- and middle-income countries by the joint working group of the World Heart Federation, the European Society of Hypertension and the European Public Health Association. *European heart journal, 38*(10), 712-719. doi:10.1093/eurheartj/ehw549

Mojduszka, E. M., Caswell, J. A., & Harris, J. M. (2001). Consumer choice of food products and the implications for price competition and government policy. *Agribusiness, 17*(1), 81-104. doi:doi:10.1002/1520-6297(200124)17:1<81::AID-AGR1004>3.0.CO;2-9

Moss, M. (2013). *Salt, sugar, fat: How the food giants hooked us*: Random House.

Mozaffarian, D., Fahimi, S., Singh, G. M., Micha, R., Khatibzadeh, S., Engell, R. E., . . . Powles, J. (2014). Global Sodium Consumption and Death from Cardiovascular Causes. *New England Journal of Medicine, 371*(7), 624-634. doi:10.1056/NEJMoa1304127

Mytton, O., Gray, A., Rayner, M., & Rutter, H. (2007). Could targeted food taxes improve health? *Journal of epidemiology and community health, 61*(8), 689-694. doi:10.1136/jech.2006.047746

NBS, N. B. o. S. (2018). Retrieved from http://www.stats.gov.cn/tjsj/pcsj/

Nevo, A. (2000). Mergers with differentiated products: The case of the ready-to-eat cereal industry. *The RAND Journal of Economics*, 395-421.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica, 69*(2), 307-342.

Park, J., Lee, J.-S., Jang, Y. A., Chung, H. R., & Kim, J. (2011). A comparison of food and nutrient intake between instant noodle consumers and non-instant noodle consumers in Korean adults. *Nutrition research and practice, 5*(5), 443-449.

Pearson-Stuttard, J., Kypridemos, C., Collins, B., Mozaffarian, D., Huang, Y., Bandosz, P., . . . O'Flaherty, M. (2018). Estimating the health and economic effects of the proposed US Food and Drug Administration voluntary sodium reformulation: Microsimulation cost-effectiveness analysis. *PLoS medicine, 15*(4), e1002551.

Powles, J., Fahimi, S., Micha, R., Khatibzadeh, S., Shi, P., Ezzati, M., . . . Mozaffarian, D. (2013). Global, regional and national sodium intakes in 1990 and 2010: a systematic analysis of 24 h urinary sodium excretion and dietary surveys worldwide. *BMJ Open, 3*(12), e003733. doi:10.1136/bmjopen-2013-003733

Praagman, J., Beulens, J. W. J., Alssema, M., Zock, P. L., Wanders, A. J., Sluijs, I., & van der Schouw, Y. T. (2016). The association between dietary saturated fatty acids and ischemic heart disease depends on the type and source of fatty acid in the European Prospective Investigation into Cancer and Nutrition–Netherlands cohort1,2. *The American Journal of Clinical Nutrition, 103*(2), 356-365. doi:10.3945/ajcn.115.122671

Ravussin, E., & Smith, S. R. (2002). Increased Fat Intake, Impaired Fat Oxidation, and Failure of Fat Cell Proliferation Result in Ectopic Fat Storage, Insulin Resistance, and Type 2 Diabetes Mellitus. *Annals of the New York Academy of Sciences, 967*(1), 363-378. doi:doi:10.1111/j.1749-6632.2002.tb04292.x

Regan, Á., Kent, M. P., Raats, M. M., McConnon, Á., Wall, P., & Dubois, L. (2017). Applying a Consumer Behavior Lens to Salt Reduction Initiatives. *Nutrients, 9*(8), 901.

Rennhoff, A. (2008). Paying for Shelf Space: An Investigation of Merchandising Allowances in the Grocery Industry. In *Journal of Agricultural & Food Industrial Organization* (Vol. 6).

Shin, H. J., Cho, E., Lee, H.-J., Fung, T. T., Rimm, E., Rosner, B., . . . Hu, F. B. (2014). Instant Noodle Intake and Dietary Patterns Are Associated with Distinct Cardiometabolic Risk

Factors in Korea. *The Journal of nutrition, 144*(8), 1247-1255. doi:10.3945/jn.113.188441
Smith-Spangler, C. M., Juusola, J. L., Enns, E. A., Owens, D. K., & Garber, A. M. (2010). Population Strategies to Decrease Sodium Intake and the Burden of Cardiovascular Disease: A Cost-Effectiveness Analysis. *Annals of Internal Medicine, 152*(8), 481-487. doi:10.7326/0003-4819-152-8-201004200-00212
Sookram, C., Munodawafa, D., Phori, P. M., Varenne, B., & Alisalad, A. (2015). WHO's supported interventions on salt intake reduction in the sub-Saharan Africa region. *Cardiovascular Diagnosis and Therapy, 5*(3), 186-190. doi:10.3978/j.issn.2223-3652.2015.04.04
Stanton, J. (2013). Taste Remains Consumers' Top Preference for New Foods and Beverages. Retrieved from https://www.foodprocessing.com/articles/2013/market-view-taste/
Stewart, J. E., Newman, L. P., & Keast, R. S. J. (2011). Oral sensitivity to oleic acid is associated with fat intake and body mass index. *Clinical Nutrition, 30*(6), 838-844. doi:https://doi.org/10.1016/j.clnu.2011.06.007
Sun, C., Yin, F., Yang, R.-z., Gong, N., & Xiao, R. (2015). Investigate and Analysis on the Situation of Instant Noodles Consumption Among College Students in Kunming City of Yunnan Province. *Food and Nutrition in China, 1*, 020.
Swinburn, B. A., Sacks, G., Hall, K. D., McPherson, K., Finegood, D. T., Moodie, M. L., & Gortmaker, S. L. (2011). The global obesity pandemic: shaped by global drivers and local environments. *The Lancet, 378*(9793), 804-814. doi:https://doi.org/10.1016/S0140-6736(11)60813-1
Vincent, D. W. (2015). The Berry–Levinsohn–Pakes estimator of the random-coefficients logit demand model. *Stata Journal, 15*(3), 854-880.
Webb, M., Fahimi, S., Singh, G. M., Khatibzadeh, S., Micha, R., Powles, J., & Mozaffarian, D. (2017). Cost effectiveness of a government supported policy strategy to decrease sodium intake: global analysis across 183 nations. *Bmj, 356*, i6699. doi:10.1136/bmj.i6699
Webster, J. L., Dunford, E. K., Hawkes, C., & Neal, B. C. (2011). Salt reduction initiatives around the world. *Journal of hypertension, 29*(6), 1043-1050.
WHO. (2013). *Global action plan for the prevention and control of NCDs 2013-2020*.
Youm, P., & Kim, S. (1998). A case-control study on dietary and other factors related to stomach cancer incidence. *Korean J Nutr, 31*(31), 62-71.
Zhen, C., Finkelstein, E. A., Nonnemaker, J. M., Karns, S. A., & Todd, J. E. (2014). Predicting the Effects of Sugar-Sweetened Beverage Taxes on Food and Beverage Demand in a Large Demand System. *American Journal of Agricultural Economics, 96*(1), 1-25. doi:10.1093/ajae/aat049
Zhu, W. (2015). Chinese consumers lose taste for instant noodles. Retrieved from http://www.thejakartapost.com/news/2015/03/23/chinese-consumers-lose-taste-instant-noodles.html

Table 2.1: Summary statistics of instant noodle brands

Brand	Sample size	Market share (%)	Price (RMB)	Serving size (g)	Sodium (g)	Energy (KJ)	Protein (g)	Carbohydrate (g)	Fat (g)
MasterKong	4,802	19.18	2.66	100	1.92	1,915.22	8.24	54.99	23.13
			(0.71)	(12.73)	(0.13)	(84.83)	(0.45)	(2.66)	(1.79)
JinMaiLang	2,212	4.23	2.09	111	2.27	1,998.93	9.46	62.21	21.08
			(0.79)	(15.58)	(0.08)	(36.11)	(0.49)	(0.71)	(0.75)
Uni-President	2,852	5.11	2.52	91	2.04	1,863.08	8.57	51.94	22.22
			(0.81)	(27.34)	(0.37)	(99.05)	(1.22)	(3.62)	(1.23)
BaiXiang	1,565	2.45	1.75	94	2.42	1,979.67	8.65	56.56	22.76
			(0.72)	(23.94)	(0.06)	(30.70)	(0.12)	(0.41)	(0.92)
FuManDuo	1,725	0.79	1.79	95	1.92	1,730.54	7.28	55.15	21.26
			(0.75)	(21.10)	(0.03)	(193.87)	(0.36)	(0.58)	(0.33)
HuaFeng	1,688	0.30	1.58	97	0.96	2,035.84	7.80	62.00	22.30
			(0.26)	(12.18)	(0.01)	(2.31)	(0.03)	(0.002)	(0.02)
Nissin	1,233	0.39	4.65	93	1.26	1,871.01	9.35	57.28	23.37
			(1.42)	(20.39)	(0.34)	(408.36)	(0.74)	(2.72)	(3.75)
WuGuDaoChang	1,319	0.74	2.35	99	1.92	1,620.20	10.73	69.01	7.35
			(0.90)	(4.44)	(0.04)	(21.98)	(0.39)	(1.46)	(1.22)
HuaLong	812	0.96	1.05	97	2.34	2,001.63	9.73	62.09	21.09
			(0.21)	(7.22)	(0.06)	(8.85)	(0.10)	(0.15)	(0.26)
Total	18,208	34.15	-	-	-	-	-	-	-

Notes: 1. Results are averages of all markets in the 2011–2012 period.
2. The values of price and nutritional components are normalized to 100 grams.
3. Serving size is rounded to the nearest integer.
4. Standard deviation is in parentheses.

Table 2.2: Results for the BLP model

Variable	Mean utility Coefficient	S.E.		Mean utility Coefficient	S.E.
Product Attributes			**Province/Megacity**		
			Baseline: AnHui		
Price	-2.507***	(0.941)	BeiJing	1.094***	(0.321)
Sodium	12.290***	(1.289)	ChongQing	0.056	(0.189)
Sodium square	-2.342***	(0.200)	FuJian	0.020	(0.219)
Fat	0.480***	(0.078)	GuangDong	-0.320	(0.274)
Fat square	-0.004***	(0.001)	GuangXi	-0.654**	(0.291)
Sodium*Fat	-0.055*	(0.029)	GuiZhou	-0.516	(0.337)
Energy	0.001***	(0.0001)	HeBei	1.535***	(0.361)
Protein	-0.310***	(0.024)	HeNan	0.859***	(0.256)
Carbohydrate	0.007	(0.008)	HeiLongJiang	0.651***	(0.144)
Brands					
Baseline: MasterKong					
JinMaiLang	-0.554***	(0.092)	HuBei	-0.437***	(0.155)
Uni-President	-0.361***	(0.055)	HuNan	-0.738***	(0.245)
BaiXiang	-1.579***	(0.098)	JiLin	0.841***	(0.166)
FuManDuo	-1.501***	(0.063)	JiangSu	0.034	(0.102)
HuaFeng	1.083***	(0.206)	JiangXi	-0.291**	(0.129)
Nissin	0.615***	(0.124)	LiaoNing	0.688***	(0.183)
WuGuDaoChang	2.968***	(0.309)	ShaanXi	0.473***	(0.114)
HuaLong	-1.129***	(0.110)	ShanDong	0.560***	(0.156)
Time effects: 4-week period					
Baseline: QW1					
QW2	0.163**	(0.075)	ShanXi	2.160***	(0.536)
QW3	0.162**	(0.072)	ShangHai	0.657***	(0.138)
QW4	-0.062	(0.069)	SiChuan	-0.941***	(0.231)
QW5	-0.215**	(0.096)	TianJin	0.958***	(0.236)
QW6	-0.271**	(0.125)	YunNan	-0.269	(0.170)
QW7	-0.310***	(0.107)	ZheJiang	-0.060	(0.082)
QW8	-0.150*	(0.079)	Constant	-24.535***	(2.225)
QW9	-0.088	(0.069)			
QW10	-0.075	(0.070)			
QW11	-0.062	(0.062)	**Random utility**		
QW12	0.042	(0.064)		Coefficient	S.E.
QW13	0.059	(0.064)	Price SD†	1.192	(1.051)
Observations	18208				

Note: Standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
†SD: Standard Deviation.

Table 2.3a: Price elasticities of demand for TOP 4 instant noodle brands

	1% rise in Price											
% change in	111	112	121	122	131	132	141	142	211	212	231	232
111	-1.4867	0.0355	0.0137	0.0016	0.0210	0.0023	0.0140	0.0022	0.0390	0.0021	0.0128	0.0009
112	0.2271	-1.6627	0.0139	0.0016	0.0211	0.0023	0.0140	0.0022	0.0392	0.0021	0.0127	0.0009
121	0.2283	0.0355	-1.6935	0.0016	0.0211	0.0022	0.0141	0.0022	0.0394	0.0021	0.0128	0.0009
122	0.2296	0.0360	0.0146	-1.6877	0.0217	0.0023	0.0145	0.0023	0.0404	0.0021	0.0141	0.0009
131	0.2204	0.0357	0.0135	0.0016	-1.6805	0.0023	0.0141	0.0022	0.0367	0.0021	0.0124	0.0009
132	0.2112	0.0358	0.0132	0.0016	0.0212	-1.6837	0.0142	0.0024	0.0354	0.0020	0.0123	0.0009
141	0.2286	0.0352	0.0133	0.0016	0.0209	0.0022	-1.6907	0.0022	0.0393	0.0021	0.0128	0.0009
142	0.2258	0.0356	0.0138	0.0016	0.0214	0.0023	0.0143	-1.6915	0.0390	0.0021	0.0125	0.0009
211	0.2306	0.0357	0.0138	0.0016	0.0210	0.0022	0.0140	0.0022	-1.6488	0.0021	0.0128	0.0009
212	0.2316	0.0360	0.0140	0.0016	0.0213	0.0022	0.0146	0.0022	0.0423	-1.7121	0.0134	0.0009
231	0.2397	0.0347	0.0139	0.0016	0.0213	0.0020	0.0151	0.0022	0.0440	0.0021	-1.7054	0.0009
232	0.2342	0.0356	0.0132	0.0016	0.0219	0.0022	0.0163	0.0026	0.0422	0.0021	0.0142	-1.7054
311	0.2285	0.0359	0.0139	0.0016	0.0214	0.0023	0.0140	0.0022	0.0394	0.0021	0.0128	0.0009
312	0.2258	0.0360	0.0139	0.0016	0.0213	0.0023	0.0139	0.0022	0.0389	0.0021	0.0126	0.0009
331	0.2372	0.0357	0.0148	0.0016	0.0217	0.0021	0.0168	0.0024	0.0456	0.0022	0.0154	0.0009
332	0.1796	0.0393	0.0100	0.0015	0.0210	0.0032	0.0122	0.0025	0.0193	0.0014	0.0075	0.0008
341	0.2382	0.0353	0.0139	0.0016	0.0216	0.0021	0.0153	0.0023	0.0453	0.0020	0.0143	0.0009
342	0.1716	0.0405	0.0087	0.0014	0.0196	0.0033	0.0118	0.0028	0.0213	0.0014	0.0079	0.0007
411	0.2557	0.0359	0.0155	0.0016	0.0192	0.0016	0.0145	0.0020	0.0529	0.0023	0.0183	0.0009
412	0.2203	0.0392	0.0133	0.0016	0.0174	0.0015	0.0109	0.0019	0.0421	0.0026	0.0099	0.0007
421	0.2767	0.0350	0.0198	0.0018	0.0213	0.0015	0.0192	0.0022	0.0579	0.0027	0.0265	0.0010
422	0.1973	0.0307	0.0150	0.0023	0.0210	0.0010	0.0144	0.0019	0.0600	0.0035	0.0155	0.0005
431	0.2713	0.0344	0.0171	0.0017	0.0210	0.0015	0.0165	0.0021	0.0546	0.0024	0.0233	0.0009
432	0.2727	0.0337	0.0208	0.0016	0.0201	0.0009	0.0178	0.0020	0.0696	0.0037	0.0242	0.0011

Note: The values are median price elasticity of all the markets.

Product number: The first number represents the brand: 1=MasterKong, 2= JinMaiLang, 3= Uni-President, 4= BaiXiang, 5= FuManDuo, 6= HuaFeng, 7= Nissin, 8= WuGuDaoChang, 9= HuaLong.

The second number represents the flavor: 1= Beef, 2= Chicken, 3= Pork, 4= Seafood

The third number represents the package shape: 1= Bag, 2=Other shapes (i.e., barrel package, box package, and cup package).

Table 2.3b: Price elasticities of demand for TOP 4 instant noodle brands (Continued)

	1% rise in Price											
% change in	311	312	331	332	341	342	411	412	421	422	431	432
111	0.0653	0.0086	0.0044	0.0007	0.0029	0.0005	0.0106	0.0010	0.0026	0.0003	0.0096	0.0007
112	0.0658	0.0085	0.0044	0.0007	0.0029	0.0005	0.0105	0.0010	0.0026	0.0003	0.0097	0.0007
121	0.0657	0.0085	0.0044	0.0007	0.0029	0.0005	0.0109	0.0010	0.0026	0.0003	0.0097	0.0007
122	0.0655	0.0083	0.0046	0.0007	0.0029	0.0005	0.0097	0.0010	0.0027	0.0004	0.0105	0.0007
131	0.0639	0.0090	0.0044	0.0007	0.0028	0.0005	0.0098	0.0010	0.0027	0.0003	0.0107	0.0007
132	0.0632	0.0090	0.0044	0.0007	0.0029	0.0005	0.0084	0.0009	0.0025	0.0004	0.0091	0.0006
141	0.0655	0.0084	0.0044	0.0007	0.0029	0.0005	0.0106	0.0010	0.0026	0.0003	0.0097	0.0007
142	0.0650	0.0087	0.0044	0.0007	0.0028	0.0005	0.0099	0.0010	0.0027	0.0003	0.0095	0.0007
211	0.0661	0.0086	0.0044	0.0007	0.0028	0.0005	0.0107	0.0010	0.0027	0.0003	0.0098	0.0007
212	0.0659	0.0084	0.0044	0.0007	0.0029	0.0005	0.0109	0.0009	0.0026	0.0003	0.0097	0.0006
231	0.0644	0.0083	0.0045	0.0007	0.0029	0.0005	0.0116	0.0010	0.0026	0.0003	0.0105	0.0007
232	0.0657	0.0092	0.0046	0.0008	0.0030	0.0005	0.0093	0.0008	0.0025	0.0003	0.0083	0.0005
311	-1.6155	0.0087	0.0044	0.0007	0.0029	0.0005	0.0106	0.0010	0.0027	0.0003	0.0094	0.0007
312	0.0664	-1.6758	0.0043	0.0007	0.0029	0.0005	0.0106	0.0010	0.0026	0.0003	0.0095	0.0007
331	0.0637	0.0082	-1.7041	0.0008	0.0029	0.0005	0.0115	0.0009	0.0028	0.0003	0.0117	0.0007
332	0.0706	0.0117	0.0039	-1.5205	0.0038	0.0005	0.0045	0.0009	0.0014	0.0004	0.0022	0.0003
341	0.0645	0.0084	0.0046	0.0007	-1.7076	0.0005	0.0109	0.0011	0.0027	0.0003	0.0109	0.0007
342	0.0674	0.0122	0.0033	0.0008	0.0039	-1.6294	0.0054	0.0008	0.0016	0.0003	0.0022	0.0003
411	0.0668	0.0075	0.0039	0.0005	0.0025	0.0005	-1.7188	0.0011	0.0027	0.0004	0.0116	0.0007
412	0.0692	0.0111	0.0014	0.0006	0.0023	0.0004	0.0124	-1.7183	0.0036	0.0003	0.0155	0.0007
421	0.0670	0.0065	0.0047	0.0005	0.0026	0.0005	0.0130	0.0010	-1.7326	0.0003	0.0131	0.0007
422	0.0395	0.0049	0.0015	0.0005	0.0014	0.0007	0.0178	0.0007	0.0086	-1.7103	0.0506	0.0006
431	0.0651	0.0064	0.0044	0.0005	0.0028	0.0005	0.0127	0.0010	0.0027	0.0003	-1.7168	0.0007
432	0.0652	0.0055	0.0024	0.0005	0.0021	0.0004	0.0286	0.0016	0.0076	0.0004	0.0569	-1.8155

Note: The values are median price elasticity of all the markets.

Product number: The first number represents the brand: 1=MasterKong, 2= JinMaiLang, 3= Uni-President, 4= BaiXiang, 5= FuManDuo, 6= HuaFeng, 7= Nissin, 8= WuGuDaoChang, 9= HuaLong.

The second number represents the flavor: 1= Beef, 2= Chicken, 3= Pork, 4= Seafood

The third number represents the package shape: 1= Bag, 2=Other shapes (i.e., barrel package, box package, and cup package).

Table 2.4: Comparison of Market Share (MS) under different scenarios (%)

Brand	Baseline	Voluntary sodium reduction from MasterKong (by 10%)	Mandated sodium reduction (by 10%)	All brands reduce 10% sodium and increase 6% fat
	Mean (std)	Change in MS Mean (std)	Change in MS Mean (std)	Change in MS Mean (std)
MasterKong	19.18 (6.88)	-5.56 (1.72)	-4.82 (1.28)	-1.67 (0.81)
JinMaiLang	4.23 (3.73)	0.54 (0.55)	-0.20 (0.25)	0.42 (0.39)
Uni-President	5.11 (1.90)	0.56 (0.34)	-0.28 (0.41)	0.67 (0.51)
BaiXiang	2.45 (3.37)	0.31 (0.47)	0.28 (0.46)	0.67 (0.87)
FuManDuo	0.79 (0.73)	0.09 (0.10)	-0.22 (0.20)	-0.11 (0.10)
HuaFeng	0.30 (0.34)	0.04 (0.05)	-0.11 (0.13)	-0.06 (0.07)
Nissin	0.39 (0.58)	0.04 (0.07)	-0.16 (0.23)	-0.08 (0.13)
WuGuDaoChang	0.74 (0.80)	0.09 (0.11)	-0.27 (0.28)	-0.27 (0.28)
HuaLong	0.96 (1.88)	0.11 (0.22)	0.03 (0.15)	0.16 (0.28)
Overall	34.15	-3.78	-5.75	-0.27

Note: Product's market share is calculated as dividing its purchase volume by the market size, brand's market share reported here is the sum of the market shares of all the products which belong to the same brand.

Table 2.5: Summary statistics of own-price elasticity estimates under different scenarios

Brand	Baseline			Voluntary sodium reduction from MasterKong (by 10%)			Mandated sodium reduction (by 10%)			All brands reduce 10% sodium and increase 6% fat		
	Median	Min	Max	Median	Min	Max	Median	Min	Max	Median	Min	Max
Overall	-1.703	-1.862	-1.487	-1.650	-1.807	-1.468	-1.627	-1.780	-1.449	-1.698	-1.852	-1.502
MasterKong	-1.686	-1.694	-1.487	-1.634	-1.650	-1.507	-1.612	-1.626	-1.478	-1.680	-1.692	-1.502
Other brands	-1.707	-1.862	-1.521	-1.656	-1.807	-1.468	-1.632	-1.780	-1.449	-1.704	-1.852	-1.514

CHAPTER 3

NUTRITIONAL QUALITY OF RETAIL FOOD PURCHASES IS NOT ASSOCIATED WITH PARTICIPATION IN THE SUPPLEMENTAL NUTRITION ASSISTANCE PROGRAM FOR NUTRITION-ORIENTED HOUSEHOLDS[*]

[*] Yu Chen, Chen Zhen and Biing-Hwan Lin. To be submitted to *Public Health.*

3.1. Abstract

We examine the association between the US Supplemental Nutrition Assistance Program (SNAP) and the nutritional quality of participants' food-at-home (FAH) purchases. Using the detailed food purchase data from the US Department of Agriculture (USDA) National Household Food Acquisition and Purchase Survey (FoodAPS), we investigate the potential heterogeneity in the association between SNAP and diet quality among consumers with different levels of nutrition attitude. We find that SNAP participation is associated with lower nutritional quality of FAH purchases among less nutrition-oriented households, but not among more nutrition-oriented households. This heterogeneity in the SNAP-nutritional quality association may have important policy implications.

Key words: SNAP participation, Nutritional quality, Low-income households, FoodAPS

3.2. Introduction

Suboptimal diet is related to increased risks of obesity and many nutrition-related non-communicable diseases, such as heart disease, type 2 diabetes and certain cancers (HHS and USDA, 2015). In 2017, poor diet was associated with 11 million deaths and loss of 255 million disability-adjusted life-years globally (Afshin et al.). There is evidence that low-income populations are more likely, than their higher-income counterparts, to purchase and consume foods of lower nutritional quality (Darmon & Drewnowski, 2008).

In the United States, the Supplemental Nutrition Assistance Program (SNAP, formerly the Food Stamp Program) is the largest domestic hunger safety net program, serving 40.4 million low-income Americans in fiscal year 2018 at a cost of $60.9 billion in food benefit. SNAP participants receive benefits through an Electronic Benefit Transfer (EBT) card that can be used to purchase most foods and beverages (except alcohol, tobacco, dietary supplements, hot foods, and foods for on-premise consumption) at SNAP-authorized stores. There is overwhelming evidence that SNAP reduces food insecurity, which is the central goal of the program (Gundersen, Kreider, & Pepper, 2017; Ratcliffe, McKernan, & Zhang, 2011). In recent years, there is a debate among policymakers and public health researchers and advocates in whether SNAP may be restructured to promote a healthier diet (Brownell & Ludwig, 2011; Levin, Barnard, & Saltalamacchia, 2017). The ongoing discussion about SNAP can be informed by the substantial line of research on the association between SNAP and nutrition outcomes. Using nationally representative datasets, some observational studies found SNAP participants to have lower-quality diets or purchases overall, as indicated by a lower score on the Healthy Eating Index (HEI) or an alternative index, than income-eligible nonparticipants(Andreyeva, Tripp, & Schwartz, 2015; Gregory, Ver Ploeg, Andrews, & Coleman-Jensen, 2013; Cindy W. Leung et al., 2012; Mancino, Guthrie, Ver Ploeg, & Lin, 2018). Results at the food/nutrient group level or by demographic group are more mixed because of the multitude of dimensions in measurement, consumer heterogeneity and differences in analytical approaches and data. For example, several studies reported that SNAP participation is not correlated with intake of total fruit and total vegetables for adults and children (Leung et al., 2013; Cindy W Leung et al., 2012); one found SNAP was associated with lower fruit intake for female participants (Fox & Cole, 2004); and one study concluded that SNAP participation increased fruit consumption (Gregory et al., 2013). In terms of grains consumption, compared with income-eligible nonparticipants, SNAP participants had a lower whole grain intake (Hilmers, Chen, Dave, Thompson, & Cullen, 2014; Cindy W Leung et al., 2012), even though total grain consumption was almost the same (Cole & Fox, 2008; Fey-Yensan, English, Pacheco, Belyea, & Schuler, 2003; Leung et al., 2013). The literature also has mixed results on the intake of milk, meats, solid fats, beverages, and added sugars (Andreyeva, Luedicke, Henderson, & Tripp, 2012; Cole & Fox, 2008; Gregory et al., 2013; Leung et al., 2014; Cindy W Leung et al., 2012; Leung & Villamor, 2011).

This study aims to fill two gaps in the literature. First, because previous studies relied on health and nutrition surveys that do not collect food price information, few controlled for the influences of food prices on diet quality while examining the SNAP-diet relationship. With food prices being one of the most important determinants of food choice, omitting the role of food prices may create biases in the statistical analysis. Second, no research has investigated the potential heterogeneity in the association between SNAP and diet quality among consumers with different levels of nutrition attitude. Addressing this will inform the debate on potential restructuring of SNAP. This analysis uses detailed food purchase data from the US Department of Agriculture (USDA) National Household Food Acquisition and Purchase Survey (FoodAPS).

We measure a household's attitude toward nutrition using its response to a question on whether the household searched the internet for nutrition information in the last 2 months. The nutritional quality of each food item is measured by the nutrient profiling algorithm of the Guiding Stars program, although the results are robust to using Healthy Eating Index-2010 (HEI-2010) as an alternative measure.

3.3. Methods

3.3.1. FoodAPS

The USDA FoodAPS was fielded between April 2012 and January 2013. 4,826 households completed the 7-day survey of food acquisitions and purchases. Our analysis focuses on items purchased for in-home consumption, defined as food and drinks brought into the home. We dropped free food acquisitions (1.93% of total food-at-home energy for low-income FoodAPS respondents) from the analysis because of the lack of prices for these foods. We focus on nine food groups: grain, vegetables, fruits, milk products, meat/beans, prepared meals/sides/salads, oils/fats/gravies, beverage, and sweet/salty snacks[8]. This classification scheme largely follows that of the ERS Tier 1 Food Group (FoodAPS, 2016).

3.3.2. Guiding Stars Program

The Guiding Stars is a summary shelf nutrition label that uses a nutrient profiling algorithm to rate the nutritional quality of food items on a 0 (least healthy) to 3-star (most healthy) scale(Fischer et al., 2011). The objective of this label is to translate nutrition facts into a rating that is easier for consumers to rank of the healthfulness of food items. We use the Guiding Stars

---

[8] "oils/fats/gravies" food group includes fats, oils, salad dressings, gravies, sauces, condiments and spices. "sweet/salty snacks" food group includes desserts, sweets, candies and salty snacks.

rating to compare the nutritional quality of food purchases between SNAP participants and income-eligible nonparticipants. For food items with calories, the nutrient profiling algorithm that generates the star rating incorporates only nutrients with a scientific consensus of significant health promotion or an associated health risk. The nutrient scores in the algorithm reflect dietary recommendations from authoritative scientific bodies (e.g., the *Dietary Guidelines for Americans*) (Fischer et al., 2011; Rahkovsky, Lin, Lin, & Lee, 2013). Based on the threshold values for each nutrient, health-promoting nutrients such as vitamins receive positive scores, and health-risking nutrients such as sodium receive negative scores. Based on the total scores received, food items are assigned a 0, 1, 2 or 3-star rating. Items with 0 star receive negative total scores and those receiving positive total scores are classified into 1 to 3 stars with 3-star offering the best nutritional quality. We calculate the gram-weighted average Guiding Stars rating of all purchased items to measure the overall nutritional quality of a household's food-at-home (FAH) purchases.

3.3.3. SNAP Participation and Eligibility

FoodAPS is representative of SNAP households and non-participant households at three income levels: below 100% of the Federal Poverty Line (FPL), between 100 and 185% of the FPL, and above 185% of the FPL. We treat households with income below 185% of the FPL as SNAP income-eligible households (Taylor & Villas-Boas, 2016; Ver Ploeg, Mancino, Todd, Clay, & Scharadin, 2015). SNAP income-eligible non-participants were oversampled in FoodAPS to allow analysis of food purchases by low-income non-participants, which is not always possible with other datasets. To avoid bias from misreported SNAP status, we include in the analysis only households whose SNAP status was administratively verified (Gregory & Smith, 2019).

3.3.4. Study Covariates

SNAP participation status is our key covariate of interest. Because SNAP participants are income-eligible for the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC), to separate their effects, we include WIC participation status as a control variable.

We measure local cost of living by the 2012 metropolitan area-level regional price parities produced by the Bureau of Economic Analysis. Households' self-rated financial condition and house ownership status are taken as indicators of financial status. Cost of healthier foods is measured as the price of starred foods relative to the price of unstarred foods. Other covariates include household total food expenditure, and indicator variables for rurality of a household's location, access to a supermarket in the census block group, food security status, and whether they visited a food pantry/bank in the past 30 days for groceries. We also included a number of demographic variables as control variables, including household composition (household size, proportion of children, and indicator variables for elderly member, Hispanic race, obese household members, smoker, and household member in poor health), and the main meal-planner's education.

3.4. Statistical Analysis

Of the 2,218 low-income households in our analysis, 1,184 households participate in the SNAP, and 1,034 households are income-eligible non-SNAP households. We first explore the association of SNAP participation with the nutritional quality of foods purchased by low-income households. Then we examine the association of SNAP participation with density of the purchased nutrients. Last, we compare the average purchase difference between SNAP participants and income-eligible non-participants by food group. All analyses incorporated sample weights and accounted for the complex survey design of FoodAPS.

We use the following equation to explore the association of SNAP with nutrition.

$$GSP_h = \theta_1 SNAP_h + \theta_2 SNAP_h \times NuSer_h + \theta_3 NuSer_h + \theta_4 P_{ratio,h} + \theta_5 X_h + \varepsilon_h \quad (1)$$

GSP_h is the gram-weighted average Guiding Stars rating across all FAH items purchased by household h, $SNAP_h$ is the indicator for SNAP participation status, $NuSer_h$ is the indicator for whether h searched for nutrition information online in the last two months, $P_{ratio,h}$ is the ratio of price of foods with stars to price of foods without stars, X_h is the vector of all other covariates discussed earlier, and ε_h is the error term. Using grams to weight item-level Guiding Stars ratings prevents the household average star rating from being unduly influenced by energy-dense foods. We use the interaction term $SNAP_h \times NuSer_h$ to capture heterogeneity in the nutrition-SNAP association that can be tracked to a household's nutrition attitude.

Second, we examine the association of SNAP participation with FAH nutrients density using equation (2) below.

$$Nutr_{i,h} = \rho_1 SNAP_h + \rho_2 SNAP_h * NuSer_h + \rho_3 NuSer_h + \rho_4 X_h + \varepsilon_{ih} \quad i = 1,\ldots,7 \quad (2)$$

where $Nutr_{i,h}$ is the amount of nutrient *i* per 100 kcal of household h's FAH purchases. Seven nutrients that significantly affect a product's Guiding stars rating are included. Four are "nutrients to limit": saturated fat, sodium, cholesterol and added sugar. The other three are "nutrients to encourage": dietary fiber, whole grain, and vitamins/minerals [9].

[9] Vitamins/minerals here is the total purchased amount of vitamin A, vitamin B-6, vitamin B-12, vitamin C, vitamin D (D2+D3), vitamin E, vitamin K (phylloquinone), iron, thiamin, riboflavin, niacin, folic acid, phosphorus, magnesium, zinc, selenium and copper.

In addition, we compare the average purchase differences between SNAP participants and income-eligible non-participants of the nine food groups. That is, in each food group, by star level, we compare the proportion of gram quantity purchased by SNAP households with that purchased by income-eligible non-SNAP households.

3.5. Results

Table 3.1 summarizes low-income households' characteristics. The average Guiding Stars rating of low-income households' FAH purchases is 0.664 points (out of a maximum 3 points). The Guiding Stars rating of SNAP participants is 0.558 points (0.173 points lower than non-SNAP participants). The statistic shows that SNAP households purchased foods with lower nutritional quality than income-eligible non-participants. We observe similar patterns when using HEI-2010 as an alternative measure of nutritional quality. The average HEI-2010 score of overall low-income households is 49.174 points, out of a maximum 100 points. SNAP households have an average score of 46.927 points, 3.664 points lower than income-eligible nonparticipants. This is consistent with the finding of a prior study that SNAP-households have a lower HEI-2010 score of FAH acquisitions than low-income nonparticipants(Mancino et al., 2018).

Compared to income-eligible non-SNAP households, SNAP households have more family members, a larger proportion of children, a larger proportion of Hispanic members, and a smaller proportion of older adults. In terms of health status, SNAP households have larger proportions of obese people, smokers, and members in poor self-rated health status. Besides, SNAP households are more likely to be food insecure, i.e., 15 percentage points higher than income-eligible non-SNAP households. Compared with income-eligible nonparticipants, larger proportions of SNAP households participate in the WIC program, as expected, and more than twice as likely to have been to a food pantry or food bank in the past 30 days for groceries than non-SNAP households. Relative to low-income nonparticipants, smaller proportions of SNAP households own a house, are satisfied with their financial condition, have post-college education, and have no supermarket within a mile of the household's census block group. The result on supermarket access is due to a higher proportion of rural low-income nonparticipants in the FoodAPS sample. SNAP households on average spend $130/month more on food, and SNAP households are more likely to live in lower-cost counties. Table 3.1 results indicate that SNAP participants and income-eligible nonparticipants differ in a number of ways. To control for the influences of observed household characteristics, we now turn to the multivariate regression results.

Table 3.2 shows the estimated associations between nutritional quality and covariates among low-income households. For less nutrition-oriented households, classified as those not searching for nutrition information online in the last two months, SNAP participation is associated with a statistically significant 0.085 points lower Guiding Stars rating than non-SNAP participants. In comparison, for more nutrition-oriented households, SNAP participation is associated with a statistically insignificant 0.013 points lower average Guiding Star rating (p-value=0.834)[10] . We find no significant association of WIC participation with FAH nutritional quality. As expected, we find that a one-unit increase in the ratio of starred food price to unstarred food price is associated with a 0.043-point lower Guiding Stars rating. A higher cost of living is associated with a higher Guiding Stars rating. Households that went to a food bank or food pantry in the past month for groceries are more likely to have a lower average Guiding Stars

[10] Although the coefficient on SNAP*NutritionSearch is not individually significant, it is comparable to the coefficient on SNAP participation in magnitude but opposite in sign. These are sufficient to push the overall estimate for this subgroup of participants to a statistical zero. In Appendix B, we also estimated equation (1) separately for participants who did not search for nutrition information and for participants who did. We arrived at the same results.

rating and so are larger households. The proportions of children and smokers in a household are inversely associated with the Guiding Stars rating of household FAH purchases. When nutritional quality is measured by the HEI-2010 score (see Appendix Table B.1), among less nutrition-oriented households, SNAP participation is associated with a statistically significant 2.003 points lower HEI-2010 score than income-eligible nonparticipants. Among more nutrition-oriented households, SNAP participation is not associated with a lower HEI-2010 score (p-value=0.670). As another robustness check, we examined the association of SNAP with nutritional quality using separate regressions for the two types of households distinguished by online nutrition search. The main result regarding the heterogeneity of SNAP association with nutritional quality remains unchanged (see Appendix Table C.1).

Comparison of nutrients purchased per 100 kcal of FAH energy between SNAP households and income-eligible non-SNAP households is shown in Table 3.3. Compared to nonparticipants, SNAP participants purchased more on added sugars but less on all three encouraged nutrients. Specifically, per 100 kcal of FAH energy, SNAP participants on average purchased 0.139 tsp. more added sugars (1.076 vs 0.937) while purchased 0.007 g less on vitamins/minerals (0.082 vs 0.089), 0.176 g less on dietary fiber (0.662 vs 0.838), and 0.011 oz. less on whole grain (0.033 vs 0.044).

Next, we assess the association of SNAP participation with nutrient density using multivariate regressions in order to control for observed differences in household characteristics. The results are shown in Table 3.4 and 3.5. None of the coefficient estimates on SNAP participation reach statistical significance. However, each coefficient on SNAP participation takes the expected sign consistent with the comparison of means in table 3.3. With the exception of sodium, the nutrient density of FAH purchases by SNAP participants is lower, than low-income nonparticipants, on encouraged nutrients and higher on nutrients to limit. Except for the nutrient density regressions for dietary fiber and vitamins/minerals, all coefficients on the interaction term “SNAP*NutritionSearch” have signs opposite to the corresponding coefficients on SNAP participation. This is consistent with the Table 3.2 result that being nutrition oriented counteracts the influence of SNAP on nutrition quality.

With respect to other covariates, WIC participation is significantly associated with 0.005 g more vitamins/minerals per 100 kcal of food purchased. Other results include food insecure households purchasing less saturated fat; and wealthier households (e.g., better self-rated financial condition or home ownership) being associated with healthier nutrient densities (e.g., less added sugar and more dietary fiber and vitamins/minerals). In terms of household demographics, household size is positively associated with added sugar purchase; a larger proportion of children is associated with purchasing more added sugar but less cholesterol and dietary fiber; proportion of older adults is negatively associated with whole grain purchase; proportion of smokers is negatively associated with dietary fiber and whole grain purchases; and higher education of a household’s primary respondent is associated with less added sugar purchase.

Finally, we compare food purchases by star rating within each food group between SNAP and income-eligible non-SNAP participants. As shown in Figure 3.1a and 3.1b, each of the nine panels represents a food group and within a panel, for SNAP and non-SNAP households, the box plot shows the average proportion of food subgroup by star rating to total household purchases on this food group. There are no 3-star milk products and meat/beans products that were purchased by low-income households in the FoodAPS sample. For 0-star subgroups, the average gram share of prepared meals/sides/salads purchased by income-eligible non-SNAP participants are larger than that of SNAP households. While for other food groups, no significant mean differences are found for this level of star rating. For starred subgroups, we find no significant mean differences for milk products between the two types of households. For other starred subgroups, compared to non-SNAP participants, the average gram share of 2-star fruit purchased by SNAP households is larger. Otherwise, the average gram shares of other starred foods purchased by SNAP households are smaller, compared to non-SNAP households, and the magnitude of the difference varies by food group.

3.6. Discussion

Previous studies found SNAP participants to have lower diet quality than their income-eligible nonparticipating counterparts (Andreyeva et al., 2015; Fox & Cole, 2004; Gregory et al., 2013; Nguyen, Shuval, Njike, & Katz, 2014). In this study, we find that SNAP participation is associated with lower nutritional quality of FAH purchases among less nutrition-oriented households, but not among more nutrition-oriented households. This heterogeneity in the SNAP-nutritional quality association may have important policy implications. For example, some researchers and public health advocates have proposed to restrict SNAP-eligible items to healthy foods (Brownell & Ludwig, 2011; Dinour, Bergen, & Yeh, 2007; Levin et al., 2017; Schwartz, 2017), similar to the WIC program which prescribes only healthier food options. Opponents to these proposals have cited possible stigma-induced reduction in SNAP enrollment and added administrative and retailer costs. As the merit of the SNAP restrictions is premised on the existence of a negative association between SNAP and nutritional quality, the lack of such an association for nutrition-oriented participants suggests that the intended benefit of the proposed changes may not reach this subgroup of SNAP population. It is even possible that low-income nutrition-oriented households become worse off if the restrictions reduce food security by discouraging participation in SNAP. Because food security is positively associated with health (Gundersen & Ziliak, 2015), there is a potential for SNAP restrictions to increase health disparity among low-income households, which is something policymakers hope to avoid.

SNAP Education (SNAP-Ed) is an optional component of SNAP that aims to increase the likelihood of healthy eating behavior among the low-income population through direct nutrition education and social marketing. There is evidence that certain SNAP-Ed interventions are effective in promoting healthier behavioral and attitudinal changes for low-income children and adults (Cates et al., 2014; Savoie et al., 2015; Williams et al., 2014). This and the dependency of the SNAP-nutrition relationship on nutrition attitude underscores the promising role of SNAP Education (SNAP-Ed) in closing the nutrition gap between less nutrition-oriented SNAP participants and low-income nonparticipants.

Among other policy-relevant results, we found the price of starred foods relative to unstarred foods to be negatively associated with nutritional quality. This is consistent with the law of demand–a tenet of economics that predicts demand to increase in response to a decline in price, As starred foods become more expensive relative to unstarred foods, the mix of purchase shifts toward unstarred foods and, hence, causes a reduction in nutritional quality. The USDA Food Insecurity Nutrition Incentive (FINI) grant program is designed to support financial incentives that reduce the relative price of fruit and vegetables for the SNAP population at farmers markets. There is mixed evidence on the program's effectiveness in increasing SNAP participants' fruit and vegetable intake (Alaofè H, 2017; Steele-Adjognon & Weatherspoon, 2017; Vericker et al., May 2019). Our result suggests that, to improve the overall nutritional quality, financial incentives have to apply to a much broader range of healthy foods.

Our study has several limitations. First, our analysis is based on household purchase data. Compared to food intake surveys, FoodAPS has the advantage of reporting both expenditures and quantities that can be used to calculate prices. However, with purchase decisions made and reported at the household level, we cannot make definitive statements about food intake at the individual level because of food waste, stockpiling and intrahousehold sharing that make the linkage between household purchase and individual intake imperfect. Stockpiling is an issue because the one-week data collection of FoodAPS likely missed some nonperishable packaged foods (e.g., sugar-sweetened beverages) that were consumed but not purchased by some households in the survey week. For households who purchased during the FoodAPS survey, the purchased amount may be higher than consumption for storable food items. However, on average, the net effect of the two opposing forces may be small. Second, our results are subject to potential omitted variable bias. This is also known as selection bias that causes the counterintuitive finding of a negative association between SNAP and food security commonly found in observational studies (Gundersen et al., 2017). Although we included a number of household characteristics to control for the effects of observed variables, there may be unobserved factors that are both determinants of SNAP participation and nutritional quality of FAH purchases. Omitting these factors would create bias in the coefficients on SNAP participation and its interaction with the indicator for nutrition search. To the extent that the same unobserved factors also influence household food security, financial condition, home ownership, and use of food pantry and food bank, we are able to reduce the bias by including these variables as controls (Chalak & White, 2011). Future studies should examine the robustness of our results using other datasets and bias reduction econometric techniques.

3.7. References

2015 – 2020 *Dietary Guidelines for Americans*. (December 2015). In (8th ed.): U.S. Department of Health and Human Services and U.S. Department of Agriculture.

Afshin, A., Sur, P. J., Fay, K. A., Cornaby, L., Ferrara, G., Salama, J. S., . . . Murray, C. J. L. Health effects of dietary risks in 195 countries, 1990-2017: a systematic analysis for the Global Burden of Disease Study 2017. *The Lancet*. doi:10.1016/S0140-6736(19)30041-8

Alaofè H, F. N., Jones K, Plano A, Taren D. (2017). Impacts of Double Up SNAP Farmers' Market Incentive Program on Fruit and Vegetable Access, Purchase and Consumption. *J Nutr Health Sci, 4*(3). doi:10.15744/2393-9060.4.304

Andreyeva, T., Luedicke, J., Henderson, K. E., & Tripp, A. S. (2012). Grocery store beverage choices by participants in federal food assistance and nutrition programs. *American journal of preventive medicine, 43*(4), 411-418.

Andreyeva, T., Tripp, A. S., & Schwartz, M. B. (2015). Dietary Quality of Americans by Supplemental Nutrition Assistance Program Participation Status: A Systematic Review. *American Journal of Preventive Medicine, 49*(4), 594-604. doi:**https://doi.org/10.1016/j.amepre.2015.04.035**

Brownell, K. D., & Ludwig, D. S. (2011). The Supplemental Nutrition Assistance Program, Soda, and USDA Policy: Who Benefits? *JAMA, 306*(12), 1370-1371. doi:10.1001/jama.2011.1382

Cates, S., Santiago, O. J., Hersey, J., Blitstein, J., Kosa, K., Singh, A., & Berman, D. (2014). Eat Smart, Live Strong Intervention Increases Fruit and Vegetable Consumption among Low-Income Older Adults. *Journal of Nutrition Education and Behavior, 46*(4), S103-S104. doi:10.1016/j.jneb.2014.04.025

Chalak, K., & White, H. (2011). Viewpoint: An extended class of instrumental variables for the estimation of causal effects. *Canadian Journal of Economics/Revue canadienne d'économique, 44*(1), 1-51. doi:10.1111/j.1540-5982.2010.01622.x

Cole, N., & Fox, M. K. (2008). *Diet quality of Americans by food stamp participation status: Data from the National Health and Nutrition Examination Survey, 1999-2004*. Retrieved from

Darmon, N., & Drewnowski, A. (2008). Does social class predict diet quality? *The American Journal of Clinical Nutrition, 87*(5), 1107-1117. doi:10.1093/ajcn/87.5.1107

Dinour, L. M., Bergen, D., & Yeh, M.-C. (2007). The Food Insecurity–Obesity Paradox: A Review of the Literature and the Role Food Stamps May Play. *Journal of the American Dietetic Association, 107*(11), 1952-1961. doi:**https://doi.org/10.1016/j.jada.2007.08.006**

Fey-Yensan, N., English, C., Pacheco, H. E., Belyea, M., & Schuler, D. (2003). Elderly food stamp participants are different from eligible nonparticipants by level of nutrition risk but not nutrient intake. *Journal of the American Dietetic Association, 103*(1), 103-107.

Fischer, L. M., Sutherland, L. A., Kaley, L. A., Fox, T. A., Hasler, C. M., Nobel, J., . . . Blumberg, J. (2011). Development and Implementation of the Guiding Stars Nutrition Guidance Program. *American Journal of Health Promotion, 26*(2), e55-e63. doi:10.4278/ajhp.100709-QUAL-238

Fox, M., & Cole, N. (2004). Nutrition and health characteristics of low-income participants: volume I, food stamp program participants and nonparticipants. E-FAN No. 04014-1. *US Department of Agriculture, Economic Research Service, Washington, DC*.

Gregory, C. A., & Smith, T. A. Salience, Food Security, and SNAP Receipt. *Journal of Policy Analysis and Management*.

Gregory, C. A., Ver Ploeg, M., Andrews, M., & Coleman-Jensen, A. (2013). Supplemental Nutrition Assistance Program (SNAP) participation leads to modest changes in diet quality.

Gundersen, C., Kreider, B., & Pepper, J. V. (2017). Partial Identification Methods for Evaluating Food Assistance Programs: A Case Study of the Causal Impact of SNAP on Food Insecurity. *American Journal of Agricultural Economics, 99*(4), 875-893. doi:10.1093/ajae/aax026

Gundersen, C., & Ziliak, J. P. (2015). Food Insecurity And Health Outcomes. *Health Affairs, 34*(11), 1830-1839. doi:10.1377/hlthaff.2015.0645

Hilmers, A., Chen, T.-A., Dave, J. M., Thompson, D., & Cullen, K. W. (2014). Supplemental Nutrition Assistance Program participation did not help low income Hispanic women in Texas meet the dietary guidelines. *Preventive medicine, 62*, 44-48.

Leung, C. W., Blumenthal, S. J., Hoffnagle, E. E., Jensen, H. H., Foerster, S. B., Nestle, M., . . . Willett, W. C. (2013). Associations of food stamp participation with dietary quality and obesity in children. *Pediatrics*, peds. 2012-0889.

Leung, C. W., Cluggish, S., Villamor, E., Catalano, P. J., Willett, W. C., & Rimm, E. B. (2014). Few changes in food security and dietary intake from short-term participation in the Supplemental Nutrition Assistance Program among low-income Massachusetts adults. *Journal of nutrition education and behavior, 46*(1), 68-74.

Leung, C. W., Ding, E. L., Catalano, P. J., Villamor, E., Rimm, E. B., & Willett, W. C. (2012). Dietary intake and dietary quality of low-income adults in the Supplemental Nutrition Assistance Program. *The American Journal of Clinical Nutrition, 96*(5), 977-988. doi:10.3945/ajcn.112.040014

Leung, C. W., Ding, E. L., Catalano, P. J., Villamor, E., Rimm, E. B., & Willett, W. C. (2012). Dietary intake and dietary quality of low-income adults in the Supplemental Nutrition Assistance Program–. *The American journal of clinical nutrition, 96*(5), 977-988.

Leung, C. W., & Villamor, E. (2011). Is participation in food and income assistance programmes associated with obesity in California adults? Results from a state-wide survey. *Public health nutrition, 14*(4), 645-652.

Levin, S. M., Barnard, N. D., & Saltalamacchia, R. E. (2017). A Proposal for Improvements in the Supplemental Nutrition Assistance Program. *American Journal of Preventive Medicine, 52*(2), S186-S192. doi:10.1016/j.amepre.2016.07.016

Mancino, L., Guthrie, J., Ver Ploeg, M., & Lin, B.-H. (2018). *Nutritional Quality of Foods Acquired by Americans: Findings From USDA's National Household Food Acquisition and Purchase Survey*. Retrieved from

National Household Food Acquisition and Purchase Survey (FoodAPS): Nutrient Coding Overview. . (November 2016).

Nguyen, B. T., Shuval, K., Njike, V. Y., & Katz, D. L. (2014). The Supplemental Nutrition Assistance Program and Dietary Quality Among US Adults: Findings From a Nationally Representative Survey. *Mayo Clinic Proceedings, 89*(9), 1211-1219. doi:**https://doi.org/10.1016/j.mayocp.2014.05.010**

Rahkovsky, I., Lin, B.-H., Lin, C.-T. J., & Lee, J.-Y. (2013). Effects of the Guiding Stars Program on purchases of ready-to-eat cereals with different nutritional attributes. *Food Policy, 43*, 100-107. doi:**https://doi.org/10.1016/j.foodpol.2013.08.013**

Ratcliffe, C., McKernan, S.-M., & Zhang, S. (2011). How Much Does the Supplemental Nutrition Assistance Program Reduce Food Insecurity? *American Journal of Agricultural Economics, 93*(4), 1082-1098. doi:10.1093/ajae/aar026

Savoie, M. R., Mispireta, M., Rankin, L. L., Neill, K., LeBlanc, H., & Christofferson, D. (2015). Intention to Change Nutrition-Related Behaviors in Adult Participants of a Supplemental Nutrition Assistance Program–Education. *Journal of Nutrition Education and Behavior, 47*(1), 81-85. doi:**https://doi.org/10.1016/j.jneb.2014.08.009**

Schwartz, M. B. (2017). Moving Beyond the Debate Over Restricting Sugary Drinks in the Supplemental Nutrition Assistance Program. *American Journal of Preventive Medicine, 52*(2, Supplement 2), S199-S205. doi:**https://doi.org/10.1016/j.amepre.2016.09.022**

Steele-Adjognon, M., & Weatherspoon, D. (2017). Double Up Food Bucks program effects on SNAP recipients' fruit and vegetable purchases. *BMC Public Health, 17*(1), 946. doi:10.1186/s12889-017-4942-z

Taylor, R., & Villas-Boas, S. B. (2016). Food Store Choices of Poor Households: A Discrete Choice Analysis of the National Household Food Acquisition and Purchase Survey (FoodAPS). *American Journal of Agricultural Economics, 98*(2), 513-532. doi:10.1093/ajae/aaw009

Ver Ploeg, M., Mancino, L., Todd, J. E., Clay, D. M., & Scharadin, B. (2015). *Where Do Americans Usually Shop for Food and how Do They Travel to Get There?: Initial Findings from the National Household Food Acquisition and Purchase Survey*: United States Department of Agriculture, Economic Research Service.

Vericker, T., Dixit-Joshi, S., Taylor, J., Giesen, L., Gearing, M., Baier, K., . . . May, L. (May 2019). *The Evaluation of Food Insecurity Nutrition Incentives (FINI) Interim Report.* . Retrieved from

Williams, P. A., Cates, S. C., Blitstein, J. L., Hersey, J., Gabor, V., Ball, M., . . . Singh, A. (2014). Nutrition-Education Program Improves Preschoolers' At-Home Diet: A Group Randomized Trial. *Journal of the Academy of Nutrition and Dietetics, 114*(7), 1001-1008. doi:**https://doi.org/10.1016/j.jand.2014.01.015**

Table 3.1: Summary statistics of low-income households' characteristics

Variable	Overall	SNAP	Income-eligible Non-SNAP
Nutritional Quality			
Guiding Stars rating	0.664 (0.016)	0.558 (0.022)	0.731^{***} (0.025)
HEI-2010 score	49.174 (0.505)	46.927 (0.496)	50.591^{***} (0.725)
Household Characteristics			
Household size (mean)	2.522 (0.081)	2.962 (0.087)	2.245^{***} (0.095)
Proportion of children (mean)	0.181 (0.009)	0.253 (0.014)	0.135^{***} (0.010)
Proportion of older adults (mean)	0.226 (0.021)	0.109 (0.019)	0.301^{***} (0.030)
Proportion of Hispanics (mean)	0.209 (0.040)	0.243 (0.051)	0.188^{*} (0.037)
Proportion of obese members (mean)	0.317 (0.010)	0.371 (0.016)	0.283^{***} (0.015)
Proportion of smokers (mean)	0.256 (0.019)	0.305 (0.020)	0.224^{**} (0.025)
Proportion of members in poor health(mean)	0.051 (0.006)	0.072 (0.011)	0.038^{**} (0.007)
Food expenditure (mean, $)	419.954 (12.070)	500.652 (14.864)	369.013^{***} (13.530)
Cost-of-living index (mean)	98.799 (1.147)	97.727 (1.094)	99.476^{***} (1.217)
WIC participation (share)	0.086 (0.008)	0.149 (0.016)	0.046^{***} (0.008)
NutritionSearch (share)	0.190 (0.013)	0.214 (0.023)	0.175 (0.019)
Household financial condition (share)	0.349 (0.015)	0.248 (0.022)	0.412^{***} (0.019)
Own house (share)	0.445 (0.028)	0.316 (0.030)	0.526^{***} (0.034)
Food pantry/food bank (share)	0.091 (0.009)	0.146 (0.015)	0.056^{***} (0.009)
Low access BG at 1 mile (share)	0.438 (0.042)	0.380 (0.044)	0.474^{***} (0.045)
Rural (share)	0.332 (0.049)	0.304 (0.042)	0.349 (0.058)
Food insecure (share)	0.338 (0.015)	0.432 (0.021)	0.278^{***} (0.018)
Primary Respondent (PR)			
10th grade or less (share)	0.144 (0.016)	0.167 (0.021)	0.130^{**} (0.016)
11th or 12th grade, no diploma	0.065 (0.011)	0.088 (0.016)	0.051^{**} (0.010)
High School diploma or GED (share)	0.329 (0.016)	0.338 (0.025)	0.323 (0.020)
College education (share)	0.332 (0.017)	0.316 (0.017)	0.342 (0.025)
Bachelor's degree (share)	0.099 (0.010)	0.076 (0.011)	0.114^{**} (0.014)
Master's degree or more (share)	0.028 (0.006)	0.015 (0.006)	0.037^{*} (0.010)
Number of Households	2,218	1,184	1,034

[1] Weighted means reported, standard errors are in parentheses and we control for survey design.
[2] *** p<0.01, ** p<0.05, * p<0.1 = statistically different from SNAP households.
[3] Definition of variables: Food expenditure – household monthly food expenditures, including both food-at-home and food-away-from-home expenditures, calculated as 4 times the reported one-week expenditures. Cost-of-living index - 2012 metropolitan area-level regional price parities from the Bureau of Economic Analysis (base=100 at the national mean); NutritionSearch – whether a household searched online nutrition information in the last 2 months; Low access BG at 1 mile – a binary indicator for low access block groups (BGs), based on not having any supermarket/supercenters within 1 mile; Household financial condition – household's self-rated financial condition is comfortable and secure; Food pantry/food bank - household went to a food bank or food pantry in past 30 days for groceries; Food insecure – household is food insecure based on USDA's 30-day Adult Food Security Scale, households with adult members in low food security and very low food security are categorized as being "food insecure".
[4] Children are defined as age ≤18, an older adult is defined as age≥65.

Table 3.2: Associations between nutritional quality and covariates among low-income households

Variables	Guiding Stars rating	
	Coefficient	Std. Err.
SNAP participation (Yes=1)	-0.085**	0.041
SNAP*NutritionSearch	0.072	0.067
NutritionSearch (Yes=1)	0.001	0.056
WIC participation (Yes=1)	0.008	0.029
Food price ratio	-0.043*	0.023
Food insecure (Yes=1)	0.014	0.039
Standardized food expenditure	0.009	0.012
Standardized cost-of-living index	0.053***	0.019
Rural (Yes=1)	0.009	0.049
Household size	-0.022*	0.012
Proportion of children	-0.290***	0.059
Proportion of older adults	0.092	0.055
Proportion of Hispanic	0.077	0.047
Proportion of obese members	-0.055	0.041
Proportion of smokers	-0.215***	0.046
Proportion of members in poor health	-0.018	0.070
Household financial condition	0.005	0.032
Own house (Yes=1)	0.043	0.043
Food pantry/food bank (Yes=1)	-0.090**	0.043
PR's highest education	0.016	0.014
Low access BG at 1 mile (Yes=1)	-0.067	0.044
Constant	0.825***	0.064

[1] *** p<0.01, ** p<0.05, * p<0.1
[2] The estimates use sample weights and control for survey design.

Table 3.3: Comparison of nutrients densities (per 100 kcal of food purchased) between SNAP and non-SNAP households

	SNAP participants (1)	Income - eligible Non-SNAP participants (2)	Mean Difference (1) - (2)
Nutrients to limit			
Saturated fat (g)	1.351 (0.023)	1.311 (0.037)	0.040
Cholesterol (g)	0.013 (0.001)	0.013 (0.0004)	0
Added sugars (tsp eq.)	1.076 (0.038)	0.937 (0.034)	0.139**
Sodium (g)	0.176 (0.007)	0.209 (0.027)	-0.033
Nutrients to encourage			
Vitamins/minerals (g)	0.082 (0.001)	0.089 (0.002)	-0.007**
Dietary fiber (g)	0.662 (0.024)	0.838 (0.034)	-0.176***
Whole grain (oz eq.)	0.033 (0.003)	0.044 (0.003)	-0.011**

[1] Weighted means reported, Standard Errors are in parentheses and we control for survey design.
[2] Statistical difference with *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4: Associations between covariates and densities (amounts per 100 kcal of food purchased) of nutrients to limit among low-income households

Dependent variable	Saturated fat (g)	Standardized Cholesterol	Added sugars (tsp eq.)	Sodium (g)
SNAP participation (Yes=1)	0.036 (0.040)	0.074 (0.070)	0.023 (0.074)	-0.042 (0.034)
SNAP*NutritionSearch	-0.043 (0.073)	-0.092 (0.162)	-0.059 (0.132)	0.020 (0.049)
NutritionSearch (Yes=1)	0.006 (0.069)	0.151* (0.083)	-0.020 (0.102)	-0.027 (0.040)
WIC participation (Yes=1)	0.042 (0.049)	0.126 (0.095)	-0.067 (0.067)	0.022 (0.023)
Food insecure (Yes=1)	-0.087* (0.043)	-0.092 (0.062)	-0.032 (0.072)	-0.031 (0.025)
Standardized food expenditure	0.021 (0.014)	0.001 (0.028)	-0.014 (0.022)	0.020* (0.011)
Standardized cost-of-living index	0.008 (0.015)	-0.002 (0.032)	-0.050** (0.022)	-0.013 (0.014)
Rural (Yes=1)	0.116** (0.043)	-0.095 (0.093)	0.020 (0.074)	-0.062 (0.058)
Household size	-0.012 (0.013)	0.003 (0.021)	0.056*** (0.018)	-0.011 (0.008)
Proportion of children	0.083 (0.086)	-0.349** (0.136)	0.255** (0.115)	-0.041 (0.036)
Proportion of elderly	0.047 (0.071)	-0.055 (0.087)	-0.075 (0.096)	0.034 (0.035)
Proportion of Hispanic	-0.083 (0.051)	0.117 (0.077)	-0.023 (0.073)	0.033 (0.033)
Proportion of obese	0.116 (0.084)	-0.005 (0.092)	-0.122* (0.067)	0.038 (0.036)
Proportion of smokers	0.119 (0.075)	0.007 (0.108)	0.211 (0.140)	0.060 (0.051)
Proportion of poor health members	-0.039 (0.090)	0.047 (0.183)	0.055 (0.114)	-0.062 (0.043)
Household financial condition	-0.034 (0.070)	0.097 (0.063)	-0.132** (0.053)	-0.037 (0.033)
Own house (Yes=1)	0.004 (0.044)	-0.021 (0.063)	-0.043 (0.058)	0.011 (0.034)
Food pantry/food bank (Yes=1)	0.107 (0.102)	0.190 (0.124)	0.014 (0.083)	0.036 (0.040)
PR's highest education	0.022 (0.016)	-0.031 (0.035)	-0.052*** (0.017)	-0.010 (0.010)
Low access BG at 1 mile (Yes=1)	-0.082 (0.054)	0.143 (0.087)	-0.040 (0.059)	0.020 (0.056)
Constant	1.230*** (0.104)	0.064 (0.178)	1.060*** (0.104)	0.276*** (0.080)

[1] *** p<0.01, ** p<0.05, * p<0.1.
[2] The estimates use sample weights and control for survey design.

Table 3.5: Associations between covariates and densities (amounts per 100 kcal of food purchased) of nutrients to encourage among low-income households

Dependent variable	Dietary fiber (g)	Vitamins/minerals (g)	Whole grain (oz.)
SNAP participation (Yes=1)	-0.076 (0.056)	-0.001 (0.003)	-0.008 (0.005)
SNAP*NutritionSearch	-0.026 (0.096)	-0.001 (0.005)	0.011 (0.016)
NutritionSearch (Yes=1)	0.043 (0.085)	0.006 (0.004)	-0.004 (0.012)
WIC participation (Yes=1)	-0.013 (0.037)	0.005** (0.002)	0.002 (0.006)
Food insecure (Yes=1)	0.030 (0.049)	0.001 (0.002)	-0.003 (0.004)
Standardized food expenditure	-0.024 (0.019)	-0.005*** (0.001)	-0.0002 (0.002)
Standardized cost of living	0.027 (0.019)	0.001 (0.001)	0.001 (0.003)
Rural (Yes=1)	-0.040 (0.051)	-0.001 (0.003)	0.003 (0.008)
Household size	-0.019 (0.013)	-0.001 (0.001)	-0.001 (0.001)
Proportion of children	-0.182** (0.070)	-0.009 (0.006)	-0.014 (0.010)
Proportion of elderly	0.074 (0.083)	-0.004 (0.006)	-0.018* (0.010)
Proportion of Hispanic	0.148*** (0.034)	0.002 (0.003)	-0.007 (0.005)
Proportion of obese	-0.069 (0.060)	-0.007 (0.004)	-0.008 (0.011)
Proportion of smokers	-0.205** (0.079)	-0.008 (0.006)	-0.029*** (0.008)
Proportion of poor health members	0.023 (0.090)	0.0003 (0.004)	0.012 (0.014)
Household financial condition	-0.016 (0.047)	0.007* (0.004)	0.004 (0.006)
Own house (Yes=1)	0.092** (0.039)	0.005** (0.002)	0.006 (0.007)
Food pantry/food bank (Yes=1)	-0.049 (0.058)	0.002 (0.004)	-0.002 (0.006)
PR's highest education	0.027 (0.023)	0.002 (0.001)	0.002 (0.002)
Low access BG at 1 mil (Yes=1)	-0.020 (0.054)	0.001 (0.003)	0.003 (0.005)
Constant	0.791*** (0.087)	0.081*** (0.006)	0.051*** (0.012)

[1] *** p<0.01, ** p<0.05, * p<0.1
[2] The estimates use sample weights and control for survey design.

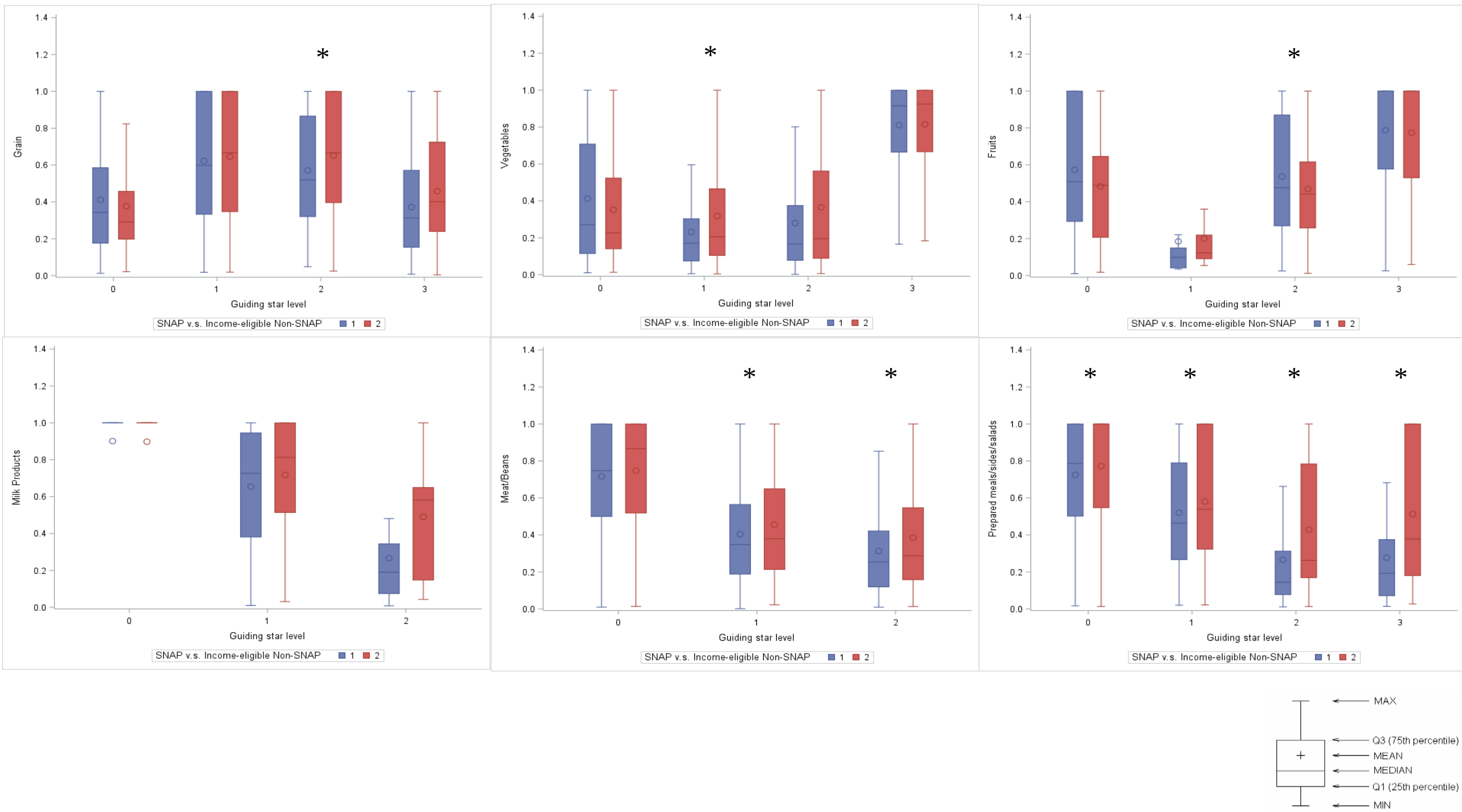

Figure 3.1a Comparison of gram share purchased by Guiding Stars rating of nine food groups between SNAP and non-SNAP households

Note: [1] * indicates that there is significant mean difference between SNAP households and income-eligible non-SNAP households at 10% significance level.
[2] Estimates use sample weights and control for survey design. The vertical axis measures the gram share of a star rating within the food group.

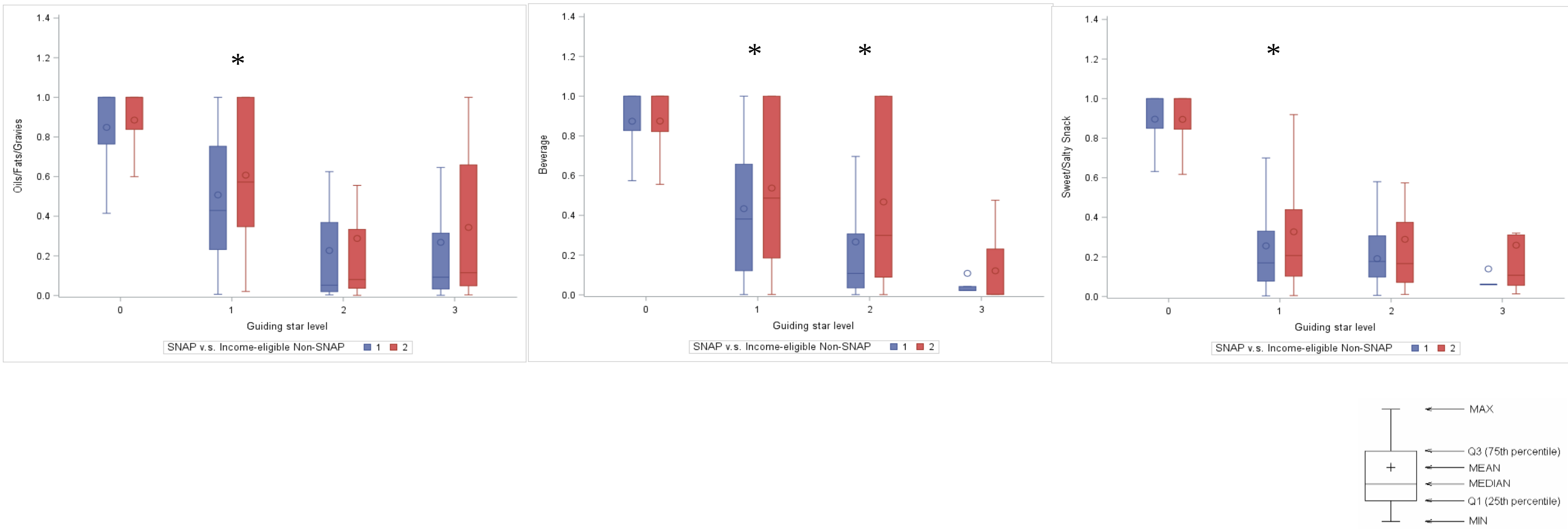

Figure 3.1b Comparison of gram share purchased by Guiding Stars rating of nine food groups between SNAP and non-SNAP households (Continued)

Note: [1] * indicates that there is significant mean difference between SNAP households and income-eligible non-SNAP households at 10% significance level.
[2] Estimates use sample weights and control for survey design. The vertical axis measures the gram share of a star rating within the food group.

CHAPTER 4

THE EFFECTS OF SNAP AND PRICE ON LOW-INCOME HOUSEHOLDS' FOOD SPENDING [*]

[*] Yu Chen and Chen Zhen. To be submitted to *Journal of Health Economics.*

4.1. Abstract

We estimate the effects of SNAP and price on low-income households' food spending, based on which we discuss food tax and subsidy strategies to improve households' nutritional status. We use the FoodAPS data combined with a two-part model to estimate the food group-specific marginal propensity to spend out of SNAP benefits and price elasticities of demand for eighteen food groups. Considering low-income households with worse food hardship are more likely to self-select into SNAP, we use state-level variation in SNAP enrollment policies and eligibility requirements and respondent-level variation in driving distance to the nearest SNAP office as instrumental variables to identify the causal effect of SNAP on food spending.

Key words: SNAP participation, Nutritional quality, Low-income households, Marginal propensity to spend, Two-part model, FoodAPS

4.2. Introduction

Low-income populations are more likely, than their higher-income counterparts, to purchase and consume foods of lower nutritional quality, such as refined grains and added sugar and fats (Darmon and Drewnowski, 2008). This question has surfaced in the context of the increasing costs of obesity and many nutrition-related non-communicable diseases, such as heart disease, type 2 diabetes and cancer (Finkelstein et al., 2009; Leung and Villamor, 2011; Wagner and Brath, 2012).

The Supplemental Nutrition Assistance Program (SNAP, formerly the Food Stamp Program) is one of the nation's leading anti-hunger programs, enrolling 17.53 percent of households in the average month of fiscal 2017 (USCB, 2019; USDA-FNS, 2019)[11]. SNAP has been shown to be an essential safety net to successfully reduce food insecurity (Gundersen et al., 2017; Mabli et al., 2013). The SNAP provides recipient households monthly benefits to support their food purchases at authorized retailers. We would hope that dietary quality would be better among program participants because of receiving additional benefits. However, prior studies suggest that SNAP participation is associated with suboptimal dietary patterns and even lower diet quality than their income-eligible nonparticipating counterparts (Andreyeva et al., 2015; Nguyen et al., 2014), and has led researchers to study how SNAP benefits are spent.

A strand of literature focuses on estimating the marginal propensity to spend (MPS) on food out of SNAP benefits, which measures how much food expenditures rise in response to a $1 increase in SNAP benefits. In earlier work, Fraker (1990), concludes that the most reasonable MPS estimates range between 0.17 and 0.47. The most recent review, Cuffey et al. (2016)

[11] Over the months of fiscal 2017, the average number of SNAP participating households is 20,828,954, and there were 118,825,921 households in the United States on average from 2013–2017.

summarizes that the estimates of MPS are between 0.16 and 0.48, with a mean of 0.30. One outstanding question is whether the SNAP-induced higher expenditures on food are translated into increased nutritional quality. This question can be addressed by estimating food group-specific MPS, which has not been investigated in the past 2 decades (Cuffey et al., 2016). One study dating back to the 1990s estimates MPS for individual food categories (Arcia et al., 1990). However, this study uses the Food Stamp Program and is limited to meat, cereals/bakery products, and vegetables.

We contribute to the literature by providing new evidence on the MPS of each of the 9 unique food groups and each group is further classified as a starred and no-star subgroups, thus giving us 18 food groups in total (the star level of food is identified by the Guiding stars program). Our estimates shed light on the food spending differences between healthy and unhealthy food, which contribute to designing targeted strategies to improve dietary quality of SNAP households.

We use the FoodAPS data combined with a two-part model to estimate the MPS on food out of SNAP benefits. We control for SNAP self-selection bias[12] by using the driving distance from the centroid of the FoodAPS household's census block group to the nearest SNAP office as well as state-level variables on SNAP eligibility rules and administrative policies as instrumental variables for endogenous SNAP participation. Our results suggest that SNAP participation increases expenditure on unhealthy food more than healthy food by $14/month, with higher estimates of MPS on no-star meat and beans, no-star snacks, and no-star beverages and lower estimates of MPS on vegetables and fruit.

[12] There is evidence that SNAP participants have higher needs or preferences for food at home than non-participants, which cause these households to self-select into the program (Wilde PE, Troy LM, Rogers BL. Food Stamps and Food Spending: An Engel Function Approach. American Journal of Agricultural Economics 2009;91; 416-430.

Aside from SNAP participation, we also take food prices into consideration. Price is one of the most important determinants of food choice (Lusk and Briggeman, 2009). Changes in food prices create incentives for low-income households to alter their eating pattern. For example, subsidies could be provided to healthier foods (e.g., fruit and vegetables) and less healthy foods could be taxed (e.g., sugar-sweetened beverages (SSB) and salty snacks) (Andreyeva et al., 2011; Dong and Lin, 2009). Andreyeva et al. (2010) reviews earlier work on price elasticity of demand for major food groups, and finds that a 10% reduction in the price of fruit and vegetables would increase their purchases by 7.0% and 5.8%, respectively, and a 10% tax on soft drinks could lead to an 8% to 10% reduction in purchases of these beverages.

Moreover, price-based interventions should target products within each food group, such as healthier and less healthy products. In our sample, for example, vegetables includes fresh vegetables as well as unhealthy products such as canned vegetables which contains high salt content (Webster et al., 2014), a possible price-based intervention could be subsidized the fresh vegetables. Therefore, examining consumers' responses to price change within a food group is needed. Harding and Lovenheim (2017) find that there exists substantial variation in price elasticities within food categories, which indicates that consumers respond differently to price changes for products within a category. For example, within vegetables and fruit category, the own-price elasticities are -1.13 for fresh fruit, -0.83 for fresh vegetables and -1.38 for canned vegetables and fruit. Zhen et al. (2014) provides price elasticities and income elasticities for 23 categories of packaged foods and beverages, in which some pairs of categories are differentiated by healthfulness. They find that substitutions are evident between whole and reduced-fat/skim milk, and between whole-grain and white bread, suggesting that households will switch to healthier products when the prices of less healthy products rise. Besides, their results show that the income elasticity is always higher for the healthier category than for the less healthy category.

Following the above research, we estimate price elasticities on food subgroups differentiated by food type and healthfulness, then we simulate low-income households' likely responses to a tax on no-star meat and beans, no-star beverage and no-star snacks and a subsidy on starred vegetables and starred whole fruits. Our results suggest that while taxes and subsidies would create incentives for consumers to consume less (or more) of targeted foods, they could have unintended consequences by possibly increasing added sugar, saturated fat and salt intake. Therefore, to improve low-income households' dietary quality, the expected benefits of any tax or subsidy must be evaluated against the potential costs.

The rest of the article is organized as follows. The next section describes the data, followed by a section on the two-part model, which is our choice of the econometric model for characterizing the household's food purchase decisions. The subsequent section provides the results on food subgroup-specific MPS out of SNAP benefits and price elasticities of demand for the 18 food groups. The second to last section discusses the results. Finally, the last section summarizes and concludes.

4.3. Data

4.3.1. FoodAPS Data

Data in this study comes from the U.S. Department of Agriculture (USDA)'s the National Household Food Acquisition and Purchase Survey (FoodAPS). A total of 4,826 households completed the survey between April 2012 and January 2013. Each sampled household was asked to provide information on the food that all members acquired over the course of seven days. Respondents were asked to scan barcodes, either on packaged food or provided in the barcode book for random-weight foods, and to record information in provided food books with receipts attached. In addition, the Primary Respondent (PR) of each household - the main food shopper or meal-planner - provided information about the household's economic and socio-demographic characteristics.

This paper analyzes households' food-at-home purchases defined as food and drinks brought into the home. We focus on nine food groups, i.e., grains, vegetables, whole fruits, milk products, meat and beans, prepared meals, fats and oils, beverages, and snacks[13]. This classification scheme largely follows that of the ERS Tier 1 Food Group (FoodAPS, November 2016). We further classify each food group to a star (1-, 2-, 3-star) and no-star subgroups, thus giving us 18 food subgroups in total.

4.3.2. State-level Sales Tax Data

Data on state-level sales tax rates for food purchased through grocery stores comes from data collected from the "Bridging the Gap" program that is supported by Robert Wood Johnson Foundation. Sales tax rates were compiled from state statutory and administrative (regulatory) laws via primary legal research and were verified by the states (Sturm et al., 2010). This data contains annual sales tax rates for sodas, bottled water, and selected snack products[14]. For other foods, we use state-level general food sales tax rates. To match the state-level sales tax rates data to the FoodAPS data, we used tax rates that were in effect in January of 2012 and 2013.

4.3.3. SNAP Participation and Eligibility

FoodAPS data is representative of SNAP households and non-participant households at three income levels: below 100% of the Federal Poverty Line (FPL), between 100 and 185% of the

---

[13] Prepared meals include prepared meals, sides, and salads; fats and oils include fats, oils, salad dressings, gravies, sauces, condiments and spices; snacks include desserts, sweets, candies, and salty snacks.
[14] Snack products include candy, chewing gum, chips, pretzels, ice cream, popsicles, milkshakes, and baked goods.

FPL, and above 185% of the FPL. We treat households with income below 185% of the FPL as SNAP income-eligible households (Taylor and Villas-Boas, 2016; Ver Ploeg et al., 2015). SNAP income-eligible non-participants were oversampled in FoodAPS to allow analysis of food purchases of low-income households, which is not always possible with other datasets. To avoid bias from misreported SNAP status, we include in the analysis only households whose SNAP status was administratively verified (Gregory and Smith, 2019). The administrative match in FoodAPS uses two sources of data, i.e., State SNAP participation records and the Anti-fraud Locator using EBT Retailer Transactions (ALERT) system data, which tracks the use of the program's EBT card.

4.3.4. Guiding Stars Program

The Guiding Stars is a summary shelf nutrition label that uses a nutrient profiling algorithm to rate the nutritional quality of food items on a 0 (least healthy) to 3-star (most healthy) scale. (Fischer et al., 2011) The objective of this label is to translate nutrition facts into a rating that is easier for consumers to rank of the healthfulness of food items. We use the Guiding Stars rating to compare the nutritional quality of food purchases between SNAP participants and income-eligible nonparticipants. For food items with calories, the nutrient profiling algorithm that generates the star rating incorporates only nutrients with a scientific consensus of significant health promotion or an associated health risk. The nutrient scores in the algorithm reflect dietary recommendations from authoritative scientific bodies (e.g., the *Dietary Guidelines for Americans*) (Fischer et al., 2011; Rahkovsky et al., 2013). Based on the threshold values for each nutrient, health-promoting nutrients such as vitamins receive positive scores, and health-risking nutrients such as sodium receive negative scores. Based on the total scores received, food items are assigned a 0, 1, 2 or 3-star rating (items with 0 star receive negative total scores and those receiving positive total scores are classified into 1 to 3 stars with 3-star offering the best nutritional quality). We calculate the gram-weighted average Guiding Stars rating of all purchased items to measure the overall nutritional quality of a household's food-at-home purchases.

4.3.5. Food Price Construction

Accurate measurement of food prices is key in interpreting the households' purchasing behavior as prices fluctuate over time and across regions, as well as in characterizing the constraints that a household faces (McKelvey, 2011). In this paper, we first construct the household-level price index P_{ch} for each food category, using a weighted product dummy method which is modified from the weighted country product dummy method (CPD) (Deaton and Dupriez, 2011; Rao, 2005). The advantage of this method is that it handles missing item-level prices and controls for item-level quality differences in the same step. The former is caused by not all households purchasing all food items in the 7-day reporting period. The latter is caused by household heterogeneity in preferences for quality, which makes the unit value (calculated as subgroup-level expenditure divided by quantity) endogenous with demand. The concept of this method is to project products' prices onto a set of location, time, household, and product dummies by running a weighted regression as equation (1).

(1) $lnP_{ich} = \alpha PSU_h + \beta WEEK_h + \gamma HH_h + \theta Product_i + \varepsilon_{ch} \qquad c = 1,\ldots,18$

Subscript i indexes the UPC, c denotes the subgroup (nine food groups, each separated into a star (1-, 2-, 3-star) and no-star subgroups), h indicates the unique household. P_{ich} is the price of UPC i in food subgroup c purchased by household h. PSU is primary sampling unit (PSU) dummy, $WEEK$ is weekly dummy, HH is the household dummy, $Product$ is product dummy, and ε_{ch} is error term. The weight in the regression is the budget share of each UPC in food subgroup c consumed by household h. The argument for the weight is that food products with large (small) budget shares should count more (less) in the calculations, and therefore the fitted model would weigh more important price observations higher than those items which are less important.

We construct the household-level price index P_{ch} using the estimated coefficients of PSU, week, and household dummies. Product fixed effects are differenced out. It is used in the price index construction in the sense that we subtracted them from raw prices to remove product heterogeneity. Further, we add state-level sales tax rate to the price index P_{ch} since grocery taxes also affect consumers' food expenditures. SNAP participants are exempt from paying local and state taxes on any of the products that they purchase with SNAP benefits. Therefore, the tax-adjusted food price is represented in equation (2) for non-SNAP households and equation (3) for SNAP households.

(2) $Price_{ch} = P_{ch} \times (1 + Tax_c) \qquad c = 1, \ldots, 18$

(3) $Price_{ch} = P_{ch} \times (1 + Tax_c \times PC_{nonSNAP}) \quad c = 1, \ldots, 18$

Where $Price_{ch}$ is the new price index for food group c of household h, Tax_c is the state-level tax rate for food group c, $PC_{nonSNAP}$ is a constant average percentage of SNAP households' food expenditure that is purchased by non-SNAP benefits, and in our analysis, $PC_{nonSNAP}$ is equal to 28.91%.

4.3.6. Study Covariates

SNAP participation status is our key covariate of interest. We measure local cost of living by the 2012 metropolitan area-level regional price parities produced by the Bureau of Economic Analysis. Tract-level median family income in the past 12 months (2012 inflation-adjusted US dollars) is also included to measure local area poverty. Households' monthly income, self-rated financial condition, house ownership status and the household average monthly income as percent of 2012 household poverty guideline are taken as indicators of financial status. We also included a number of demographic variables as control variables, including household's composition (household size, proportions of children, older adults, Hispanic race, obese household members, smokers, and household members in poor health), and the main meal-planner's education. Other covariates include indicator variables for rurality of a household's location, access to the supermarket in the census block group, food security status, and whether family members visited a food pantry or food bank in the past 30 days for groceries, and whether a household searched online nutrition information in the last 2 months. We also include tax-adjusted prices of all 18 food groups.

4.4. Methodology

4.4.1. Two-Part Model

The dependent variables in our analysis are the monthly expenditures on each of the 18 food groups, and the data on food expenditures feature a spike at zero and a skewed distribution (see Figure 4.1a and 4.1b). Accounting for food subgroup-level nonpurchases in the (short) one-week reporting period in the demand model is important because simply excluding these zeros may produce biased results. We, therefore, employ the two-part model to overcome the problem of censored dependent variables. The two-part model is suitable for modeling continuous non-negative outcomes with a large proportion of zero values and a skewed distribution, and has been widely used in health economics and health services research, such as modeling medical expenditures (Cawley and Meyerhoefer, 2012; Zhou et al., 2017).

We ran separate two-part models for each of 18 food groups to quantify the effects of SNAP and price on low-income households' spending separately on each food group. The two-part model estimates the probability of spending on a specific food group (i.e., no-star beverage) in the first part, and then estimate how much a household spends conditional on having positive spending in the second part. The predictions from each part are then combined to generate predicted spending of no-star beverage. To be specific, for households' expenditures on food group *c*, the zeros are handled using a model for the probability of a positive expenditure, given in equation (4), and for the positive expenditures, the model is represented in equation (5):

(4) $\emptyset(Exp_{ch} > 0) \ = \ \Pr(Exp_{ch} > 0|\boldsymbol{X_h}) \ = \ F(\boldsymbol{X_h}\boldsymbol{\delta})$

(5) $\emptyset(Exp_{ch}|Exp_{ch} > 0, \boldsymbol{X_h}) \ = g(\boldsymbol{X_h}\boldsymbol{\gamma})$

where Exp_{ch} is the monthly expenditure of food subgroup *c* by household h. $\boldsymbol{X_h}$ is a vector of explanatory variables. $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ are the corresponding vectors of parameters to be estimated, *F* is the cumulative distribution function of an independent and identically distributed error term, typically chosen to be from Logit or Probit distributions, and g is an appropriate density function for $Exp_{ch}|Exp_{ch} > 0$.

The likelihood function for an observation can be written as equation (6):

(6) $\emptyset(Exp_{ch}) \ = \ \{1 - F(\boldsymbol{X_h}\boldsymbol{\delta})\}^{I(Exp_{ch}=0)} \ \times \{F(\boldsymbol{x}\boldsymbol{\delta})g(\boldsymbol{X_h}\boldsymbol{\gamma})\}^{I(Exp_{ch}>0)}$

where $I(\cdot)$ denotes the indicator function. Then, the log-likelihood function is equation (7):

(7) $\ln\emptyset(Exp_{ch}) = I(Exp_{ch} = 0) \cdot \ln\{1 - F(\boldsymbol{X_h}\boldsymbol{\delta})\} \ + \ I(Exp_{ch} > 0) \cdot [\ln\{F(\boldsymbol{X_h}\boldsymbol{\delta})\} \ +$

$\ln\{g(\boldsymbol{X_h}\boldsymbol{\gamma})\}]$

Because the $\boldsymbol{\delta}$ and $\boldsymbol{\gamma}$ parameters are additively separable in the log-likelihood function for each observation, the models for the zeros and the positives can be estimated separately. The overall mean can be written as the expectations from the first and second parts of the model, as equation (8):

(8) $E(Exp_{ch}|\boldsymbol{X_h}) = \Pr(Exp_{ch} > 0|\boldsymbol{X_h}) \times E(Exp_{ch}|Exp_{ch} > 0, \boldsymbol{X_h})$

In this analysis, the first part, $\Pr(Exp_{ch} > 0|\boldsymbol{X_h})$, is modeled using a Probit model. The second part, $E(Exp_{ch}|Exp_{ch} > 0, \boldsymbol{X_h})$ is specified in a generalized linear model (GLM) framework with a "log link" and Gamma distribution. The "log link" as shown in equation (10), relates the conditional mean to the covariates, and the Gamma distribution has a variance function that is proportional to the square of the mean function, as shown in equation (11).

(9) $E(Exp_{ch}|Exp_{ch} > 0, \boldsymbol{X_h}) = \exp(\boldsymbol{X_h\gamma}) = g^{-1}(\boldsymbol{X_h\gamma})$

(10) $g(E(Exp_{ch}|Exp_{ch} > 0, \boldsymbol{X_h})) = ln(E(Exp_{ch}|Exp_{ch} > 0, \boldsymbol{X_h})) = \boldsymbol{X_h\gamma}$

(11) $Var((Exp_{ch}|Exp_{ch} > 0, \boldsymbol{X_h})) \propto (E(Exp_{ch}|Exp_{ch} > 0, \boldsymbol{X_h}))^2$

After getting the estimates from the Probit and GLM models, the prediction of the expected Exp_{ch}, $(\widehat{Exp_{ch}}|\boldsymbol{X_h})$ can be constructed by multiplying predictions from both parts, observation by observation, that is,

(12) $\widehat{Exp_{ch}}|\boldsymbol{X_h} = \widehat{\Pr}(Exp_{ch} > 0|\boldsymbol{X_h}) \times (\widehat{Exp_{ch}}|Exp_{ch} > 0, \boldsymbol{X_h})$

where $\boldsymbol{X_h}$ includes SNAP participation status, food prices and other covariates discussed before. SNAP participation status is our key covariate of interest. It is notable that households in most need of food assistance are also more likely to participate in SNAP, resulting in self-selection bias, which is a challenge for our estimation. To solve this problem, in the Probit model, we use the household's driving distance to the nearest SNAP office as well as state-level SNAP eligibility rules and administrative policies as instrumental variables for SNAP participation status. When we estimate the GLM model, we construct an exogenous index for SNAP participation status to solve the endogeneity problem, using equation (13).

(13) $SNAP_h = \alpha_1 Dist_h + \alpha_2 {Dist_h}^2 + \boldsymbol{\rho Policy_s} + \tau_1 HHsize_h + \tau_2 ln(Inc\_tr_h) + \tau_3 PPov_h + \varepsilon_h$

where $SNAP_h$ is the SNAP participation status, $Dist_h$ is the (standardize) driving distance from the centroid of the household's census block group to the nearest SNAP office; $\boldsymbol{Policy_s}$ is a vector of state-level SNAP eligibility rules and administrative policies[15]; $HHsize_h$ is household size, Inc_tr_h is the tract-level median family income in the past 12 months (2012 inflation adjusted U.S. dollar), $PPov_h$ is the (standardized) household average monthly income as a percent of household poverty guideline, and ε_h is error term. The index for SNAP participation status is constructed as the predicted probability of SNAP participation using the estimated coefficients of driving distance as well as state-level SNAP eligibility rules and administrative policies from equation (13).

4.4.2. Marginal Propensity to Spend (MPS)

The average change in food spending attributable to SNAP participation for each food group, compared to income-eligible non-SNAP households, was calculated by subtracting the average predicted spending for SNAP households with the SNAP participation variable set to 0, from the average predicted spending for the same households with the SNAP participation variable set to 1.

[15] State-level SNAP eligibility rules (or administrative policies) include: whether the State has been granted a waiver to use a telephone interview in lieu of a face-to-face interview at recertification, without having to document household hardship (1= no waiver); the interaction of distance and telephone interview granted status at recertification; whether the State requires fingerprinting of SNAP applicants (1= required); whether the State allows households to submit a SNAP application online (1= allowed); standardized per capita outreach expenditure (i.e., the sum of Federal, State, and grant outreach spending in nominal dollars (in thousands)); whether the State excludes at least one vehicles in the household from the SNAP asset test (1 = yes); whether the State uses the simplified reporting option that reduces requirements for reporting changes in household circumstances (for households with earnings) (1 = yes); whether the state operates a combined application project for recipients of supplemental security income (SSI), so that SSI recipients are able to use a streamlined SNAP application process (1 = yes); and the proportion of SNAP units with earnings with 1-6 month recertification periods.

The impact of SNAP participation on a household's spending on each food group is defined as $\theta = \hat{\alpha}/\hat{\beta}$. Where $\hat{\beta}$ and $\hat{\alpha}$ represent the estimated marginal effects of SNAP from logit model and from two-part model, using equation (14) and (15), respectively.

(14) $SNAP_h = \beta SNAP\_index_h + \varepsilon_h$

(15) $Exp_{ch} = \alpha SNAP\_index_h + \boldsymbol{\omega x_h} + \varepsilon_{ch} \qquad c = 1,\ldots,18$

where $SNAP\_index_h$ is the index for SNAP participation status of household h, $\boldsymbol{x_h}$ is a vector of all the other study covariates and $\boldsymbol{\omega}$ are corresponding parameters, and ε_h and ε_{ch} are error term.

The MPS on each food group out of SNAP benefit is calculated as

$\text{MPS} = \frac{\text{average change of food spending}}{\text{SNAP benefit}}$, here the "SNAP benefit" is an average value (\$282.76) which is reported by SNAP households in FoodAPS. We further calculate the overall MPS by adding up MPS values of all 18 food groups.

4.4.3. Price Elasticity of Demand

We calculate own- and cross-price elasticities of demand for 18 food groups. An own-price elasticity reflects changes in the purchase quantity of a food group with changes in its own price, and a cross-price elasticity reflects changes in demand for a food group when prices of other food groups change. These price elasticities are important from a policy perspective in that relative shifts in prices through taxation or subsidies can affect demand for food groups.

The price elasticity of demand, ε_{ij} , is derived from equation (16) and (17).

(16) $\frac{\partial Exp_i}{Exp_i} \times \frac{P_j}{\partial P_j} = \frac{\partial P_i}{P_i} \times \frac{P_j}{\partial P_j} + \frac{\partial Q_i}{Q_i} \times \frac{P_j}{\partial P_j}$

(17) $\varepsilon_{ij} = \frac{\partial Exp_i}{Exp_i} \times \frac{P_j}{\partial P_j} - \frac{\partial P_i}{P_i} \times \frac{P_j}{\partial P_j}$

where *i* and *j* indicate food groups, and the own- and cross-price elasticity of demand can be expressed as equation (18).

$$(18)\quad \begin{cases} \varepsilon_{ii} = \frac{\partial Exp_i}{\partial P_j} \times \frac{P_j}{Exp_i} - 1 & \text{for } i = j \\ \varepsilon_{ij} = \frac{\partial Exp_i}{\partial P_j} \times \frac{P_j}{Exp_i} & \text{for } i \neq j \end{cases}$$

To calculate $\frac{\partial Exp_i}{\partial P_j} \times \frac{P_j}{Exp_i}$, from the two-part model, we know that

(19) $E(Exp_i|\boldsymbol{X}) = Pr(Exp_i > 0|\boldsymbol{X}) \times E(Exp_i|Exp_i > 0, \boldsymbol{X})$, therefore,

(20) $\frac{\partial E(Exp_i|\boldsymbol{X})}{\partial P_j} \times \frac{P_j}{E(Exp_i|\boldsymbol{X_h})} =$

$$\left(\frac{\partial Pr(Exp_i > 0|\boldsymbol{X})}{\partial P_j} \times E(Exp_i|Exp_i > 0, \boldsymbol{X}) + Pr(Exp_i > 0|\boldsymbol{X}) \times \frac{\partial E(Exp_i|Exp_i > 0, \boldsymbol{X})}{\partial P_j}\right) \times \frac{P_j}{E(Exp_i|\boldsymbol{X})}$$

All the calculations were estimated using Stata/MP 14.2, and the standard errors were computed via the bootstrap method.

4.5. Results

Table 4.1 summarizes the characteristics of low-income households. Around 53 % of SNAP income-eligible households in our analysis participate in the SNAP. Relative to income-eligible nonparticipants, SNAP households have more family members, larger proportion of children, larger proportion of Hispanic members, and smaller proportion of older adults. In terms of health, SNAP households have larger proportion of obese people, smokers, and members with poor self-reported health status. Besides, SNAP households are more likely to be food insecure, i.e., 15 percentage points higher than income-eligible non-SNAP households. Compared with income-eligible nonparticipants, larger proportion of SNAP households has been to a food pantry or food bank in the past 30 days for groceries. In contrast, small shares of SNAP households own a house, are satisfied with their financial condition, have post-college education, and have no supermarket within a mile of the household's census block group. Additionally, SNAP households on average have higher monthly income, while the county-level cost of living and the census tract-level household annual median income where the SNAP households reside are lower.

Turning to the first set of our main findings, Table 4.2 shows the marginal propensity to spend (MPS) on food at home out of an increase in SNAP benefit. Ordinary least squares (OLS) and two-part model estimates point in the same direction. The overall MPS is 0.326 to 0.348 for the OLS and instrumental variable (IV) two-part model, respectively. Although the overall MPS estimates are similar, there are important differences between the OLS and instrumental variable MPS estimates at the food group level. For example, all MPS estimates from IV two-part model are significant, while in OLS model, MPS estimates are insignificant for starred whole fruit, starred milk products, and starred beverages. Besides, for food groups that account for a large share of household's monthly food expenditure, MPS estimates on no-star meat and beans, starred meat and beans, and no-star snacks in OLS are larger than MPS estimates in IV two-part model. While MPS estimate on no-star beverage in OLS is smaller than MPS estimate in IV two-part model.

In our analysis, low-income households on average spent about $338/month on food, with large expenditures on no-star meat and beans ($45), no-star snacks ($44), starred meat and beans ($36), and no-star beverages ($29). SNAP households on average receive benefit of $282.76/month. Estimates from the two-part model show that SNAP participation could increase food expenditure by $98, in which starred food expenditure increases $42 and no-star food expenditure increases $56, with MPS out of SNAP benefits being 0.149 for starred food and

0.198 for no-star food, respectively [16]. Expenditures of all food groups are increased, especially for no-star meat and beans, no-star snacks and no-star beverages, their expenditures increase by around $12, $11, and $10, respectively, with relatively high MPS out of SNAP benefits being 0.042, 0.038 and 0.036, respectively. In contrast, expenditures on no-star vegetables (e.g., canned mixed vegetables), no-star whole fruit (e.g., canned whole fruit), starred whole fruit and starred milk products are increased by $1.686, $0.649, $2.347 and $0.877, respectively, and all have MPS less than 0.01.

Price is another primary determinant of food consumption patterns. Especially for low-income households, high food prices affect their purchases and nutrients intake (Drewnowski, 2010). To understand low-income households' responses to price changes, we estimate own- and cross-price elasticities of demand for 18 food groups. Mean estimates and standard errors are presented in Table 4.3a - 4.3d.

Overall, mean own-price elasticity estimates (the values in the diagonal of Table 4.3a - 4.3d) for 18 food groups range from -1.216 (no-star meat and beans) to -0.741 (starred vegetables). Nine food groups have own-price elasticities between -0.74 and -0.99 (i.e., consistent with customary characterization of the demand response to food prices as being inelastic), specifically, including grains (no-star products -0.994 and starred products -0.926), starred vegetables (-0.741), starred whole fruit (-0.799), no-star milk products (-0.991), no-star fats and oils (-0.961), beverages (no-star products -0.961 and starred products -0.979) and starred snacks (-0.989). To interpret, for example, a 10% price increase in starred vegetables will lead to a 7.41% drop in its purchase quantity. Own-price elasticities of other food groups are elastic.

[16] The numbers are calculated by adding MPS of all the starred food groups and all no-star food groups, respectively.

Cross-price elasticities are smaller than own-price elasticities (in terms of absolute values), and most cross-price elasticities are negative and significant, indicating a complementary relationship, that is, as the price of one food group rises, purchases of both food groups decrease. Substitutions are evident between no-star vegetables and starred vegetables, between starred whole fruit and starred milk products, between no-star vegetables and starred milk products, between no-star milk products and starred prepared meals, and between starred prepared meals and no-star fats/oils.

For negative cross-price elasticities, a larger value (in terms of absolute value) indicates a stronger complementary relationship between the two food groups. For example, if the price of no-star snacks increase (by, say, 10%), compared to other food groups, the quantities of no-star prepared meals and no-star beverages will decrease more (by 1.31% and 1.21%, respectively). Similarly, increasing the price of no-star meat and beans results in a larger decrease of no-star beverages and no-star prepared meals purchases, and increasing the price of no-star fats and oils results in a larger decrease of no-star meat and beans and no-star prepared meals purchases. For starred food, if the price of starred snacks increases, the quantity purchases of starred grains, starred whole fruit and starred milk products will decrease more. Besides, increasing the price of starred fats and oils will lead to more quantity decreases of starred meat and beans and starred vegetables.

4.6. Discussion

Estimation of the effects of SNAP benefits on food spending has received substantial attention. A strand of literature focuses on estimating the marginal propensity to spend (MPS) on food out of SNAP benefit. Fraker (1990) found that the MPS on food out of SNAP is in the range of 0.17-0.47, which translates into additional food expenditures of between \$0.17 and \$0.47 for every dollar of SNAP benefit. Hoynes and Schanzenbach (2009) used county variation in the adoption of the program from 1963 - 1975 to identify the impact of food stamps, and they found that the MPS on food out of food stamps is 0.163 to 0.318. Bruich (2014) used retail scanner data with method-of-payment information to study the effect of SNAP benefit reduction in 2013, and estimated that MPS on food out of SNAP benefits is 0.3. In our analysis, we find that after participating in SNAP, households increase spending by about $98 per month, equivalent to more than one-third of their monthly SNAP benefit, thus implying an overall MPS out of SNAP benefits is around 0.35, which is in line with prior studies. Besides, prior estimates of low-income households' MPS out of cash income are generally at or below 0.1 (Cuffey et al., 2016; Hoynes and Schanzenbach, 2009), smaller than the MPS of SNAP benefit, which is interpreted as evidence that SNAP increases food spending by more than an equivalent cash-transfer system.

After participating in SNAP, household's expenditure on no-star meat and beans increase $11.8/month, accounting for the largest share of households' total purchases that use SNAP benefits. Among the no-star meat and beans products purchased by low-income households, bacon, sausage and lunch meat account for 36% of the total purchased gram, and these foods have been associated with increased cancer risk (Bouvard et al., 2015; Cross et al., 2010). Two other large food groups in terms of expenditures are found on no-star snacks and no-star beverages (around $10/month on each food group). While for vegetables and fruit, their purchases merely increased by $5.69 and $3 per month. This observation implies that SNAP participation has the role of increasing households' food purchase, while SNAP households could have lower dietary quality because of their much larger purchases on unhealthy food rather than healthy foods.

The increasing burden of diet-related chronic diseases has prompted policymakers and researchers to explore strategies to improve diets, which has proved challenging to date. Increasing attention has been paid to the use of economic incentives to change the relative prices of selected foods, for example, through adding taxes to energy-dense nutrient-poor food which are rich in sugar, fat, and oil (e.g., sugar-sweetened beverages and snacks) or providing price subsidies to nutrient-rich food (e.g., vegetables and fruit) (Pearson-Stuttard et al., 2017; Powell and Chaloupka, 2009). In our analysis, we explore the effects of adding taxes on no-star meat and beans, no-star snacks and no-star beverages, considering that low-income households' large spending on these food. And following prior studies, we simulate the effects of subsidies on fruit and vegetables.

For no-star meat and beans, a 10% increase in price will lead to a drop in its purchase quantity of 12.16%. Simultaneously, quantities of no-star prepared meals and no-star beverages will also decrease, by 1.98% and 2.03%, respectively. Additionally, no-star meat and beans purchases will decrease because of the reduction in the prices of starred vegetables and starred milk products. That is, if the prices of starred vegetables decrease 10%, no-star meat and beans will decrease 0.19%, and if the prices of starred milk products decrease 10%, no-star meat and beans will decrease 1.15%. Among no-star snacks, an 10% price increase would reduce quantity purchased by 10.04%. For no-star beverages, in which soft drinks account for 53% of the total purchased grams (by low-income households), a 10% increase in its price will lead to a 9.61% drop in its purchase quantity and a 0.28% increase in the quantity of starred beverage.

Prior studies showed that levying excise taxes on food was a possible way to address the growing prevalence of obesity and overweight. Kuchler et al. (2004) estimated that based on a unitary elastic demand (own-price elasticity = -1.0), a 10% price increase of salty snacks, induced by a national sales tax, could reduce body weight by 0.5 kg per year. Besides, Zhen et al. (2014) estimated that if the price of sugar-sweetened beverage (SSB) was increased half-cent per ounce (about 26% increase in average retail price) by an excise tax, it would reduce per capita daily calorie intake by 13.2 kcal for low-income population and they predicted a weight reduction of 0.37 kg/person per year. Although there exists potential public health benefits, concerns remain in the event of higher prices resulting from increased taxes. First, it may cause undesirable side effects of purchasing other nutrient-poor food. As Zhen et al. (2014) found, an SSB price increase will increase sodium and fat intakes as a result of product substitution. Our estimate suggests that a price increase of no-star beverage will lead to more purchase on no-star vegetables (e.g., canned mixed vegetables), and a price increase of no-star snacks will increase no-star grains purchase (e.g., ready-to-eat cereal with high sugar content). Second, taxes are treated as being potentially regressive by disproportionately affecting lower-income households who spend a larger proportion of their household budget on food (Sanders, 2016).

Turning to fruit and vegetables, they could help in reducing the incidence of cardiovascular diseases (He et al., 2007; He et al., 2006). However, for low-income households, high price is a barrier for them to purchase (Drewnowski, 2010). As shown in our analysis, low-income households spend lower on vegetables and fruit, compared to other food groups, with spending around $24/month on vegetables and $17/month on whole fruits. To promote the consumption of fruits and vegetables by reducing their prices, Andreyeva et al. (2010) summarized that a 10% price reduction is on average associated with a 7% increase in spending for fruits and a 5.8% increase for vegetables. In our analysis, assuming there are price subsidies for starred whole fruits and starred vegetables, a 10% price reduction on these foods would encourage households to increase starred whole fruits and starred vegetables purchases by 8.0%

and 7.4%, respectively. This finding suggests that price subsidy would encourage the purchases of vegetables and fruits among low-income households and thus may be effective in reducing the rate of obesity (Powell et al., 2013). However, like food tax, price subsidy could also have unintended consequences. For example, under a price subsidy on fruit and vegetables, households might purchase more of other foods that high in saturated fat and sodium, and our analysis shows that reducing the price of starred whole fruits will increase no-star snacks and no-star fats and oil consumption.

4.7. Conclusion

In this study, we use USDA's FoodAPS data to study the effect of SNAP participation on the food purchases of low-income households as well as their responses to food prices change, based on which we discuss food tax and subsidy strategies to improve households' nutritional status.

We estimate a two-part model for 18 food groups (i.e., 9 unique food groups that are further classified as star and no-star food groups), controlling for household-level and area-level characteristics, as well as prices of all food groups. Instrumental variables are used to correct for the self-selection bias caused by endogenous SNAP participation. Our findings suggest that after enrolling in SNAP, households increase food spending by about $100 a month, equivalent to more than one-third of their monthly SNAP benefit, implying an MPS out of SNAP benefit of 0.35. It is notable that participating in SNAP causes spending on no-star meat and beans, no-star snacks and no-star beverages to increase more than those on vegetables, whole fruit and starred milk products. This implies that the observed lower overall dietary quality of SNAP participants compared to low-income nonparticipants may be causally linked to the program.

We also estimate the effects of food taxes and subsidies on low-income households' purchases by increasing prices of no-star meat and beans, no-star beverage and no-star snacks, and reducing prices of starred vegetables and starred whole fruits. We find that food taxes and subsidies have the potential to encourage the targeted nutrient-rich food and decrease the targeted nutrient-poor food purchases, while concerns remain that they may have unintended consequences of purchasing other nutrient-poor food that high in sugar, saturated fat and sodium. For example, a price increase of no-star beverages and no-star snacks could lead to larger purchase of no-star vegetables (e.g., canned mixed vegetables) and no-star grains (e.g., ready-to-eat cereal with high sugar). Similarly, a price subsidy on fruit and vegetables could lead households to purchase more of no-star snacks and no-star fats and oils.

This highlights the complexity of using targeted food taxes and subsidies to improve low-income households' nutrition outcomes. Therefore, the design of these financial incentives should be done with care. One strategy may be deriving an optimal package of taxes and subsidies on several food products to reach the goal of supporting healthy eating. Besides, it may be more effective to interact with other types of interventions such as providing nutrition information that contributes to enhancing the effectiveness of these strategies. Finally, promising strategies need to be evaluated and tested to ultimately improve dietary quality among low-income households.

4.8. References

Andreyeva T, Chaloupka FJ, Brownell KD. Estimating the potential of taxes on sugar-sweetened beverages to reduce consumption and generate revenue. Preventive Medicine 2011;52; 413-416.

Andreyeva T, Long MW, Brownell KD. The Impact of Food Prices on Consumption: A Systematic Review of Research on the Price Elasticity of Demand for Food. American Journal of Public Health 2010;100; 216-222.

Andreyeva T, Tripp AS, Schwartz MB. Dietary Quality of Americans by Supplemental Nutrition Assistance Program Participation Status: A Systematic Review. American Journal of Preventive Medicine 2015;49; 594-604.

Arcia GJ, Crouch LA, Kulka RA. Impact of the WIC Program on Food Expenditures. American Journal of Agricultural Economics 1990;72; 218-226.

Bouvard V, Loomis D, Guyton KZ, Grosse Y, Ghissassi FE, Benbrahim-Tallaa L, Guha N, Mattock H, Straif K. Carcinogenicity of consumption of red and processed meat. The Lancet Oncology 2015;16; 1599-1600.

Bruich GA. The effect of SNAP benefits on expenditures: New evidence from scanner data and the November 2013 benefit cuts. Harvard University. Mimeograph 2014.

Cawley J, Meyerhoefer C. The medical care costs of obesity: An instrumental variables approach. Journal of Health Economics 2012;31; 219-230.

Cross AJ, Ferrucci LM, Risch A, Graubard BI, Ward MH, Park Y, Hollenbeck AR, Schatzkin A, Sinha R. A Large Prospective Study of Meat Consumption and Colorectal Cancer Risk: An Investigation of Potential Mechanisms Underlying this Association. Cancer Research 2010;70; 2406-2414.

Cuffey J, Beatty TKM, Harnack L. The potential impact of Supplemental Nutrition Assistance Program (SNAP) restrictions on expenditures: a systematic review. Public Health Nutrition 2016;19; 3216-3231.

Darmon N, Drewnowski A. Does social class predict diet quality? The American Journal of Clinical Nutrition 2008;87; 1107-1117.

Deaton A, Dupriez O. Purchasing Power Parity Exchange Rates for the Global Poor. American Economic Journal: Applied Economics 2011;3; 137-166.

Dong D, Lin B-H. 2009. Fruit and Vegetable Consumption by Low-Income Americans: Would a Price Reduction Make a Difference? (Ed)^(Eds). 2009.

Drewnowski A. The cost of US foods as related to their nutritive value. The American Journal of Clinical Nutrition 2010;92; 1181-1188.

Finkelstein EA, Trogdon JG, Cohen JW, Dietz W. Annual medical spending attributable to obesity: payer-and service-specific estimates. Health affairs 2009;28; w822-w831.

Fischer LM, Sutherland LA, Kaley LA, Fox TA, Hasler CM, Nobel J, Kantor MA, Blumberg J. Development and implementation of the guiding stars nutrition guidance program. American Journal of Health Promotion 2011;26; e55-e63.

FoodAPS. November 2016. National Household Food Acquisition and Purchase Survey (FoodAPS): Nutrient Coding Overview. In: ERS USDoA (Ed)^(Eds). November 2016.

Fraker T. The effects of food stamps on food consumption: a review of the literature. Current perspectives on food stam p program participation (USA) 1990.

Gregory CA, Smith TA. Salience, Food Security, and SNAP Receipt. Journal of Policy Analysis and Management 2019;38; 124-154.
Gundersen C, Kreider B, Pepper JV. Partial Identification Methods for Evaluating Food Assistance Programs: A Case Study of the Causal Impact of SNAP on Food Insecurity. American Journal of Agricultural Economics 2017;99; 875-893.
Harding M, Lovenheim M. The effect of prices on nutrition: Comparing the impact of product- and nutrient-specific taxes. Journal of Health Economics 2017;53; 53-71.
He FJ, Nowson CA, Lucas M, MacGregor GA. Increased consumption of fruit and vegetables is related to a reduced risk of coronary heart disease: meta-analysis of cohort studies. Journal Of Human Hypertension 2007;21; 717.
He FJ, Nowson CA, MacGregor GA. Fruit and vegetable consumption and stroke: meta-analysis of cohort studies. The Lancet 2006;367; 320-326.
Hoynes HW, Schanzenbach DW. Consumption Responses to In-Kind Transfers: Evidence from the Introduction of the Food Stamp Program. American Economic Journal: Applied Economics 2009;1; 109-139.
Kuchler F, Tegene A, Harris JM. 2004. Taxing snack foods: what to expect for diet and tax revenues. (Ed)^(Eds). 2004.
Leung CW, Villamor E. Is participation in food and income assistance programmes associated with obesity in California adults? Results from a state-wide survey. Public Health Nutrition 2011;14; 645-652.
Lusk JL, Briggeman BC. Food Values. American Journal of Agricultural Economics 2009;91; 184-196.
Mabli J, Ohls J, Dragoset L, Castner L, Santos B. 2013. Measuring the effect of Supplemental Nutrition Assistance Program (SNAP) participation on food security. (Ed)^(Eds). Mathematica Policy Research; 2013.
McKelvey C. Price, unit value, and quality demanded. Journal of Development Economics 2011;95; 157-169.
Nguyen BT, Shuval K, Njike VY, Katz DL. The Supplemental Nutrition Assistance Program and Dietary Quality Among US Adults: Findings From a Nationally Representative Survey. Mayo Clinic Proceedings 2014;89; 1211-1219.
Pearson-Stuttard J, Bandosz P, Rehm CD, Penalvo J, Whitsel L, Gaziano T, Conrad Z, Wilde P, Micha R, Lloyd-Williams F. Reducing US cardiovascular disease burden and disparities through national and targeted dietary policies: A modelling study. PLoS medicine 2017;14; e1002311.
Powell LM, Chaloupka FJ. Food Prices and Obesity: Evidence and Policy Implications for Taxes and Subsidies. The Milbank Quarterly 2009;87; 229-257.
Powell LM, Chriqui JF, Khan T, Wada R, Chaloupka FJ. Assessing the potential effectiveness of food and beverage taxes and subsidies for improving public health: a systematic review of prices, demand and body weight outcomes. Obesity Reviews 2013;14; 110-128.
Rahkovsky I, Lin B-H, Lin C-TJ, Lee J-Y. Effects of the Guiding Stars Program on purchases of ready-to-eat cereals with different nutritional attributes. Food Policy 2013;43; 100-107.
Rao D. ON THE EQUIVALENCE OF WEIGHTED COUNTRY‐PRODUCT‐DUMMY (CPD) METHOD AND THE RAO‐SYSTEM FOR MULTILATERAL PRICE COMPARISONS. Review of Income and Wealth 2005;51; 571-580.

Sanders B. 2016. A Soda Tax Would Hurt Philly's Low-Income Families. (Ed)^(Eds), vol. 2019. Philadelphia; 2016.
Sturm R, Powell LM, Chriqui JF, Chaloupka FJ. Soda Taxes, Soft Drink Consumption, And Children's Body Mass Index. Health Affairs 2010;29; 1052-1058.
Taylor R, Villas-Boas SB. Food Store Choices of Poor Households: A Discrete Choice Analysis of the National Household Food Acquisition and Purchase Survey (FoodAPS). American Journal of Agricultural Economics 2016;98; 513-532.
USCB. 2019. "QuickFacts: United States.". (Ed)^(Eds). United States Census Bureau.; 2019.
USDA-FNS. 2019. Supplemental Nutrition Assistance Program. (Ed)^(Eds). United States Department of Agriculture Food and Nutrition Service (FNS). 2019.
Ver Ploeg M, Mancino L, Todd JE, Clay DM, Scharadin B. Where Do Americans Usually Shop for Food and how Do They Travel to Get There?: Initial Findings from the National Household Food Acquisition and Purchase Surveys. United States Department of Agriculture, Economic Research Service; 2015.
Wagner K-H, Brath H. A global view on the development of non communicable diseases. Preventive Medicine 2012;54; S38-S41.
Webster J, Trieu K, Dunford E, Hawkes C. Target Salt 2025: A Global Overview of National Programs to Encourage the Food Industry to Reduce Salt in Foods. Nutrients 2014;6; 3274-3287.
Wilde PE, Troy LM, Rogers BL. Food Stamps and Food Spending: An Engel Function Approach. American Journal of Agricultural Economics 2009;91; 416-430.
Zhen C, Finkelstein EA, Nonnemaker JM, Karns SA, Todd JE. Predicting the Effects of Sugar-Sweetened Beverage Taxes on Food and Beverage Demand in a Large Demand System. American Journal of Agricultural Economics 2014;96; 1-25.
Zhou X, Shrestha SS, Luman E, Wang G, Zhang P. Medical Expenditures Associated With Diabetes in Myocardial Infarction and Ischemic Stroke Patients. American Journal of Preventive Medicine 2017;53; S190-S196.

Table 4.1: Summary statistics of low-income households' characteristics

Variable	Overall	SNAP	Income-eligible Non-SNAP
Household Characteristics			
Household size (mean)	2.522 (0.081)	2.962 (0.087)	2.245*** (0.095)
Proportion of children (mean)	0.181 (0.009)	0.253 (0.014)	0.135*** (0.010)
Proportion of older adults (mean)	0.226 (0.021)	0.109 (0.019)	0.301*** (0.030)
Proportion of Hispanics (mean)	0.209 (0.040)	0.243 (0.051)	0.188* (0.037)
Proportion of obese members(mean)	0.317 (0.010)	0.371 (0.016)	0.283*** (0.015)
Proportion of smokers (mean)	0.256 (0.019)	0.305 (0.020)	0.224** (0.025)
Proportion of poor health members (mean)	0.051 (0.006)	0.072 (0.011)	0.038** (0.007)
Household average monthly income (mean, $)	1818.107 (50.192)	2034.856 (77.221)	1681.283*** (55.896)
Tract-level median household annual income (mean, $)	53479 (1412.904)	50027 (1591.110)	55657*** (1711.510)
Cost of living (mean)	98.799 (1.147)	97.727 (1.094)	99.476*** (1.217)
NutritionSearch (share)	0.190 (0.013)	0.214 (0.023)	0.175 (0.019)
Household financial condition (share)	0.349 (0.015)	0.248 (0.022)	0.412*** (0.019)
Own house (share)	0.445 (0.028)	0.316 (0.030)	0.526*** (0.034)
Food pantry/food bank (share)	0.091 (0.009)	0.146 (0.015)	0.056*** (0.009)
Low access BG at 1 mile (share)	0.438 (0.042)	0.380 (0.044)	0.474*** (045)
Rural (share)	0.332 (0.049)	0.304 (0.042)	0.349 (0.058)
Food insecure (share)	0.338 (0.015)	0.432 (0.021)	0.278*** (0.018)
Primary Respondent's Educational Characteristics			
10th grade or less (share)	0.144 (0.016)	0.167 (0.021)	0.130** (0.016)
11th or 12th grade, no diploma (share)	0.065 (0.011)	0.088 (0.016)	0.051** (0.010)
H.S. diploma or GED (share)	0.329 (0.016)	0.338 (0.025)	0.323 (0.020)
College education (share)	0.332 (0.017)	0.316 (0.017)	0.342 (0.025)
Bachelor's degree (share)	0.099 (0.010)	0.076 (0.011)	0.114** (0.014)
Master's degree or more (share)	0.028 (0.006)	0.015 (0.006)	0.037* (0.010)
Number of Households	2,218	1,184	1,034

[1] Weighted means reported, standard errors are in parentheses and we control for survey design.
[2] *** p<0.01, ** p<0.05, * p<0.1 = statistically different from SNAP households.
[3] Definition of variables: Proportion of poor health members– the share of people that in a household rates their health condition as "poor"; Cost of living - 2012 metropolitan area-level regional price parities produced by the Bureau of Economic Analysis; NutritionSearch – whether a household searched online nutrition information in the last 2 months; Low access BG at 1 mile – a binary indicator for low access block groups, based on supermarket/supercenters within 1 mile; Household financial condition – household's self-rated financial condition is comfortable and secure; Food pantry/food bank - Household went to a food bank or food pantry in past 30 days for groceries; Food insecure – household is food insecure based on USDA's 30-day Adult Food Security Scale, households in low food security and very low food security among adults are described as "food insecure".
[3] Children here are defined as age less than or equal to 18 years old, the elderly is defined as age equal to or over 65 years old.

Table 4.2: Summary Statistics of Marginal Propensity to Spend (MPS) on food out of SNAP benefit.

		OLS			Two-part Model			Average monthly expenditure ($, by Low-income households)
		Coeff.	Std. Err.	MPS	Marginal Effect	Std. Err.	MPS	
Grains	No-star	2.329***	0.635	0.008	3.396***	0.049	0.012	6.775
	Starred	3.805***	1.284	0.013	7.696***	0.122	0.027	21.619
Vegetables	No-star	1.004**	0.387	0.004	1.686***	0.027	0.006	3.183
	Starred	2.330*	1.300	0.008	4.004***	0.120	0.014	20.916
Whole Fruit	No-star	1.090***	0.341	0.004	0.649***	0.047	0.002	1.808
	Starred	1.563	1.223	0.006	2.347***	0.156	0.008	16.170
Milk Products	No-star	4.429***	1.508	0.016	7.484***	0.138	0.026	26.734
	Starred	0.087	0.514	0.000	0.877***	0.043	0.003	3.535
Meat and Beans	No-star	15.272***	2.484	0.054	11.757***	0.298	0.042	45.213
	Starred	14.587***	2.729	0.052	8.008***	0.294	0.028	36.342
Prepared Meals	No-star	9.754***	1.740	0.034	4.907***	0.173	0.017	23.848
	Starred	4.917***	1.078	0.017	5.797***	0.095	0.021	13.783
Fats and Oils	No-star	3.942***	0.885	0.014	5.322***	0.082	0.019	12.317
	Starred	1.795***	0.537	0.006	3.033***	0.045	0.011	5.694
Beverages	No-star	8.097***	1.783	0.029	10.088***	0.160	0.036	29.387
	Starred	1.733	1.839	0.006	7.007***	0.104	0.025	17.389
Snacks	No-star	14.177***	2.871	0.050	10.843***	0.219	0.038	44.094
	Starred	1.401**	0.674	0.005	3.426***	0.068	0.012	9.291
Total		92.312		0.326	98.327		0.348	338.098

Note: 1. *** p<0.01, ** p<0.05, * p<0.1

2. The food group classification scheme largely follows that of the ERS Tier 1 Food Group, except that we classify 100% Fruit and vegetable juices to beverage category, and no-rating (because of zero calorie) diet drinks are categorized to “unstarred beverage”. Prepared meals include prepared meals, sides, and salads; fats and oils include fats, oils, salad dressings, gravies, sauces, condiments and spices; snacks include desserts, sweets, candies, and salty snacks.

3. The average monthly SNAP benefits (reported last received by SNAP households) is $282.76.

Table 4.3a. Price elasticities of demand (Means and Standard Errors (SE)) for 18 food groups.

1% rise in Price % change in	Grains No-star	Grains Starred	Vegetables No-star	Vegetables Starred	Whole Fruit No-star	Whole Fruit Starred	Milk Products No-star	Milk Products Starred	Meat and Beans No-star
Grains	**-0.994**	**-0.187**	**-0.008**	**-0.026**	**-0.006**	**0.023**	**0.034**	**-0.105**	**-0.032**
No-star	**(0.002)**	**(0.007)**	**(0.001)**	**(0.004)**	**(0.0004)**	**(0.003)**	**(0.004)**	**(0.004)**	**(0.003)**
Grains	**-0.041**	**-0.926**	**-0.012**	**0.062**	**-0.012**	**-0.126**	**0.021**	**0.066**	**-0.134**
Starred	**(0.004)**	**(0.006)**	**(0.001)**	**(0.005)**	**(0.001)**	**(0.004)**	**(0.007)**	**(0.006)**	**(0.004)**
Vegetables	**-0.007**	**0.028**	**-1.010**	**0.025**	**-0.002**	**-0.009**	**-0.082**	**0.048**	**-0.031**
No-star	**(0.003)**	**(0.005)**	**(0.001)**	**(0.005)**	**(0.0005)**	**(0.003)**	**(0.006)**	**(0.003)**	**(0.003)**
Vegetables	0.003	**-0.025**	**0.022**	**-0.741**	**-0.022**	-0.003	0.004	**0.044**	-0.012
Starred	(0.005)	**(0.008)**	**(0.002)**	**(0.006)**	**(0.001)**	(0.006)	(0.010)	**(0.006)**	(0.007)
Whole Fruit	**0.014**	**0.046**	**0.011**	**0.012**	**-1.004**	**-0.083**	**-0.046**	**-0.017**	**-0.011**
No-star	**(0.002)**	**(0.005)**	**(0.001)**	**(0.004)**	**(0.001)**	**(0.004)**	**(0.007)**	**(0.003)**	**(0.003)**
Whole Fruit	0.013	**0.130**	**0.031**	**0.134**	**0.001**	**-0.799**	**-0.113**	**0.157**	**-0.117**
Starred	(0.007)	**(0.015)**	**(0.002)**	**(0.011)**	**(0.001)**	**(0.015)**	**(0.011)**	**(0.008)**	**(0.010)**
Milk Products	**-0.075**	**-0.018**	**0.009**	**0.079**	**-0.014**	**-0.057**	**-0.991**	**-0.018**	**-0.086**
No-star	**(0.003)**	**(0.004)**	**(0.001)**	**(0.004)**	**(0.001)**	**(0.003)**	**(0.005)**	**(0.004)**	**(0.003)**
Milk Products	**0.019**	0.004	**0.003**	**-0.013**	**-0.004**	**0.028**	**-0.017**	**-1.022**	**-0.026**
Starred	**(0.002)**	(0.003)	**(0.001)**	**(0.004)**	**(0.001)**	**(0.002)**	**(0.004)**	**(0.002)**	**(0.002)**
Meat and Beans	**0.033**	**-0.064**	**0.013**	**0.019**	**-0.015**	**-0.024**	-0.012	**0.115**	**-1.216**
No-star	**(0.005)**	**(0.007)**	**(0.002)**	**(0.010)**	**(0.001)**	**(0.005)**	(0.008)	**(0.006)**	**(0.004)**

Table 4.3b. Price elasticities of demand (Means and Standard Errors (SE)) for 18 food groups (Continued).

1% rise in Price % change in	Grains No-star	Grains Starred	Vegetables No-star	Vegetables Starred	Whole Fruit No-star	Whole Fruit Starred	Milk Products No-star	Milk Products Starred	Meat and Beans No-star
Meat and Beans	**-0.031**	-0.005	**-0.006**	**0.034**	**-0.031**	**-0.054**	**0.094**	**-0.027**	**-0.151**
Starred	**(0.007)**	(0.011)	**(0.001)**	**(0.008)**	**(0.001)**	**(0.006)**	**(0.009)**	**(0.006)**	**(0.006)**
Prepared Meals	**-0.020**	**-0.085**	**-0.030**	**0.182**	-0.002	**-0.014**	**-0.078**	**0.048**	**-0.198**
No-star	**(0.005)**	**(0.010)**	**(0.002)**	**(0.011)**	(0.001)	**(0.006)**	**(0.008)**	**(0.008)**	**(0.006)**
Prepared Meals	**-0.015**	**-0.038**	**0.004**	**0.083**	**-0.014**	**-0.027**	**0.052**	**-0.028**	**-0.120**
Starred	**(0.004)**	**(0.007)**	**(0.001)**	**(0.006)**	**(0.001)**	**(0.005)**	**(0.010)**	**(0.005)**	**(0.004)**
Fats and Oils	-0.004	-0.007	**0.010**	**0.071**	**-0.024**	**-0.070**	**-0.142**	**0.012**	**-0.135**
No-star	(0.005)	(0.005)	**(0.001)**	**(0.006)**	**(0.001)**	**(0.004)**	**(0.008)**	**(0.005)**	**(0.005)**
Fats and Oils	**-0.031**	**-0.033**	**0.008**	**0.021**	-0.002	**-0.021**	**0.019**	0.003	**-0.024**
Starred	**(0.003)**	**(0.005)**	**(0.001)**	**(0.004)**	(0.001)	**(0.004)**	**(0.005)**	(0.005)	**(0.003)**
Beverages	**0.037**	**-0.113**	**-0.019**	**0.026**	**-0.012**	0.001	-0.019	**0.110**	**-0.203**
No-star	**(0.005)**	**(0.009)**	**(0.002)**	**(0.006)**	**(0.001)**	(0.007)	(0.013)	**(0.009)**	**(0.006)**
Beverages	**-0.158**	-0.005	**-0.021**	**0.099**	**-0.012**	**-0.192**	**-0.063**	**-0.082**	**-0.130**
Starred	**(0.010)**	(0.010)	**(0.004)**	**(0.007)**	**(0.001)**	**(0.007)**	**(0.012)**	**(0.006)**	**(0.007)**
Snacks	**-0.117**	**-0.079**	0.003	**0.158**	**-0.056**	**-0.112**	**-0.126**	**0.123**	**-0.137**
No-star	**(0.006)**	**(0.010)**	(0.002)	**(0.010)**	**(0.001)**	**(0.006)**	**(0.009)**	**(0.013)**	**(0.006)**
Snacks	**-0.031**	**-0.030**	**0.013**	**0.014**	**-0.005**	**-0.022**	**0.015**	**-0.018**	**-0.066**
Starred	**(0.003)**	**(0.006)**	**(0.001)**	**(0.005)**	**(0.001)**	**(0.004)**	**(0.006)**	**(0.004)**	**(0.004)**

Table 4.3c. Price elasticities of demand (Means and Standard Errors (SE)) for 18 food groups (Continued)

1% rise in Price % change in	Meat and Beans Starred	Prepared Meals No-star	Prepared Meals Starred	Fats and Oils No-star	Fats and Oils Starred	Beverages No-star	Beverages Starred	Snacks No-star	Snacks Starred
Grains	**-0.044**	**-0.023**	**-0.047**	**-0.048**	**0.007**	**-0.045**	**-0.038**	**0.016**	**-0.029**
No-star	**(0.002)**	**(0.003)**	**(0.004)**	**(0.003)**	**(0.001)**	**(0.003)**	**(0.002)**	**(0.004)**	**(0.005)**
Grains	**-0.060**	**-0.158**	**-0.065**	**-0.024**	**-0.029**	**-0.087**	**-0.018**	**-0.059**	**-0.140**
Starred	**(0.003)**	**(0.005)**	**(0.005)**	**(0.004)**	**(0.002)**	**(0.003)**	**(0.002)**	**(0.005)**	**(0.008)**
Vegetables	**-0.031**	**-0.043**	-0.001	**-0.020**	**-0.012**	**0.042**	**-0.007**	**-0.045**	**-0.051**
No-star	**(0.003)**	**(0.003)**	(0.004)	**(0.003)**	**(0.001)**	**(0.003)**	**(0.001)**	**(0.003)**	**(0.005)**
Vegetables	**-0.092**	**-0.114**	**-0.037**	**-0.008**	**-0.056**	0.0004	**-0.047**	**-0.100**	**-0.049**
Starred	**(0.005)**	**(0.007)**	**(0.005)**	**(0.003)**	**(0.001)**	(0.003)	**(0.002)**	**(0.005)**	**(0.009)**
Whole Fruit	**-0.053**	**-0.016**	0.001	**-0.025**	**-0.007**	0.003	**-0.003**	-0.012	0.009
No-star	**(0.002)**	**(0.004)**	(0.004)	**(0.002)**	**(0.0005)**	(0.002)	**(0.002)**	(0.003)	(0.006)
Whole Fruit	**-0.052**	**-0.184**	**-0.136**	**-0.010**	**-0.024**	**-0.115**	**-0.064**	0.006	**-0.176**
Starred	**(0.007)**	**(0.008)**	**(0.008)**	**(0.004)**	**(0.002)**	**(0.005)**	**(0.003)**	(0.006)	**(0.012)**
Milk Products	**-0.031**	**-0.093**	**0.029**	**-0.024**	**-0.024**	**-0.057**	**-0.026**	**-0.008**	**-0.058**
No-star	**(0.002)**	**(0.004)**	**(0.004)**	**(0.003)**	**(0.001)**	**(0.003)**	**(0.002)**	**(0.003)**	**(0.007)**
Milk Products	**-0.010**	**-0.024**	**-0.019**	-0.001	**0.004**	**-0.019**	**-0.014**	**-0.029**	**-0.161**
Starred	**(0.002)**	**(0.003)**	**(0.003)**	(0.001)	**(0.001)**	**(0.002)**	**(0.001)**	**(0.002)**	**(0.005)**
Meat and Beans	**-0.076**	**-0.040**	**-0.109**	**-0.075**	**-0.043**	**-0.073**	**-0.043**	**-0.063**	0.017
No-star	**(0.006)**	**(0.007)**	**(0.007)**	**(0.004)**	**(0.001)**	**(0.005)**	**(0.002)**	**(0.006)**	(0.010)

Table 4.3d. Price elasticities of demand (Means and Standard Errors (SE)) for 18 food groups (Continued)

1% rise in Price % change in	Meat and Beans Starred	Prepared Meals No-star	Prepared Meals Starred	Fats and Oils No-star	Fats and Oils Starred	Beverages No-star	Beverages Starred	Snacks No-star	Snacks Starred
Meat and Beans	**-1.088**	**-0.015**	**-0.067**	**-0.043**	**-0.043**	**-0.051**	**-0.068**	**-0.013**	**-0.020**
Starred	**(0.005)**	**(0.007)**	**(0.006)**	**(0.003)**	**(0.002)**	**(0.006)**	**(0.003)**	**(0.004)**	**(0.011)**
Prepared Meals	0.002	**-1.138**	**-0.149**	**-0.111**	**-0.029**	**-0.051**	**-0.067**	**-0.131**	**-0.055**
No-star	(0.005)	**(0.007)**	**(0.009)**	**(0.005)**	**(0.001)**	**(0.005)**	**(0.003)**	**(0.005)**	**(0.012)**
Prepared Meals	**-0.050**	**-0.168**	**-1.051**	**0.051**	**-0.038**	**-0.047**	**-0.053**	**-0.010**	**-0.058**
Starred	**(0.003)**	**(0.007)**	**(0.004)**	**(0.004)**	**(0.001)**	**(0.004)**	**(0.003)**	**(0.006)**	**(0.009)**
Fats and Oils	**-0.068**	**-0.033**	**0.034**	**-0.961**	**-0.036**	**-0.026**	**-0.031**	**-0.015**	**0.044**
No-star	**(0.004)**	**(0.005)**	**(0.005)**	**(0.003)**	**(0.001)**	**(0.003)**	**(0.002)**	**(0.002)**	**(0.008)**
Fats and Oils	**-0.059**	0.001	**0.012**	-0.001	**-1.022**	**-0.012**	**-0.012**	**-0.049**	**0.017**
Starred	**(0.003)**	(0.004)	**(0.005)**	(0.004)	**(0.0005)**	**(0.002)**	**(0.001)**	**(0.006)**	**(0.006)**
Beverages	0.002	**-0.183**	**-0.032**	**-0.018**	**-0.028**	**-0.961**	**-0.062**	**-0.121**	-0.005
No-star	(0.003)	**(0.008)**	**(0.008)**	**(0.005)**	**(0.001)**	**(0.003)**	**(0.002)**	**(0.007)**	(0.010)
Beverages	**-0.094**	**-0.174**	**-0.075**	**0.055**	**0.014**	**0.028**	**-0.979**	-0.008	**-0.061**
Starred	**(0.004)**	**(0.007)**	**(0.010)**	**(0.005)**	**(0.002)**	**(0.004)**	**(0.006)**	(0.004)	**(0.010)**
Snacks	**-0.069**	**-0.189**	**-0.130**	**0.025**	**-0.035**	**-0.073**	**-0.044**	**-1.004**	**-0.082**
No-star	**(0.005)**	**(0.008)**	**(0.007)**	**(0.004)**	**(0.001)**	**(0.007)**	**(0.003)**	**(0.003)**	**(0.011)**
Snacks	**-0.015**	**-0.153**	**0.077**	**-0.019**	**-0.016**	**-0.007**	**-0.043**	**-0.031**	**-0.989**
Starred	**(0.002)**	**(0.005)**	**(0.005)**	**(0.003)**	**(0.001)**	**(0.003)**	**(0.001)**	**(0.003)**	**(0.005)**

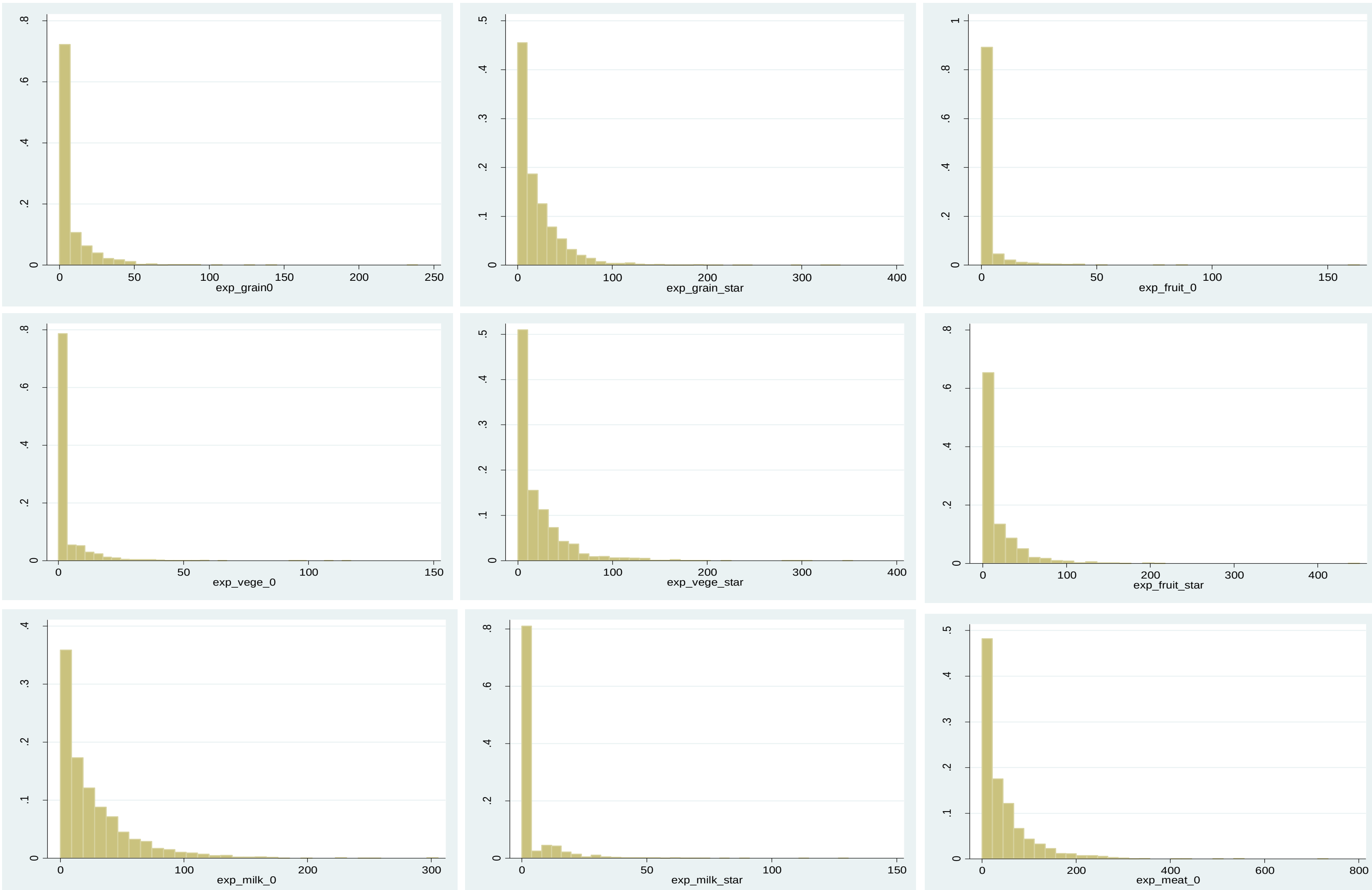

Figure 4.1a The distribution of expenditure by food category

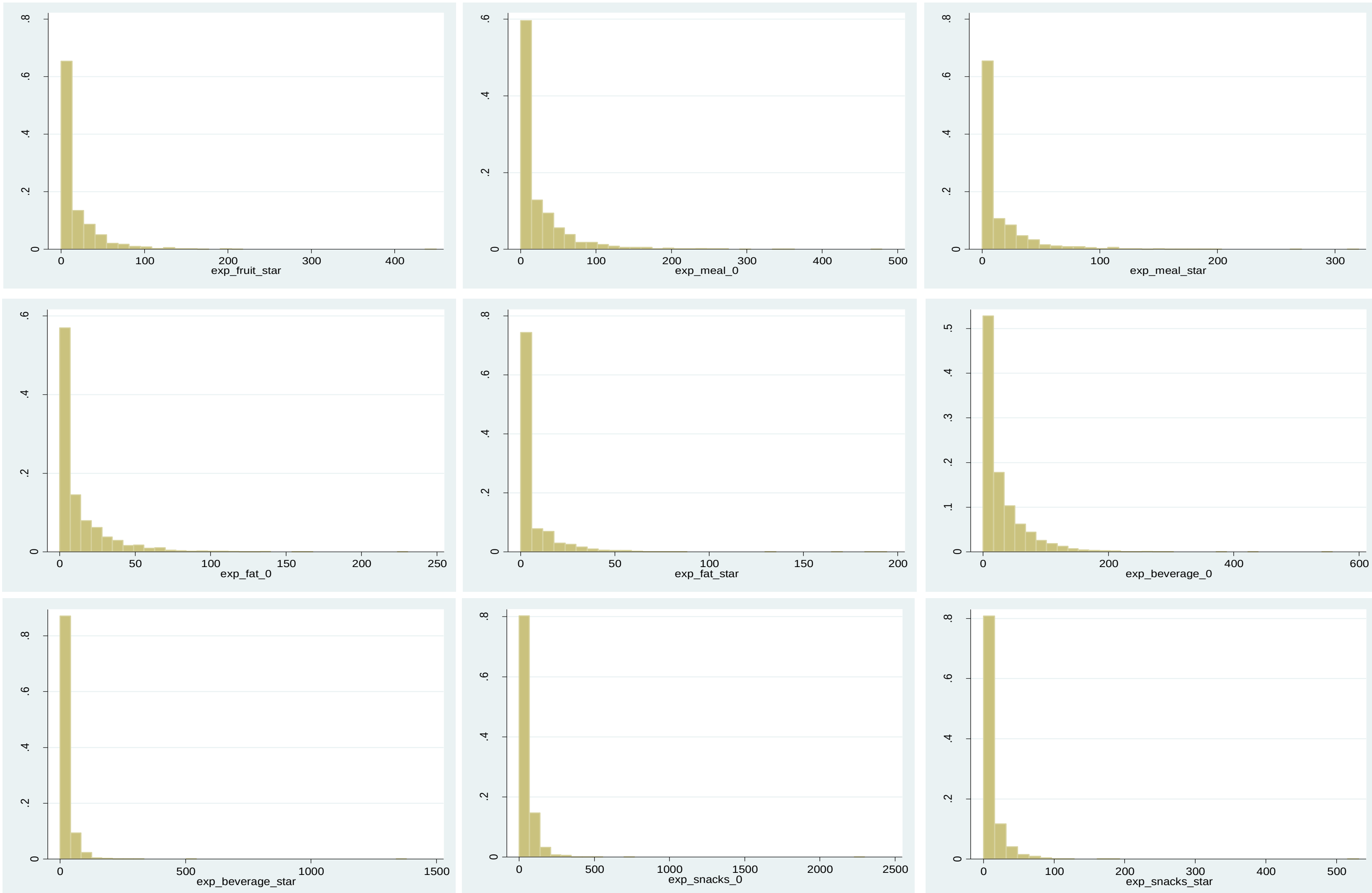

Figure 4.1b The distribution of expenditure by food category (continued)

CHAPTER 5

CONCLUSION

Suboptimal diet is related to increased risks of many nutrition-related non-communicable diseases, such as heart disease, type 2 diabetes and certain cancers (HHS and USDA, 2015). This has raised concerns regarding the sodium content of the foods that we consume. Two main sodium reduction strategies are widely discussed in prior studies, one is to call for efforts by the food industry to voluntarily reduce sodium in their products and the other is to set mandatory standards for the sodium content of foods.

To assess the feasibility of these two strategies from a consumer demand angle, we focus our analysis on the Chinese instant noodle market and we simulate the impact of each sodium reduction strategy on the demand for instant noodles using the random-coefficients logit model. We find that if a company unilaterally lowers sodium amounts across its product line, it will lose market share to its competitors. This provides the evidence on the challenges that voluntary sodium reduction strategy faces. The positive valuation of saturated fat by consumers suggests that if a mandated sodium reduction is implemented through regulation, manufacturers could compensate the negative impact on sales by reformulating their products to contain higher levels of saturated fat, which would offset the health benefits gained from a reduction in sodium. As we know, fat over-consumption can increase the risk of illnesses, such as obesity, heart diseases and diabetes.Therefore, sodium reduction strategies need to be designed to help achieve the safe levels of sodium in consumers' diet without loss of consumers' acceptance of foods and to avoid the unintended consequences.

Low-income households are more likely, than high-income households, to purchase and consume foods of lower nutritional quality, such as refined grains and added sugar and fats (Darmon and Drewnowski, 2008). In the U.S., the Supplemental Nutrition Assistance Program (SNAP) provides recipient households monthly benefits to support their food purchases at authorized retailers. In the last two chapters of this dissertation, we focus on evaluating the association between SNAP with nutritional quality of food-at-home purchases among low-income households, as well as exploring the effects of SNAP and prices on low-income households' food spending.

First, we find that SNAP participation is associated with lower nutritional quality of FAH purchases among less nutrition-oriented households, but not among more nutrition-oriented households. This heterogeneity in the SNAP-nutritional quality association may have important policy implications. For example, some researchers proposed to restrict SNAP-eligible items to healthy foods (Brownell & Ludwig, 2011; Dinour, Bergen, & Yeh, 2007; Levin et al., 2017; Schwartz, 2017). Opponents to these proposals have cited possible stigma-induced reduction in SNAP enrollment. As the merit of the SNAP restrictions is premised on the existence of a negative association between SNAP and nutritional quality, the lack of such an association for nutrition-oriented participants suggests that the intended benefit of the proposed changes may not reach this subgroup of SNAP population. Besides, the dependency of the SNAP-nutrition relationship on nutrition attitude underscores the promising role of SNAP Education (SNAP-Ed) in closing the nutrition gap between less nutrition-oriented SNAP participants and low-income nonparticipants.

In addition, we find the price of starred foods relative to unstarred foods to be negatively associated with nutritional quality. As starred foods become more expensive relative to unstarred foods, the mix of purchase shifts toward unstarred foods and, hence, causes a reduction in nutritional quality. The USDA Food Insecurity Nutrition Incentive (FINI) grant program is designed to support financial incentives that reduce the relative price of fruit and vegetables for the SNAP population at farmers markets. Our result suggests that financial incentives have to apply to a much broader range of healthy foods to improve the overall nutritional quality.

In term of how the SNAP benefits are spent on food, we find that the overall marginal propensity to spend on food out of SNAP benefit is 0.35. SNAP participants spend more on no-star meat and beans, no-star snacks and no-star beverages to increase more than those on vegetables, whole fruit and starred milk products. This implies that the observed lower overall dietary quality of SNAP participants compared to low-income nonparticipants may be causally linked to the program.

We also find that food taxes and subsidies have the potential to encourage the targeted nutrient-rich food and decrease the targeted nutrient-poor food purchases, while concerns remain that they may have unintended consequences of purchasing other nutrient-poor food that high in sugar, saturated fat and sodium. This highlights the complexity of using targeted food taxes and subsidies to improve low-income households' nutrition outcomes. Therefore, the design of these financial incentives should be done with care, and the promising strategies need to be evaluated and tested to ultimately improve dietary quality among low-income households.

References

2015 – 2020 Dietary Guidelines for Americans. (December 2015). In (8th ed.): U.S. Department of Health and Human Services and U.S. Department of Agriculture.

Brownell, K. D., & Ludwig, D. S. (2011). The Supplemental Nutrition Assistance Program, Soda, and USDA Policy: Who Benefits? JAMA, 306(12), 1370-1371. doi:10.1001/jama.2011.1382

Dinour, L. M., Bergen, D., & Yeh, M.-C. (2007). The Food Insecurity–Obesity Paradox: A Review of the Literature and the Role Food Stamps May Play. Journal of the American Dietetic Association, 107(11), 1952-1961. doi:https://doi.org/10.1016/j.jada.2007.08.006

Levin, S. M., Barnard, N. D., & Saltalamacchia, R. E. (2017). A Proposal for Improvements in the Supplemental Nutrition Assistance Program. American Journal of Preventive Medicine, 52(2), S186-S192. doi:10.1016/j.amepre.2016.07.016

Schwartz, M. B. (2017). Moving Beyond the Debate Over Restricting Sugary Drinks in the Supplemental Nutrition Assistance Program. American Journal of Preventive Medicine, 52(2, Supplement 2), S199-S205. doi:https://doi.org/10.1016/j.amepre.2016.09.022

APPENDIX A: Additional Tables

Table A.1a: Price elasticities of demand for all instant noodle products, all provinces

	1% rise in Price											
% change in	111	112	121	122	131	132	141	142	211	212	231	232
111	-1.4867	0.0355	0.0137	0.0016	0.0210	0.0023	0.0140	0.0022	0.0390	0.0021	0.0128	0.0009
112	0.2271	-1.6627	0.0139	0.0016	0.0211	0.0023	0.0140	0.0022	0.0392	0.0021	0.0127	0.0009
121	0.2283	0.0355	-1.6935	0.0016	0.0211	0.0022	0.0141	0.0022	0.0394	0.0021	0.0128	0.0009
122	0.2296	0.0360	0.0146	-1.6877	0.0217	0.0023	0.0145	0.0023	0.0404	0.0021	0.0141	0.0009
131	0.2204	0.0357	0.0135	0.0016	-1.6805	0.0023	0.0141	0.0022	0.0367	0.0021	0.0124	0.0009
132	0.2112	0.0358	0.0132	0.0016	0.0212	-1.6837	0.0142	0.0024	0.0354	0.0020	0.0123	0.0009
141	0.2286	0.0352	0.0133	0.0016	0.0209	0.0022	-1.6907	0.0022	0.0393	0.0021	0.0128	0.0009
142	0.2258	0.0356	0.0138	0.0016	0.0214	0.0023	0.0143	-1.6915	0.0390	0.0021	0.0125	0.0009
211	0.2306	0.0357	0.0138	0.0016	0.0210	0.0022	0.0140	0.0022	-1.6488	0.0021	0.0128	0.0009
212	0.2316	0.0360	0.0140	0.0016	0.0213	0.0022	0.0146	0.0022	0.0423	-1.7121	0.0134	0.0009
231	0.2397	0.0347	0.0139	0.0016	0.0213	0.0020	0.0151	0.0022	0.0440	0.0021	-1.7054	0.0009
232	0.2342	0.0356	0.0132	0.0016	0.0219	0.0022	0.0163	0.0026	0.0422	0.0021	0.0142	-1.7054
311	0.2285	0.0359	0.0139	0.0016	0.0214	0.0023	0.0140	0.0022	0.0394	0.0021	0.0128	0.0009
312	0.2258	0.0360	0.0139	0.0016	0.0213	0.0023	0.0139	0.0022	0.0389	0.0021	0.0126	0.0009
331	0.2372	0.0357	0.0148	0.0016	0.0217	0.0021	0.0168	0.0024	0.0456	0.0022	0.0154	0.0009
332	0.1796	0.0393	0.0100	0.0015	0.0210	0.0032	0.0122	0.0025	0.0193	0.0014	0.0075	0.0008
341	0.2382	0.0353	0.0139	0.0016	0.0216	0.0021	0.0153	0.0023	0.0453	0.0020	0.0143	0.0009
342	0.1716	0.0405	0.0087	0.0014	0.0196	0.0033	0.0118	0.0028	0.0213	0.0014	0.0079	0.0007
411	0.2557	0.0359	0.0155	0.0016	0.0192	0.0016	0.0145	0.0020	0.0529	0.0023	0.0183	0.0009
412	0.2203	0.0392	0.0133	0.0016	0.0174	0.0015	0.0109	0.0019	0.0421	0.0026	0.0099	0.0007
421	0.2767	0.0350	0.0198	0.0018	0.0213	0.0015	0.0192	0.0022	0.0579	0.0027	0.0265	0.0010
422	0.1973	0.0307	0.0150	0.0023	0.0210	0.0010	0.0144	0.0019	0.0600	0.0035	0.0155	0.0005
431	0.2713	0.0344	0.0171	0.0017	0.0210	0.0015	0.0165	0.0021	0.0546	0.0024	0.0233	0.0009
432	0.2727	0.0337	0.0208	0.0016	0.0201	0.0009	0.0178	0.0020	0.0696	0.0037	0.0242	0.0011

Note: The values are median price elasticity of all the markets.

Table A.1b: Price elasticities of demand for all instant noodle products, all provinces (Continued)

	1% rise in Price											
% change in	311	312	331	332	341	342	411	412	421	422	431	432
111	0.0653	0.0086	0.0044	0.0007	0.0029	0.0005	0.0106	0.0010	0.0026	0.0003	0.0096	0.0007
112	0.0658	0.0085	0.0044	0.0007	0.0029	0.0005	0.0105	0.0010	0.0026	0.0003	0.0097	0.0007
121	0.0657	0.0085	0.0044	0.0007	0.0029	0.0005	0.0109	0.0010	0.0026	0.0003	0.0097	0.0007
122	0.0655	0.0083	0.0046	0.0007	0.0029	0.0005	0.0097	0.0010	0.0027	0.0004	0.0105	0.0007
131	0.0639	0.0090	0.0044	0.0007	0.0028	0.0005	0.0098	0.0010	0.0027	0.0003	0.0107	0.0007
132	0.0632	0.0090	0.0044	0.0007	0.0029	0.0005	0.0084	0.0009	0.0025	0.0004	0.0091	0.0006
141	0.0655	0.0084	0.0044	0.0007	0.0029	0.0005	0.0106	0.0010	0.0026	0.0003	0.0097	0.0007
142	0.0650	0.0087	0.0044	0.0007	0.0028	0.0005	0.0099	0.0010	0.0027	0.0003	0.0095	0.0007
211	0.0661	0.0086	0.0044	0.0007	0.0028	0.0005	0.0107	0.0010	0.0027	0.0003	0.0098	0.0007
212	0.0659	0.0084	0.0044	0.0007	0.0029	0.0005	0.0109	0.0009	0.0026	0.0003	0.0097	0.0006
231	0.0644	0.0083	0.0045	0.0007	0.0029	0.0005	0.0116	0.0010	0.0026	0.0003	0.0105	0.0007
232	0.0657	0.0092	0.0046	0.0008	0.0030	0.0005	0.0093	0.0008	0.0025	0.0003	0.0083	0.0005
311	-1.6155	0.0087	0.0044	0.0007	0.0029	0.0005	0.0106	0.0010	0.0027	0.0003	0.0094	0.0007
312	0.0664	-1.6758	0.0043	0.0007	0.0029	0.0005	0.0106	0.0010	0.0026	0.0003	0.0095	0.0007
331	0.0637	0.0082	-1.7041	0.0008	0.0029	0.0005	0.0115	0.0009	0.0028	0.0003	0.0117	0.0007
332	0.0706	0.0117	0.0039	-1.5205	0.0038	0.0005	0.0045	0.0009	0.0014	0.0004	0.0022	0.0003
341	0.0645	0.0084	0.0046	0.0007	-1.7076	0.0005	0.0109	0.0011	0.0027	0.0003	0.0109	0.0007
342	0.0674	0.0122	0.0033	0.0008	0.0039	-1.6294	0.0054	0.0008	0.0016	0.0003	0.0022	0.0003
411	0.0668	0.0075	0.0039	0.0005	0.0025	0.0005	-1.7188	0.0011	0.0027	0.0004	0.0116	0.0007
412	0.0692	0.0111	0.0014	0.0006	0.0023	0.0004	0.0124	-1.7183	0.0036	0.0003	0.0155	0.0007
421	0.0670	0.0065	0.0047	0.0005	0.0026	0.0005	0.0130	0.0010	-1.7326	0.0003	0.0131	0.0007
422	0.0395	0.0049	0.0015	0.0005	0.0014	0.0007	0.0178	0.0007	0.0086	-1.7103	0.0506	0.0006
431	0.0651	0.0064	0.0044	0.0005	0.0028	0.0005	0.0127	0.0010	0.0027	0.0003	-1.7168	0.0007
432	0.0652	0.0055	0.0024	0.0005	0.0021	0.0004	0.0286	0.0016	0.0076	0.0004	0.0569	-1.8155

Note: The values are median price elasticity of all the markets.

Product number: The first number represents the brand: 1=MasterKong, 2= JinMaiLang, 3= Uni-President, 4= BaiXiang, 5= FuManDuo, 6= HuaFeng, 7= Nissin, 8= WuGuDaoChang, 9= HuaLong.

The second number represents the flavor: 1= Beef, 2= Chicken, 3= Pork, 4= Seafood

The third number represents the package shape: 1= Bag, 2=Other shapes (Include barrel package, box package and cup package).

Table A.1c: Price elasticities of demand for all instant noodle products, all provinces (Continued)

% change in	1% rise in Price 111	112	121	122	131	132	141	142	211	212	231	232
511	0.2243	0.0344	0.0134	0.0016	0.0209	0.0023	0.0145	0.0023	0.0385	0.0019	0.0140	0.0008
512	0.2078	0.0367	0.0116	0.0014	0.0203	0.0024	0.0126	0.0021	0.0353	0.0020	0.0102	0.0008
521	0.2548	0.0314	0.0205	0.0021	0.0231	0.0015	0.0226	0.0023	0.0569	0.0022	0.0314	0.0010
531	0.2119	0.0320	0.0161	0.0018	0.0237	0.0022	0.0189	0.0025	0.0389	0.0017	0.0162	0.0009
532	0.1976	0.0526	0.0053	0.0019	0.0231	0.0030	0.0194	0.0030	0.0419	0.0021	0.0126	0.0005
541	0.2784	0.0317	0.0258	0.0021	0.0270	0.0016	0.0297	0.0034	0.0704	0.0025	0.0386	0.0012
542	0.2143	0.0330	0.0198	0.0023	0.0287	0.0026	0.0402	0.0054	0.0469	0.0012	0.0288	0.0010
611	0.2606	0.0348	0.0166	0.0016	0.0222	0.0019	0.0168	0.0023	0.0544	0.0023	0.0204	0.0010
612	0.2131	0.0285	0.0175	0.0020	0.0181	0.0019	0.0126	0.0015	0.0290	0.0007	0.0055	0.0008
621	0.2650	0.0349	0.0177	0.0016	0.0213	0.0018	0.0160	0.0022	0.0551	0.0024	0.0206	0.0009
631	0.2573	0.0353	0.0165	0.0017	0.0217	0.0018	0.0160	0.0023	0.0530	0.0022	0.0173	0.0009
641	0.2743	0.0343	0.0193	0.0016	0.0209	0.0015	0.0181	0.0022	0.0585	0.0024	0.0259	0.0009
711	0.2041	0.0343	0.0117	0.0016	0.0231	0.0036	0.0167	0.0033	0.0311	0.0015	0.0112	0.0008
712	0.1808	0.0396	0.0090	0.0013	0.0199	0.0026	0.0123	0.0027	0.0231	0.0015	0.0076	0.0008
731	0.2147	0.0470	0.0082	0.0013	0.0211	0.0034	0.0135	0.0028	0.0319	0.0014	0.0095	0.0007
732	0.1676	0.0392	0.0092	0.0014	0.0208	0.0028	0.0121	0.0028	0.0217	0.0014	0.0076	0.0008
741	0.1326	0.0314	0.0139	0.0017	0.0235	0.0036	0.0162	0.0033	0.0174	0.0013	0.0096	0.0006
742	0.1859	0.0393	0.0094	0.0013	0.0206	0.0027	0.0123	0.0026	0.0236	0.0015	0.0082	0.0008
811	0.2593	0.0352	0.0174	0.0017	0.0236	0.0019	0.0204	0.0027	0.0545	0.0024	0.0222	0.0010
812	0.2433	0.0350	0.0155	0.0017	0.0258	0.0024	0.0217	0.0031	0.0537	0.0026	0.0223	0.0010
821	0.2575	0.0336	0.0196	0.0019	0.0258	0.0021	0.0245	0.0030	0.0550	0.0025	0.0256	0.0010
822	0.2381	0.0338	0.0145	0.0021	0.0293	0.0030	0.0242	0.0035	0.0506	0.0023	0.0280	0.0012
831	0.2477	0.0341	0.0186	0.0019	0.0264	0.0020	0.0248	0.0031	0.0525	0.0024	0.0252	0.0010
832	0.2448	0.0359	0.0181	0.0021	0.0322	0.0023	0.0283	0.0037	0.0533	0.0025	0.0286	0.0013
911	0.2243	0.0340	0.0139	0.0016	0.0216	0.0022	0.0145	0.0023	0.0426	0.0020	0.0126	0.0009
931	0.2435	0.0309	0.0163	0.0020	0.0244	0.0021	0.0228	0.0028	0.0553	0.0022	0.0278	0.0012
941	0.2862	0.0305	0.0339	0.0029	0.0315	0.0012	0.0470	0.0035	0.0777	0.0024	0.0417	0.0017

Note: The values are median price elasticity of all the markets.
Product number: The first number represents the brand: 1=MasterKong, 2= JinMaiLang, 3= Uni-President, 4= BaiXiang, 5= FuManDuo, 6= HuaFeng, 7= Nissin, 8= WuGuDaoChang, 9= HuaLong. The second number represents the flavor: 1= Beef, 2= Chicken, 3= Pork, 4= Seafood. The third number represents the package shape: 1= Bag, 2=Other shapes (Include barrel package, box package and cup package).

Table A.1d: Price elasticities of demand for all instant noodle products, all provinces (Continued)

% change in	1% rise in Price 311	312	331	332	341	342	411	412	421	422	431	432
511	0.0632	0.0082	0.0046	0.0007	0.0029	0.0005	0.0096	0.0008	0.0024	0.0004	0.0088	0.0005
512	0.0647	0.0098	0.0032	0.0007	0.0027	0.0005	0.0096	0.0011	0.0025	0.0003	0.0069	0.0006
521	0.0558	0.0050	0.0048	0.0006	0.0028	0.0004	0.0144	0.0007	0.0035	0.0003	0.0170	0.0006
531	0.0474	0.0059	0.0043	0.0007	0.0030	0.0005	0.0113	0.0007	0.0028	0.0004	0.0124	0.0004
532	0.0638	0.0089	0.0097	0.0008	0.0043	0.0003	0.0137	0.0004	0.0032	-	0.0030	0.0001
541	0.0566	0.0048	0.0060	0.0007	0.0029	0.0004	0.0175	0.0009	0.0038	0.0005	0.0225	0.0007
542	0.0451	0.0062	0.0044	0.0011	0.0029	0.0005	0.0046	0.0012	0.0032	0.0005	0.0122	0.0006
611	0.0643	0.0069	0.0049	0.0008	0.0030	0.0005	0.0132	0.0008	0.0028	0.0003	0.0127	0.0007
612	0.0771	0.0092	0.0017	0.0005	0.0030	0.0007	0.0200	0.0000	0.0011	-	0.0012	-
621	0.0659	0.0072	0.0049	0.0007	0.0029	0.0005	0.0130	0.0009	0.0027	0.0004	0.0120	0.0007
631	0.0659	0.0076	0.0048	0.0007	0.0029	0.0005	0.0125	0.0009	0.0027	0.0003	0.0118	0.0007
641	0.0669	0.0062	0.0049	0.0006	0.0027	0.0004	0.0136	0.0009	0.0028	0.0005	0.0138	0.0007
711	0.0616	0.0103	0.0057	0.0011	0.0038	0.0005	0.0038	0.0003	0.0021	0.0003	0.0029	0.0003
712	0.0677	0.0121	0.0037	0.0009	0.0036	0.0005	0.0058	0.0010	0.0019	0.0003	0.0025	0.0005
731	0.0714	0.0128	0.0047	0.0009	0.0038	0.0005	0.0053	0.0005	0.0018	0.0003	0.0020	0.0003
732	0.0696	0.0120	0.0037	0.0008	0.0039	0.0005	0.0045	0.0007	0.0017	0.0003	0.0023	0.0003
741	0.0565	0.0104	0.0053	0.0011	0.0044	0.0006	0.0009	0.0004	0.0010	0.0003	0.0013	0.0001
742	0.0666	0.0118	0.0040	0.0008	0.0035	0.0005	0.0054	0.0007	0.0020	0.0002	0.0030	0.0004
811	0.0621	0.0075	0.0053	0.0008	0.0031	0.0006	0.0125	0.0010	0.0029	0.0003	0.0122	0.0007
812	0.0616	0.0082	0.0054	0.0008	0.0032	0.0006	0.0099	0.0010	0.0029	0.0004	0.0096	0.0006
821	0.0586	0.0070	0.0058	0.0009	0.0030	0.0005	0.0112	0.0008	0.0030	0.0005	0.0121	0.0006
822	0.0570	0.0072	0.0060	0.0012	0.0038	0.0006	0.0052	0.0005	0.0033	0.0005	0.0077	0.0004
831	0.0580	0.0067	0.0054	0.0009	0.0030	0.0005	0.0104	0.0008	0.0028	0.0004	0.0118	0.0006
832	0.0567	0.0069	0.0063	0.0010	0.0031	0.0005	0.0046	0.0010	0.0029	0.0014	0.0074	0.0004
911	0.0647	0.0078	0.0042	0.0007	0.0031	0.0005	0.0107	0.0010	0.0026	0.0004	0.0099	0.0006
931	0.0582	0.0063	0.0054	0.0008	0.0035	0.0006	0.0108	0.0008	0.0033	0.0005	0.0121	0.0005
941	0.0571	0.0038	0.0051	0.0004	0.0028	0.0002	0.0176	0.0012	0.0071	0.0005	0.0277	0.0006

Note: The values are median price elasticity of all the markets.
Product number: The first number represents the brand: 1=MasterKong, 2= JinMaiLang, 3= Uni-President, 4= BaiXiang, 5= FuManDuo, 6= HuaFeng, 7= Nissin, 8= WuGuDaoChang, 9= HuaLong. The second number represents the flavor: 1= Beef, 2= Chicken, 3= Pork, 4= Seafood. The third number represents the package shape: 1= Bag, 2=Other shapes (Include barrel package, box package and cup package).

Table A.1e: Price elasticities of demand for all instant noodle products, all provinces

	1% rise in Price													
% change in	511	512	521	531	532	541	542	611	612	621	631	641	711	712
111	0.0080	0.0007	0.0014	0.0017	0.0003	0.0019	0.0003	0.0007	0.0005	0.0008	0.0013	0.0007	0.0006	0.0011
112	0.0081	0.0007	0.0014	0.0017	0.0003	0.0019	0.0003	0.0007	0.0005	0.0008	0.0013	0.0007	0.0006	0.0010
121	0.0081	0.0007	0.0014	0.0017	0.0003	0.0019	0.0003	0.0007	0.0005	0.0008	0.0013	0.0007	0.0006	0.0011
122	0.0082	0.0006	0.0014	0.0017	0.0003	0.0019	0.0003	0.0007	0.0004	0.0009	0.0012	0.0007	0.0006	0.0013
131	0.0078	0.0006	0.0014	0.0017	0.0003	0.0019	0.0003	0.0006	0.0002	0.0008	0.0011	0.0007	0.0006	0.0011
132	0.0079	0.0007	0.0014	0.0017	0.0003	0.0018	0.0003	0.0005	0.0004	0.0007	0.0010	0.0006	0.0006	0.0012
141	0.0079	0.0007	0.0014	0.0017	0.0003	0.0019	0.0003	0.0007	0.0005	0.0008	0.0013	0.0007	0.0006	0.0011
142	0.0083	0.0006	0.0014	0.0017	0.0003	0.0019	0.0003	0.0006	0.0004	0.0008	0.0012	0.0007	0.0006	0.0011
211	0.0080	0.0007	0.0014	0.0017	0.0003	0.0019	0.0003	0.0007	0.0005	0.0008	0.0013	0.0007	0.0006	0.0011
212	0.0082	0.0007	0.0014	0.0017	0.0003	0.0018	0.0003	0.0007	0.0005	0.0008	0.0013	0.0007	0.0006	0.0011
231	0.0085	0.0006	0.0014	0.0017	0.0003	0.0019	0.0003	0.0007	0.0005	0.0008	0.0013	0.0007	0.0006	0.0011
232	0.0090	0.0006	0.0013	0.0019	0.0003	0.0019	0.0003	0.0006	0.0004	0.0007	0.0011	0.0006	0.0006	0.0013
311	0.0080	0.0007	0.0014	0.0017	0.0003	0.0019	0.0003	0.0007	0.0005	0.0008	0.0013	0.0007	0.0006	0.0010
312	0.0080	0.0007	0.0014	0.0017	0.0003	0.0019	0.0003	0.0007	0.0005	0.0008	0.0013	0.0007	0.0006	0.0011
331	0.0090	0.0006	0.0014	0.0017	0.0003	0.0019	0.0003	0.0006	0.0003	0.0008	0.0013	0.0008	0.0006	0.0013
332	0.0061	0.0007	0.0003	0.0020	0.0004	0.0012	0.0002	0.0004	0.0004	0.0005	0.0007	0.0003	0.0006	0.0018
341	0.0087	0.0006	0.0014	0.0018	0.0003	0.0019	0.0003	0.0007	0.0004	0.0009	0.0013	0.0007	0.0006	0.0011
342	0.0063	0.0007	0.0002	0.0022	0.0003	0.0011	0.0002	0.0004	0.0003	0.0004	0.0007	0.0003	0.0006	0.0017
411	0.0097	0.0007	0.0015	0.0015	0.0002	0.0022	0.0003	0.0008	0.0011	0.0009	0.0016	0.0008	0.0003	0.0005
412	0.0083	0.0007	0.0012	0.0012	0.0003	0.0017	0.0002	0.0008	0.0001	0.0009	0.0017	0.0009	0.0003	0.0005
421	0.0110	0.0006	0.0018	0.0015	0.0002	0.0022	0.0003	0.0007	0.0006	0.0009	0.0017	0.0009	0.0003	0.0005
422	0.0111	0.0005	0.0011	0.0035	-	0.0021	0.0001	0.0021	-	0.0027	0.0019	0.0012	0.0008	0.0016
431	0.0100	0.0006	0.0018	0.0017	0.0003	0.0022	0.0003	0.0008	0.0006	0.0009	0.0016	0.0008	0.0004	0.0006
432	0.0098	0.0008	0.0014	0.0012	0.0001	0.0017	0.0002	0.0014	-	0.0013	0.0028	0.0016	0.0008	0.0005

Note: The values are median price elasticity of all the markets.

Product number: The first number represents the brand: 1=MasterKong, 2= JinMaiLang, 3= Uni-President, 4= BaiXiang, 5= FuManDuo, 6= HuaFeng, 7= Nissin, 8= WuGuDaoChang, 9= HuaLong.

The second number represents the flavor: 1= Beef, 2= Chicken, 3= Pork, 4= Seafood

The third number represents the package shape: 1= Bag, 2=Other shapes (Include barrel package, box package and cup package).

Table A.1f: Price elasticities of demand for all instant noodle products, all provinces (Continued)

	1% rise in Price												
% change in	731	732	741	742	811	812	821	822	831	832	911	931	941
111	0.0018	0.0012	0.0006	0.0006	0.0067	0.0005	0.0012	0.0003	0.0013	0.0002	0.0045	0.0021	0.0034
112	0.0018	0.0013	0.0006	0.0006	0.0066	0.0005	0.0012	0.0003	0.0013	0.0002	0.0045	0.0021	0.0033
121	0.0019	0.0013	0.0006	0.0006	0.0066	0.0005	0.0012	0.0003	0.0013	0.0002	0.0046	0.0021	0.0034
122	0.0020	0.0014	0.0006	0.0007	0.0071	0.0005	0.0012	0.0003	0.0013	0.0002	0.0046	0.0022	0.0034
131	0.0018	0.0013	0.0006	0.0006	0.0070	0.0005	0.0012	0.0003	0.0013	0.0002	0.0044	0.0022	0.0036
132	0.0018	0.0013	0.0005	0.0006	0.0063	0.0005	0.0011	0.0003	0.0013	0.0002	0.0039	0.0020	0.0038
141	0.0019	0.0013	0.0006	0.0006	0.0068	0.0005	0.0012	0.0003	0.0013	0.0002	0.0046	0.0021	0.0034
142	0.0018	0.0013	0.0006	0.0006	0.0067	0.0005	0.0012	0.0003	0.0013	0.0002	0.0043	0.0021	0.0035
211	0.0019	0.0013	0.0006	0.0006	0.0067	0.0005	0.0012	0.0003	0.0013	0.0002	0.0045	0.0022	0.0034
212	0.0019	0.0013	0.0005	0.0006	0.0067	0.0005	0.0012	0.0003	0.0013	0.0002	0.0046	0.0021	0.0034
231	0.0018	0.0013	0.0005	0.0006	0.0067	0.0005	0.0012	0.0003	0.0013	0.0002	0.0049	0.0022	0.0033
232	0.0020	0.0015	0.0006	0.0007	0.0068	0.0005	0.0011	0.0003	0.0013	0.0002	0.0048	0.0025	0.0035
311	0.0018	0.0013	0.0005	0.0006	0.0067	0.0005	0.0012	0.0003	0.0013	0.0002	0.0046	0.0021	0.0034
312	0.0018	0.0013	0.0006	0.0006	0.0066	0.0005	0.0012	0.0003	0.0013	0.0002	0.0045	0.0021	0.0034
331	0.0019	0.0014	0.0005	0.0007	0.0071	0.0005	0.0012	0.0003	0.0013	0.0002	0.0053	0.0022	0.0034
332	0.0022	0.0019	0.0006	0.0015	0.0044	0.0004	0.0009	0.0002	0.0010	0.0002	0.0028	0.0018	0.0035
341	0.0017	0.0013	0.0005	0.0006	0.0069	0.0005	0.0012	0.0003	0.0013	0.0002	0.0052	0.0022	0.0034
342	0.0025	0.0019	0.0006	0.0013	0.0039	0.0004	0.0008	0.0002	0.0009	0.0002	0.0034	0.0017	0.0019
411	0.0011	0.0007	0.0005	0.0003	0.0074	0.0005	0.0013	0.0003	0.0014	0.0002	0.0058	0.0025	0.0031
412	0.0011	0.0006	0.0004	0.0003	0.0071	0.0003	0.0011	0.0002	0.0012	0.0001	0.0038	0.0020	0.0024
421	0.0011	0.0007	0.0004	0.0003	0.0083	0.0005	0.0013	0.0003	0.0015	0.0002	0.0074	0.0027	0.0034
422	0.0016	0.0016	0.0011	0.0009	0.0089	0.0005	0.0009	0.0001	0.0009	0.0002	0.0152	0.0028	0.0032
431	0.0012	0.0008	0.0005	0.0003	0.0077	0.0005	0.0013	0.0003	0.0014	0.0001	0.0066	0.0024	0.0034
432	0.0011	0.0008	0.0006	0.0002	0.0090	0.0003	0.0012	0.0002	0.0011	0.0001	0.0069	0.0019	0.0021

Note: The values are median price elasticity of all the markets.

Product number: The first number represents the brand: 1=MasterKong, 2= JinMaiLang, 3= Uni-President, 4= BaiXiang, 5= FuManDuo, 6= HuaFeng, 7= Nissin, 8= WuGuDaoChang, 9= HuaLong.

The second number represents the flavor: 1= Beef, 2= Chicken, 3= Pork, 4= Seafood

The third number represents the package shape: 1= Bag, 2=Other shapes (Include barrel package, box package and cup package).

Table A.1g: Price elasticities of demand for all instant noodle products, all provinces (Continued)

	1% rise in Price													
% change in	511	512	521	531	532	541	542	611	612	621	631	641	711	712
511	-1.6931	0.0006	0.0013	0.0017	0.0004	0.0019	0.0003	0.0006	0.0005	0.0008	0.0011	0.0006	0.0006	0.0012
512	0.0077	-1.6610	0.0007	0.0021	0.0003	0.0017	0.0003	0.0006	0.0003	0.0007	0.0012	0.0006	0.0005	0.0011
521	0.0117	0.0005	-1.7399	0.0017	0.0003	0.0025	0.0003	0.0011	0.0001	0.0010	0.0018	0.0009	0.0005	0.0006
531	0.0102	0.0005	0.0020	-1.6706	0.0003	0.0025	0.0003	0.0008	0.0001	0.0009	0.0015	0.0006	0.0007	0.0017
532	0.0148	0.0008	0.0002	0.0017	-1.7294	0.0007	0.0002	0.0003	-	0.0002	0.0002	0.0001	0.0007	0.0038
541	0.0119	0.0005	0.0024	0.0019	0.0003	-1.7873	0.0004	0.0011	-	0.0009	0.0021	0.0010	0.0006	0.0014
542	0.0122	0.0006	0.0028	0.0023	0.0002	0.0034	-1.6797	0.0014	-	0.0007	0.0010	0.0003	0.0015	0.0019
611	0.0103	0.0006	0.0016	0.0017	0.0004	0.0021	0.0003	-1.7380	0.0005	0.0009	0.0016	0.0008	0.0007	0.0012
612	0.0029	0.0006	0.0000	0.0025	-	-	-	0.0052	-1.5791	0.0044	0.0022	0.0023	0.0026	0.0034
621	0.0101	0.0006	0.0014	0.0019	0.0003	0.0019	0.0003	0.0009	0.0005	-1.7218	0.0017	0.0009	0.0007	0.0008
631	0.0097	0.0006	0.0016	0.0017	0.0003	0.0021	0.0003	0.0008	0.0005	0.0009	-1.7003	0.0008	0.0007	0.0011
641	0.0100	0.0006	0.0020	0.0017	0.0002	0.0024	0.0003	0.0009	0.0006	0.0010	0.0018	-1.7460	0.0004	0.0007
711	0.0066	0.0005	0.0005	0.0033	0.0002	0.0011	0.0002	0.0006	0.0003	0.0007	0.0011	0.0003	-1.6071	0.0031
712	0.0065	0.0007	0.0004	0.0023	0.0004	0.0010	0.0002	0.0004	0.0004	0.0005	0.0007	0.0003	0.0007	-1.6384
731	0.0074	0.0007	0.0002	0.0019	0.0004	0.0008	0.0002	0.0003	0.0003	0.0004	0.0007	0.0002	0.0006	0.0023
732	0.0069	0.0006	0.0003	0.0022	0.0004	0.0012	0.0002	0.0004	0.0002	0.0004	0.0006	0.0003	0.0006	0.0016
741	0.0054	0.0005	0.0005	0.0044	0.0002	0.0021	0.0002	0.0006	0.0003	0.0008	0.0011	0.0002	0.0006	0.0027
742	0.0064	0.0007	0.0003	0.0022	0.0004	0.0012	0.0002	0.0004	0.0003	0.0004	0.0007	0.0003	0.0007	0.0017
811	0.0100	0.0006	0.0015	0.0018	0.0003	0.0020	0.0003	0.0006	0.0002	0.0009	0.0015	0.0007	0.0007	0.0015
812	0.0100	0.0005	0.0013	0.0021	0.0004	0.0016	0.0003	0.0006	0.0002	0.0008	0.0012	0.0006	0.0007	0.0021
821	0.0103	0.0006	0.0017	0.0018	0.0003	0.0021	0.0003	0.0006	0.0003	0.0008	0.0012	0.0007	0.0006	0.0023
822	0.0102	0.0005	0.0019	0.0023	0.0004	0.0014	0.0003	0.0006	0.0001	0.0007	0.0007	0.0004	0.0007	0.0033
831	0.0108	0.0005	0.0018	0.0019	0.0004	0.0020	0.0003	0.0006	0.0001	0.0008	0.0013	0.0008	0.0006	0.0018
832	0.0096	0.0005	0.0018	0.0018	0.0006	0.0023	0.0005	0.0005	-	0.0006	0.0005	0.0004	0.0007	0.0026
911	0.0089	0.0006	0.0014	0.0019	0.0003	0.0021	0.0003	0.0008	0.0004	0.0008	0.0013	0.0008	0.0006	0.0012
931	0.0107	0.0005	0.0020	0.0027	0.0004	0.0026	0.0003	0.0009	0.0002	0.0008	0.0014	0.0007	0.0006	0.0017
941	0.0127	0.0005	0.0026	0.0018	-	0.0028	0.0005	0.0016	0.0016	0.0014	0.0021	0.0014	0.0010	0.0004

Note: The values are median price elasticity of all the markets.
Product number: The first number represents the brand: 1=MasterKong, 2= JinMaiLang, 3= Uni-President, 4= BaiXiang, 5= FuManDuo, 6= HuaFeng, 7= Nissin, 8= WuGuDaoChang, 9= HuaLong. The second number represents the flavor: 1= Beef, 2= Chicken, 3= Pork, 4= Seafood. The third number represents the package shape: 1= Bag, 2=Other shapes (Include barrel package, box package and cup package).

Table A.1h: Price elasticities of demand for all instant noodle products, all provinces (Continued)

	1% rise in Price												
% change in	731	732	741	742	811	812	821	822	831	832	911	931	941
511	0.0019	0.0013	0.0005	0.0006	0.0065	0.0005	0.0012	0.0003	0.0013	0.0002	0.0046	0.0022	0.0033
512	0.0017	0.0014	0.0006	0.0006	0.0060	0.0004	0.0010	0.0002	0.0011	0.0002	0.0036	0.0017	0.0025
521	0.0017	0.0010	0.0005	0.0004	0.0089	0.0005	0.0016	0.0003	0.0016	0.0002	0.0088	0.0029	0.0035
531	0.0020	0.0017	0.0008	0.0015	0.0083	0.0004	0.0012	0.0002	0.0013	0.0002	0.0067	0.0028	0.0042
532	0.0040	0.0026	0.0005	0.0029	0.0058	0.0006	0.0021	0.0001	0.0008	0.0002	0.0129	0.0020	-
541	0.0019	0.0015	0.0005	0.0011	0.0112	0.0006	0.0016	0.0003	0.0019	0.0002	0.0111	0.0038	0.0038
542	0.0017	0.0020	0.0008	0.0056	0.0129	0.0005	0.0011	0.0006	0.0033	0.0003	0.0121	0.0051	0.0052
611	0.0021	0.0015	0.0006	0.0006	0.0079	0.0005	0.0013	0.0003	0.0014	0.0002	0.0067	0.0024	0.0030
612	0.0047	0.0029	0.0019	0.0093	0.0009	0.0004	0.0004	0.0002	0.0006	-	0.0014	0.0011	0.0017
621	0.0018	0.0013	0.0008	0.0004	0.0071	0.0005	0.0012	0.0003	0.0013	0.0002	0.0062	0.0022	0.0035
631	0.0020	0.0013	0.0005	0.0005	0.0072	0.0005	0.0012	0.0003	0.0013	0.0002	0.0058	0.0022	0.0031
641	0.0015	0.0012	0.0005	0.0004	0.0073	0.0004	0.0013	0.0003	0.0015	0.0002	0.0058	0.0026	0.0026
711	0.0031	0.0032	0.0007	0.0054	0.0060	0.0005	0.0009	0.0002	0.0008	0.0001	0.0034	0.0016	0.0054
712	0.0022	0.0017	0.0006	0.0011	0.0043	0.0004	0.0009	0.0002	0.0009	0.0002	0.0031	0.0018	0.0024
731	-1.5533	0.0023	0.0007	0.0030	0.0048	0.0004	0.0008	0.0002	0.0009	0.0002	0.0031	0.0015	0.0025
732	0.0021	-1.6251	0.0006	0.0013	0.0040	0.0004	0.0011	0.0003	0.0010	0.0003	0.0034	0.0018	0.0043
741	0.0029	0.0032	-1.6011	0.0064	0.0044	0.0005	0.0008	0.0002	0.0009	0.0001	0.0025	0.0012	0.0019
742	0.0023	0.0017	0.0006	-1.6379	0.0045	0.0004	0.0009	0.0002	0.0010	0.0003	0.0028	0.0019	0.0043
811	0.0021	0.0017	0.0006	0.0010	-1.7074	0.0005	0.0012	0.0003	0.0013	0.0002	0.0063	0.0024	0.0035
812	0.0023	0.0019	0.0008	0.0017	0.0085	-1.7373	0.0013	0.0003	0.0014	0.0002	0.0059	0.0025	0.0042
821	0.0025	0.0022	0.0007	0.0019	0.0098	0.0005	-1.7715	0.0003	0.0014	0.0002	0.0074	0.0030	0.0038
822	0.0050	0.0033	0.0008	0.0050	0.0108	0.0009	0.0011	-1.7544	0.0014	0.0003	0.0095	0.0041	0.0052
831	0.0022	0.0019	0.0007	0.0012	0.0092	0.0005	0.0012	0.0003	-1.7653	0.0002	0.0068	0.0027	0.0041
832	0.0036	0.0026	0.0007	0.0030	0.0099	0.0008	0.0013	0.0002	0.0013	-1.8096	0.0067	0.0033	0.0062
911	0.0019	0.0013	0.0005	0.0008	0.0075	0.0005	0.0012	0.0003	0.0013	0.0002	-1.7026	0.0023	0.0033
931	0.0024	0.0018	0.0007	0.0014	0.0104	0.0006	0.0015	0.0003	0.0016	0.0003	0.0107	-1.7282	0.0037
941	0.0004	0.0005	0.0006	0.0002	0.0173	0.0009	0.0020	0.0003	0.0028	0.0002	0.0191	0.0067	-1.8620

Note: The values are median price elasticity of all the markets.

Product number: The first number represents the brand: 1=MasterKong, 2= JinMaiLang, 3= Uni-President, 4= BaiXiang, 5= FuManDuo, 6= HuaFeng, 7= Nissin, 8= WuGuDaoChang, 9= HuaLong. The second number represents the flavor: 1= Beef, 2= Chicken, 3= Pork, 4= Seafood. The third number represents the package shape: 1= Bag, 2=Other shapes (Include barrel package, box package and cup package)

APPENDIX B: Robustness Check

Associations between HEI-2010 score and covariates of low-income households

We also evaluated the nutritional quality of household FAH food purchases as measured by the 2010 Healthy Eating Index (HEI-2010) which has been widely used in studies to assess diet quality. The HEI-2010 score uses a density approach to set standards, such as servings per 1,000 calories or as a percentage of calories. The HEI-2010 ranges from 0 to 100 and is the sum of 12 component scores, each of which measures conformance to an aspect of the 2010 *Dietary Guidelines for Americans* (DGA). The scores increase with relative increases in dietary constituents that are encouraged such as fruit and decrease with relative increases in dietary constituents that are recommended in moderation such as added sugars. We computed household-level HEI-2010 scores based on the one-week purchases collected by FoodAPS and a higher HEI-2010 score represents higher nutritional quality of food purchases.

Our results show that SNAP participation is associated with a 2.003-point lower HEI score among less nutrition-oriented households while no significant association is detected among more nutrition-oriented households (p-value=0.670), the results are consistent with those based on the Guiding stars rating. We find that a one-unit increase in the ratio of starred food price to unstarred food price is associated with a 1.962-point lower HEI-2010 score. Households with more members, larger proportions of children and smokers are associated with lower HEI-2010 scores. Besides, we also find that wealthier households (e.g., home ownership), households with higher food expenditure, larger proportions of Hispanic, and higher main meal-planner's education are associated with higher HEI-2010 scores.

Table B.1: Associations between HEI-2010 score and covariates among low-income households

	HEI-2010 score	
	Coefficient	SE
SNAP participation (Yes=1)	-2.003*	0.992
SNAP*NutritionSearch	1.159	2.274
NutritionSearch (Yes=1)	1.446	1.686
WIC participation (Yes=1)	1.320	0.896
Food price ratio	-1.962**	0.752
Food insecure (Yes=1)	-1.208	0.990
Standardized food expenditure	2.358***	0.601
Standardized cost-of-living index	0.596	0.489
Rural (Yes=1)	-0.161	1.500
Household size	-1.162***	0.307
Proportion of children	-4.614***	1.460
Proportion of older adults	-0.512	1.553
Proportion of Hispanic	1.990*	1.138
Proportion of obese members	-1.554	1.828
Proportion of smokers	-9.016***	1.227
Proportion of members in poor health	3.390	2.393
Household financial condition	1.450	1.271
Own house (Yes=1)	2.316*	1.199
Food pantry/food bank (Yes=1)	0.465	1.829
PR's highest education	0.620*	0.345
Low access BG at 1 mile (Yes=1)	-1.070	1.408
Constant	54.748***	2.009

[1] *** p<0.01, ** p<0.05, * p<0.1
[2] All estimates use sample weights and control for survey design.

APPENDIX C: Robustness Check

Associations of SNAP with nutritional quality separately for households distinguished by online nutrition search

Equation (1) in the main text restricts the coefficients on the household characteristic variables to be the same between less and more nutrition-oriented households. We now relax this restriction by running separate regressions for the two types of households. Appendix Table C.1 reports the results. 471 households are defined as more nutrition-oriented households because they searched online for nutrition information in the last 2 months. Among these households, SNAP is not associated with the nutritional quality of FAH purchases, the same holds for WIC. Households with more members and larger proportions of children and smokers are more likely to have lower nutritional quality of food purchase. If the households have no access to a supermarket within 1 mile of their census block group, they tend to have lower nutritional quality.

The remaining 1,747 low-income households are classified as less nutrition-oriented households because they did not search for nutrition online. For these households, SNAP participation is associated with a statistically significant 0.089 points lower Guiding Stars rating than non-SNAP participants. We find that a one-unit increase in the ratio of starred food price to unstarred food price is associated with a 0.055-point lower Guiding Stars rating. Households with larger proportions of children and smokers are more likely to have a lower Guiding Stars rating, while households with a larger proportion of older adults tend to have a higher rating. In addition, higher cost of living is associated with higher Guiding Stars rating, and if households went to the food bank or food pantry in the past month for grocery, they tend to have a lower rating.

Table C.1: Associations between nutritional quality and covariates among low-income households

Guiding Stars rating	More nutrition-oriented households		Less nutrition-oriented households	
	Coefficient	Std. Err.	Coefficient	Std. Err.
SNAP participation (Yes=1)	-0.009	0.053	-0.089**	0.042
WIC participation (Yes=1)	0.013	0.077	0.005	0.033
Food price ratio	0.023	0.076	-0.055**	0.024
Food insecure (Yes=1)	-0.078	0.074	0.041	0.041
Standardized food expenditure	0.038	0.030	0.005	0.010
Standardized cost-of-living index	0.024	0.039	0.063***	0.021
Rural (Yes=1)	0.113	0.088	-0.019	0.043
Household size	-0.050*	0.026	-0.015	0.012
Proportion of children	-0.285**	0.133	-0.262***	0.067
Proportion of older adults	-0.010	0.208	0.114*	0.060
Proportion of Hispanic	0.100	0.072	0.070	0.050
Proportion of obese members	-0.097	0.104	-0.041	0.044
Proportion of smokers	-0.403***	0.107	-0.176***	0.049
Proportion of members in poor health	-0.130	0.212	0.020	0.079
Household financial condition	0.014	0.088	0.011	0.039
Own house (Yes=1)	-0.046	0.058	0.064	0.047
Food pantry/food bank (Yes=1)	-0.099	0.106	-0.084**	0.041
PR's highest education	0.026	0.031	0.014	0.013
Low access BG at 1 mile (Yes=1)	-0.252***	0.089	-0.019	0.045
Constant	0.986***	0.200	0.762***	0.069
Number of households	471		1,747	

[1] *** p<0.01, ** p<0.05, * p<0.1

[2] The estimates use sample weights and control for survey design. More nutrition-oriented households are those who reported searching for nutrition information online in the last two months. Less nutrition-oriented households are those who did not.