The Effect of Grocery Shopping Frequency on the Healthfulness of Food Purchases

Jeta Rudi[1] , Metin Çakir[2]

[1] PhD student in the Department of Applied Economics, University of Minnesota – Twin Cities.
[2] Assistant professor in the Department of Applied Economics, University of Minnesota – Twin Cities.

Paper prepared for presentation at the EAAE-AAEA Joint Seminar ‘Consumer Behavior in a Changing World: Food, Culture, Society”

March 25 to 27, 2015
Naples, Italy

Preliminary Draft. Please do not quote or cite.

The Effect of Grocery Shopping Frequency on the Healthfulness of Food Purchases

Jeta Rudi[1], Metin Çakir[2]

This version: September 2014

Abstract: This study measures the impact of shopping frequency on the healthfulness of food purchases. Using household level panel data on food purchases, I find that a higher shopping frequency leads to more healthful food purchases. A 10 percent increase in shopping trips during the course of a month, leads to a 3.4 to 4.8 percentage points' increase in the share of expenditures on healthful foods. I further explore if the impact of interest is different for population subgroups that likely face higher monetary and/or time constraints. I find that while positive, the impact of shopping frequency on the healthfulness of food purchases is lower for subgroups such as the working-poor and single-headed working households with children, compared to the rest of the population. The results are robust across different econometric model specifications.

Key-words: shopping frequency, food purchases, time constraints, diet quality.

[1] Jeta Rudi is a PhD student in the Department of Applied Economics, University of Minnesota – Twin Cities.
[2] Metin Çakir is an assistant professor in the Department of Applied Economics, University of Minnesota – Twin Cities.

I. Introduction

In the recent past, there has been an increase in the rate of chronic and acute diseases in the American population (Just and Payne, 2009). Poor diet quality is linked to four major causes of death in the United States: coronary heart disease, cancer, stroke and type 2 diabetes (Beatty et al. 2014). Policy makers are concerned with diet quality since it has direct impacts on the health outcomes of the population. For example, government programs such as Supplemental Nutrition Assistance Program (SNAP) and School Breakfast and Lunch Programs specifically target healthy eating. Also, in order to help individuals make healthy food choices, the U.S. Department of Agriculture and the Department of Health and Human Services have set the Dietary Guidelines for Americans which specify the amount and distribution of different types of foods to be consumed each day (DGA, 2010).[1] There are many factors that impact consumer food choices. Researchers have explored the impacts of socio-demographic, economic and environmental factors on food choices. However, the impact of time constraints in making healthy food choices has been scarcely analyzed. This study adds to the literature on factors that affect the healthfulness of food purchases. Specifically, I investigate how shopping frequency affects the healthfulness of food purchases by using household level panel data on grocery purchases.

Previous studies on the healthfulness of household food purchases found that socio-demographic factors such as income, gender, race and level of education impact food purchases and diet quality (Rankin et al. 1998, Xie et al. 2003, Cullen et al. 2007). In general, studies find that consumers with higher income and level of education, White consumers, and females have better diet quality. Also, factors such as food insecurity and poverty status are found to negatively affect diet quality (Rose 1999, Bhattacharya et al. 2004).

The two main resources for households are money and time, both of which are important inputs into healthy eating behavior. Previous literature has explored the impact of monetary constraints on diet quality, both in terms of prices paid (Drewnowski and Darmon, 2005; Monsivais et al. 2010) and household income (Xie et al. 2003). The main findings are that higher household incomes and lower prices of healthful foods can improve diet quality. Level of income

[1] Other institutions, such as the World Health Organization (WHO) in conjunction with the Food and Agriculture Organization of the United Nations (FAO) and the National Health Service in the United Kingdom, also provide dietary guidelines and recommendations.

can also play an important role on the impacts of government programs on improving healthy eating. For example, a recent study by Beatty et al. (2014) shows that while diet quality of the US households is slowly improving, poor households and households with very poor diet quality show significantly less improvements than the rest of the population. In another study, Davis and You (2011) analyze the impacts of time and money in reaching the Thrifty Food Plan (TFP) target for single-headed households.[2] They conclude that time, rather than money, is the most binding constraint to satisfying the TFP (Davis and You, 2011). However, the impact of time has been scarcely analyzed in the context of healthy eating behavior. Household time constraints can have important implications for household shopping behavior. For example, time-short households may not travel long distances for shopping, shop less frequently, and spend less time shopping.

This study is also related to the literature on food deserts[3]. Studies on food deserts generally focus on the effects of distance to store on diet quality. However, the results of these studies are mixed. For example, Rose and Richards (2004) find that higher distance to the store is found to be correlated with low consumption of fresh fruits for SNAP participants. Yet, in a more recent study Cummins et al. (2014) evaluated the opening of a new supermarket in a "food desert" community in Philadelphia and found no changes in respondents' consumption of fresh fruits and vegetables compared to their consumption before the supermarket opening.

Household time constraints affect the frequency of their shopping trips, which in turn can affect healthfulness of their purchases. For example, households are often advised to purchase groceries in bulk in order to avoid "impulse" purchases (Hogbin et al., 1999). This advice assumes that lower shopping frequency is associated with healthier food purchases. In this study, I explore whether evidence supports this assumption. One channel through which intuitively this assumption may not hold is considering the shelf life of food products. Foods can be classified as having short or long shelf life. Generally, foods with short shelf lives (i.e. fresh fruits and vegetables) are healthful foods that nutritionists and policymakers recommend for increased consumption.

[2] The Thrifty Food Plan (TFP) is a low-cost meal plan that satisfies USDA's Dietary Guidelines for Americans. The plan assumes that all foods purchased are to be consumed at home. The TFP serves as the basis for calculating the Supplemental Nutrition Assistance Program (SNAP) allotments.

[3] The USDA – Agricultural Marketing Service defines food deserts as "urban neighborhoods and rural towns without ready access to fresh, healthy, and affordable food. Instead of supermarkets and grocery stores, these communities may have no food access or are served only by fast food restaurants and convenience stores that offer few healthy, affordable food options."
More information is available at: http://apps.ams.usda.gov/fooddeserts/foodDeserts.aspx

However, foods with long shelf lives usually include pre-prepared and processed foods, which are high in sodium and other nutrients recommended for decreased consumption. Hence, a low shopping frequency might lead to more purchases of foods with long shelf lives, and hence less healthful foods.

To the author's knowledge, the only study investigating the relation between shopping frequency and healthfulness of food purchases is by Beatty (2008). Using Canadian household data, Beatty (2008) establishes a positive correlation between more dispersed expenditures and purchases of healthful foods. The first contribution of this study is that it extends Beatty's (2008) analysis in several dimensions. Using panel data and instrumental variable methods, I establish the causality link between shopping frequency and the healthfulness of food purchases. Further, I incorporate additional control variables given the findings of the recent literature on factors correlated with the two main variables of interest. In a variation of the model, I also control for the impact of food prices, which is largely ignored in the literature. Finally, given that there is no unique diet that is considered healthful, I use two different measures of the healthfulness of food purchases following Volpe et al. (2013), to assess the robustness of the results.[4] The second contribution of this study is that it investigates whether the impact of interest is different for households that are likely to face the highest time and/or monetary constraints. Such households include: the working-poor and single-headed households with children. The results of this study may be used to inform diet quality recommendations by policy-makers to the general population, as well as recommendations by nutritionist in nutrition education programs.

This study finds that a 10 percent increase in shopping frequency increases the share of expenditures on healthful foods by 3.18 to 4.83 percentage points. The results are robust across model specifications in terms of the positive impact of shopping frequency on the healthfulness of food purchases. In most model specifications, the covariates also exhibit the expected sign. The remainder of the paper is structured as follows. Section II discusses the literature on eating behavior and its health implications, as well as provides information on methods to measure the healthfulness of food purchases. Section III provides information on the data used to implement the analysis. Section IV describes the empirical model and the identification strategy. Section V

[4] The measurements reflect how closely the food basket reflects USDA's Dietary Guidelines for Americans. Note however, that there has been some criticism from nutrition experts on the adequacy of USDA's DGA (Gifford 2002).

provides the results from the various model specifications and discusses the sensitivity of the results. Finally, section VI concludes with a discussion of the implications of the results and provides suggestions for future research.

II. Background & Food Purchases' Healthfulness Measurements

According to a data brief by the National Center for Health Statistics (NCHS), in 2009-2010 approximately 16.9 percent of American children and adolescents and 35.7 percent of adults were obese, with the percentage being slightly higher for women (35.8%) compared to men (35.5%). The increased prevalence of obesity in the American population has been tied to increased risks from numerous health conditions, including hypertension, heart diseases, several types of cancers and type 2 diabetes (Just and Payne, 2009). Finkelstein et al. (2009) estimate that the medical costs attributed to obesity in 2008 were approximately $147 billion, an 87 percent increase from the 1998 estimate of $78.5 billion. Poor diet quality is directly linked to the prevalence of obesity in the American population. Hence, researchers and policy-makers are interested in understanding the underlying factors that affect diet quality and the mechanisms through which policy and diet recommendations may mitigate the problem.

In the recent past, nutrition experts have designed various ways to measure diet healthfulness. Such indices take into account types of foods that are recommended for increased/decreased consumption, as well as factors such as variety, adequacy, balance and moderation (Kim et al. 2003). Examples of such indices include: the Healthy Eating Index (HEI), the Diet Quality Index – International (DQI-I), and the Revised Children's Diet Quality Index (RC-DQI) (Guenther et al. 2008; Kranz and McCabe 2013; Kim et al. 2003). The HEI index measures how closely the diet reflects USDA's recommendations included in the Dietary Guidelines for Americans and the Food Pyramid. The DQI-I incorporates diet issues that are typically not faced in the US but are a major issue in the developing world, such as under-nutrition. Finally, the RC-DQI measures the specific nutritional needs of children. When studying the diet quality of the American population, the HEI is one of the preferred measures to determine how closely the diet reflects USDA's Dietary Guidelines for Americans. However, because I do not observe nutritional information of specific food products, I cannot use the *HEI Score*.

Alternatively, I follow Volpe et al. (2013) methodology of measuring the healthfulness of food purchases.

In order to assess the healthfulness of food purchases, Volpe et al. (2013) use six measurements, all of which are based on the USDA's Dietary Guidelines for Americans. They use the Quarterly Food-at-Home Price Database (QFAHPD) database as the starting point for the construction of such measurements. The QFAHPD database aggregates individual products reported in the Nielsen Homescan Panel database into 52 categories and provides price indices for each category by MSA/Year/Quarter. More detailed information on the construction of this database is provided by Todd et al. (2010). Volpe et al. (2013) use the QFAHPD categorization and separate the 52 food categories into "healthful" and "not healthful" based on whether the USDA recommends them for increased consumption or reduced consumption. Then, the first food healthfulness indicator, *HealthExpShare*, measures the share of expenditures attributed to healthful foods. The second indicator, *HealthExpShareQ* is similar to the first except it uses quantities instead of prices. However, these indicators do not account for USDA's recommendations on portions for the different types of foods (i.e. variety and balance in the diet). Hence, Volpe et al. (2013) develop three additional scores to take into account USDA's recommendations on expenditure shares for different food categories. Since USDA's aggregation of different foods into categories does not exactly coincide with those in the QFAHPD database, the authors aggregate the goods further to make the two sets of categories comparable. Then, they construct three additional scores, *USDAScore1*, *USDAScore2*, and *USDAScore3*, which reflect how closely household expenditures mimic USDA's recommendations. The difference between *USDAScore1* and *USDAScore2* is related to how food groups with no purchases are treated. The authors impute values of zero for the former, but do not do any imputation for the latter. *USDAScore3* is different from the first two in that it separates out the food groups for which households report higher or lower expenditures than recommended by USDA. Finally, the authors construct another score based on the *HEI Score* by combining data on nutrient characteristics of foods (which are not reported in the Nielsen Homescan Panel dataset) from the 2003-2004 National Health and Nutrition Examination Survey.[5] In this study, I make use of *HealthExpShare* and

[5] Please refer to Volpe and Okrent (2012) and Volpe et al. (2013) for a detailed explanation on the motivation and technical details behind the construction of each of these scores.

HealthExpShareQ scores. Appendix A includes further detail about the construction of these two scores.

III. Data

In order to carry out the empirical analysis, I use 2004 Nielsen Homescan data which includes information on food purchases reported by a panel of households. To participate in the panel, consumers who are at least 18 years old register online and provide their demographic information. Based on their demographics Nielsen picks a subset of consumers and provides them with a scanner to record barcodes of the purchased items in each shopping trip (Einav et al. 2009). The incentive to participate is the accumulation of points, which can be redeemed for merchandise (Einav et al. 2009). The sample of households covers 52 metropolitan markets in the United States. The resulting dataset includes purchase information on price and quantity of products, product characteristics, promotion, type of store, and timing of the purchase. In addition to purchase information, the dataset also includes household demographic information, such as household size and composition, presence of children and income. The heads of households also report their age, gender, level of educational attainment, hours worked and occupation. Except for gender, which is a binary variable, the rest of the variables on household characteristics are categorical.

Households remain in the sample for an average of 11.4 (out of 12 possible) months. For the purpose of this study, I create the shopping frequency variable as the number of shopping trips that resulted in non-zero expenses during the course of a timeframe t. Also, I use the variables on labor status and hours worked for household heads to explore any differences in the impact of shopping frequency on the healthfulness of food purchases between dual-headed versus single-headed households with children. I also impute a poverty status variable, given information on household composition and income bracket. I then investigate whether the impact of interest is different for households below the poverty line that report positive hours of work, compared to the rest of the population. Finally, using information on household expenditures and store type information available in the Nielsen Homescan database, I calculate the share of purchases in supercenter and club stores by household and time frame.[6] Table 1 provides summary of statistics for the full benchmark sample.

Table 1: Sample Summary of Statistics (N=465,102)		
Variable	**Mean**	**St. Deviation**
HealthExpShare	19.75	13.78
Frequency (*t*=1 month)	7.92	4.75
Household Income	$54,224	$37,501
Household Size	2.37	1.32
Child <18 present (%)	0.7	8.4
Male Head Education (Nielsen Bracket)[1]	2.95	2.07
Female Head Education (Nielsen Bracket)	3.65	1.6
Male Head Employment (Nielsen Bracket)	1.91	1.4
Female Head Employment (Nielsen Bracket)	1.47	1.39
White (%)	82.44	0.38
Black (%)	9.74	29.65
Asian (%)	2.19	14.64
Other Race (%)	5.63	23.04
Total Food Expenditures (1 month)	$95.63	$65.30
Total Expenditures on Healthful Foods (1 month)	$18.61	$17.24
Supercenter Expenditure Share (%)	2.18	5.56
Grocery Stores, 2007, by Zip Code	222.05	375.83
Supercenters, 2007, by Zip Code	8.66	11.52
Working Poor Households (%)	0.45	6.69
Single-Headed Households with Children (%)	0.03	1.73

Source: Nielsen data and author's calculations.

[1] Table A.1 in the Appendix contains information on Nielsen's brackets and variable definitions.

As previously stated, in this analysis I adopt the approach developed by Volpe et al. (2013) in order the measure the healthfulness of food purchases score. To do so, the first step is to aggregate food products into food categories. Following Volpe et al. (2013), I use the QFAHPD database and aggregate all products reported by the households into these categories. The QFAHPD database does not make available the information on which products each of the 52 food

[6] I classify as supercenters the stores classified as supercenters and club stores by Nielsen. All other store types are categorized as non-supercenter. Those include supermarket stores, small grocery stores, gas stations, etc.

categories contains. Given that the sample includes a very large number of individual food products, seeking to replicate the aggregation strategy used in constructing QFAHPD is highly time demanding and is susceptible to many errors. To get around this issue, I use Nielsen's reported aggregate variables, namely product module and product group, to match individual products to the 52 QFAHPD food categories.[7] One of the challenges is that Nielsen's aggregate variables do not provide sufficient information to classify dairy and certain meat products as containing low-fat versus regular-fat, as well as classify grains as whole versus refined. Yet, this distinction is important because USDA recommends low-fat dairy and meat products for increased consumption, and regular-fat dairy and meat products for decreased consumption. In addition, USDA recommends whole grains products for increased consumption and refined grains products for decreased consumption. I classify all dairy and meat products as having regular-fat content, and all grains as being refined-grains. This leads to an underestimation of purchases of healthful foods. In order to address this problem, I also report the results when these two types of food categories are excluded from the analysis. Table 2 reports the aggregate food categories, USDA recommendations for each group, and the mean household expenditures for each category for the households in the sample.[8]

[7] The information on how specifically the Nielsen product module and product groups are utilized to mimic the QFAHPD categorization, is available upon request from the author.

[8] I follow Volpe et al. (2013) in classifying food categories as USDA Healthful/Unhealthful.

Table 2: Average Expenditure Shares for QFAHPD Food Categories			
Food Group	Category	USDA Healthful	Mean Expenditure Share
1	Fresh/Frozen fruit	Yes	0.06
2	Canned Fruit	Yes	0.03
3	Fruit Juice	Yes	0.06
4	Fresh/Frozen dark green vegetables	Yes	0.03
5	Canned dark green vegetables	Yes	0.01
6	Fresh/Frozen orange vegetables	Yes	0.02
7	Canned orange vegetables	Yes	0.02
8	Fresh/Frozen starchy vegetables	Yes	0.04
9	Canned starchy vegetables	Yes	0.02
10	Fresh/Frozen select nutrient vegetables	Yes	0.04
11	Canned select nutrients	Yes	0.03
12	Fresh/Frozen other vegetables	Yes	0.06
13	Canned other vegetables	Yes	0.03
14	Frozen/Dried Legumes	Yes	0.02
15	Canned Legumes	Yes	0.02
16	Whole grain bread, rolls, rice, pasta, cereal	Yes	--
17	Whole grain flour and mixes	Yes	--
18	Whole grain frozen/ready to cook	Yes	--
19	Other bread, rolls, rice, pasta, cereal	No	0.07[a]
20	Other flour and mixes	No	0.04[b]
21	Other frozen/ready to cook grains	No	0.10[c]
22	Low fat milk	Yes	--
23	Low fat cheese	Yes	--
24	Low fat yogurt & other dairy	Yes	--
25	Regular fat milk	No	0.08[d]
26	Regular fat cheese	No	0.08[e]
27	Regular fat yogurt & other dairy	No	0.06[f]
28	Fresh/frozen low fat meat	Yes	--
29	Fresh/frozen regular fat meat	No	0.08[g]
30	Canned meat	No	--
31	Fresh/frozen poultry	Yes	0.10
32	Canned poultry	Yes	--
33	Fresh/frozen fish	Yes	0.08
34	Canned fish	Yes	0.04

Continued.

Table 2: Continued			
Food Group	Category	USDA Healthful	Mean Expenditure Share
35	Raw nuts and seeds	Yes	0.07
36	Processed nuts, seeds and nut butters	Yes	0.04
37	Eggs	Yes	0.03
38	Oils	Yes	0.05
39	Solid fats	No	0.04
40	Raw sugars	No	0.04
41	Non-alcoholic carbonated beverages	No	0.11
42	Non-carbonated caloric beverages	No	0.08
43	Water	Yes	0.06
44	Ice cream and frozen desserts	No	0.08
45	Baked good mixes	No	0.05
46	Packaged sweets/baked goods	No	0.09
47	Bakery items, ready to eat	No	0.06
48	Frozen entrees and sides	No	0.12
49	Canned soups, sauces, prepared foods	No	0.07
50	Packaged snacks	No	0.07
51	Ready to cook meals and sides	No	0.10
52	Ready to eat deli items (hot and cold)	No	0.07

Source: Food categories (QFAHPD), USDA Healthful (Volpe et al. 2013), Mean Expenditures (Author's calculations using Nielsen data).
[a] Includes combined expenditures in food groups 16 and 19.
[b] Includes combined expenditures in food groups 17 and 20.
[c] Includes combined expenditures in food groups 18 and 21.
[d] Includes combined expenditures in food groups 22 and 25.
[e] Includes combined expenditures in food groups 23 and 26.
[f] Includes combined expenditures in food groups 24 and 27.
[g] Includes combined expenditures in food groups 28 and 29.

IV. Empirical Model and Strategy

There are many factors that impact the healthfulness of food purchases. The main goal of this study is to test the hypothesis that an increase in shopping frequency positively impacts the healthfulness of food purchases, ceteris paribus. A second goal is to compare and contrast the magnitude and direction of the impact for various types of households that tend to face bigger monetary or time constraints. That is, in addition to analyzing the impact of shopping frequency on the healthfulness of food purchases for the general population, I also investigate if this impact is different for households below the poverty line that report positive hours of work, and for single-headed households with children. The motivation to do this comes from two different sources. The first is the finding by Aguiar and Hurst (2007) that households may substitute time with money. The authors show that doubling the grocery shopping frequency leads to a decrease in prices paid by 7-10 percent. However, working-poor households and to some extent, single-headed households with children, may not be able to engage in such substitution of time with money since they likely face high constraints in both. The second is that increasing shopping frequency for households that have low shopping frequency (because of time constraints) may yield a different effect compared to households that have a high shopping frequency (because of higher time availability). Hence, I hypothesize that for such households, the impact of shopping frequency on the healthfulness of the food purchases is different compared to the rest of the population.

In order to identify the impact of shopping frequency on the healthfulness of food purchases, I employ regression analysis to control for confounding variables suggested by the theory and empirical studies on consumer food choice. For household i and time period t, the benchmark model specification is as follows:

$$H_{itm} = \alpha_0 + \beta_1 F_{it} + \sum_{k=1}^{52} \gamma_k P_{kt} + \delta S_{it} + \sum_{j=1}^{J} \theta_j HC_{jit} + \varepsilon_{itm} \tag{1}$$

where H denotes the healthfulness measure of the food purchases, and subscript m denotes which of the two measures outlined above is utilized. The variable of interest, F, is a discrete variable that gives the shopping frequency in a specific time frame t for household i, and hence β_1 is the main parameter of interest. For ease of interpretation, I use the logarithmic form of shopping frequency in the model estimation. Control variables include the set of price indices P for the 52 food categories denoted by k; the share of total food expenditures in a supercenter store S, and a set of j household characteristics HC. Finally, ε_{itm} denotes the idiosyncratic error term.

A few issues regarding the model specification need to be addressed before further investigating estimation strategy. The first issue is that in order to measure shopping frequency, a time frame needs to be specified over which one may observe the number of times households report to have visited grocery stores. In the benchmark analysis, I specify the time frame to be a period of four weeks. Given that this time frame is arbitrary, I check the robustness of the results under different time frame specifications (i.e. 2 and 6 weeks).

A second issue deals with the set of price indices for the 52 categories included in the model specification. Microeconomic theory suggests that prices of all possible food products impact consumers' choices (and hence the healthfulness of food purchases). However, including all the individual prices of the thousands of individual products would decrease the degrees of freedom significantly, hence making it difficult to estimate the model. Instead, I use the price indices for the 52 food categories reported in the QFAHPD database. The price indices are constructed using Nielsen Homescan data, and they vary by market group.[9] The market groups available through QFAHPD do not precisely match the specification of the market groups in the Nielsen dataset. Again, I match the two sets of specifications of the market groups using information from both datasets.[10] One of the limitations of using this approach is that prices do not vary by food basket purchases or households, but rather only vary by market group and time.

I control for store format in the model specification through the inclusion of shares of food expenditures at supercenters, S_{it}. I do this because Volpe et al. (2013) finds that store format impacts the healthfulness of food purchases. Additionally, it is likely that store format and shopping frequency are highly correlated. For example, households may tend to visit convenience stores more often (and also make fewer purchases), compared to supercenter-format stores. Therefore, if it were excluded, the coefficient of interest, β_1, would be biased because there would be an omitted variable problem. Finally, following the findings of the empirical literature, I include the following household characteristics in the model: income, education level and employment status for the head(s) of household, race, household size, and presence and age of children. Information about the rationale behind including these control variables is provided in Table A.1 in the Appendix.

In order to make use of the panel nature of the data, I use household fixed effects to control for household unobserved heterogeneity, such as food preferences and attitudes towards health. However, including household fixed effects means that the impacts of observable time invariant

[9] Refer to Todd et al. (2010) for a summary of the methodology used to construct these price indices for the 52 food categories.

[10] Additional information on how I match the two market groups is available upon request.

household characteristics will not be determined. Hence, I estimate the model with and without household fixed effects. Following the literature, I also include year and quarter fixed effects to control for seasonality.

As indicated above, one of the contributions of this study is to analyze if the impact of shopping frequency on the healthfulness measure is different for households below the poverty line with head(s) that report positive hours of work. I refer to such households as the "working poor." The working poor households face both monetary and time constraints in achieving a healthy diet. To explore the difference, I modify the benchmark model given in (1) by including a dummy variable indicating that the household is below the poverty line and reports positive hours of work. I further interact this dummy variable with the shopping frequency variable to determine whether the impact of shopping frequency is different for the working-poor households. The model specification becomes:

$$H_{itm} = \alpha_0 + \beta_2 F_{it} + \zeta_1 W_{it} + \eta_1 F_{it} W_{it} + \sum_{k=1}^{52} \gamma_k P_{kt} + \delta S_{it} + \sum_{j=1}^{J} \theta_j HC_{jit} + \varepsilon_{itm} \tag{2}$$

where W_{it} is the dummy variable equal to one if the household is below the poverty line and reports positive hours of work. The coefficient of the interaction between purchase frequency and the working-poor status dummy variable, $\beta_2 + \eta_1$, is the impact of shopping frequency on healthfulness of food purchases for the working poor households, β_2 gives the same impact for the rest of the households (control group).

A final modification of the model is to explore if the impact of interest is different for single-headed households with children. Similar to the working-poor households, single-headed households with children where the head is employed, face enormous time constraints and likely have a low frequency of visits to the grocery store. Hence, I hypothesize that increasing the shopping frequency for such households yields a different impact on the healthfulness of food purchases compared to the rest of the population. Formally, I estimate:

$$H_{itm} = \alpha_0 + \beta_3 F_{it} + \zeta_2 Y_{it} + \eta_2 F_{it} Y_{it} + \sum_{k=1}^{52} \gamma_k P_{kt} + \delta S_{it} + \sum_{j=1}^{J} \theta_j HC_{jit} + \varepsilon_{itm} \tag{3}$$

where Y_{it} is a dummy variable equal to one if the household is single-headed and the head reports positive hours of work. The coefficient of the interaction between purchase frequency and the dummy variable of interest, $\beta_3 + \eta_2$, is the impact of shopping frequency on healthfulness of food purchases for the working single-headed households, β_3 gives the same impact for the rest of the households.

In the three model specifications above, reverse causality may impose a threat to the identification strategy outlined thus far. That is, it could be the case that the healthfulness of food purchases dictates how often a consumer visits a grocery store. For example, consumers who prefer to purchase healthier foods may visit the grocery store more frequently. I take an instrumental variables, IV, approach to identify the causal effect of shopping frequency on healthfulness of food purchases. I use the number of supermarket and grocery stores as well as the number of supercenter and club stores in an area as instruments for shopping frequency. An increase in the number of stores increases the options available to the households living in an area. Similarly, an increase in the number of stores decreases the distance to the nearest store, on average. Both of these factors are likely positively correlated with grocery shopping frequency. Finally, I formally investigate the relevance of the instrumental variables by testing if $Cov(F, G_i) \neq 0$, where G denotes the number of stores variable, and i specifies the type of the store. A maintained assumption under this IV strategy is that the number of stores is predetermined, thereby exogenous to households' food purchase decisions. The data on the number of grocery stores and supermarket and club stores are obtained from the Food Environment Atlas project, USDA-ERS. The data on number of supermarket and grocery stores, and supercenter and club stores, are at the county level, for year 2007. The summaries of statistics for the two instrumental variables are included in Table 1. I estimate the three models using OLS, OLS with FE and 2SLS.

V. Results

The results from the benchmark model (eq. 1) are reported in Table 1 below. The measurement of food purchase healthfulness is *FoodExpShare*, which is multiplied by 100 so that it ranges from 0 to 100. For example, *FoodExpShare*=30 implies that 30 percent of the household's budget is spent on food categories recommended for increased consumption by the USDA. I use a logarithmic transformation of shopping frequency in order to ease the interpretation of the results. The information on all other covariates is provided on Table A.1 in Appendix A. Here I report the results of various model specifications, including basic OLS, IV, Fixed Effects, and models controlling for prices. Since there are many missing prices for category/market group/year/quarter combinations, the sample size reduces significantly if the prices of all food categories are included. Hence, I take a slightly different approach and control for prices of fruits and vegetables (food categories 1-15) in column 5, and for the prices of certain processed foods (food categories 41-42 & 44-52) in column 6. This approach is based on the findings by Drewnowski and Darmon (2005) that healthful foods tend to be more expensive than foods high in added sugars and fat. The coefficient estimates for prices are not reported in Table 1 but are available upon request from the author.

The benchmark results suggest that the impact of shopping frequency on the healthfulness of food purchases is positive and significant both statistically and in terms of economic impact. For example, a 10 percent increase in shopping frequency leads to an increase of 3.6 in the healthfulness score in the baseline model with covariates (column 2). This indicates that at the mean, if households increase shopping frequency by 10 percent in a given month, the share of expenditures on USDA healthful food categories increases by 3.6 percentage points. The results are robust across the model specifications, and the impact ranges from 3.2 to 4.8 percentage points. The only exception is the coefficient estimate using the log of the number of grocery stores and log of the number of supercenters in household's area as instrumental variables for household's shopping frequency. The usual methods of assessing the validity of the instruments used indicate that the instruments are weak. That is, in the first stage equation, the two instrumental variables where jointly statistically insignificant. Thus, I only report the IV results in Table 1 for completeness. The rest of the results give a more or less expected picture. In line with literature findings, the results suggest that income and education are positively correlated with a higher healthfulness of food purchases' score. Similarly, higher minimum hours worked for the head(s) of household lead to a decrease in healthfulness score. This is expected since these households are likely more time constrained and have less time to dedicate to food preparation and mostly rely on pre-prepared and processed foods. Controlling for household size, the presence of children younger than 18 years old increases the healthfulness score. This suggests that for households of similar sizes, the presence of children (versus only of adults) leads to an increase in the share of expenditures on healthful foods. A result that is contrary to the findings of previous studies is that White consumers purchase less healthy food. Finally, contrary to the findings by Volpe et al.

(2013), I find that a higher share of expenditures in supercenters is associated with a higher healthfulness of food purchases' score.

To assess the sensitivity of the results, I have also estimated the model by excluding all dairy, meat and grain food categories from the analysis. I do this, because as discussed in the data section, it is impossible to differentiate between low-fat and regular-fat dairy and meat products, and whole-grain and refined-grain products. Yet, the USDA recommends some of these food categories for increased consumption and others for decreased consumption. The estimation results are reported on Table B.1 in Appendix B. The results fail to be robust across these two different samples. The results from the reduced sample indicate a negative impact of shopping frequency on the *HealthExpShare* score, while the rest of the covariates have the same sign as in the full sample estimation. Further analysis of differences in food categories (beyond healthful and unhealthful) is required in order to understand the reason behind the discrepancy of the results.

I further assess the sensitivity of the results by conducting the analysis using the *HealthExpShareQ* score. The results remain very similar to those reported on Table 1 and are available upon request from the author. Finally, using the *HealthExpShare* score and the benchmark sample, I assess the robustness of the results using a 2 week and 6 week time frame. The results are reported on Table B.2 and Table B.3 respectively. They show that the impact of shopping frequency on the healthfulness of food purchases' score is robust across time frame specification.

Table 3: Selected Results of Estimating Eq. (1) - HealthExpShare						
	Basic OLS	OLS w/Controls	IV: Log Groc. Stores and Log Supercenters	Fixed Effects	OLS w/ Prices_ F&V	OLS w/Prices_ Processed
Log Frequency	0.376***	0.361***	10.796**	0.483***	0.339***	0.318***
	(0.037)	(0.037)	(4.519)	(0.031)	(0.059)	(0.057)
Child Under 18		0.787	1.832**	0.935***	0.992	0.969
		(0.519)	(0.932)	(0.241)	(0.631)	(0.612)
Min Hours Worked		-0.771***	-0.089	-0.763***	-0.750***	-0.730***
		(0.033)	(0.292)	(0.015)	(0.039)	(0.038)
Max Education		0.809***	1.027***	0.821***	0.785***	0.801***
		(0.045)	(0.104)	(0.021)	(0.054)	(0.053)
White		-1.244***	-2.078***	-1.459***	-1.528***	-1.379***
		(0.114)	(0.409)	(0.054)	(0.137)	(0.135)
HH Income[1]		0.151***	0.159***	0.159***	0.170***	0.160***
		(0.013)	(0.020)	(0.006)	(0.016)	(0.016)
HH Size		-1.183***	-1.801***	-1.181***	-1.216***	-1.199***
		(0.035)	(0.278)	(0.016)	(0.042)	(0.041)
Supercenter Exp Share		7.736***	6.459***	8.578***	8.287***	8.117***
		(0.135)	(0.557)	(0.115)	(0.217)	(0.206)
Constant	19.020***	18.960***	-0.150	20.933***	13.113***	30.218***
	(0.082)	(0.241)	(8.208)	(0.169)	(1.233)	(0.972)
Market Group FE				Yes		
Quarter FE				Yes		
Prices Healthful[2]					Yes	
Prices Unhealthful[3]						Yes

N	465,102	465,102	414,431	465,102	166,435	184,405
Adj. R^2	0.0004	0.0312	0.0066	0.0450	0.0373	0.0359
Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01						

[1] HH Income in $10,000; [2] Price indices for food categories 1-15; [3] Price indices for food categories 41-42 and 44-52

The results from estimating equations (2) and (3) are presented in Table 2 below. The results indicate that for population subgroups that face higher time and/or money constrains, the impact of shopping frequency on the healthfulness of food purchases is overall positive, but lower compared to the rest of the population. For example, a 10 percent increase in shopping frequency per month leads to a 2.6 - 4.4 percentage point increase in the share of expenditures on USDA healthful foods for the working-poor household. The difference compared to the rest of the population is 1.6 – 2.3 percentage points. For households with single working parents, the difference compared to the rest of the population is 0.2 - 0.7 percentage points. In both cases, the differences are relatively significant in economic terms. The difference is statistically significant for the working-poor households, but not so for households with single-working parents. A caveat in these results is that a very small part of the sample falls in any of these two categories. As indicated on Table 1, only 0.45 percent of the sample is working-poor households, and only 0.03 percent of the sample is households with single-working parents. Despite this shortcoming, these results indicate that changing behavior for these households (i.e. increasing shopping frequency) will not lead to as high of an impact on the healthfulness of food purchases as for the rest of the population. These two (often overlapping) population subgroups have a lower average shopping frequency and lower average *HealthExpShare* scores compared to the rest of the sample.[11] The lack of time available to engage in food preparation at home may explain why the impact of shopping frequency is not very high for such households. For example, at the same level of time constraints, increasing shopping frequency may increase the purchases of fresh fruits and vegetables hence leading to an increase in diet quality. However, such households may continue to purchase pre-prepared foods instead of purchasing ingredients to prepare healthful meals at home (that require more time input). As a result, the overall impact of shopping frequency on the healthfulness of food purchases is not as high as for the rest of the population.

[11] The mean shopping frequency (per month) for the working-poor households is 7.18, for the households with single-working parents it is 6.65 and for the rest of the population (excluding these two subgroups) it is 7.93.

Table 4: Selected Results of Estimating Eqs. (2) and (3) - HealthExpShare						
	Basic OLS	OLS w/Controls	Fixed Effects	Basic OLS	OLS w/Controls	Fixed Effects
Log Frequency	0.380***	0.422***	0.673***	0.376***	0.417***	0.666***
	(0.037)	(0.037)	(0.031)	(0.037)	(0.037)	(0.031)
LogFreq*WorkingPoor	-0.180**	-0.163**	-0.231***			
	(0.076)	(0.076)	(0.058)			
Working Poor HH	-0.511	0.714	1.235**			
	(0.857)	(0.841)	(0.513)			
LogFreq*SingleWorkParent				-0.064	-0.069	-0.018
				(0.313)	(0.311)	(0.264)
Single Working Parent HH				-3.105	-0.363	-0.614
				(3.280)	(3.257)	(2.113)
Child under 18		0.579	0.739***		0.604	0.760***
		(0.522)	(0.241)		(0.533)	(0.246)
Max Education		0.866***	0.887***		0.867***	0.888***
		(0.042)	(0.019)		(0.042)	(0.019)
White		-0.957***	-1.156***		-0.955***	-1.154***
		(0.114)	(0.054)		(0.114)	(0.054)
HH Size		-1.065***	-1.066***		-1.066***	-1.067***
		(0.034)	(0.016)		(0.034)	(0.016)
Supercenter Exp Share		7.838***	8.896***		7.839***	8.899***
		(0.135)	(0.115)		(0.135)	(0.115)
Constant	19.019***	17.870***	19.579***	19.021***	17.873***	19.588***
	(0.082)	(0.237)	(0.167)	(0.082)	(0.237)	(0.167)
Market Group FE			Yes			Yes
Quarter FE			Yes			Yes
N	465,102	465,102	465,102	465,102	465,102	465,102
Adj. R^2	0.0005	0.0256	0.0390	0.0004	0.0256	0.0390

Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01

VI. Conclusions

The prevalence of obesity and other health issues that are a direct result of diet quality still pose a great challenge for the American population. This study has investigated the impact of time constraints on diet quality. Specifically, it has tested the hypothesis that an increase in shopping frequency leads to an increase in the healthfulness of food purchases. Using American household panel data, I have shown that on average, a 10 percent increase in shopping frequency per month leads to an increase of the share of expenditures on healthful foods by approximately 3.4 – 4.8 percentage points. The positive impact of shopping frequency on the healthfulness of food purchases is robust across time frame specifications and healthfulness score specifications. I have further shown that for working-poor households and for households with single-working parents, an increase in shopping frequency leads to a smaller positive impact of the healthfulness of food purchases compared to the rest of the population. I have argued that this may be driven by the fact that such households have lower time availability to engage in home food production, which translates into smaller gains in diet quality from an increased shopping frequency.

The results of this study should be integrated in recommendations by policy-makers on how to reach a healthful diet. Most notably, the usual recommendation of "purchasing foods in bulk" should be revised in light of these results. While the policy makers cannot directly mandate how individuals spend their time and the frequency of their shopping trips, the results are potentially still useful for policy. For example, recent literature on "food deserts" suggests that increasing the number of store availability does not translate into better diets, at least not so in the short term. Hence, future research should investigate how store availability in a community and households' time constraints interact in their impact on the healthfulness of food purchases.

As any study, this one is not without limitations. There is some evidence that not all Nielsen households report their purchases accurately. Einav et al. (2009) show that the opportunity cost of time for the head of the household is correlated with the amount of error in reporting the purchases. If the error is normally distributed in the types of products, this may not be a huge concern in the main coefficient of interest. However, if such households for example tend to consistently under-report their purchases of fresh fruits and vegetables, or of processed foods, then it would lead to biased results. Similarly, if certain types of households consistently underreport the purchases of unhealthful foods (for self-image or other issues), the results of this study would suffer from bias. Future research should investigate if households tend to record certain food types with larger error than other types of foods.

In estimating the impact of shopping frequency on the healthfulness of food purchases for certain subgroups (working-poor and single-headed working households with children), I have relied upon a very small sample size. Future studies should use a longer panel or use population weights in order to obtain more concise estimates. In addition to addressing the limitations of this study, future research should investigate whether the results are robust to other ways of measuring the healthfulness of food purchases. Additional work may also be done in further investigating the impact of time constraints in diet quality. One possible venue of exploration is exploring the impact of time spent in various food related activities (e.g. grocery shopping, travel associated with grocery shopping, home food preparation and cleaning-up) on the healthfulness of food purchases. It is important to establish how time constraints in a broader sense (i.e. all food related activities) impact the healthfulness of food purchases for home consumption as well as the consumption of food away from home.

References

Aguiar, B. M., & Hurst, E. (2007). Life-Cycle Prices and Production. *The American Economic Review*, *97*(5), 1533–1559.

Beatty, T. K. M. (2008). Expenditure Dispersion and Dietary Quality: Evidence from Canada. *Health Economics*, *1014*(17), 1001–1014.

Beatty, T. K. M., Lin, B.-H., & Smith, T. a. (2014). Is Diet Quality Improving? Distributional Changes in the United States, 1989-2008. *American Journal of Agricultural Economics*, *Advance Ac*, 1–21.

Bhattacharya, J., Currie, J., & Haider, S. (2004). Poverty, food insecurity, and nutritional outcomes in children and adults. *Journal of Health Economics*, *23*(4), 839–62.

Centers for Medicare & Medicaid Services (CMS). National Health Expenditures Data – Historical. Last Modified: 01/07/2014. Accessed 03/21/2014. http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsHistorical.html

Chamness, B. E., Zollinger, T. W., Thompson, W. R., Ainsworth, B. E., Lewis, C. K., & Coffing, J. M. (2013). *Actively Moving America to Better Health* (pp. 1–127).

Cullen, K., Baranowski, T., Watson, K., Nicklas, T., Fisher, J., O'Donnell, S., … Missaghian, M. (2007). Food category purchases vary by household education and race/ethnicity: results from grocery receipts. *Journal of the American Dietetic Association*, *107*(10), 1747–52.

Cummins, S., Flint, E., & Matthews, S. a. (2014). New neighborhood grocery store increased awareness of food access but did not alter dietary habits or obesity. *Health Affairs*, *33*(2), 283–91.

Davis, G. C., & You, W. (2011). Not enough money or not enough time to satisfy the Thrifty Food Plan? A cost difference approach for estimating a money–time threshold. *Food Policy*, *36*(2), 101–107.

Einav, L., Leibtag, E., & Nevo, A. (2009). Recording discrepancies in Nielsen Homescan data: Are they present and do they matter? *Quantitative Marketing and Economics*, *8*(2), 207–239.

Finkelstein, E. A., Trogdon, J. G., Cohen, J. W., & Dietz, W. (2009). Annual medical spending attributable to obesity: payer-and service-specific estimates. *Health Affairs*, *28*(5), w822–w831.

Gifford, K. D. (2002). Dietary Fats, Eating Guides, and Public Policy: History, Critique, and Recommendations. *The American Journal of Medicine*, *113 (9B)*, 89S–106S.

Guenther, P. M., Reedy, J., & Krebs-Smith, S. M. (2008). Development of the Healthy Eating Index-2005. *Journal of the American Dietetic Association*, *108*(11), 1896–901.

Hogbin, M., Davis, C., & Escobar, A. (1999). *Preparing Nutritious Meals at Minimal Cost* (pp. 1–30).

Just, D. R., & Payne, C. R. (2009). Obesity: can behavioral economics help? *Annals of behavioral medicine : a publication of the Society of Behavioral Medicine*, *38 Suppl 1*, S47–55.

Kim, S., Haines, P. S., Siega-riz, A. M., & Popkin, B. M. (2003). The Diet Quality Index-International (DQI-I) Provides an Effective Tool for Cross-National Comparison of Diet Quality as Illustrated by China and the United States. *The Journal of Nutrition*, *133*, 3476–3484.

Kranz, S., & McCabe, G. P. (2013). Examination of the five comparable component scores of the diet quality indexes HEI-2005 and RC-DQI using a nationally representative sample of 2-18 year old children: NHANES 2003-2006. *Journal of Obesity*, *2013*, 1–12.

Lin, B., Guthrie, J., & Frazão, E. (1999). Nutrient Contribution of Food Away From Home. In E. Frazão (Ed.), *Americans' Eating Habits: Changes and Consequences* (pp. 213–242). Washington, DC: U.S. Department of Agriculture.

Munoz, K. A., Krebs-Smith, S. M., Ballard-Barbash, R., & Cleveland, L. E. (1997). Food Intakes of US Children and Adolescents Compared With Recommendations. *Pediatrics*, *100*(3), 323–329.

Rankin, J. W., Winett, R. A., Anderson, E. S., Bickley, P. G., Moore, J. F., Leahy, M., … Gerkin, R. E. (1998). Food Purchase Patterns at the Supermarket and their Relationship to Family Characteristics. *Journal of Nutrition Education*, *30*(2), 81–88.

Rose, D. (1999). Economic Determinants and Dietary Consequences of Food Insecurity in the United States. *The Journal of Nutrition*, *129*, 517S–520S.

Rose, D., & Richards, R. (2004). Food store access and household fruit and vegetable use among participants in the US Food Stamp Program. *Public Health Nutrition*, *7*(8), 1081–8.

Todd, J. E., Mancino, L., Leibtag, E., & Tripodo, C. (2010). *Methodology Behind the Quarterly Food-at-Home Price Database* (pp. i–37).

U.S. Department of Agriculture (USDA) & U.S. Department of Health and Human Services. (2010). *Dietary Guidelines for Americans 2010*.

Volpe, R., & Okrent, A. (2012). Assessing the Healthfulness of Consumers ' Grocery Purchases. *US Department of Agriculture; Economic Research Service*, (Economic Information Bulletin Number 102).

Volpe, R., Okrent, A., & Leibtag, E. (2013). The Effect of Supercenter-format Stores on the Healthfulness of Consumers' Grocery Purchases. *American Journal of Agricultural Economics*, *95*(3), 568–589.

Xie, B., Gilliland, F. D., Li, Y.-F., & Rockett, H. R. (2003). Effects of Ethnicity, Family Income, and Education on Dietary Intake among Adolescents. *Preventive Medicine*, *36*(1), 30–40.

Appendix A – Additional Information on Variable Definitions

This section includes information on the two food purchases' healthfulness scores proposed by Volpe et al. (2013), which I have adopted in this study.

The *HealthExpShare* (*HealthExpShareQ*) score uses expenditures (quantities) of healthful foods as a share of total expenditures (quantities). Quantities for each food group are obtained by dividing expenditures by prices, and then summing over quantities of individual product within each food group. In the expressions below, exp denotes expenditures, $quant$ denotes quantity, and $healthful$ denotes the food groups that are recommended for increased consumption by USDA. Households are denoted with subscript i, the 52 food groups are denoted with subscript g, and t denotes the time frame (2, 4 or 6 weeks).

$$HealthExpShare_{it} = \frac{\sum_g exp_{igt} | q \in healthful}{\sum_{g=1}^{52} exp_{igt}} \tag{A1}$$

$$HealthExpShareQ_{it} = \frac{\sum_g quant_{igt} | q \in healthful}{\sum_{g=1}^{52} quantity_{igt}} \tag{A2}$$

Table A.1: Explanatory Variables' Definition and Motivation for Inclusion

Variable	Definition	Motivation for Inclusion
Household Income	Annual income brackets, converted into US dollars in the analysis. [1]	Studies have shown that household income is positively related to diet quality (see for example, Mushi-Brunt et al. 2007, Xie et al. 2003, Cullen et al. 2007).
Household Size	Number of household members, top-coded at 9 members.	Larger households may have different patterns of grocery shopping frequency and/or preferences for food healthfulness compared to smaller households.
Children <18 yrs old	Number of household children under the age of 18.	Children have different dietary needs compared to adults (Munoz et al. 1997).
Education	Highest education level of male/female head of household. **1** - grade school, **2** - some high school, **3** - graduated high school, **4** - some college, **5** - graduated college, **6 -** post college grad. [2]	Previous studies have established the link between education and diet quality as well as between education and obesity (Cullen et al. 2007, Xie et al. 2007).
Hours Worked	Number of hours worked per week, by male/female head of the household. **0** - none, **1** - under 30 hours, **2** - 30-34 hours, **3** - 35+ hours. [3]	Employment status and the number of hours worked may be linked to dietary needs. They are also likely highly correlated with the grocery shopping frequency. If one of the household heads is unemployed or working part time, he/she has more time to engage in household activities such as grocery shopping and food preparation.
Race/Ethnicity	Binary variables identifying households as White, Black, Asian or as belonging to another race.	Households of different ethnicities/races exhibit different food preferences and diet qualities (Cullen et al. 2007).

Continued.

Table A.1: Continued		
Variable	**Definition**	**Motivation for Inclusion**
Poor-Working Households	A binary variable indicating that the household is poor and both heads of household are employed full time (in the case of single-headed households, the head is employed full time). [4]	The working-poor households face both monetary and time constraints. As a result, I investigate if the impact of shopping frequency on food basket healthfulness is different for this population subgroup compared to the rest of the population.
Single-headed households with children	A binary variable indicating that the household is single-headed and at least one child younger than 18 years old is present in the household.	Single-headed household with children likely face high time constraints. As a result, I investigate if the impact of shopping frequency on food basket healthfulness is different for this population subgroup compared to the rest of the population.
Supercenter Expenditure Share	The share of food expenditures in club/supercenter stores during the time frame *t*. [5]	Higher share of food expenditures at supercenter stores leads to less healthful food purchases (Volpe et al. 2013).

[1] Nielsen Homescan database includes 16 household income brackets for year 2004. For the purpose of impact estimation, I impute the income level to be the median of income range. For example, household in income bracket 10 (range: $12,000 -$14,999) are imputed a household income value of $13,499.50.

[2] I keep the same education categories as reported in Nielsen Homescan database. However in regression analysis I control for the highest level of education attained by any of the heads of household.

[3] I control for the minimum hours worked by the head(s) of household. This is done because if at least one of the heads of household is working less than full time, he or she may have more time available to engage in household activities such as grocery shopping.

[4] I define households as below the poverty line using the imputed income variable, information on household size, and information on 2004 Poverty Guidelines provided here: http://aspe.hhs.gov/poverty/04poverty.shtml.

[5] I calculate the share of expenditures in club/supercenter format stores using information on purchases in the course of a month, as well as store type information provided in the Nielsen Homescan database.

Appendix B – Sensitivity Analysis Results

Table B.1: Results of Estimating Eq. (1) With Limited Food Categories[1] - HealthExpShare	Basic OLS	OLS w/Controls	Fixed Effects	OLS w/ Prices_ F&V	OLS w/Prices_ Processed
Log Frequency	-0.289***	-0.312***	-0.139***	-0.336***	-0.342***
	(0.048)	(0.047)	(0.041)	(0.076)	(0.073)
Child under 18		1.224*	1.399***	1.389*	1.417*
		(0.703)	(0.318)	(0.842)	(0.818)
Min Hours Worked		-1.213***	-1.195***	-1.165***	-1.141***
		(0.044)	(0.020)	(0.052)	(0.051)
Max Education		1.393***	1.417***	1.354***	1.372***
		(0.061)	(0.028)	(0.072)	(0.071)
White		-0.689***	-1.040***	-0.923***	-0.837***
		(0.154)	(0.072)	(0.183)	(0.181)
HH Income[2]		0.218***	0.219***	0.234***	0.223***
		(0.018)	(0.008)	(0.021)	(0.021)
HH Size		-1.400***	-1.388***	-1.433***	-1.414***
		(0.048)	(0.022)	(0.056)	(0.055)
Supercenter Exp Share		8.232***	10.114***	9.066***	8.863***
		(0.167)	(0.147)	(0.270)	(0.255)
Constant	27.635***	25.260***	28.747***	15.935***	39.674***
	(0.103)	(0.324)	(0.221)	(1.629)	(1.293)
Market Group FE			Yes		
Quarter FE			Yes		
Prices Healthful				Yes	
Prices Unhealthful					Yes
N	463,713	463,713	463,714	165,889	183,775
Adj. R^2	0.0001	0.0316	0.046	0.0376	0.0373
Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01					

[1] The food categories include: Grains (16-21), Dairy (22-27), and Meat (28-29).

[2] HH Income in $10,000.

Table B.2: Results of Estimating Eq. (1) with a 2 week time frame - HealthExpShare						
	Basic OLS	OLS w/Covariates	IV: Log Groc Stores and Log Supercenters	Fixed Effects	OLS w/ Prices_ F&V	OLS w/Prices_ Processed
Log Frequency	0.246***	0.147***	9.308**	0.304***	0.148***	0.133***
	(0.033)	(0.033)	(3.878)	(0.028)	(0.053)	(0.051)
Child under 18		0.736	1.447*	0.889***	1.026	1.061*
		(0.524)	(0.771)	(0.220)	(0.639)	(0.620)
Min Hours Worked		-0.788***	-0.259	-0.780***	-0.763***	-0.746***
		(0.033)	(0.220)	(0.014)	(0.039)	(0.039)
Max Education		0.810***	0.983***	0.825***	0.821***	0.834***
		(0.046)	(0.083)	(0.019)	(0.055)	(0.054)
White		-1.168***	-1.665***	-1.380***	-1.446***	-1.302***
		(0.115)	(0.266)	(0.050)	(0.139)	(0.137)
HH Income[1]		0.156***	0.170***	0.167***	0.172***	0.162***
		(0.013)	(0.018)	(0.006)	(0.016)	(0.016)
HH Size		-1.200***	-1.736***	-1.199***	-1.231***	-1.216***
		(0.035)	(0.236)	(0.015)	(0.043)	(0.042)
Supercenter Exp Share		8.192***	6.414***	8.667***	8.405***	8.290***
		(0.109)	(0.749)	(0.097)	(0.179)	(0.169)
Constant	19.346***	19.366***	8.638*	21.369***	14.600***	31.586***
	(0.060)	(0.236)	(4.483)	(0.148)	(1.234)	(0.974)
Market group FE				Yes		
Quarter FE				Yes		
Prices Healthful					Yes	
Prices Unhealthful						Yes
N	886,211	886,211	789,392	886,211	317,025	350,856
Adj. R^2	0.0001	0.0217	0.0048	0.0304	0.0255	0.0249
Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01						

[1] Household income in $10,000.

Table B.3: Results of Estimating Eq. (1) with a 6 week time frame - HealthExpShare						
	Basic OLS	OLS w/Covariates	IV: Log Groc Stores and Log Supercenters	Fixed Effects	OLS w/ Prices_ F&V	OLS w/Prices_ Processed
Log Frequency	0.396***	0.427***	9.601**	0.521***	0.413***	0.377***
	(0.041)	(0.041)	(4.616)	(0.034)	(0.065)	(0.062)
Child under 18		0.790	1.752*	0.922***	0.819	0.895
		(0.518)	(0.941)	(0.260)	(0.625)	(0.607)
Min Hours Worked		-0.758***	-0.140	-0.752***	-0.744***	-0.727***
		(0.032)	(0.305)	(0.016)	(0.039)	(0.038)
Max Education		0.807***	1.014***	0.821***	0.792***	0.807***
		(0.045)	(0.109)	(0.023)	(0.054)	(0.053)
White		-1.305***	-2.060***	-1.521***	-1.567***	-1.414***
		(0.114)	(0.430)	(0.059)	(0.136)	(0.134)
HH Income[1]		0.149***	0.146***	0.155***	0.166***	0.155***
		(0.013)	(0.018)	(0.007)	(0.016)	(0.016)
HH Size		-1.186***	-1.720***	-1.181***	-1.208***	-1.195***
		(0.035)	(0.280)	(0.018)	(0.042)	(0.041)
Supercenter Exp Share		7.608***	6.891***	8.633***	8.250***	8.116***
		(0.156)	(0.354)	(0.131)	(0.247)	(0.235)
Constant	18.856***	18.750***	-1.865	20.672***	13.292***	30.280***
	(0.104)	(0.248)	(10.289)	(0.189)	(1.238)	(0.974)
Market Group FE				Yes		
Quarter FE				Yes		
Price Healthful					Yes	
Price Unhealthful						Yes
N	313,675	313,675	279,514	313,675	112,287	124,430
Adj. R^2	0.0005	0.0379	0.0096	0.0550	0.0456	0.0438
Standard errors in parentheses; * p<0.10; ** p<0.05; *** p<0.01						

[1] Household income in $10,000.