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Journal of Food Distribution Research
Volume XLII, Number 3
November 2011

Table of Contents

Journal of Food Distribution Research
Volume 42, Issue 3

The Cost of Dietary Variety: A Case of Fruit and Vegetables

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Abstract

The 2010 Dietary Guidelines Advisory Committee and MyPyramid recommend eating a variety of vegetables and fruit; for vegetables, this recommendation is coupled with specific weekly serving recommendations. This study used a linear programming model to show the cost of increasing variety in fruit and vegetable consumption when meeting the Dietary Guidelines for Americans fruit and vegetable consumption recommendations with no within-group variety. Efficacy of efforts to promote increased dietary variety may be limited by economic disincentives associated with purchasing a greater variety of fruit and vegetables.

Keywords: Dietary Variety, Linear Programming, Marginal Cost of Variety, Dietary Guidelines for Americans

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Introduction

The 2010 Dietary Guidelines Advisory Committee (DGAC) and MyPyramid recommend including a variety of different foods in the diet. Recommendations are age, gender, and physical activity dependent. Although no specific recommendations for variety are given for fruit, there are for vegetables, with specific amounts of the following categories being recommended: dark green, red/orange, dried beans/peas, starchy, and other. The 2005 Healthy Eating Index (HEI), developed by the US Department of Agriculture (USDA) in conjunction with the Center for Nutrition Policy and Promotion (CNPP), is a scoring system used to determine diet quality, with a higher score indicating a higher quality diet (Guenther et al., 2007). The score is determined by assessing a number of components, which taken together call for dietary variety: total fruit, whole fruit (non-juice), total vegetables, dark green and orange vegetables and legumes, total grains, whole grains, milk, meat and beans, oils, saturated fatty acids, and sodium. The previous HEI was less specific on types of vegetables, fruit, and grains, but an explicitly included component was "variety" (Kennedy et al. 1995), with the highest score for this component received if 16 or more different foods in three days were consumed.

Although dietary variety has been emphasized, little work has been done to estimate the cost associated with dietary variety. This is of particular importance given the higher cost associated with fruit and vegetables relative to many energy-dense, nutrient-poor foods (Drewnowski 2010), and the dramatic increases in food costs when variety is introduced, as shown in our study. We examined the cost of increasing dietary variety while meeting the MyPyramid recommendations. The objectives of the study were to determine: (1) the cost of increasing variety in a diet that meets the MyPyramid recommendations for intake of fruit and vegetables, and (2) how the magnitude of the marginal cost of variety for fruit and vegetable intake changes as the degree of dietary variety is increased.

Fruit and vegetables are naturally low in fat and saturated fatty acids, and have no cholesterol. They are also rich sources of dietary fiber; vitamins, including folate and vitamin C; minerals, such as selenium, magnesium, and potassium; and phytochemicals, including carotenoids and lutein. Consumption of fruit and vegetables is associated with a wide range of health benefits including reduced risk of coronary heart disease, hypertension, stroke, type 2 diabetes, and some types of cancer. A variety of forms, i.e. fresh, frozen, canned, 100% juice or dried, can be consumed to meet the requirements (MyPyramid). Despite extensive, coordinated public health campaigns by government collaboration with industry, most individuals do not meet the recommendations for fruit or vegetables (Blanck et al. 2008; Kimmons et al. 2009). Intake actually declined slightly from 1994-2005 (Blanck et al. 2008). Although there are a number of reasons why people do not consume fruit and vegetables, cost is likely to be a major reason.

Previous Studies

Foote et al. (2004) discussed three types of dietary variety: (1) total variety, which considers the total number of unique foods in the diet; (2) between-group variety, which considers the number of different food groups represented in the diet; and (3) within-group variety, which considers the number of different foods from within the same food group (e.g. carrots and sweet potatoes in the red/orange vegetable group category). However, while the Dietary Guidelines for Americans (DGA) endorses dietary variety and provides some information on variety among groups of vegetables, specific recommendations are not given. The present study considers the issue of within-group variety and its impact on food cost.

Determining the health benefits of including a variety of foods in the diet has been of interest. McCrory et al. (1999) found that low variety of vegetables and high variety of sweets, carbohydrates, snacks, condiments, and entrees promoted long-term increases in energy intake, and were positively related to body fatness. However, heeding the warning of increased variety in energy-dense foods as noted by McCrory et al. (1999), Foote et al. (2004) emphasized the importance of increasing dietary variety to ensure nutrient adequacy while "maintaining a proper energy balance." Dietary variety was found to be positively related to nutrient intake, negatively related to sodium and sugar consumption, and positively related to intake of Vitamin C (Drewnowski et al. 1997), which the 2005 DGAC identified as a shortfall nutrient in adults. Kant et al. (1993) counted the number of different food groups included in the diet (varying from 1 to 5) and found that individuals omitting one of the food groups were at a higher risk of early mortality. Steyn et al. (2006) found food variety and dietary diversity to be related to height-for-age and weight-for-age in South African children 1 to 8 years of age. Characterizing what is meant by an appropriate amount of food variety has been of interest (Kant 1996), with studies using various measures, one of the most recent being developed by Drescher et al. (2007). While these previous studies show evidence that dietary variety is important for human health, little work has examined the relationship between variety and food cost.

Socioeconomic status has been linked to consumption of a diet that includes variety (Darmon and Drewnowski 2008). Older people obtain greater dietary variety than younger people (Drewnowski et al. 1997), with McCrory et al. (1999) finding this result specific to vegetables. Estaquio et al. (2008) found that, among French adults, those more likely to meet the 5-a-day fruit and vegetable recommendation were older, more highly educated, moderate alcohol drinkers, nonsmokers, and, in the case of women, engaged in greater physical activity. These studies did not, however, focus on whether the cost of dietary variety impacted consumption among the demographic groups studied.

Economists have also shown interest in determining factors associated with increased dietary variety. Lee and Brown (1989) found food expenditure to be positively related to overall dietary variety. Stewart and Harris (2004) found that vegetable expenditures were positively related to vegetable variety. Thiele and Weiss (2003) and Moon et al. (2002) studied the demand for variety in Germany and Bulgaria, respectively. Both found dietary variety to be positively associated with consumer income.

A number of studies have used linear programming (LP) in the development of individual diets. Increasing the weights of cost constraints (to reduce the overall cost of the diet) on average French diets had detrimental effects on diet (Darmon, Ferguson, and Briend 2002). This finding was consistent with results of Drewnowski and Specter (2004), which noted energy-dense foods cost less than more nutrient-dense, less energy-dense, foods (i.e. fruits and vegetables). The present study utilizes LP models to examine the impact of dietary variety on food costs.
Previous studies in this journal have dealt with consumer acceptance of various foods (Haines 2000; Regmi and Unnevehr 2006) and food accessibility (Godwin and Tegegne 2006), but we are aware of none that have addressed the cost of dietary variety.

Data

Since an LP model was used to examine the impact of increasing fruit and vegetable variety on food cost, prices of a variety of food items were required. Cost per consumable cup (terminology used by Cassady, Jetter, and Culp (2007), discussed in greater detail later) of each of 101 fruit and vegetable items was calculated using their respective average cost per ounce across 60 large full-service grocery stores in the Baton Rouge, LA, metropolitan area. Fruit and vegetable prices were recorded over a 3-week period in 2009: January 5 – January 24. Limiting the period to 3 weeks allowed for examination of prices at one point in time, with minimal variation in prices.

Six individuals were involved in collecting the data: two faculty members, two research associates, and two students in the Department of Agricultural Economics and Agribusiness and the School of Human Ecology at Louisiana State University. The group conducted the first collection of supermarket pricing data together and discussed how to handle situations such as when a product was missing or a designated product size was unavailable. This was done so as to ensure consistency among recorders. The lowest-priced item within the designated size category was recorded, regardless of brand. If a sale item was available for the item / size / form combination and it was the lowest-priced, then it was recorded. It is recognized that optimal combinations of fruit and vegetables chosen by the LP model would change by season, but the impact of variety on cost would likely be similar to that found in the present study. Of the 60 stores, 26 were independents, 11 were considered supercenters (Wal-Mart or Super Target), and 23 were other national or regional chain stores.

Cost per ounce was calculated for each fruit or vegetable item. Fresh produce items may be priced on a piece or per pound basis. For items priced by piece, the USDA National Nutrient Database for Standard Reference-22 (SR-22) was used to determine the average weight of an individual produce item. When there were multiple sizes available from which to choose for weight designation, the medium size was selected. From that size, an average weight was provided by SR-22. From that weight and price collected from the store survey, a cost per ounce was determined. The cost per ounce for each item was then averaged across the 60 stores.

To convert from cost per ounce to cost per consumable cup, the following method was used. The MyPyramid lists daily and weekly dietary recommendations in terms of consumable cups, so price per consumable cup was calculated for each fruit or vegetable, in accordance with SR-22. Similar to Cassady, Jetter, and Culp (2007), price per consumable cup of each fruit or vegetable was calculated accounting for refuse, since a portion of each item is not consumable (e.g., an apple has 10% refuse). Grams per consumable cup and amount of non-refuse associated with each fruit or vegetable item was determined via SR-22.

Methodology

Fruit Linear Programming Model

For a 2000-kcal diet, the MyPyramid recommends consuming 14 cups of fruit per week. This is the recommendation for males ≥14 years and women 19-30 years of age (thus, the largest segment of the population). For our study, the goal was to find the cost minimizing combination of fruit that met the weekly fruit intake recommendations, while introducing variety constraints to determine how increasing within-group variety impacted the total cost of one week's consumption of fruit. As such, the objective function of the LP model was to minimize the cost of meeting the MyPyramid dietary weekly fruit consumption recommendations for this diet:

$$(1)\ Minimize\ Z = \sum_{f=1}^{24} c_f x_f$$

where c_f is the cost per consumable cup of fruit type *f* (there were 24 fruit types available in the store survey database) and x_f is consumable cups of fruit type *f*. *Z* is minimized subject to a weekly fruit consumption constraint, $\sum_{f=1}^{21} x_f \geq 14$, and fruit variety constraints, $\sum_{f=1}^{m} x_f \geq$ RHS, where *m* is the number of fruits introduced into the diet over the one-week period and RHS is the right-hand side value, which is dependent on degree of variety. In addition, $x_f \geq 0$ for *f* = 1…24.

Table 1 shows selected fruits ranked from lowest to highest in price per consumable cup. By adjusting RHS values for the fruit variety constraints (thereby adjusting the limits of variety), each fruit was introduced sequentially to the LP model to add variety in ascending order from the lowest cost per consumable cup to the highest. With adjustment of the RHS values for variety constraints, products were introduced to evenly distribute the consumed amount of each fruit.

Table 1. Fruit Average Price Per Consumable Cup Ranked from Lowest to Highest Cost.

Fruit Item (*n* = 14)	**Average Price Per Consumable Cup of Fruit Ranked Low to High**
Fresh orange juice (may be sold as reconstituted from concentrate)	$0.29
Bananas	$0.38
Apples	$0.41
Canned pineapple	$0.61
Bartlett pears	$0.63
Nectarines	$0.71
Peaches	$0.73
Canned fruit cocktail	$0.82
Grapes	$0.82
Plums	$0.94
Avocados	$1.04
Watermelon	$1.22
Cantaloupe	$1.47
Grapefruit	$1.48

Additional fruit considered but not included because of higher price or a different form of the same fruit includes applesauce, blueberries, canned peaches, canned pears, frozen concentrate orange juice, mandarin oranges, navel oranges, satsumas, and strawberries.

For example, to ensure at least two fruit types were included in the solution, RHS values of the fruit variety constraints for both the second-least expensive fruit, bananas, and the least expensive fruit, fresh orange juice (this may be from concentrate, but not sold in frozen concentrate form), were seven. These constraints ensured that the individual consumed seven cups of each product for the week. Remaining variety constraints were introduced in a similar manner, with RHS values adjusting for all of the products as each additional fruit item was introduced. Variety constraints extend only to 14 to allow for the smallest portion of each fruit consumed to be one consumable cup. In cases where there were multiple forms of the same fruit, such as frozen concentrated orange juice and fresh orange juice, or fresh and canned peaches, only the less expensive item was introduced for variety. We do not assume that each of the items is "nutritionally equivalent," whether by type of fruit (e.g., orange or apple) or form (e.g., canned or fresh).

Vegetable Linear Programming Model

For a male aged ≥14 years, the MyPyramid recommends 21 cups of vegetables per week, with designated numbers of consumable cups in 5 separate vegetable categories. Table 2 (see Appendix) shows the 5 vegetable groups and MyPyramid recommendations for associated 1-week vegetable intake in consumable cups. Also shown are the vegetables from our store survey list belonging in each group. The survey list included 80 vegetable items, in fresh, frozen and canned forms. The LP model developed to assess the cost of increasing the degree of variety of vegetables in the weekly diet included constraints to ensure the individual would meet the MyPyramid recommendations for minimum consumption of each vegetable group. Thus, the model assessed the cost of adding greater variety by introducing constraints that increase variety within each vegetable group, for within-group variety.

The objective function was to minimize the cost of meeting the MyPyramid weekly vegetable consumption recommendations for a male aged ≥14 years:

$$(2) \qquad Minimize\ Z = \sum_{t=1}^{5} \sum_{n=1}^{80} c_{t,n} x_{t,n}$$

where $c_{t,n}$ is the cost per consumable cup of vegetable *t*, product *n* and $x_{t,n}$ is the consumable cups of vegetable *t,* product *n.* Similar to the procedure with fruit, price per consumable cup of vegetables for each vegetable category was ranked from lowest to highest to determine which products yielded the lowest cost of meeting the weekly dietary vegetable requirement of 21 consumable cups. Since MyPyramid has additional recommendations on numbers of consumable cups within each vegetable group, for each group, a constraint was introduced to ensure consumption of at least the required number of consumable cups. Thus, *Z* is minimized subject to: $\sum_{n=1}^{80} x_{t,n} \geq 21$, the weekly vegetable consumption constraint; $\sum_{n=1}^{12} x_{1,n} \geq 3$, the dark green vegetable consumption constraint; $\sum_{n=13}^{21} x_{2,n} \geq 2$, the orange vegetable consumption constraint; $\sum_{n=22}^{38} x_{3,n} \geq 3$, the dry beans and peas consumption constraint; $\sum_{n=39}^{48} x_{4,n} \geq 6$, the starchy vegetable consumption constraint; $\sum_{n=49}^{80} x_{5,n} \geq 7$, the other vegetable consumption constraint; and $\sum_{f=1}^{n} x_{t,n} \geq$ RHS, the vegetable variety constraints, where *n* is the number of vegetables introduced into the diet. Variety constraints were applied within each vegetable group and varied in both the number of vegetables *n* and the RHS, depending on the vegetable group composition and consumption recommendations for each group. In addition, $x_{t,n} \geq 0$ for *t* = 1…5 and *n* = 1….80.

Variety constraints became binding as additional variety was forced into solution, similar to the fruit model. However, since vegetables had multiple categories, for subsequent variety constraints, an additional vegetable was added to each of the vegetable categories. As with fruit, the smallest serving for each vegetable was set as one consumable cup. Once the within-group variety of vegetables reached an evenly distributed number and servings of one cup of each vegetable group were in solution, no further variety constraints were added for that group. In cases where there were multiple forms of the same vegetable, such as canned whole potatoes and fresh baking potatoes, only the lowest priced was included. In the case of starchy vegetables, there were only four different starchy vegetables in the database, so only four variety constraints could be added.

Results

Fruit Analysis

Fruit LP model results are included in Table 3 and Figure 1. The minimum cost of 14 consumable cups of fruit per week was estimated to be $4.05, which would be obtained if an individual consumed only fresh orange juice to meet the recommended weekly fruit requirement. It is noted, however, that the DGA recommends no more than one-third of fruit servings come from 100% fruit juice. Consuming a different fruit for each consumable cup per week cost $11.49, which can be considered the total cost (TC). The marginal costs associated with introducing each additional degree of variety (we term this the marginal cost of variety, MCV) are also shown.

Table 3. Total Cost and Marginal Cost of Variety for Increased Variety, Meeting the MyPyramid Fruit Intake Recommendations; Fruit Costs Averaged for 60 Large Grocery Stores.

Degree of Variety	Total Cost for Weekly Fruit Servings of 14 Consumable Cups	Marginal Cost of Variety
1	$4.05	…
2	$4.68	$0.63
3	$5.02	$0.34
4	$5.88	$0.86
5	$6.46	$0.59
6	$7.03	$0.57
7	$7.49	$0.46
8	$7.90	$0.41
9	$8.29	$0.39
10	$8.79	$0.50
11	$9.30	$0.51
12	$9.93	$0.63
13	$10.81	$0.88
14	$11.49	$0.68

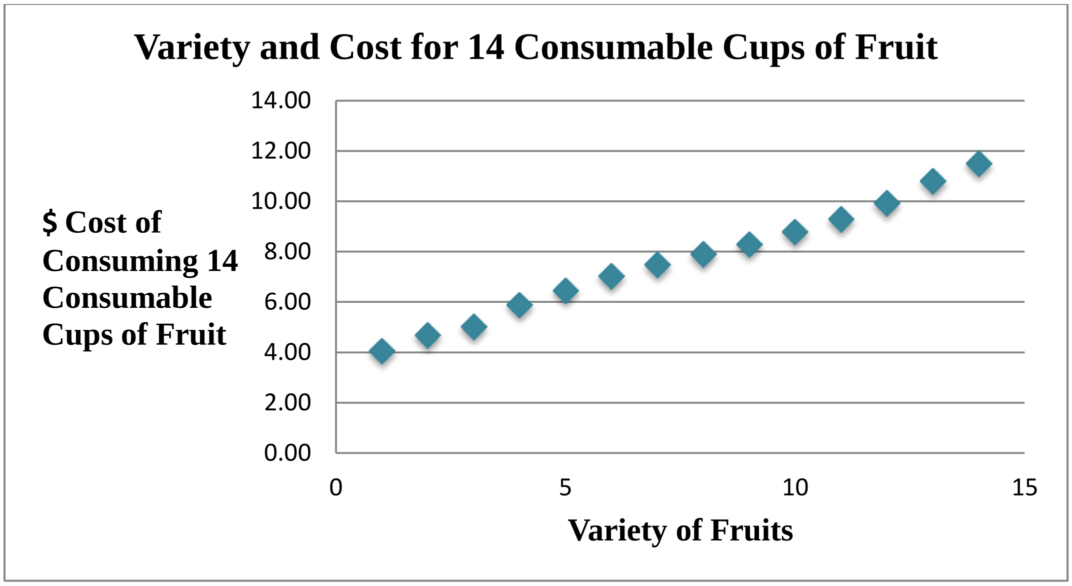

Figure 1. Plot of Points for the Cost of Consuming 14 Consumable Cups of Fruit for an Increasing Degree of Variety.

Results show that the TC increases as numbers of fruit included in the weekly fruit diet increase. The MCV remains positive as variety increases, fluctuating somewhat depending upon the prices of each additional fruit entering the weekly fruit consumption, so the MCV would not necessarily be a "smooth" graph. What is particularly striking is that full variety (14 different fruit types) costs nearly three times as much as the no-variety scenario. If greater refuse is associated with greater variety (and this is reasonable to expect since some fruit are not expected to be available in 1-cup servings), then the magnitude of differences would be greater, with higher MCVs.

Vegetable Analysis

Vegetable LP results are shown in Table 4 and Figure 2. The minimum cost for an individual to consume the recommended 21 consumable cups of vegetables per week, while also eating the recommended level of vegetables in each vegetable category, is estimated to be $5.13. Note that this minimum cost assumes a degree of between-group variety, as one vegetable from each of the five vegetable categories is consumed. However, since only one vegetable in each category is consumed, there is no within-group variety. Similar to the LP results for fruit and as expected, the MCV remains positive as variety is increased – or an additional vegetable is introduced in each category. The MCV generally increases at a decreasing rate, partly because the maximum number of one-cup servings is reached at two cups for orange vegetables, three cups for dark green vegetables and dry beans, and four cups for starchy vegetables, so less and less additional variety is introduced as more variety is introduced in the "other vegetables" group. As with the fruit model, changes in the MCV were not uniform in magnitude, fluctuating as variety was introduced. Because there is significant between-group variety even with the least variety in the vegetable group, and within-group variety does not increase to the degree it does with fruit (for example, only two vegetables in the orange vegetable category versus 14 in the fruit group constitute full variety), the increase in cost is not as extensive as it is with fruit. For vegetables, the increase is from $5.13 with no within-group variety to $6.90 with full variety.

Table 4. Total and Marginal Costs of Meeting the MyPyramid Vegetable Intake Recommendations; Vegetable Costs Averaged for 60 Large Grocery Stores.

Degree of Variety	Cost for Weekly Vegetable Servings of 21 Consumable Cups	Marginal Cost of Variety
1	$5.13	…
2	$5.76	$0.63
3	$6.04	$0.28
4	$6.46	$0.42
5	$6.66	$0.20
6	$6.79	$0.13
7	$6.90	$0.11

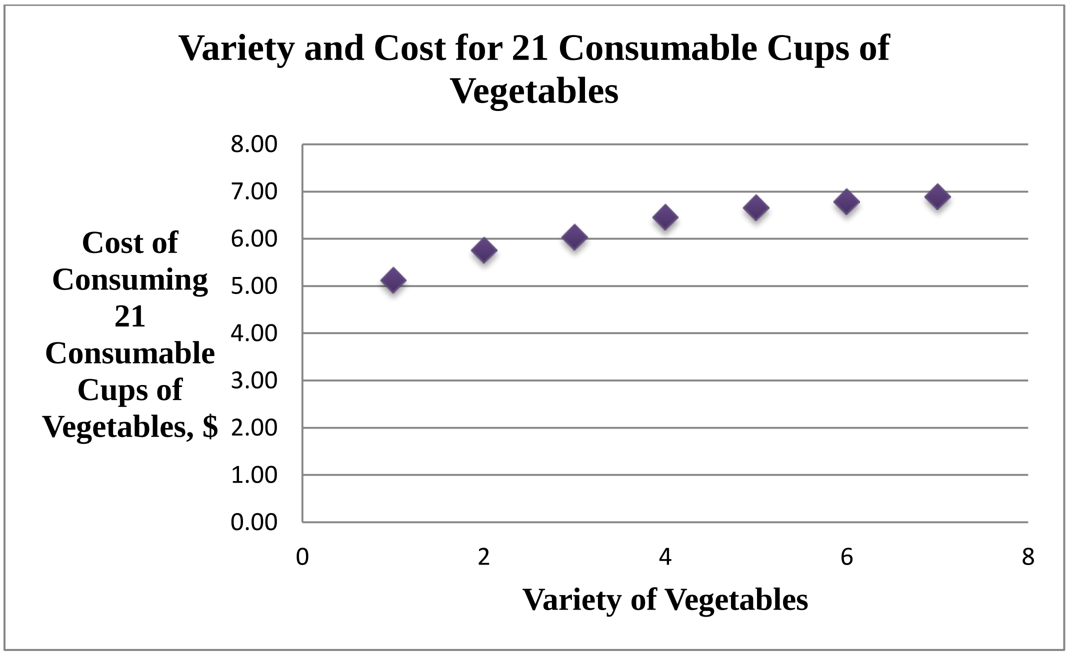

Figure 2. Plot of Points for the Cost of Consuming 21 Consumable Cups of Vegetables for an Increasing Degree of Variety.

Conclusions

Results of this study showed that increasing the degree of within-group variety for both fruit and vegetables increased the cost of meeting the MyPyramid recommendations. The analysis showed, based on average costs of fruit and vegetables at large grocery stores in the Baton Rouge, LA, metropolitan area, that as variety increases within both the fruit and vegetable categories, the cost of meeting the weekly MyPyramid recommendations for each food group also increases. The MCV for fruit remained positive as degree of variety was increased, and the magnitude was striking. In the case of vegetables, induced binding of the last few variety constraints caused the MCV to increase throughout, but meeting between-group variety constraints throughout led to less dramatic increases in TC from "no within-group variety" to full within-group variety.

The Centers for Disease Control and Prevention has replaced the "5 A Day" program with the "Fruits and Veggies-More Matters" campaign to promote the consumption of a greater variety of fruit and vegetables to promote better health. Our study showed that, for the vegetables and fruit we priced, assuming one-cup servings, maximizing the variety included in a diet of fruit and vegetables that meets the MyPyramid recommendations costs more than double the amount associated with no dietary variety. The totals are $9.18/week ($4.05 fruit + $5.13 vegetables) for no variety and $18.39 ($11.49 fruit + $6.90 vegetables) when adequate variety is accounted for. Thus, for a male aged ≥14 years, moving from no fruit variety to complete variety (defined in this study as 14 different items over the course of the week) while meeting the DGA would increase the cost of fruit by almost $30/month. The results for vegetables are less dramatic, assuming between-group variety is maintained throughout, but within-group variety increases. These results assume all purchased fruit and vegetables were consumed (no refuse), an assumption that is limiting since some fruit and vegetable products are not available as one piece, but as bunches, cans with >1 cup, etc. Our MCV estimates would thus be "on the low side" if refuse increases with variety. In all, this suggests that consumers have rather strong economic incentives to limit the variety of foods consumed. The efficacy of advocacy efforts for increased dietary variety such as the "Fruits and Veggies-More Matters" campaign may be constrained by the correlation of rising costs with increased fruit and vegetable variety for patrons of large grocery stores, especially among low-income consumers.

The USDA Food and Nutrition Service has advocated the use of Supplemental Nutrition Assistance Program (SNAP) benefits at farmers' markets and other venues that sell assortments of fruit and vegetable items. Such efforts may be an important component in improving the economic incentives of consumers to purchase and consume fruit and vegetables in order to meet the MyPyramid fruit and vegetable recommendations. However, greater variety without specific program provisions to encourage it is unlikely if SNAP benefits are not high enough to cover the costs associated with variety.

A limitation to this study is that we surveyed stores once, during January, 2008, in one metropolitan area. Due to seasonality, the specific food economic environment of 2008, and location, prices of specific items are not expected to be entirely representative of those to be found during a different season, year, or location. As such, the magnitudes of MCV and TC will differ somewhat depending upon those factors. However, the concept of an increasing TC and associated positive MCV will hold, and in general, the cost of variety is likely to be substantial.

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Appendix

Table 2. List of the 5 Vegetable Groups with Consumption Recommendations

Vegetable Groups	MyPyramid Weekly Recommendation Male ≥14 Years Old	Products Introduced with Successive Increases in Variety Constraints, Low to High Costs	Price Per Consumable Cup	Other Vegetables Not Chosen by LP Model Due to Higher Price
Dark Green	3	1) Fh romaine lettuce 2) C turnip greens 3) C spinach	1) $0.36 2) $0.48 3) $0.48	Fh broccoli, fh spinach, fh collard greens, fh kale greens, fh mustard greens, fh turnip greens, fz broccoli, fz spinach, fz mustard greens
Red/Orange	2	1) Fh whole carrots 2) C yams	1) $0.30 2) $0.39	Fh sweet potatoes, fh butternut squash, fh acorn squash, c carrots, c sweet potatoes, c pumpkin, fz carrots
Dry Beans and Peas	3	1) C black beans 2) C black-eyed peas 3) C kidney beans	1) $0.36 2) $0.44 3) $0.44	D black beans, d black-eyed peas, d kidney beans, d lentils, d lima beans, d pinto beans, d great northern beans, c baked beans, c lima beans, c garbanzo beans, c great northern beans, c pinto beans, fz lima beans
Starchy	6	1) Fh red potatoes 2) C green peas 3) Fh baking potatoes 4) C whole kernel corn	1) $0.28 2) $0.31 3) $0.31 4) $0.45	Fh corn on the cob, c creamed corn, c white potatoes, fz green peas, fz corn
Other	7	1) Fh green cabbage 2) Fh cucumbers 3) Fh red cabbage 4) C cut green beans 5) Fh eggplant 6) Fh yellow onions 7) Fh iceberg lettuce	1) $0.11 2) $0.14 3) $0.18 4) $0.25 5) $0.31 6) $0.31 7) $0.32	Fh brussels sprouts, fh cauliflower, fh celery, fh green pepper, fh okra, fh green onions, fh radishes, fh yellow squash, fh zucchini squash, fh green beans, fh red beets, fh turnips, c artichokes, c asparagus, c beets, c mixed vegetables, c mushrooms, c okra, c okra and tomatoes, c diced tomatoes, fz cauliflower, fz green beans, fz mixed vegetables, fz cut okra

C=canned, D=dried, Fh=fresh, Fz=frozen

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Hedonic Analysis of Retail Egg Prices Using Store Scanner Data: An Application to the Korean Egg Market

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Abstract

The objective of this study is to identify product characteristics that affect retail prices of fresh eggs. The study develops a hedonic price model to estimate implicit prices of product attributes of Korean fresh eggs. Then, the estimated shadow prices of attributes are used to identify a preference ranking of different levels of the same attribute and the relative importance of the attributes. The study uses store-level scanner data which include prices, sales quantities, and product attributes for all egg transactions for an entire one-year period. Unlike many earlier hedonic price models, the model developed in this study considers the potential effect of quantity sold in estimating implicit prices of attributes. Results suggest that sales quantity is one of important variables in hedonic price models, and therefore omitting the quantity variable could lead to a biased result, particularly when prices and sales vary widely across observations. Results also indicate that Korean consumers put a significantly high value on fertile, organic, free-range-feeding, and larger sized eggs, plus smaller package sizes. The findings could help both producers and retailers formulate better production and marketing strategies by focusing on these attributes.

Keywords: hedonic price, store scanner data, Korean egg market, attribute, marketing

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Today's consumers want an ever-widening variety of food products with various characteristics of nutrition, convenience, food safety, environment, and other traits. Following the trend in consumers' preferences, food markets have become highly differentiated and have turned gradually to smaller niche markets that tailor their products for more precisely defined market. With the changes in food markets, retailers and producers must understand consumer needs in each of the segmented markets. The knowledge of consumer needs in the niches can be used to achieve better market positions and reputations for retailers and producers (Kotler and Armstrong, 2004).

Consumer needs in the differentiated food markets can be analyzed with various research methods. However, the hedonic pricing method, devised by Court (1939) and later further developed by many studies such as Becker (1965), Lancaster (1966), Muth (1966), and Rosen (1974), is considered as one of the most appropriate methods. In the hedonic pricing method, hedonic prices are defined as implicit prices of attributes, which represent the price of each attribute decomposed from the price paid for a differentiated product. Econometrically, the implicit prices are estimated by regressing product prices on various product attributes. The estimated implicit prices provide useful information for consumer preferences on alternative levels of each attribute and on the relative importance across attributes for developing marketing strategies.

Several studies have applied the hedonic pricing model for various agricultural and food markets. A few examples include Brorsen, Grant, and Rister (1984) for rice, Espinosa and Goodwin (1991) for wheat, Tronstad, Huthoefer, and Monke (1992) for apples, Misra and Bondurant (2000) for cotton seeds, Huang and Lin (2007) for fresh tomatoes, Roheim, Gardiner and Asche (2007) for frozen processed sea food, and Martinez-Garmendia (2009) for carbonated soft drinks. Although many studies in the literature provide hedonic price analyses for various agricultural and food products, not many studies focus on the egg market with one exception (Karipidis et al., 2005). They apply the hedonic price model for the Greek egg market and show retail egg prices are affected by several product attributes including nutritional and production-related attributes. Although their study provides some insights on consumer behavior in egg markets, the findings of their study could have limited implications because the study relies only on 175 data points obtained from shelves of selected retail stores.

The present study applies the hedonic model for the Korean egg market to identify product characteristics that affect retail prices of fresh eggs. More specifically, first a hedonic price model for the Korean fresh egg market is developed to estimate implicit prices of product attributes of fresh eggs. Then, the estimated shadow prices of eggs are used to identify a preference ranking of different levels of the same attribute and the relative importance among attributes. Unlike Karipidis et al. (2005), this study uses store-level scanner data which include prices, sales quantities, and product attributes for all egg transactions for an entire one year period. The electronically scanned store data are expected to provide more detailed and accurate information on consumer behavior in egg retail markets than market-level or surveyed data. Unlike many earlier hedonic price models, the model developed in this study considers the potential effect of quantity sold in estimating implicit prices of attributes. Typically, hedonic price models do not include quantity variable in the model assuming inelastic supply. The use of the hedonic model has focused on inelastic supply goods that usually make a single transaction. Such markets include automobile, machinery, real estate, and highly perishable and expensive goods like tuna. However, prices and sales quantities vary considerably by transaction by transaction in the egg market. When price is lower, people tend to buy more eggs and vice versa. Therefore, including the sales volume variable in the model is imperative to estimate implicit prices of egg attributes particularly when store scanner data are used for the estimation.

The food purchase habits and dietary patterns of Korean egg consumers are rapidly changing from relatively homogeneous to highly differentiated products. Consumers recognize a variety of benefits from making healthy choices that reach beyond basic nutrition. Today's shoppers think eating healthy foods have emotional, physical, and even cosmetic benefits. To meet the changes in consumer demand, Korean egg producers have begun to produce organic, free-range, fertile, and nutrient-enhanced specialty eggs, and retailers have actively promoted these eggs in the market. Therefore, the present study on implicit prices of such attributes evaluated at the retail level will be very helpful to enhance production and marketing strategies of Korean egg producers and retailers.

Review of Previous Studies

In classical microeconomic consumer theory, consumer choice is based on the maximization of a utility function that specifies the quantities consumed subject to a financial constraint. A major point of criticism is that the neo-classical theory of consumer demand does not take the intrinsic properties of goods into consideration and therefore can't deal with problems like the introduction of new commodities and quality variations. One way to address this limitation is to adopt the hedonic hypothesis that goods do not by themselves provide utility to the consumer, but instead are valued for their utility-bearing attributes.

A few studies such as Becker (1965), Lancaster (1966), and Muth (1966), break away from the traditional approach and derive consumer utility not directly from goods but from properties or characteristics of goods. Such an extension makes it possible to study heterogeneous goods like housing, automobiles, and other complex goods within the framework of the classical consumer theory. While still considering utility-bearing characteristics, Rosen (1974) extends the previous studies by focusing on properties of market equilibrium. Rosen's framework is based on the notion that "goods do not possess final consumption attributes but rather are purchased as inputs into self-production functions for ultimate characteristics (Rosen 1974)."

In Rosen's framework, the attributes are represented by a vector of coordinates $v = (v_1, v_2, \ldots, v_n)$, where v_i measures the amount of the *i*th characteristic contained in each good. A price $P(v) = P(v_1, v_2, \ldots, v_n)$ is defined at each point on the plane and guides both consumer and producer choices regarding packages of characteristics bought and sold. The function $P(v)$ is identical with the set of hedonic prices and is determined by some market clearing conditions. As usual, market clearing prices, $P(v)$, fundamentally are determined by the distributions of consumer tastes and producer costs. Firms try to maximize profits by changing the product quantity and attributes. Equilibrium can be described by the intersection of supply and demand functions. From this equilibrium, we can understand how sellers determine the value of the products they offer and how consumers value the products they buy. In the long-run equilibrium, a hedonic function represents the minimum price at which attributes can be supplied and the maximum price at which they will be purchased.

Empirical work for Rosen's hedonic price model requires a two-step procedure. The first step is to regress observed differentiated products' prices, P, on those product's characteristics, v, using the best fitting functional form. Next, using the regression results, one can compute a set of implicit marginal prices, $(\frac{\partial P(v)}{\partial v_i}) * \bar{\mathrm{p}}$, for each buyer and seller, evaluated at the amounts of characteristics actually bought and sold, where $\bar{\mathrm{P}}$ is the mean price.

The hedonic price approach has been applied for various food and agricultural products. Brorsen, Grant, and Rister (1984) studied the price structure in the rice market in the United States and developed a framework to analyze quality differentials for rough rice prices observed in bid/acceptance markets and the probability of whether or not producers will accept bids based on those differentials. Espinosa and Goodwin (1991) considered a hedonic price model for alternative quality characteristics of wheat. The results indicate that standard grading characteristics as well as alternative end-use quality characteristics influence wheat prices. Stanley and Tschirhart (1991) estimated implicit prices of breakfast cereal characteristics. The cereal market was chosen because consumers can gather information easily about cereal characteristics either through experience, advertising or package labeling. Tronstad, Huthoefer, and Monke (1992) focused on product attributes of apples for U.S. consumers. Results suggest that size, storage method, grade, and seasonality are the most important influences on the price of apples. Harris (1997) employed hedonic analysis to demonstrate that consumers value taste more than nutrition when they purchase frankfurters. Huang and Lin (2007) analyzed household purchases of fresh tomatoes and determined the magnitude of the price premium paid for the organic tomatoes by estimating a hedonic price model. Roheim, Gardiner and Asche (2007) also conducted a hedonic analysis for the frozen processed seafood market in the United Kingdom.
Although many of the hedonic analysis approaches have been conducted on agricultural products, the hedonic analysis model has rarely been applied to eggs. One exception is research conducted for the Greek egg industry (Karipidis et al., 2005). Karipidis et al. (2005) estimated the effects of product attributes, production methods, distribution and product image on retail egg prices. A few other studies in the literature focused on egg market although they did not use the hedonic method (Kinnucan and Nelson, 1993; Ness and Gerhardy, 1994; Fearne and Lavelle, 1996; Schmit and Kaiser, 1998; Gilbert, 2000; Kuney and Zeidler, 2001).

Kinnucan and Nelson (1993) analyzed the effects of increased vertical control on the egg industry performance as measured by the farm price spread. Ness and Gerhardy (1994) studied quality and freshness attributes of eggs using conjoint analysis. The study focused on establishing the link between consumer preferences for alternative products and products that can be offered by producers and retailers. Fearne and Lavelle (1996) demonstrated the importance of effective marketing communication and the potential for adding value to the basic egg. They found that there was a polarization of egg consumers, with free-range egg consumers at one extreme, largely influenced by bird welfare, and battery egg consumers at the other, for whom functional properties and value for money were the major factors determining egg purchasing behavior. Schmit and Kaiser (1998) estimated a model of the domestic demand for eggs in

United States. Empirical results indicate that most of the observed change in egg demand could be explained by dietary cholesterol concerns. They also find that advertising efforts over the past several years have resulted in net benefits to egg producers largely when considering inelastic supply responses. Gilbert (2000) examined consumer interests in functional nutrition for disease prevention and health enhancement. He finds that increased egg consumption is being driven by consumer interest in health benefits that reach beyond dietary avoidance strategies to positive nutrition strategies. Kuney and Zeidler (2001) attempted to measure the quality of eggs offered to consumers in large supermarkets in various regions of the United States.

The Model

As discussed in the previous section, the Rosen's hedonic pricing model describes an equilibrium price determined simultaneously by both sides of the market in terms of the amount of product attributes supplied by producers and demanded by consumers. Therefore, the empirical framework requires an estimation of both demand and supply equations simultaneously. However, many researchers have used a single equation approach arguing that product attributes supplied by producers tend to be highly inelastic (Wilson, 1984; McConnell and Strand, 2000; Kristofferson and Rickertsen, 2007). In this case, empirical hedonic price models requires only market clearing prices rather than both demand and supply schedules. Following most previous studies, a single hedonic price equation that represents market quilibrium conditions at some point of time is estimated in this study.

A few hedonic pricing models for consumer packaged goods in the literature have used grocery store data collected with scanners or by hand. One limitation of such data is that price is set by supplier without any buyer involvement at least in the short run. A supplier could sell the same SKU (stock keeping unit) at two different prices in two separate but otherwise identical stores with identical consumer bases. Therefore, when everything else is the same, one would expect that the stores with the lower price would sell more SKU units than the stores with the higher price. Given the volatility in prices and sales across weeks and stores in consumer packaged goods, not including quantity sold in the hedonic model would not capture the dynamics in the store and would get in the way of measuring the hedonic prices of the attributes composing the SKU. Martinez-Garmendia (2009) developed a hedonic price model that includes quantity sold as one of independent variables and showed that hedonic pricing method without quantity would lead to a biased estimation of consumer preference. Since this study uses scanner data collected from packaged egg trades in Korea, quantity sold is included as one of independent variables.

For estimating a hedonic egg price model, a functional form needs to be determined. A double-log functional form is chosen for analysis because its coefficients can be easily interpreted as price flexibilities, and the double-log form has been successfully used in similar previous studies (Carroll, Anderson, Martinez-Garmendia, 2001; Martinez-Garmendia, 2009). Then, a double log functional form of hedonic egg price for product *i* at time *t* is represented as:

$$
\begin{aligned}
(1)\quad lnPrice_{it} = {} & \beta_0 + \beta_1 lnQuantity_{it} + \beta_2 Fertile_{it} + \beta_3 Nutrition_{it} \\
& + \beta_4 (Fertile_{it} * Nutrition) + \beta_5 Organic_{it} + \beta_6 Antibioticfree_{it} \\
& + \beta_7 Freerange_{it} + \beta_8 (Antibioticfree * Freerange_{it}) + \beta_9 Giftpackage_{it} \\
& + \beta_{10} Ecopackage_{it} + \beta_{11} Certified_{it} + \sum_{j=2}^{4} \gamma_j Size_{ijt} + \sum_{k=2}^{6} \delta_k Pkgsize_{ikt} \\
& + \sum_{l=2}^{4} \omega_l Season_{ilt} + \sum_{m=2}^{5} \theta_m Branch_{imt} + \varepsilon_{it},
\end{aligned}
$$

where *Price* is price per egg; *Quantity* is sales volume (the number of eggs sold); *Fertile* represents fertile eggs; *Nutrition* represents nutritionally enhanced eggs produced with extra feed supplements; *Organic* denotes eggs produced using only organic feeds.[1]. *Antibioticfree* denotes eggs produced without feeding antibiotics; *Freerange* denotes eggs produced from free range farms; *Giftpackage* denotes eggs packed in gift packages; *Ecopackage* denotes eggs packaged with environmental friendly packages; and *Certified* represents eggs labeled with NACF certification logo[2]. Two interaction terms (*Fertile* Nutrition and Antibioticfree* Freerange*) are considered in the model to account for interaction effects between major attributes. Because cross-tabulation results show other interaction terms are either mutually exclusive (*Organic* and *Antibioticfree*) or identical with a single attribute (the interaction term between *Organic* and *Freerange* is identical with *Organic*, and the term between *Giftpackage* and *Ecopackage* is identical with *Giftpackage*), these terms are not included in equation (1). Four dummy variables are included in the model: *Size* represents egg size; *Pkgsize* is the package size; *Season* represents the seasonality of egg sales; *Branch* represents five different store branches located in Seoul and its surrounding cities and should account for store-specific promotion and marketing strategies; and the last term ε represents stochastic errors for equation (1).

In most cases, eggs produced for human consumption are unfertilized because laying hens are kept without a rooster. Scientifically, fertile eggs (*Fertile*) are known to be no more nutritious than non-fertile eggs. However, many consumers in Korea believe fertile eggs are a delicacy and are nutritious. Therefore, a higher price is charged for fertile eggs in the market. Nutritionally enhanced eggs (*Nutrition*) are produced by feeding supplements of medicinal herbs, particularly ginseng, and high protein. Consumers tend to prefer nutritionally enhanced (*Nutrition)*, organic

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[1] Organic certification and labeling programs for agricultural products follow regulations set by the the National Agricultural Products Quality Management Service (NAQS), which is the official certification body designated by the Korean government. Organic and antibiotics free products are separately certified by NAQS in Korea. Organic livestock certification is granted only to the livestock products produced with organic feeds following the NAQS guidelines. Antibiotic-free certification is granted to the livestock products produced without using antibiotics. However, no government certification system is available for other specialty eggs such as fertile, free range, and nutritionally enhanced eggs.

[2] Korean agricultural cooperatives have approximately 2.4 million member farmers, 1,187 member cooperatives, and one cooperative federation called the National Agricultural Cooperative Federation (NACF).The NACF provides various services to member farmers and cooperatives, which include farm credits, feeds and seeds, fertilizers, farm machineries, and other items. The NACF is also a major player in marketing farm products in Korea. For example, the NACF had a 48 percent market share in selling farm products in 2007 (Kim, Ahn, and Sohn, 2008). Agricultural products with the NACF logo are produced by member farmers and are considered as high quality products.

(*Organic*), antibiotic free (*Antibioticfree*), and free range feeding (*Freerange*) eggs over eggs produced with traditional feed and production systems. Unlike typical egg containers/packages, gift packages (*Giftpackage)* are specially designed packages with gift wraps. Traditionally, agricultural products such as meat, fruits, and eggs have been used as gifts for special occasions in Korea. Environmentally friendly packages (*Ecopackage*) are made from mostly paper clay that can be easily decomposed after disposal while other containers generally use plastic materials. Certified eggs (*Certified)* have the NACF certification logo on packages. Food safety is also an important issue when consumers purchase agricultural and food products in Korea. The NACF certification label could increase consumer trust of products. Four dummy variables are constructed to represent egg size: $Size_1$ (44 gram to 51 gram), $Size_2$ (52 gram to 59 gram), $Size_3$ (60 gram to 67 gram), and $Size_4$ (over 68 gram). Six different package sizes are included in the data. They are $Pkgsize_1$ with 6 eggs, $Pkgsize_2$ with 10 eggs, $Pkgsize_3$ with 15 eggs, $Pkgsize_4$ with 20 eggs, $Pkgsize_5$ with 30 eggs, and $Pkgsize_6$ with 60 eggs. As specified in equation (1), we omit one variable for each of the dummy variable categories such as *Size*, *Pkgsize*, *Season*, and *Branch* to avoid the perfect collinearity problem.

Data

Data used in this study include purchases of all eggs from five large NACF supercenters located in Seoul and surrounding areas in Korea for the 2009 whole year. Egg prices and sales data of retail supercenters were collected from the data server of the Information Technology Center of NACF for each transaction of product code. Prices were measured in Korean Won (KRW) per egg, and sales quantities were measured by the number of eggs. Corresponding egg attributes for each product code were obtained from labels of egg packages on the shelves of each supercenter. The store scanner data included 2,590,525 transactions for the year 2009, which were aggregated daily for each product code and each store. The data set includes a total of 65,182 observations for 122 products.

Table 1 lists descriptive statistics for variables used in the hedonic price model. The mean of price per egg (*Price*) is 249.21 KRW (approximately $0.20 applying an exchange rate, $1 = 1,246 KRW), and a wide range of price is observed: 92.7 to 617.1 KRW ($0.07 to $0.50). Fertile (*Fertile*) and nutritionally enhanced (*Nutrition*) eggs are 30% and 22% of total observations, respectively. Organic (*Organic*), antibiotics free (*Antibioticfree*), and free range (*Freerange*) eggs are 2%, 75%, and 23%, respectively[3]. In terms of packaging, 22% and 86% of eggs use gift packaging (*Giftpackage*) and environmentally friendly packaging (*Ecopackage*), respectively, and 8% of eggs are certified and labeled with the NACF logo (*Certified*). Among all egg size groups, $Size_3$ is the most popular size in the data set. Out of six package sizes, $Pkgsize_2$, $Pkgsize_3$, *and* $Pkgsize_5$ are the most common package sizes. Our data shows egg sales are almost evenly distributed across seasons, and $Branch_5$ has the highest sales among five branches throughout the year.

[3] These attributes are not mutually exclusive. Approximately 20% of eggs have both antibiotic free and free range attributes. No organic, antibiotics free, or free range eggs account for only 22% in the dataset. Korean consumers, particularly those living in Seoul area, show strong preference for food safety- and animal-friendly eggs.

Table 1. Descriptive Statistics of Data Used for Hedonic Price Model Estimation

Variable	Mean	Description
Rice	249.21	Price per egg (KRW)
Quantity	829.64	Number of eggs sold daily by product code and store
Fertile	0.30	1 for fertile egg; 0 otherwise
Nutrition	0.22	1 for nutritionally enhanced egg; 0 otherwise
Fertile Nutrition*	0.08	1 for fertile and nutritionally enhanced egg; 0 otherwise
Organic	0.02	1 for organic egg; 0 otherwise
Antibioticfree	0.75	1 for antibiotics free egg; 0 otherwise
Freerange	0.23	1 for free range egg; 0 otherwise
Antibioticfree Freerange*	0.19	1 for antibiotics free and free range egg; 0 otherwise
Giftpackage	0.22	1 for gift package; 0 otherwise
Ecopackage	0.86	1 for environmentally friendly package; 0 otherwise
Certified	0.08	1 for certified eggs; 0 otherwise
$Size_1$	0.03	1 for 44g to 51g per egg; 0 otherwise
$Size_2$	0.27	1 for 52g to 59g per egg; 0 otherwise
$Size_3$	0.49	1 for 60g to 67g per egg; 0 otherwise
$Size_4$	0.21	1 for over 68g per egg; 0 otherwise
$Pkgsize_1$	0.01	1 for package with 6 eggs; 0 otherwise
$Pkgsize_2$	0.29	1 for package with 10 eggs; 0 otherwise
$Pkgsize_3$	0.35	1 for package with 15 eggs; 0 otherwise
$Pkgsize_4$	0.02	1 for package with 20 eggs; 0 otherwise
$Pkgsize_5$	0.32	1 for package with 30 eggs; 0 otherwise
$Pkgsize_6$	0.01	1 for package with 60 eggs; 0 otherwise
$Season_1$	0.23	1 for January to March; 0 otherwise
$Season_2$	0.24	1 for April to June; 0 otherwise
$Season_3$	0.26	1 for July to September; 0 otherwise
$Season_4$	0.27	1 for October to December; 0 otherwise
$Branch_1$	0.16	1 for Branch1; 0 otherwise
$Branch_2$	0.20	1 for Branch2; 0 otherwise
$Branch_3$	0.18	1 for Branch3; 0 otherwise
$Branch_4$	0.22	1 for Branch4; 0 otherwise
$Branch_5$	0.24	1 for Branch5; 0 otherwise
Number of obs.	65,182	

Empirical Results

The estimation of equation (1) raises three econometric issues: endogeneity, autocorrelation, and heteroscedasticity. First, the endogeneity needs to be checked because equation (1) includes a quantity variable that could be endogenous and therefore could be correlated with the stochastic error terms. A simple endogeneity test suggested by Hausman (1978) finds the evidence of endogeneity of the quantity variable. Secondly, since the data used in this data include a panel nature with time series (daily) and cross sectional observations, both autocorrelation and heteroscedasticity tests were conducted. The autocorrelation test indicates that there no autocorrelation problem exists in the model. However, the hypothesis for homoskedasticity of error terms is rejected based on a Lagrange multiplier test. To address the endogeneity and heteroskedasticity problems, we use the generalized method of moments (GMM) procedure with two unique instrumental variables: egg size and daily number of transactions. [4] The identification of the instrumental variables has been tested following Hansen (1982), and the test result indicates that over-identifying restrictions are valid in the model.

Table 2 shows estimates of coefficients, corresponding standard errors, and marginal implicit prices. Marginal implicit prices are calculated by multiplying the average price to the partial derivative of price with respect to each product attribute. As shown in Table 2, all variables are statistically significant at the 1% level. R^2 indicates that the change in egg prices in the Korean market is well represented by the change in the set of independent variables of equation (1).
As expected, sales quantity is negatively related to price. A 1% increase in egg quantity results in a 0.05% decrease in egg price. The statistical significance of *LnQuantity* shows the existence of volume effect in determining egg price. Fertile, organic, and free-range eggs show relatively high implicit prices. Marginal implicit prices of these eggs are \$0.06, \$0.11, and \$0.03 per egg, respectively. The estimated implicit prices show a strong potential for developing niche markets for fertile, organic, and free-range eggs.

Although gift packaging and environmental-friendly packaging positively influences the price, packaging methods do not seem to have a large impact on egg prices. However, certification shows a relatively high value over eggs with no NACF certification. The NACF certification label is well recognized and highly valued in Korea because consumers believe that NACF products are supplied mostly by their cooperative members and are carefully inspected before certified and labeled.

As expected, egg prices are found to increase with egg size. The larger the egg size, the higher the price at retail stores. Differentials of marginal implicit prices between the smallest size and $Size_2$, $Size_3$, and $Size_4$ are \$0.04, \$0.05, and \$0.05 per egg, respectively. Package size is also an important price determining factor in Table 2. The price differentials between the smallest package size and $Pkgsize_2$, $Pkgsize_3$, $Pkgsize_4$, $Pkgsize_5$, and $Pkgsize_6$ are \$0.10, \$0.10, \$0.09, \$0.14, and \$0.15, respectively. Results suggest that both per egg and package sizes are two major factors of determining egg values for fresh egg shoppers in the retail market. The shoppers show a strong preference for larger eggs and smaller packages, probably for their convenience. Egg prices also show seasonal variation. Prices in $Season_1$, January to March, tend to be higher than prices for the rest of the year. Egg prices differ across branches, which reflect different pricing and promotion schemes across branches.

Table 2. GMM Estimation Results of the Hedonic Price Model

Variable	Estimate[a]	Standard Error	Marginal Implicit Prices in KRW [b]	Marginal Implicit Prices in US Dollar[c]
Intercept	5.8954	0.0118		
lnQuantity	-0.0507	0.0011		
Fertile	0.3290	0.0049	76.28	0.06
Nutrition	0.0590	0.0021	6.90	0.01
*Fertile*Nutrition*	-0.1043	0.0046		
Organic	0.5715	0.0030	142.42	0.11
Antibioticfree	0.0185	0.0018	10.17	0.01
Freerange	0.0979	0.0051	42.51	0.03
*Antibioticfree*Freerange*	0.0969	0.0028		
Giftpackage	0.0598	0.0013	14.90	0.01
Econpackage	0.0172	0.0020	4.29	0.00
Certified	0.0979	0.0033	24.40	0.02
$Size_2$	0.1891	0.0063	47.13	0.04
$Size_3$	0.2396	0.0061	59.71	0.05
$Size_4$	0.2595	0.0065	64.67	0.05
$Pkgsize_2$	-0.5124	0.0126	-127.70	-0.10
$Pkgsize_3$	-0.4778	0.0126	-119.07	-0.10
$Pkgsize_4$	-0.4306	0.0130	-107.31	-0.09
$Pkgsize_5$	-0.6864	0.0132	-171.06	-0.14
$Pkgsize_6$	-0.7375	0.0136	-183.79	-0.15
$Season_2$	-0.0076	0.0018	-1.90	0.00
$Season_3$	-0.0139	0.0019	-3.46	0.00
$Season_4$	-0.0507	0.0020	-12.63	-0.01
$Branch_2$	0.0552	0.0020	13.77	0.01
$Branch_3$	0.0711	0.0017	17.22	0.01
$Branch_4$	-0.0166	0.0017	-4.13	0.00
$Branch_5$	-0.0143	0.0020	-3.56	0.00
R^2	0.8844			
Number of obs.	65,182			

[a]All estimates are statistically significant at the 1% level.
[b]Marginal implicit prices in KRW are calculated as: $\frac{\partial P}{\partial v_i} * \overline{p}$, where v_i is the i[th] attribute in the model , and $\overline{P}$ is the mean price at 249.21 KRW($0.20).
[c]Exchange rate: $1 = 1,240 KRW.

Conclusion

Korean fresh eggs are increasingly differentiated following consumers' recent trends of dietary habits. Consumers tend to make healthy choices that reach beyond basic nutrition considering emotional, physical and even cosmetic benefits. To cope with recent changes in the Korean fresh egg market, farmers and retailers have actively marketed organic, free-range, fertile, and nutrient-enhanced specialty eggs. The objective of this study is to identify product characteristics that affect retail prices of fresh eggs in the Korean egg market. This study develops a hedonic price model to estimate implicit pries of product attributes of Korean fresh eggs. Then, the estimated shadow prices of attributes are used to identify a preference ranking of different levels of the same attribute and relative importance of attributes.

Results show that all coefficients from a double-log hedonic price model are statistically significant at the 1% level, which suggests all quality attributes considered in the model significantly affect retail price. The significance of quantity coefficient suggests an existence of the volume effect in the fresh egg retail markets in Korea, and therefore, ignoring quantity variable in hedonic price models could lead to a biased result particularly when prices and sales vary widely across observations. Major attributes affecting the retail price of eggs include the status of fertility, organic and free-range feeding, and egg and package sizes. Shoppers at the NACF retail outlets tend to pay \$0.06, \$0.11, \$0.03 and \$0.02 more each for fertile, organic, free-range-feeding, and store brand eggs, respectively. The shoppers also prefer bigger eggs to smaller eggs. For example, consumers paid \$0.05 more for the biggest sized egg (over 68g) compared to the smallest egg (44g to 51g) when all other characteristics are held constant. In terms of package size, the shoppers prefer smaller package sizes while paying \$0.15 more per egg for the smallest package size (6 eggs) compared to the largest package size (60 eggs). Results indicate that Korean consumers put significantly high value on fertile, organic, free-range-feeding, and larger sized eggs, plus smaller package sizes. These findings could help both producers and retailers formulate better production and marketing strategies by focusing on these attributes.

One caveat in interpreting findings in the present study is that our findings are based on the data collected from five NACF supercenters in Seoul and adjacent vicinities. Therefore, they may not reflect the overall behavior of Korean fresh egg consumers because the demographic distribution of shoppers in the data set may differ from general Korean fresh egg consumers.[5] However, many previous studies have surveyed shoppers of these supercenters and have used the data to analyze overall Korean consumer behavior (Park, Jung, and Kim, 2007 for pork; Roh, Han, and Chung, 2007 and Chung, Boyer, and Han, 2009 for beef). Another limitation of this study is that our empirical model does not include consumers' demographic characteristics. A better analysis can be conducted with a hedonic price model that is equipped with consumers' demographic information such as gender, education, age, income, occupation, and other traits. However, unlike home scanned data, most store scanned data, including data used in this study, do not have information on shoppers' demographic characteristics. Therefore, the hedonic price model estimated in this study is limited to focus on sales volume and product attributes.

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Self Efficacy as a Mediator of the Relationship between Dietary Knowledge and Behavior

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Abstract

Translating the dietary knowledge among individuals into healthy behavior remains a challenging task. This study examines the causal relationship between dietary knowledge and behavior by including self-efficacy in the models.

A series of regression models were developed based on Baron and Kenny (1986) to assess whether self-efficacy mediated the link between the predictor variables and dietary behavior. Regression analyses supported the hypothesized relationships that self-efficacy mediates effects of dietary knowledge and social influences on dietary behavior. Self-efficacy also accounted for variance in eating behavior not explained by knowledge or demographic variables.

Keywords: dietary knowledge, dietary behavior, self-efficacy

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Introduction and Objectives

Increased availability of nutritional information has been successful in enhancing public awareness of the importance of healthy diet and lifestyles. The important issue is whether enhanced nutrition and health awareness has any significant impact on consumers' actual dietary behavior. The data from the healthy eating index (HEI) show that although dietary quality has improved over the past years, the diets of most Americans need improvements in several aspects (Kennedy et al. 1999; Guo et al. 2004). Previous studies have examined the influence of health behavior through informational campaigns, followed by the expected change in the attitude and desired behavioral changes in areas like smoking, obesity, and HIV/AIDS (Perry et al. 1980; Stern et al. 1982; Nwokocha and Nwakoby 2002.) While the above studies have reported mixed results of success, studies evaluating the relationship between nutrition knowledge and dietary behavior have found no direct correlation between the two (Putler and Frazao 1994; Sapp 1991).

Clearly, the evidence from the above studies suggests that the impact of additional information and knowledge on actual consumer behavior is an empirical issue. This is in contrast to the premises of the rational choice theory which is the basis for traditional neoclassical theory of demand and consumer choice (e.g., Mas-Colell, Whinston and Green 1995). The implausibility of the rational choice axioms has been documented by many economists including, among others, the Nobel Prize Laureate Kahneman (1994), or more recently Miljkovic (2005). Therefore, translating the dietary knowledge among individuals into healthy behavior remains a challenging task for economic modelers, and in turn the food and health policy makers. Relying on behavioral sciences theories such as the social cognitive theory (SCT), the objective of this study is to examine the causal relationship between dietary knowledge and behavior by including self-efficacy in the models.

Self-efficacy is defined as a person's ability of exerting self-control in changing his/her behavior. Hence, the objective of this study may be more specifically stated as to empirically address the question of whether the predictor variables such as dietary knowledge affect only self-efficacy, or dietary behavior, or both. The self-efficacy component of the SCT has been widely used by many researchers to explain human behavior with regard to, for example, phobias (Bandura 1983) , smoking (Schinke et al. 1985), drug use (Hays and Ellickson 1990), addiction (Marlatt Baer, and Quigley) and food choices (Parcel et al. 1995; Steptoe, et al. 1995). Researchers have suggested that self-belief that includes self-efficacy plays a mediating role in relation to cognitive activities. Bandura (1997) explained self-efficacy belief as "beliefs in one's capability to organize and execute the courses of action required to manage prospective situation." A large amount of previous research has generally supported the basic notion proposed by Bandura (1986 and 1997) that efficacy beliefs mediate the effects of skills on performance by influencing effort, persistence and perseverance (Schunk 1991; Bouffard-Bouchard 1990; and Schunk and Hanson 1985). Corwin et al. (1999) reported that many components from SCT including self-efficacy had significant correlation with the diet related behavior of children. In a study among fourth graders, she reported that the mean dietary exposures scores for low-fat food selection was significantly higher for those children who had scored highest levels of confidence about lower fat food choices than those with lower levels of confidence.

Another study designed to examine the social-cognitive determinants of health behaviors including physical exercise, smoking, alcohol consumption, and preventive nutrition (Schwarzer and Renner 2000) distinguished between action self-efficacy (preintention) and coping self-efficacy (postintention) as two phases of optimistic self- beliefs. The study reported that the importance of perceived self-efficacy increased with the age of the respondent and their body weight.

A person's health related self efficacy is influenced by his/her health knowledge and other socio-demographic background information. Since self-efficacy itself is explained by the dietary knowledge of individuals (Slater 1989), it is likely to play a mediating role in the relationship between healthy behaviors and dietary knowledge. Consumers with higher levels of self-efficacy are more likely to sustain a healthy behavior with regard to food choices compared to those with lowers level of self-efficacy.

Theoretical and Empirical Models

The preceding discussion points to a causal flow from dietary knowledge (hereafter, we call these predictor variables) and socio-demographic characteristics to self-efficacy and/or dietary behavior. At this point, an empirical question that remains to be determined is whether the predictor variables affect only self-efficacy, or dietary behavior, or both. We propose a mediation model here. More specifically, we hypothesize that (a) the predictor and socio-demographic variables influence both self-efficacy and dietary behavior, and (b) these variables influence dietary behavior primarily via their link to dietary knowledge. For example, when consumers possess a high level of dietary knowledge, they are predisposed to exert a greater control over their diets and lifestyle, thereby adopting a healthy dietary behavior.

The hypotheses above underscore the notion of mediation. In other words, the mediation approach recognizes that consumers' self-control (efficacy) over diet and lifestyle can mediate the effects of the predictor variables (dietary knowledge) on the dietary behavior (Baron and Kenny 1986). Figure 1 (as adapted from Baron and Kenny 1986) illustrates this modeling approach using self-efficacy as mediators of the relationship between dietary behavior and predictor variables. The figure depicts three causal paths in a model of how overall dietary behavior is formed: (i) the direct impact of the predictors on dietary behavior (path a); (ii) the path from the predictors to the mediators (path b); and (ii) the impact of mediators on dietary behavior (path c).

In this study, the mediating hypothesis is tested using the following four criteria adopted from Judd and Kenny (1981) and Baron and Kenny (1986): a) the self-efficacy of individuals (mediator) has a statistically significant impact on dietary behavior; b) dietary knowledge and socio-demographic variables (predictors) have significant influence on dietary behaviors; c) dietary knowledge exerts a significant influence on diet related self-efficacy of individuals; and d) the effects of dietary knowledge is either diminished or no longer significant when self-efficacy is controlled for the dietary behavior equations.

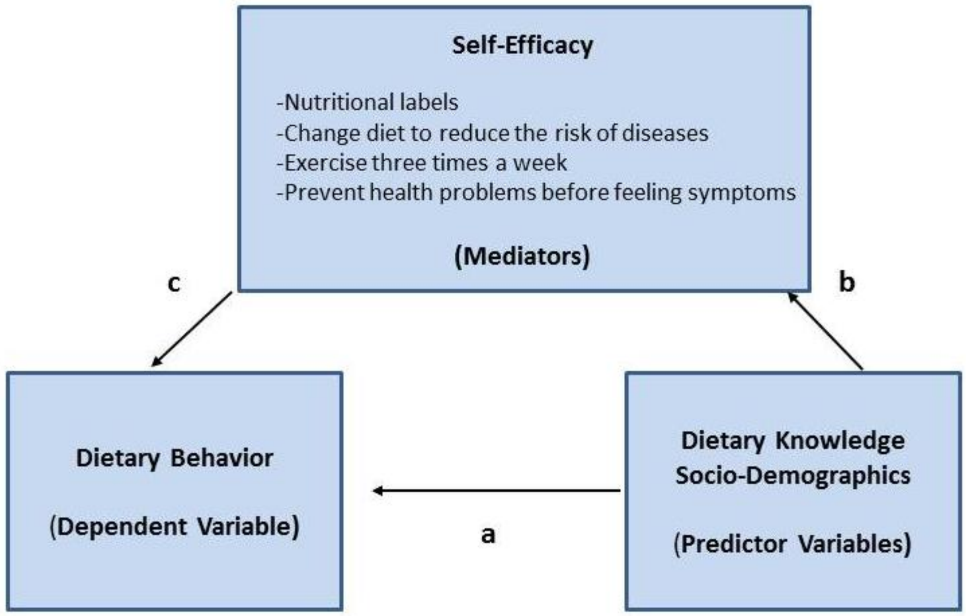

Figure 1. Conceptual model depicting the mediating role of self-efficacy between dietary behavior and predictor variables (adapted from Baron and Kenny, 1986).

Following Baron and Kenny (1986) and Judd and Kenny (1981), a series of regression models were developed to assess whether self-efficacy mediated the link between the predictor variables and dietary behavior:

Model 1: BEHAVIOR = b10 + b11 DIETARY KNOWLEDGE + e

Model 2: BEHAVIOR = b20 + b21 DIETARY KNOWLEDGE +b22 FFICACY + e

Model 3: BEHAVIOR = b30 + b31 DIETARY KNOWLEDGE + b32 FFICACY +b33 AGE + b34 GENDER + b35 INCOME+ b36 EDUC+ b37 RACE+ b38 HOUSEHOLD SIZE + e

Comparing estimated coefficients across Models 1 - 3 allows us to assess whether self-efficacy mediates the effects of the predictor variables on dietary behavior. To illustrate, assume that dietary knowledge exerts a statistically significant influence on behavior in Model 1. If dietary knowledge in the Model 2 has a negligible effect on behavior, it indicates that the effect of dietary knowledge is largely transmitted via the degree of self-control consumers can exercise on their diet and lifestyle. Second, if the effect of self-efficacy in Model 3 differs little from that in Model 2, it suggests that impacts of efficacy on diet behavior remain stable despite the presence of other predictors (socio-economic profile) in the model. The last case is a combination of the previous two: although the effects of efficacy in Model 3 are smaller than those in Model 2, they remain statistically significant. This indicates that the effects of dietary knowledge are partially mediated by efficacy.

The empirical model posits that a participant's dietary behavior is a function of dietary knowledge, self control (efficacy) in changing health behavior with regard to food choices and life-style and various socio-economic characteristics of individuals. We are interested in explaining consumption intensity with regard to fruits, vegetables, and nutrients such as cholesterol and fat rather than number of times someone consumed them in the past. The model, therefore, can be formally written as:

$$Uj = \beta' Zj + \varepsilon j$$

Where Uj is a participant's actual dietary behavior and Zj is a vector of explanatory variables including participant's socio-economic profile. Although Uj is unobserved, what is observed is the expressed intensity of consumption represented by the rank-ordered dependent variables, R, where:

$$R = 0 \text{ if } Uj \leq 0$$
$$R = 1 \text{ if } 0 < Uj \leq \mu 1$$
$$R = 2 \text{ if } \mu 1 < Uj \leq \mu 2$$
$$R = w \text{ if } \mu w\text{-}2 < Uj$$

where the μ's are the threshold variables or cutoff points that provide the ranking of intensity in consuming specific dietary item. The lowest ranked outcome, R=0 represents the situation when a statement (e.g. I eat a lot of) regarding a specific dietary item does not represent a participant at all. Highest ranked outcome, R=w, represents the situation when a statement represents "extremely well."

The dependent variable in the models were measured using ordinal measures (1,2,3, 4 and 5.) Hence, an ordered probit model (Long 1997; Greene 1993) was used to conduct the regression analysis. Value of 1 indicated when a statement regarding a dietary item (e.g. I eat a lot of fresh fruits) did not describe a participant "at all"; value of 2 indicated that it described "slightly"; value of 3 indicated that it described "somewhat"; value of 4 indicated that it described "very well" and value of 5 indicated that it described "extremely well."

The Data

In the summer of 2007, a national survey among United States household was conducted. The survey was administered online by Ipsos-Observer, a private consulting firm specializing in consumer research and public opinion poll on socially important issue including tracking trends in food consumption. This firm maintains an on-line panel that consists of 400,000 households. Approximately stratified by geographic regions, income, education, and age to correspond to the 2000 US census, a sample of 9000 households were drawn out of the online panel in a manner that is representative of the US population. A total of 3,456 households completed the surveys, resulting in a 38.4% response rate. Sample households were sent e-mails soliciting information regarding their food consumption behavior and household characteristics. Each e-mail included a unique URL (keyed to the respondent's ID) to direct the respondent to the survey website. In addition to socio-economic characteristics of sample households, survey instruments included questions relating to three key components in the mediating model: dietary knowledge, dietary behavior and diet related self-efficacy.

Respondents were asked dietary behavior questions about fresh fruits, fresh vegetables, fat and cholesterol (Table 1). They were asked to respond as to how well the statements described their dietary behavior using a scale of one to five where one represented "not at all" and five represented "extremely well." Four statements to measure diet related self-efficacy were read to the participants in the survey (Table 2). The respondents were asked "How likely are you to read nutritional labels on food packages carefully", "How likely are you to change diet to reduce the risk of certain diseases", "How likely are you to exercise at least three times per week" and "How likely are you to prevent health problems before feeling any symptoms" Respondents' reported self-efficacy were recorded on a 5-point scale. All responses were first coded such that the higher values represented high level of self-efficacy. Respondents were asked to respond as to how well the statements described the self-control (efficacy) in changing health behavior with regard to food choices and life-style. The lowest degree of self-control was represented by the response "extremely unlikely" and the highest degree of self control was represented by the response "extremely likely." The percentage of respondents who reported each level of self-control were reported in Table 2. A test was conducted to evaluate the internal consistency of the four statements. The computed test statistic showed that the four statements had a high level of consistency (Cronbach's α = 0.84) in measuring levels of self-efficacy. A composite self-efficacy index was created by summing up the reported scores for each statement and dividing by four. The higher the index value the higher the overall level of self control.

Table 1. Food Consumption Behavior of US households (n=3056).

How well each of the statements describes you?	**I eat a lot of *fresh fruits***	**I eat a lot of *fresh vegetables***	**I am actively trying to consume *less fat* in my diet**	**I am actively trying to consume *less cholesterol* in my diet**
1 = Not at all	5.9%	5.5%	8.1%	12.2%
2 = Slightly	19.8%	17.0%	13.4%	16.1%
3 = Somewhat	33.8%	33.0%	31.8%	31.0%
4 = Very well	25.9%	29.2%	31.8%	26.7%
5 = Extremely well	14.5%	15.2%	14.9%	13.9%

Table 2. Reported level of self-control (Efficacy) in changing health behavior with regard to food choices and life-style (n=3056).

	Percentage of Respondents				
How likely are you to:	**1 = Extremely Unlikely**	**2 = Slightly**	**3 = Somewhat**	**4 = Very much**	**5 = Extremely Likely**
Read nutritional labels on food packages very carefully?	12.5%	19.5%	27.8%	24.6%	15.5%
Change diet to reduce the risk of certain diseases?	23.3%	18.9%	28.9%	20.1%	8.7%
Exercise at least three times per week?	25.9%	20.2%	19.6%	17.3%	16.9%
Prevent health problems before feeling any symptoms	9.0%	17.9%	35.2%	27.5%	10.4%

Note. Cronbach' s consistency test (α) was 0.85

A knowledge of the diet health relationship was measured using an instrument similar to the one used by Moorman and Matulich, (1993), who defined health knowledge as the extent to which consumers have enduring health-related cognitive structures Respondents were asked to link or match each of the eleven nutrients (i.e., sodium, calcium, vitamin A, protein, vitamin C, iron, vitamin D, carbohydrates, saturated fat, potassium, and dietary fiber) with an appropriate health consequence from a list: high blood pressure, strong bones, healthy eyes, amino acids, anticancer power, oxygen, absorb calcium, conversion to sugar and fueling the body, cardiovascular disease, and balancing sodium. An index of dietary knowledge was constructed by adding all correct answers for each respondent. Hence, the index ranges from a minimum of 0 (representing no dietary knowledge) to a maximum of 11 (representing highest dietary knowledge.) The mean dietary knowledge score was 6.09 (Table 3) which means an average respondent could provide six correct matches out of eleven.

Table 3 reports descriptive statistics for other (socio-economic) explanatory variables -including gender, age, household income, education level of the respondent, household size and ethnic background. Over 50% of the respondents were female. The average age of the respondent was 50 years. Household income was reported in income groups represented by numerical values. For example, 1 represented less than $5,000 and 25 represented more than $250,000. In the analysis, mid-points in each income group were used to obtain household income in dollars. The average household income among the sample respondents was $67,377. Average household size was 2.6 members. Nearly three fourths of respondents were white.

Table 3: Description of other explanatory variables used in the analysis.

VARIABLES	DESCRIPTION	Mean	Std. Deviation
Dietary Knowledge	Total number of dietary questions answered correctly (0 to 11).	6.085	3.142
Socio demographics			
Gender	1 = female; 0 = male	0.501	0.500
Age	Respondents' age in years	49.722	14.754
Income	1 = less than $5,000; 25 = $250,000 or more	$67,377	$38,292
Education	1 = college or more than college education; 0= otherwise	0.649	0.477
Household Size	Number of household member	2.612	1.399
Ethnic background	1 if white; 0 otherwise	0.734	0.442

A Pearson correlation matrix including all the independent variables was generated to examin any potential multicollinearity in the regression models. While many coefficients were statistically significant at 0.05 level, the size of the coefficient was very small. The largest coefficient was 0.21. Hence, it was determined that multicollinearity was unlikely in the proposed regression models

.

Results and Implications

Ordered probit models for each of the four dietary behaviors: fresh fruits, fresh vegetables, fat and cholesterol were run and reported in Tables 4 to 7 (see Appendix). For all models the null hypotheses that all parameters were jointly equal to zero were rejected using $\chi 2$ statistics at the 0.01 significance level. Based on the collinearity diagnostics (Belsley et al., 1980), no collinearity problems were detected in the analyses. Marginal effects of the independent variables were also estimated but not reported due to the space consideration. Initially, only knowledge was used as the explanatory variable. Self-efficacy and socio-demographic variables were added in subsequent runs.

The coefficients for the relationship between dietary behavior and knowledge are positive and significant, as one may have expected, in Model 1 of the all four dietary behaviors. This result suggests only that more dietary knowledge translates into more responsible and healthy dietary behavior, but it does not explain or clarify the mechanism or the process which leads more dietary knowledge to transfer into more responsible and healthy dietary behavior. This aspect of the problem is explained in Models 2 and 3.

In Model 2, when the influence of self-efficacy was added, the impact of dietary knowledge decreased but remained statistically significant for vegetables and fat while it became statistically insignificant for fruits and cholesterol. The coefficients measuring the impact of the self-efficacy on dietary behavior are all positive, statistically significant, and much larger in size than the coefficients associated with the knowledge variable. The pseudo R-squared for each of the four dietary items increased by a huge magnitude when self-efficacy was added to the models. All the above results from the regression analysis of Model 2 supported the hypothesized relationships that self-efficacy mediates effects of dietary knowledge and social influences on dietary behavior for each of the four dietary items.

Self-efficacy also accounted for variance in eating behavior not explained by knowledge or demographic variables. However, the effect of self-efficacy on dietary behavior in Model 3, albeit remaining statistically significant, decreased substantially in the cases of both fat and cholesterol. Moreover, the pseudo R-squared in these two regressions decreased when demographic variables were added. While the impact of all demographic variables on the dietary habits in fruit consumption behavior equation is statistically significant, and the impact of all demographic variables but the education is statistically significant in the vegetables consumption behavior equation, the demographic variables had almost no impact on consumption of fat (except age) and cholesterol (except the household size).

The above results indicate that self-efficacy is the most important mechanism in impacting fat and cholesterol consumption, while it is only one of the factors impacting the consumption of both fruits and vegetables. This should come as no surprise: healthy nutrition implies eating more of fruits and vegetables for most people while cutting out the consumption of fat and cholesterol. Consuming more of anything is hardly considered a sacrifice while consuming less of something often demands a great deal of self-control and discipline. The results in this study are consistent with results in other studies which show that dieting, weight control and preventive nutrition can be governed by self-efficacy beliefs. In intervention programs, clients with higher level of self-control were less likely to relapse into their previous habit than those with lower level of self-control (Chambliss and Murray 1979; Furhrmann and Kuhl 1998;

Schnoll and Zimmerman 2001; Long and Stevens. 2004; Luszczynska et al. 2007). Yet there is no clear unique solution as for what the means to inducing dietary self-efficacy may be. For example, some studies suggest that goal setting is the most critical way to induce self-efficacy in dietary behavior (e.g., Robinson 1999; Baldwin and Galciglia 1997). Other studies suggest that goal setting and self-monitoring combined increase the self-efficacy scores significantly (e.g., Schnoll and Zimmerman 2001). Also, other aspects of self-regulation and behavioral training such as problem identification, problem solving, self-evaluation, or reinforcement may be critical in inducing dietary self-efficacy (Hardeman et al. 2000). Hence, interventions and health promotion campaigns should seek to directly address factors influencing diet related self-efficacy instead of focusing on disseminating information only. In practice, for example, we often see healthy foods such as fruits and vegetables being introduced on the menus of school and college cafeterias or in restaurants. The availability of healthy foods coupled with self-efficacy driven by dietary knowledge is likely to lead to an increased consumption of healthy foods. At the same time, most restaurants and cafeterias sell foods rich in fat and cholesterol alongside the healthy foods. Also, while often the consumers are aware of the negative impact fat and cholesterol may have on their health due to numerous educational activities by health and nutrition professionals, the low cost of that food coupled with the sugar enhanced, taste improving additives proves to be irresistible to the average consumer (Miljkovic, Nganje, and de Chastenet 2008). It has been shown that sweetened foods, i.e., an increased consumption of sugar, leads first to sugar addiction and second to carbohydrate addiction and increased consumption of fats (Miljkovic and Nganje 2008). Hence unavailability of unhealthy food or its availability at higher cost due to "fat tax," especially to children and adolescents who develop taste for unhealthy foods at an early age, seems to be a reasonable pro-active approach to influence diet related self-efficacy.

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Appendix

Table 4. Mediation by *efficacy* in the relationship between dietary knowledge and fruit consumption behavior: An Ordered Probit Model

	Model1		Model2		Model3	
Variables	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
ONE	1.399	0.000	0.265	0.000	-0.154	0.142
KNOW	0.028	0.000	0.002	0.706	-0.006	0.317
EFFICACY			0.563	0.000	0.551	0.000
AGE					0.005	0.000
GENDER					0.215	0.000
INCOME					0.001	0.005
EDUCA					0.090	0.036
RACE					-0.125	0.003
HHSIZE					0.043	0.001
Mu(1)	0.914	0.000	1.012	0.000	1.025	0.000
Mu(2)	1.812	0.000	2.006	0.000	2.031	0.000
Mu(3)	2.628	0.000	2.910	0.000	2.945	0.000
Pseudo-R-Squared*	0.01		0.32		0.35	

*$R^2_{ML} = 1 - \exp(-G^2/N)$, where $G^2 = -2 \ln [L(M_\alpha)/L(M_\beta)]$; M_α = restricted likelihood, M_β = Unrestricted Likelihood, and N=Number of observation (Maddala. 1983).

Table 5. Mediation by *efficacy* in the relationship between dietary knowledge and vegetable consumption behavior: An Ordered Probit Model

	Model1		Model2		Model3	
Variables	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
ONE	1.361	0.000	0.171	0.008	-0.415	0.000
KNOW	0.041	0.000	0.016	0.005	0.007	0.286
EFFICACY			0.592	0.000	0.579	0.000
AGE					0.008	0.000
GENDER					0.246	0.000
INCOME					0.002	0.000
EDUCA					0.050	0.243
RACE					-0.115	0.007
HHSIZE					0.041	0.002
Mu(1)	0.853	0.000	0.955	0.000	0.976	0.000
Mu(2)	1.756	0.000	1.962	0.000	2.002	0.000
Mu(3)	2.649	0.000	2.960	0.000	3.016	0.000
Pseudo-R-Squared*	0.03		0.36		0.39	

*$R^2_{ML} = 1 - \exp(-G^2/N)$, where $G^2 = -2 \ln [L(M_\alpha)/L(M_\beta)]$; M_α = restricted likelihood, M_β = Unrestricted Likelihood, and N=Number of observation (Maddala. 1983).

Table 6. Mediation by *efficacy* in the relationship between dietary knowledge and fat consumption behavior: An Ordered Probit Model

	Model1		**Model2**		**Model3**	
Variables	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
ONE	1.087	0.000	-0.617	0.000	0.524	0.000
KNOW	0.055	0.000	0.019	0.002	0.025	0.000
EFFICACY			0.889	0.000	0.128	0.000
AGE					0.006	0.000
GENDER					0.034	0.368
INCOME					0.001	0.125
EDUCA					0.012	0.773
RACE					-0.003	0.942
HHSIZE					0.006	0.656
Mu(1)	0.621	0.000	0.782	0.000	0.607	0.000
Mu(2)	1.507	0.000	1.902	0.000	1.481	0.000
Mu(3)	2.475	0.000	3.120	0.000	2.439	0.000
Pseudo-R-Squared*	0.05		0.60		0.26	

*$R^2_{ML} = 1 – \exp(-G^2/N)$, where $G^2 = -2 \ln [L(M_\alpha)/L(M_\beta)]$; M_α = restricted likelihood, M_β = Unrestricted Likelihood, and N=Number of observation (Maddala. 1983).

Table 7. Mediation by *efficacy* in the relationship between dietary knowledge and cholesterol consumption behavior: An Ordered Probit Model

	Model1		**Model2**		**Model3**	
Variables	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
ONE	0.932	0.000	-0.662	0.000	0.384	0.000
KNOW	0.040	0.000	-0.009	0.147	0.004	0.542
EFFICACY			0.846	0.000	0.333	0.000
AGE					0.002	0.077
GENDER					-0.023	0.556
INCOME					0.000	0.382
EDUCA					-0.012	0.773
RACE					-0.054	0.201
HHSIZE					-0.038	0.004
Mu(1)	0.598	0.000	0.748	0.000	0.590	0.000
Mu(2)	1.413	0.000	1.768	0.000	1.416	0.000
Mu(3)	2.265	0.000	2.839	0.000	2.279	0.000
Pseudo-R-Squared*	0.03		0.60		0.29	

*$R^2_{ML} = 1 – \exp(-G^2/N)$, where $G^2 = -2 \ln [L(M_\alpha)/L(M_\beta)]$; M_α = restricted likelihood, M_β = Unrestricted Likelihood, and N=Number of observation (Maddala. 1983).

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Impacts of School District Characteristics on Farm-to-School Program Participation: The Case for Oklahoma

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Abstract

Farm-to-School (FTS) programs exist in 50 states. However, many FTS efforts have failed due to operating costs, local food availability, and distribution logistics. There is almost no literature examining the factors impacting FTS program implementation and success, although such information could have value to policy makers, school administrators, and producers interested in FTS. More than half of Oklahoma's schools provided information on their child nutrition programs, their means of food procurement, and their experiences with FTS (or lack thereof). This information was used in a logit model to examine the correlations between certain school characteristics and participation in FTS programs.

Keywords: Farm-to-School, locally grown, program adoption, logit model

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Introduction

Farm-to-School (FTS) programs have gained national recognition and policy support since the original 1996-1997 pilot projects were implemented by schools in California and Florida (National FTS Network 2009). In 2000, USDA's Initiative for Future Agricultural and Food Systems supported the establishment of the National FTS Program, serving as a catalyst for program development, research, and policy (USDA-CSREES 2008). The following year, the USDA Agricultural Marketing Service organized numerous FTS workshops nationwide. The 2002 and 2008 Farm Bills each included a section promoting the purchase of locally produced food (USDA-ERS 2008). Institutions receiving funding under the Child Nutrition Act of 1966 are encouraged to purchase unprocessed agricultural products, both locally grown and locally raised, to the maximum extent practicable and appropriate (USDA-ERS 2008). In 2011, according to the National FTS Network (2011), FTS activities included 48 states, involving approximately 9,756 schools and 2,255 school districts.

In terms of policy, practice, and perception, FTS programs connect schools with local farms, allowing school food service directors to purchase produce from local farmers. The program aims to help farmers by promoting the consumption of local produce and expanding market opportunities. At the same time, FTS programs are expected to impact trends in childhood obesity and diabetes by increasing the number of fresh fruits and vegetables in school meals; thus improving child nutrition while decreasing caloric intake.

Challenges to FTS Program Implementation

Numerous issues pertain to FTS, including operation costs, food supply, program adoption, and distribution logistics. Although more than 9,000 schools nationwide participate in FTS programs of some sort (National FTS Network 2011), not all of the FTS programs designed and implemented have been successful. FTS literature exists on program costs and benefits for specific cases and suggestions for implementing FTS programs. However, there is virtually no literature examining the probability of school participation in a FTS program, nor is there literature identifying the characteristics that support successful program implementation at schools. Distribution issues are one of the main barriers to FTS adoption (Berkenkamp 2006; Vogt and Kaiser 2006; and Zajfen 2008), but they alone do not determine the probability of successful FTS implementation at a school.

Despite institutional budget constraints and economic uncertainties, FTS has been adopted nationwide and is continually gaining more recognition. Thus, information regarding program adoption may be useful to food and agricultural policy makers, school food service directors, and producers interested in FTS. The primary objective of this USDA-funded study was to gather information and develop reference materials for those considering implementation of FTS, but not to justify FTS programs or suggest policies for encouraging/supporting FTS programs.

Why FTS?

There are various reasons why producers (farmers) and non-producer stakeholders (school food service directors, communities, parents, children, and warehouses or distributors) participate in FTS. Unlike other school-based programs, FTS closely links food service directors, parents, gardeners, farmers, and community members, giving each group the opportunity to become actively involved in schoolchildren's health and creating a positive outlook towards school food programs. However, while some of the motivations behind FTS participation are shared among producers and non-producer stakeholders, the basic premise behind FTS participation for each group is inherently different.

Research shows that food service directors participate in FTS programs to: support the local economy (Izumi et al. 2006; Oklahoma Food Policy Council, 2003; Vogt and Kaiser 2006), have access to a fresher product (Izumi et al. 2006; Oklahoma Food Policy Council 2003; Vogt and Kaiser 2006), and increase fruit and vegetable consumption among children (Izumi, Wright, and Hamm 2009; Joshi and Azuma 2009). Communities are willing to support FTS programs because they provide fresh food from known sources to consumers (Bellows, Dufour, and Bachmann 2003; Sanger and Zenz 2004). There are also perceptions among consumers that local farms have produce with superior taste and quality when compared to distance-sourced produce (Bellows, Dufour, and Bachmann, 2003). The National FTS Network sprouted from the desire to support community-based food systems, strengthen family farms, and improve student health by reducing childhood obesity (Center for Food and Justice 2009).

For the producers, FTS is an additional market outlet where geographic proximity limits competition. Recent research and interviews with farmers who participate in FTS show that FTS accounts for only a small fraction of business for the farmers, in many cases averaging only 5-10% of sales volume (Joshi and Azuma 2009). However, many farmers express the desire to participate and feel FTS could become a more profitable program in the future. According to a study in Vermont, all farmers involved in the Burlington School Food Project enjoyed the opportunity to educate students about their farms and recognized the potential FTS provided for direct marketing opportunities (Schmidt and Kolodinsky 2006). A study of six California farmers reported profits and quantities related to FTS were too small to contribute to an overall profit margin; nevertheless, the farmers want to nurture the program for its potential direct-marketing benefits (Joshi and Azuma 2009). Like food service directors and communities, the farmers consider FTS a program that is in line with their own values and creates synergy among farmers, school personnel, children, and other community members (Ohmart 2002).

In most instances, small-sized local farms would not be able to competitively market their products directly or "almost directly" to schools without an established FTS program. Small-scale farms have historically been perceived as inefficient since they lack the ability to cut costs with economies of scale (Buitenhuys et al. 1983). In addition, school cafeterias traditionally operate with extremely tight time and budget constraints (Izumi, Wright, and Hamm 2009), with the "big three" items – meat-based entrees, milk, and bread – consuming a majority of the food dollars and fresh produce purchases constituting a small budget percentage. However, political influence from small farmers and advocates for both localism and fresher/healthier foods has penetrated the school food system and localism-related policy incentives provide both small farms and tight-budgeted schools the ability to participate in FTS. Coincidentally, this political activism is similar to the rent-seeking activities foreseen by Orden and Paarlberg (2001), who predicted that process-defined farmers and like-minded consumer activists would try to persuade government to regulate agricultural products according to production processes, which can include localism and efforts to promote minimally processed foods.

Farmers marketing locally-grown foods are able to pursue a formerly untapped market opportunity as a result of these consumer trends and rent-seeking efforts. With government and community support for programs such as FTS, small- and medium-sized farms are able to compete with larger farms despite their inability to take advantage of economies of size. It is imperative to acknowledge that FTS, like many government programs, is not solely based on market-clearing supply and demand and is therefore subject to certain inefficiencies. These inefficiencies reinforce the necessity of examining programs such as FTS and identifying means to become more efficient.

Examining Program Participation – Previous Studies

Although previous studies related to FTS program participation are practically non-existent, a review of existing literature shows that many efforts have been made to quantify both consumer interest in locally-grown foods and the efficiency of school lunch programs. Several of these previous studies have relevance for efforts aimed at successful FTS program induction. The following studies all serve as important guides to identifying the potential for FTS adoption by schools.

Govindasamy et al. (1998) used logistical models to evaluate consumer awareness and willingness to buy local produce. Produce origin was not a statistically significant descriptive variable in their models. Produce quality was considered the most important factor by both consumers who bought and/or who were willing to buy local produce. (Govindasamy et al. 1998).

Maurer (1984) used national data to estimate the effects of meal program characteristics on lunch and breakfast programs. The specific program characteristics were breakfast program availability, open campus policy, à la carte service availability, vending machine availability, number of meal choices, and offered verses served meals. Maurer found students from low-income families were more likely to participate in breakfast and lunch programs than those from high-income families. In addition, students tended to participate in the programs regularly (four or five days a week) or not at all. Results also showed students were slightly more likely to participate in lunch programs at schools with breakfast programs.

Ham, Hiemstra, and Yoon (2002) described an ordinary least squares approach to determine what factors affect school lunch participation. The authors determined that the following independent variables affected participation: lunch price, school enrollment, closed or open campus policies, on-site or satellite food production systems, offered versus served lunch, and percentage of students eligible for free or reduced lunch. Ham, Hiemstra, and Yoon found that price had a large impact on the change in paid-lunch participation.

Gleason (1995) used a probit model to estimate participation rates in the National School Lunch Program (NSLP) and the School Breakfast Program. Gleason found that free and reduced meal certification status of students was strongly related to NSLP participation. The author noted that "more than three-fourths of certified students eat a school lunch on a given day, compared with fewer than half who pay the full price" (Gleason 1995, 215).

Murray (2005) reported descriptive statistics on the characteristics of colleges participating in FTS and found the most frequently cited program barrier was coordinating purchases and delivery of commodities.

Data and Methods

To determine the characteristics that best impact a school's decision to participate in FTS, the Oklahoma Child Nutrition Survey was jointly conducted by the Robert M. Kerr Food and Agricultural Products Center at Oklahoma State University, the Oklahoma Department of Education (ODE), and the Oklahoma Department of Agriculture, Food, and Forestry (ODAFF). The sample frame consisted of food service directors, child nutritionists, superintendents, and other school personnel from Oklahoma school districts. The Oklahoma FTS program identified districts participating in FTS, henceforth referred to as FTS participants and distinguished from non-FTS participants.

The following information was obtained via the created Child Nutrition survey: school district size, current suppliers of fruits and vegetables to the schools, the portion of the schools' food budget allocated for fruits and vegetables, produce preferences, and even distributors utilized by the schools when placing food orders. The state requires school districts each year to pursue bids and enter into contracts with primary foodservice providers, even though auxiliary providers can be used for certain items. Because of the primary provider requirement, the ability of a school to participate in FTS may be impacted by the chosen provider.

A final response rate of 52% was achieved involving 276 school districts. Tables 1-8 provide frequency breakdowns of responses to questions deemed most relevant for the logistic model. Fifty-five percent of responding districts had less than 500 students, which is consistent with the number of small rural school districts in the state, and 36% had between 500 and 2,500 students. A breakdown of the district size and students served can be found in Table 1 (see Appendix A). Breakfast programs were prevalent in almost all responding FTS and non-FTS schools, although the presence of summer feeding programs varied more significantly between FTS (45%) and non-FTS (25%) schools (Table 2). Conversely, the non-FTS schools were more inclined to have closed campus lunch policies for high schools than the FTS schools, 72% to 55%, respectively.

As shown in Table 3, the prevalence of free/reduced meals as a percent of total provided meals was quite high. Seventy-six percent of all districts reported having more than 50% of their total provided meals as free/reduced meals. The percentages varied by school district size, with only the 5,000-10,000 student schools having a majority (67%) of schools with less than 25% free/reduced meals.

Table 2. Breakfast and summer feeding programs and campus policy according to FTS participation

Do your schools participate in breakfast programs? If so, how many students do you serve per day with the breakfast program?[a]

		No breakfast program	Breakfast program
Non-FTS participant	Number	13[b]	231
	Percent	5[b]	95
FTS participant	Number	0	29
	Percent	0	100

Do any of the schools within your district house a summer feeding program?[c]

		No summer feeding program	Summer feeding program
Non-FTS participant	Number	183	62
	Percent	75	25
FTS participant	Number	16	13
	Percent	55	45

Is your school district a closed or an open campus for high-school students during lunch hours?[d]

		Closed campus policy	Open campus policy
Non-FTS participant	Number	171	66
	Percent	72	28
FTS participant	Number	16	13
	Percent	55	45

[a]N=273. [b]Among non-FTS participants, 13 (5%) do not have a breakfast program. [c]N=274. [d]N=266.

Table 3. Free and reduced meals received according to district size

	District size						
Free and reduced meals (%)	< 500	500-1,000	1,000-2,500	2,500-5,000	5,000-10,000	> 10,000	All districts
< 25%	1%[b]	4%	9%	0%	67%	14%	4%[c]
25% to 50%	17%	22%	27%	38%	0%	14%	20%
51% to 75%	48%	54%	56%	46%	33%	43%	50%
> 75%	34%	20%	9%	15%	0%	29%	26%

[a]N=273. [b]One percent of the respondents with district size of 500 students or less reported less than 25% of the students receive free and reduced meals. [c]Across all district sizes, 4% reported less than 25% of the students receive free and reduced meals.

Table 4 provides information on the schools' experiences with FTS programs in the state. Sixteen (6%) had participated in a statewide pilot program several years ago, but did not pursue FTS efforts beyond the pilot program. Twenty-eight (10%) indicated they were active in the current state FTS program, while another 29 (11%) indicated they work with local farmers for at least some small portion of their produce requirements but not within the structure of the state's FTS program. Table 5 (see Appendix B) provides an overview of the more common distributor firms for schools' food items, including fresh produce and frozen/preserved produce items.

Table 4. Type of FTS program participation by responding school districts[a]

	Pilot program	Statewide program	Working with local farmers	None of these
Number	16[b]	28	29	218
Percent	6[b]	10	11	79

[a]N=276 [b]Of the 276 collected responses, 16 respondents (6%) participated in the FTS pilot program.

Weekly produce deliveries were most prevalent among responding school districts, with 77% of non-FTS schools and 82% of FTS school receiving fresh produce on a weekly basis (Table 6). The second most-used delivery schedule for produce was twice-per-week, at 14% and 18% for non-FTS and FTS schools, respectively. Regardless of the regularity of deliveries, fresh produce represented less than 15% of total food budgets for 89% of non-FTS schools and 79% of FTS schools, and most of those produce purchases were for precut and bagged items (Table 7).

Overall, the schools believed that FTS programs benefited a broad range of stakeholders (Table 8). A larger percentage of respondents felt that farmers benefited from the program (84%) compared to students (81%), schools (74%), or the community (62%). By far, the responding schools viewed delivery scheduling as the greatest barrier to FTS program success (54%), much more so than availability of produce (13%), seasonality of production (12%), or even costs (9%).

Table 6. Produce delivery frequency according to FTS participation[a]

		Once a month	Twice a month	Once a week	Twice a week
Non-FTS participant	Number	8[b]	12	178	33
	Percent	3[b]	5	77	14
FTS participant	Number	0	0	23	5
	Percent	0	0	82	18

[a]N=259 [b]Among non-FTS participants, 8 (3%) have produce delivered once a month.

Table 7. Fresh produce expenditure and percentage of fruits and vegetables precut and bagged

Percentage of food budget spent on fresh produce[a]

		Percentage				
		<5%	5% to 15%	16% to 25%	26% to 50%	>50%
Non-FTS participant	Number	85[b]	125	6	7	14
	Percent	36[b]	53	3	3	6
FTS participant	Number	7	15	0	2	4
	Percent	25	54	0	7	14

Percentage of precut and bagged fruits and vegetables received

		Percentage				
		10%	25%	50%	75%	100%
Non-FTS participant	Number	85	62	44	28	4
	Percent	38	28	20	13	2
FTS participant	Number	7	12	2	7	0
	Percent	25	43	7	25	0

[a]N=265
[b]Among non-FTS participants, 85 (36%) allocate less than 5% of their food budget to produce.
[c]N=251

Table 8. Perceived beneficiaries of and barriers to FTS

"In your opinion, who benefits from Farm-to-School? Please check all that apply."[a]

	Schools	Students	Farmers	Community	Other
Number	135[b]	148	152	112	5
Percent	74[b]	81	84	62	3

"What do you feel is the greatest barrier to a successful Farm-to-School program within your district?"[c]

	Costs	Delivery	Seasonality	Health concerns	Availability of products	Other
Number	18	107	24	13	25	12
Percent	9	54	12	7	13	6

[a]N=182 [b]135 respondents (74%) stated schools benefit from FTS. [c]N=199

Logistic and probit models are often used for estimating dichotomous variables; however, the logit is easier to compute and provides odds ratios useful for interpretation of coefficients. The utility function of the school districts when choosing whether or not to participate in FTS is

a random utility function, which is shown in equation 1,

$$(1) \qquad U_{ij} = V_{ij} + \varepsilon_{ij}$$

where j represents the districts and i is the choice option of participating (FTS) or not participating (NFTS) in the program. U_{ij} is the district's utility defined by a deterministic (V_{ij}) and a stochastic (ε_{ij}) component. Assuming V_{ij} is linear in parameters, the utility function may be expressed as equation 2,

$$(2) \qquad V_{ij} = \beta_0 + \sum_{k=1}^{6} \beta_k X_{kij}$$

X_{kij} represents characteristic k (k=1,…, 6) of the j^{th} district for the i^{th} choice option. β_k is the coefficient associated with X_{kij}. The district utility is not observable but the choice to participate or not to participate in FTS is observable. A district chooses to participate in the program when the utility of participating is greater than the utility of not participating; thus, the probability for a district to participate in FTS program can be described by equation 3, assuming the distribution of the error terms (stochastic component) is independent and identical:

$$(3) \qquad \text{Prob } (FTS) = P(U_{FTSj} > U_{NFTSj})$$

A binary logistic model could be used to fit the regression, as show in equations 4 and 5, with NFTS as the reference category where the parameter estimates are normalized to zero and P_j denoting the probability that the j^{th} district chooses to participate in FTS. The probability for a district to participate in FTS program can be expressed in equation 4:

$$(4) \qquad P_j(FTS) = \frac{exp(\beta_k X_{kj})}{1 + exp(\beta_k X_{kj})}$$

where X_{kj} is a particular explanatory variable for district characteristic k and β_k is the coefficient associated with X_{kj}. The empirical model used for the analysis is seen in equations 5:

$$(5) \qquad P_j(FTS) \quad = \beta_0 + \sum_{k=1}^{K} \beta_k X_{kij}$$

Detailed definitions of all independent variables are provided in Table 9 (see Appendix C). Equation 6 represents the deterministic portion of the utility function, which is expressed as the sum product of the parameters of the independent variables listed,

$$\text{(6)}\quad P_j(FTS) = \beta_0 + \beta_1 SIZE_j + \beta_2 SUMMERP_j + \beta_3 REDUCED_j + \beta_4 CMPSPOLICY_j + \beta_5 DELFREQ_j + \beta_6 PROCESSED_j + \beta_7 DISTRIBUTOR_j + \beta_8 BUDGET_j$$

The explanatory variables include district size (SIZE), the percentage of free and reduced meals received by the student population (REDUCED), district participation in summer feeding programs (SUMMERP), campus policy during lunch period (CMPSPOLICY), commonly used produce vendors (DISTRIBUTOR), delivery frequency of produce (DELFREQ), percentage of the school's fresh produce purchases that are pre-cut and bagged (PROCESSED), and the share of a school nutrition budget utilized for produce purchases (BUDGET). Descriptions and summary statistics for these explanatory variables are provided in Table 9 (see Appendix C).

Breakfast program participation and a class variable for the school's choice of primary food distributor were originally included in the model, but were removed to avoid multicollinearity. Breakfast program participation is a continuous variable closely correlated to district size, i.e. participation in breakfast programs increased as district size increased. Primary distributor choice closely correlates to chosen produce distributors because of an Oklahoma requirement for each school to contract with a primary distributor that provides a majority of the school's food items, so often the distributors that provided other food items also provided fresh produce.

Using SAS® and maximum likelihood estimation (Allison 1999), the logistic model predicted the probability of schools participating in FTS. Because interpretation of the coefficients in logistic models are not intuitive, alternative means of understanding coefficients are used. The marginal effect is estimated using equation 7,

$$\text{(7)}\qquad \frac{\partial P_j}{\partial X_{kj}} = \frac{exp(\beta_k X_{kj})}{\left[1 + exp(\beta_k X_{kj})\right]^2}\beta_k$$

Applying this equation, if the base or reference equation contains X_{kj} values equal to their means, then the change in probability can be observed for an incremental unit change or 1% increase in X_{kj}. Marginal effects are used to measure changes in probability of participation in the FTS program due to given changes in the independent or explanatory variables.

A restricted model using only SIZE, CMPSPOLICY, DELFREQ, DISTRIBUTOR, and BUDGET as explanatory variables was also developed. Log likelihood ratio tests indicated that the unrestricted model did not fit the data significantly better than the restricted model. However, results from both models are included.

Model Results and Implications

Table 10 lists the independent variables from the unrestricted model along with their marginal probabilities. Of the eight listed variables, only five were statistically significant at the 10% level or higher and therefore included in the restricted model. Marginal probabilities for the restricted model are shown in Table 11.

Table 10. Results of the unrestricted FTS participation logit model

Item	Estimate	Standard Error	Change in probability
Intercept	-3.0179	1.3123	--
SIZE***	0.0004	0.0001	0.0024%
REDUCED	-0.0181	0.0161	-0.1121%
SUMMERP	-0.0760	0.6148	-0.4706%
CMPSPOLICY*	0.9062	0.5243	5.6117%
DELFREQ*	0.2496	0.1430	1.5457%
PROCESSED	-0.0074	0.0113	-0.0459%
DISTRIBUTOR**	-1.7854	0.8083	-11.0561%
BUDGET***	3.5007	1.3849	21.6782%

***, **, and * indicates significance at the 1%, 5%, and 10% levels, respectively.

Table 11. Results of the restricted FTS participation logit model

Variables	Estimate	Standard Error	Change in probability
Intercept	-4.3583	0.8462	--
SIZE***	0.0004	0.0001	0.0029%
CMPSPOLICY*	0.9008	0.5073	5.9067%
DELFREQ *	0.2298	0.1389	1.5068%
DISTRIBUTOR**	-1.7478	0.8032	-11.4607%
BUDGET***	3.5140	1.3117	23.0421%

***, **, and * indicates significance at the 1%, 5%, and 10% levels, respectively.

According to the logistic model, district size, campus policy, delivery frequency of produce, produce distributor used, and the percentage of the budget allocated to produce purchases were all correlated to FTS participation. All variables, with the exception of the contracted produce distributor, had a positive association with FTS participation.

Statistics suggest a positive relationship between the probability of FTS participation and a district's student population, indicating that larger school districts may be more inclined to initiate a FTS purchasing regimen. This unearths a more dynamic aspect of FTS. The program can only exist if there are willing consumers and suppliers. Both the schools' and the farmers' needs must be met in order for a FTS program to be successful and sustainable. According to interviews with a few farmers participating in FTS, it is more convenient and profitable to supply higher volumes of produce to schools with large orders (i.e. larger school districts) as opposed to delivering smaller quantities to numerous schools. By doing so, the farmer minimizes transportation costs and time spent on coordinating orders.

The proportion of a district's cafeteria budget also significantly affected the probability of FTS adoption. With increasing amounts of a food budget allocated to purchasing produce, FTS participation became more likely among districts. Given the percentage of a budget was on a scale with equidistant values, the likelihood of FTS participation within a district increased by 23% when increasing the proportion of money allocated to fruits and vegetables by one level. Similarly, delivery frequency, a categorical variable, had a positive influence on FTS adoption.

The remaining variables in the restricted model were dichotomous. School districts with an open campus policy were six percent more likely to participate in FTS than districts with a closed campus policy. This can be explained by market competition. Cafeteria food must appeal to students to compete with other restaurants and food chains if a school has an open campus policy. Advertising locally grown, fresh fruits and vegetables on salad bars is one way some schools chose to market their cafeteria food.

Districts that use smaller, local/in-state distributors were more likely to foster FTS programs than those that contracted with larger regional/national distributors. Findings from a follow-up survey of food distributor representatives suggest that this may in part be due to the challenge of large distributors to economically justify reserving valuable warehouse space for small volumes of seasonally-limited local produce purchased by a small percentage of their clients. Many larger distributors expressed interest in participating in FTS programs, and some have worked with the state FTS program. However, coordinating procurement from several small, independent farmers with the ordering schedules of schools can be cumbersome. Representatives also stated that the verification and delivery of locally-grown FTS produce to schools was more costly to the distributor, unless the order was a large one for a district of substantial size. Conversely, smaller distributors may be more likely to work with local farmers to coordinate procurement and distribution of smaller produce quantities while using the “local” marketing angle to differentiate their products and services from those of their larger competitors.

Conclusions

States with strong local food initiatives may have the potential for adoption of FTS programs, if school district and state policies – as well as logistics – result in satisfactory farmer-school transactions. Identifying the school district characteristics associated with participation may help food service directors and farmers target their FTS programs towards school districts more likely to adopt and succeed with FTS programs.

Using a logit procedure, a binary choice model was specified to represent the dichotomous decision to participate in FTS. The probability of FTS participation by Oklahoma schools was significantly impacted by factors such as district size, frequency of produce deliveries, the type of food distributors used by the schools, and the share of school food budgets allocated to fruits and vegetables. Marginal effects were calculated to measure the effects of changes in the explanatory variables on the probability of FTS participation.

Overall, the results indicate that larger school districts with open campus policies, using smaller/dispersed food distributors (as opposed to large, regional distributors), and the preferences/ability for more frequent food deliveries by schools are indicative of schools inclined to participate in FTS programs. Schools with larger budget shares set aside for produce have more options for purchasing fresh fruits and vegetables and are more likely to participate in FTS.

Because food distributors play a large role in FTS participation, this information might be useful to farmers considering FTS participation, since local schools may prefer to have produce deliveries coordinated through third-party distributors so that all food deliveries occur at a specified time.

Future research might benefit from identifying factors other than characteristics of districts, such as the availability of FTS program information to the school's nutrition program director and the influence of stakeholders and/or the state FTS program organizer. For example, all of the school personnel from districts currently participating in Oklahoma's FTS program have had close contact with the very charismatic Oklahoma FTS coordinator. Furthermore, it might be useful to observe the opinions of food service and school personnel towards local food initiatives, or even determine willingness-to-pay for a FTS program.

This study provides a unique insight into a state FTS program and the willingness of schools to participate in the program. Viability of the program is not solely contingent on the willingness of schools, but that of the farmers and even distributors involved in the food marketing chain. Applying the methods of this study to FTS programs in other states may assist the National FTS Network in achieving more targeted and more successful FTS programs.

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Appendix A.

Table 1. District size and number of students served according to district size

	District size[a]					
	< 500	500-1,000	1,000-2,500	2,500-5,000	5,000-10,000	> 10,000
Number	153[b]	54	45	13	3	8
Percent	55[b]	20	16	5	1	3
	Range of number of students served[c]					
	< 500	500-1,000	1,000-2,500	2,500-5,000	5,000-10,000	> 10,000
Number	179	50	27	7	4	6
Percent	66	18	10	3	1	2

[a]N=276 [b]153 respondents (55%) reported a school district of 500 students or less. [c]N=273

Appendix B.

Table 5. Distributors for fresh produce and all items

From what distributor(s) does your school district receive food items including any form of fruits and vegetables?[a] *	
Small distributors	22%[b]
U.S. Foods*	15%
Sysco*	11%
Grocery Stores	11%
Tankersley Food Company	6%
Tom E. Boggs	6%
Mid-America*	5%
Performance Food Group*	5%
Ben E. Keith*	5%
Vinyards	3%
Buddy's Produce	3%
Tulsa Fruits & Produce	3%
Southwest Food Service*	2%
Thomas Brothers-Tulsa	1%
Okie Produce	1%
Frontier Produce	1%
Thomas Brothers-OKC	0%
Regarding the list below, which distributor(s) provide(s) fresh fruits and vegetables (i.e.: whole produce, cut, or bagged)?[c]	
Small distributors	18%
U.S. Foods*	13%
Sysco*	12%
Grocery Stores	11%
Tankersley Food Company	9%
Ben E. Keith*	6%
Tom E. Boggs	5%
Mid-America*	4%
Vinyards	4%
Performance Food Group*	4%
Buddy's Produce	4%
Tulsa Fruits & Produce	4%
Southwest Food Service*	2%
Thomas Brothers-Tulsa	2%
Okie Produce	1%
Frontier Produce	1%
Thomas Brothers-OKC	0%

[a]N=261
[b]N=Across all districts, 22% buy all food items from small distributors.
[c]N=257
*National or "large" regional (more than 4 states) distributor

Appendix C.

Table 9. Description of variables used in the FTS logit model

Variable	Description	Mean	Standard Deviation	Min	Max
SIZE	District size (continuous variable ranging from 0-40,000 students)	1396.6800	4184.1600	44.0000	41195.0000
REDUCED	Student population receiving free and reduced meals (continuous variable ranging from 0-100%)	63.1721	18.3875	9.8300	100.0000
SUMMERP	Existing summer feeding program (yes = 1, no = 0)	0.2737	0.4467	0.0000	1.0000
CMPSPOLICY	Campus policy during lunch hours (open = 1, closed = 0)	0.2970	0.4578	0.0000	1.0000
DELFREQ	Frequency of produce delivery (1 = once a month, 2 = twice a month, 4 = once a week, 8 = twice a week)	4.4015	1.6309	1.0000	8.0000
PROCESSED	Amount of produce received pre-cut and bagged (continuous variable ranging from 10-100%)	32.2510	24.1870	10.0000	100.0000
DISTIBUTOR	Distributor used for produce (less common, small distributor and grocery store = 0, commonly used, large distributor = 1)	0.2879	0.4537	0.0000	1.0000
BUDGET	Amount of cafeteria food budget allocated to fresh produce (continuous variable ranging from 0 to 70%)	0.1121	0.1438	0.0029	0.6667

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Examining the Effectiveness of Nutrition Information in a Simulated Shopping Environment

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Abstract

We conduct an experiment with grocery store shoppers using an onsite survey to examine the effectiveness of nutrition labels provided on grocery store shelves. We measure effectiveness of the nutrition labels in terms of how well the labels attract attention and if they affect shopper behavior. Based on our sample, we find that shelf label nutrition information not only attracts shopper attention but affects shopper behavior as well. Further, we find the effect is moderated by a shopper's propensity to use nutrition information. Our results suggest providing nutrition information via grocery store shelf labels may be a useful medium to convey nutrition information to shoppers. Additionally, increasing interest in nutrition information and the ability to use the information can have important implications.

Keywords: nutrition labels, grocery stores, experiment

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Introduction

Due to the current obesity epidemic in the US and abroad, there is growing interest in helping consumers make healthier choices. Although manufacturers in the US are already required by the Nutrition Labeling and Education Act of 1990 to provide nutrition facts panels on almost all processed food products, other methods of providing nutrition information are being developed by manufacturers and retailers. One method that is becoming prevalent with retailers across the US is grocery store chains offering their own nutrition information on their store shelves along with price and unit price information using proprietary labels and rating methods[1]. In general, these labels offer a reduced summary of information that is provided on nutrition facts panels often using a scoring metric such as a hundred-point-system or a star rating.

These grocery store nutrition labels not only enhance the image of the retailer, but they may also benefit consumers by helping to direct them to healthier choices; especially if the information is accurate, easy to access and easy to comprehend for consumers. Berning et al (2010) demonstrate positive consumer preferences for this type of grocery store nutrition labels provided by grocery stores in the US. Similarly, Balcombe, Fraser and Di Falco (2010) find support for the traffic light system used in the United Kingdom which identifies nutritional quality on product packages using a traffic light symbol.

For this study, we create our own grocery store shelf label based on a common template and include a section to provide nutrition claims. We present these labels to shoppers using quasi-experimental methods to examine the effectiveness of shelf label nutrition information. We measure the effectiveness of shelf label nutrition information using two criteria: 1. if it attracts attention; 2. if it affects behavior. Accounting for individual differences, we find that prominent nutrition labels are effective at attracting attention and this effect is enhanced by a prominent unit price label. Alternatively, less prominent nutrition labels are no different at attracting attention than providing no nutrition label at all. In terms of effectiveness, this emphasizes the importance of providing visible information to shoppers.

We further find that shoppers provided with shelf label nutrition information select a greater share of healthy products than shoppers who are not provided with nutrition information. Not surprisingly, this effect is moderated by a shopper's consciousness of nutrition label information.

As more grocery store chains offer nutrition information to consumers on their shelf space it is important to understand the impact of such marketing information on consumer behavior. This study provides evidence that this type of information can be used to both attract consumer attention and influence the products they select. However, the display of the information is an important consideration. Increasing shoppers' interest in nutrition information and their ability to use the information can have important implications as well. Policymakers interested in dealing with the obesity epidemic may want to become more involved with how retailers and manufacturers provide their own proprietary nutrition information.

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[1] An example is the Nuval nutrition scoring system which is being used by retail grocery stores across the country.

Motivation

A significant amount of research suggests that simpler forms of nutrition information may be more beneficial to shoppers than complex forms, such as nutrition facts panels. Levy and Fein (1998) find that nutrition labels that require calculations do not appear to be helpful to consumers and Viswanathan (1994) points to the importance of summary information in facilitating the usage of nutrition information and that verbal presentation of nutrition information lead to a greater degree of usage than numerical. Additionally, Verbeke (2005) finds that nutrition information is likely to be effective when it addresses specific informational needs and can be processed and used by its target audience. Consequently, proprietary nutrition labels provided by grocery stores which provide simpler forms of nutrition information may be beneficial to consumers. In particular, Feunkes et al. (2008) suggest that simple labels may be more useful in quick decision environments as consumers need less time to evaluate simpler, front-of-pack labels versus more complex labels. With a large number of goods, side-by-side comparison of many complicated nutrition labels may be overwhelming for shoppers. In a review of research of consumer understanding of nutrition labels, Cowburn and Stockley (2005) suggest that improvements in nutrition labeling, in particular non-numerical interpretational aids like verbal descriptions, could contribute to making the point-of-purchase environment more conduce to selection of healthy choices.

In the United Kingdom a voluntary traffic light system (TLS) has been added to the front of food product packages to help consumers make healthier choices. Food products with TLS labels indicate whether the food has high, medium or low amounts of fat, saturated fat, sugars and salt. A recent study finds that consumers were more likely to identify healthier foods using the TLS (Kelly et al. 2009). Balcombe, Fraser and Di Falco (2010) find that shoppers understand the TLS label system and appear to use the TLS to avoid “red light” foods, which are foods of poorer nutritional quality.

Given the growing interest and potential benefit from providing nutrition information to consumers in alternative formats, nutrition information provided by grocery stores may provide an effective method for providing shoppers with nutrition information. Such proprietary store labels have already emerged in several grocery store chains displayed alongside grocery store shelf labels. Shelf labels are located at the point of purchase on the shelf label and require little additional effort by consumers to acquire. Shelf labels already provide price and unit price information and may also be used to provide nutrition information in a manner that is easier for shoppers to process than traditional nutrition facts panels.

An important question to be answered is how effective are nutrition labels provided by grocery stores. There are many approaches that can be taken to examine the effectiveness of product labels. In their meta-analysis of warning labels literature, Argo and Main (2004) identify five dimensions of warning label effectiveness that represent a sequential processing of information: attention, reading and comprehension, recall, judgments and behavioral compliance. While all five dimensions are also relevant to understanding how shoppers might process nutrition information, we focus on the first and last steps in the sequential process: how well nutrition labels attract attention and how effective shelf label nutrition information is at affecting behavior.

Attention broadly encompasses measures of noticeability, awareness, attention and recognition. Specifically, attention can be defined "as the selection or prioritization for processing of certain categories of information" (Wells and Matthews 1994). In a grocery store with a large number of items and an extensive amount of product information, nutrition labels that are effective must appear as enough of a priority to warrant a shopper to allocate time to processing the label. Conversely, if a label is not noticeable, then clearly the label will not be effective.

There are several factors that appear to influence how well labels attract attention. Not surprisingly, the vividness of the display of the label plays a role in how well it attracts attention. Young and Wogalter (1990) note that vividness-enhancing characteristics such as font size, color, spacing, level of specificity, and symbols improve comprehension and recall of verbal warning messages and better identify semantic meanings. Adams and Edworthy (1995) find text size having the greatest effect on perceived urgency of warning labels, followed by border width. As such, we expect that shelf labels that are bold and vivid will be more effective in terms of attracting attention.

While attracting attention is an important consideration for advertising nutritional quality, more relevant to grocery stores and policy makers is the effect of shelf label nutrition information on shopper behavior, i.e. behavioral compliance. Nutrition labels act as an informative advertising by identifying qualitative attributes that shoppers cannot identify by themselves.[2] If superior nutritional content is viewed as a vertically differentiating characteristic (i.e. healthy food is better than unhealthy food), then, ceteris paribus, healthy items will be preferred by shoppers. As such, we might expect nutrition labels identifying such characteristics to complement or enhance the image of healthy items, making those healthy items more desirable for purchase. Based on the assumption that healthy foods are viewed as better than unhealthy, we hypothesize that shoppers who are presented shelf label nutrition information will select a larger share of healthier items than shoppers who are not.

Experimental Approach

We surveyed 1200 shoppers at three store locations of the same grocery chain in the East Bay, California area. The 3 stores are located in areas with high, medium and low median incomes. Survey participants were given a set of instructions with a survey and were compensated with a $10 store gift card upon completion of the survey.

In the instructions, each participant is given a hypothetical shopping list comprised of four products: salad dressing, mayonnaise-type products (this includes Miracle Whip brand products), microwave popcorn and peanut butter. Participants were shown the same pictures of 12 different types of each product as they might appear on an actual grocery store shelf. They were asked to select products from each product category as if they were actually shopping for the products. Further, they could select multiple brands and quantities in each product group, but were asked

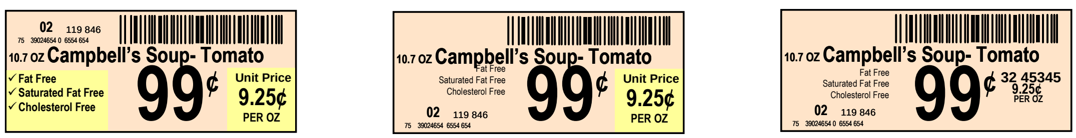
[2] In theory, shoppers can identify nutritional content by themselves. However, the process would be prohibitively expensive for most consumers.

to select at least one item from each product group.[3] If participants didn't see a product they would normally buy, or would not normally buy the product, they were asked to assume that they were shopping for a house guest or friend who wanted the product.

The products were selected to appeal to a large number of shoppers; that is, shoppers generally have some experience purchasing some of these items. These items also vary in nutritional content within each product category.

Treatments

Shelf labels were presented below each product item. On each label, we varied the presentation of unit price (two levels) and nutrition information (three levels) for a total of six different shelf label treatments (Figure 1). The unit price and nutrition information were displayed as either low prominence or high prominence where prominence refers to the display information in term of font, text size, and text highlighting. The nutrition labels also had a treatment of not present. The prices and unit prices did not vary across treatments as the primary interest was the effect of labels rather than prices. The six different surveys were randomly distributed to the survey participants.



High prominence nutrition label and high prominence unit price label	Low prominence nutrition label and high prominence unit price label	Low prominence nutrition label and low prominence unit price label

Figure 1. Shelf Label Treatment Examples

The nutrition information provided on the labels is based on USDA standards for nutrition claims. The USDA (2004) has standards for claims regarding six nutritional items: calories, fat, saturated fat, cholesterol, sodium and sugar. An example of a nutritional claim is *low fat* or *cholesterol free*.

Survey Participant Characteristics

We gathered demographic information from the survey participants (Table 1 provides a description of the sample population). In addition to identifying age, gender, household size, education and income, we developed some other measures as well. The household shopping

[3] Some surveys appeared to be completed without a firm understanding of the survey. For example, some respondents, for unknown reasons, selected every possible item for all four product categories. To systematically remove outliers we deleted any survey in which the participant select more than $20 per person for any item. We also tried removing surveys using a limit of $10 per person which caused little change in the results.

performed is a self-reported measure of how much of household shopping the survey participant is responsible for. In addition, participants were asked to answer nine, seven-point Likert scale questions regarding their nutrition consciousness (Figure 2). Composite scores for each individual's nutrition consciousness were created which are intended to represent self-reported level of nutrition consciousness; the Cronbach alpha- score was $\alpha = .92$. The nutrition consciousness score is a continuous variable in the range of 9 and 63. We also scored participants price label consciousness using five, seven-point Likert scale questions (Figure 3**,** $\alpha = .92$). The price consciousness score is a continuous variable in the range of 5 and 35. Finally, participants were scored on three, seven-point questions regarding their use of nutrition information (Figure 4, $\alpha = .93$). These three questions were used to create a composite measure of the shopper's consciousness of nutrition information. The nutrition label consciousness score is a continuous variable in the range of 3 and 21.

Table 1. Demographic Characteristics of Survey Respondents

Demographic	**Mean**	**Standard Deviation**	
age (years)	41.4	17.1	
gender (female)	65.3%	--	
household size	3.5	1.8	
household shopping performed	66.3%	31.2%	
nutrition consciousness score	43.5	13.8	
Level of Education	**Percentage**	**Level of Education**	**Percentage**
grade school	3.3%	2-year associate degree	9.6%
some high school	8.4%	4-year bachelor degree	14.8%
graduated from high school	21.2%	some graduate school	5.2%
some college	26.9%	graduate degree	10.6%
Annual Household Income (gross)	**Percentage**	**Annual Household Income (gross)**	**Percentage**
$0-5,000	5.1%	$50,001-60,000	8.6%
$5,001-10,000	4.6%	$61,001-70,000	7.6%
$10,001-15000	4.0%	$70,001-80,000	7.6%
$15,001-20,000	3.5%	$80,001-90,000	6.4%
$20,001-25,000	5.7%	$90,001-100,000	4.2%
$25,001-30,000	6.1%	$100,001-111,000	5.4%
$30,001-40,000	8.7%	$110,001-120,000	2.5%
$40,001-50,000	11.4%	over $120,000	8.7%

1. My diet is nutritionally balanced.
2. I try to monitor the number of calories I consume daily.
3. I try to consume a healthy amount of calories each day.
4. I try to avoid high levels of fat in my diet.
5. I try to avoid high levels of saturated fat in my diet.
6. I try to avoid high levels of cholesterol in my diet.
7. I try to avoid high levels of sodium in my diet.
8. I try to avoid high levels of sugar in my diet.
9. I am interested in nutritional information about the food I eat.

Figure 2. Survey Questions used to Calculate Nutrition Consciousness Scores

1. I am not willing to go to extra effort to find lower prices..
2. I will grocery shop at more than one store to take advantage of low prices..
3. The money saved by finding low prices is usually not worth the time and effort.
4. I would never shop at more than one store to find low prices.
5. The time it takes to find low prices is usually not worth the effort..

Figure 3. Survey Questions used to Calculate Nutrition Consciousness Scores

1. In general, how often do you read the NUTRITION FACTS panel that reports nutrient information on food products?
2. In general, how interested are you in reading nutrition and health-related information?
3. I really care about reading nutrition information and nutrition labels..

Figure 4. Survey Questions used to Calculate Nutrition Consciousness Scores

Attention Effect: Analysis and Results

After performing the shopping survey shoppers are asked to rate how noticeable the nutrition information was using a seven point scale anchored by *not noticeable* (score of 0) and *very noticeable* (score of 7). To test how noticeable the nutrition information was for each individual *i* across treatment groups, we estimate the value of the scale as a function of the treatment variables using an ordered probit with robust standard errors:

$$(1) \qquad score_i = \alpha_0 + \alpha_{unit} \cdot D_{unit} + \alpha_{low} \cdot D_{low} + \alpha_{high} \cdot D_{high} + \mu_i ,$$

where each D is a dummy variable for each treatment, α are parameters to be estimated and μ is an error term. We also examine the interaction of the treatment effects and include several demographic variables (Z) with conformable matrix β specified as:

$$score_i = \alpha_0 + \alpha_{unit} \cdot D_{unit} + \alpha_{low} \cdot D_{low} + \alpha_{high} \cdot D_{high} + \alpha_{unit*low} \cdot D_{unit} \cdot D_{low} + \alpha_{unit*high} \cdot D_{unit} \cdot D_{high} + \beta \cdot Z_i + \mu_i \quad (2)$$

The estimate of the primary treatment effect (Table 2, column 1) shows that the high prominence nutrition label has a significant impact at a 10 percent level on whether or not the nutrition information was noticeable (0.15). The low prominence nutrition label had no significant effect. This demonstrates that the high prominence nutrition label had an effect on how noticeable the nutrition information appeared.

The interaction of the high prominence nutrition information and high prominence unit price information (Table 2, column 2) is larger and significant at the 5 percent level. Again, the low prominence nutrition information is not significant. Interacting the nutrition information and unit price treatment values reveals how both types of information complement each other in terms of attracting attention.

Table 2. The Effect of Nutrition Label Treatments on Attention

DV= score of noticeable nutrition information			
Variable			
Low prominence nutrition	-0.0144	-0.141	-0.202
label treatment	-0.0868	-0.123	-0.147
High prominence nutrition	0.150*	-0.0508	-0.0455
label treatment	-0.0874	-0.124	-0.143
unit price treatment	-0.0402	-0.256**	-0.240*
	-0.0702	-0.127	-0.135
Low prominence nutrition label	--	0.245	0.312
treatment X unit price treatment		-0.174	-0.207
High prominence nutrition label	--	0.401**	0.379**
treatment X unit price treatment		-0.175	-0.19
Age	--	--	0.00579**
			-0.00248
Gender (female = 1)	--	--	0.0112
			-0.0801
Household size	--	--	0.0254
			-0.0255
Education	--	--	-0.036
			-0.0235
Nutrition label consciousness score	--	--	0.0301***
			-0.00873
Price consciousness score	--	--	-0.0139**
			-0.00552
Nutrition consciousness score	--	--	0.0132***
			-0.00371
Observations	882	882	794

Robust standard error below estimates
***p<0.01, **p<0.05, *p<0.1

Finally, we add several covariates to our model. This includes not only demographic variables, but dummy variables to capture differences in treatment locations (three locations) and days of the survey (three days). With these covariates included, the interaction of high prominence nutrition information and high prominence unit price information is still significant. This suggests that the high prominence nutrition information has a significant impact in different locations and as the survey took place over time. We also find that older shoppers, those that identify themselves as being nutritionally conscious (*nutrition consciousness score*) and conscious of nutrition information (*nutrition label consciousness score)* tend to have a higher rating of how noticeable the nutrition information was. Alternatively, those that are more price conscious (*price consciousness score*) have a lower attention score for the nutrition labels.

Overall, these initial results emphasize the importance of display in providing nutrition label information to shoppers. The more prominent the nutrition information, the more likely that they will attract shopper attention. Further, the results demonstrates how the display of certain types of information can complement one another. Specifically, prominent unit price information and high prominence nutrition information tend to stand out the most.

Behavioral Compliance: Analysis and Results

Given that that we find varying levels of attention due to our shelf label treatments, we next examine if the labels have any effect on behavior. A common metric used in examining micro-level changes in food demand is expenditure share, where expenditure share represents the percentage of total expenditures allocated to a given product. We examine the effect of shelf label nutrition information on behavioral compliance in terms of the expenditure share of healthy items purchased. Defining each of the products in the survey as x_j, we categorized each product as healthy (x_h) or unhealthy (x_i), where $h,i \in j$. Dropping individual subscript, we calculate the expenditure share for healthy items as: $\sum(x_h \cdot p_h) \big/ \sum(x_j \cdot p_j)$ where *p* is the price paid for each item. An increase in expenditure share represents a move toward healthier product choices; a decrease represents a move toward more unhealthy products. We estimate the effect of the different label treatments on the expenditure share of healthy items for each product category. Again, omitting the individual subscript and the constant term for simplicity, the estimated model is specified as:

$$\frac{\sum(x_h \cdot p_h)}{\sum(x_j \cdot p_j)} = \alpha_{unit} \cdot D_{unit} + \alpha_{PR\times Unit} \cdot D_{unit} \cdot PR + \alpha_{low} \cdot D_{low} + \alpha_{L\times Low} \cdot D_{Low} \cdot L + \alpha_{High} \cdot D_{High} + \alpha_{L\times High} \cdot D_{High} \cdot L + \beta \cdot Z + \varepsilon \quad (3)$$

The α and β terms are parameters to be estimated and ε is an error term. The unit price (D_{unit}), low prominence nutrition (D_{low}) and high prominence nutrition (D_{high}) dummy variables represent the unit price, low prominence nutrition label and high prominence nutrition label treatments respectively. These terms are used to capture any direct treatment effect. Because there is likely to be significant heterogeneity, the unit price treatment is also interacted with the *price consciousness* variable (*PR*) to estimate how individual awareness of price information effects this treatment. Similarly, the low and high prominence nutrition label treatments are interacted with the *nutrition label consciousness* variable (*L*) to determine how individual awareness of nutrition information effects the nutrition label treatments.

For the dependent variable, we define healthy items by the number of nutritional claims presented on a given label. Shelf labels with more nutrition claims should stand out more than labels with fewer claims. Therefore, we expect that labels with more claims will be more effective at attracting attention. Given the previously discussed sequential processing of information, it follows that shelf labels that are more effective at attracting attention will also be more effective at affecting behavior. We then expect that the more nutrition claims on a shelf label, the greater the effect on consumer behavior. For example, a shelf label with one nutrition claim, e.g. *low sodium*, may have less of an effect on behavior than a label with three claims, e.g. *low sodium, low fat, low calories*. Shoppers who are exposed to shelf label nutrition information may be more likely to select items with three nutrition claims than items with just one nutrition claim. Ultimately, we are testing how nutrition information acts as a visual cue for shoppers and not necessarily the effect of the actual informational content each nutrition claim provides. That is, we estimate how the presence of more nutrition claims impacts behavior and do not explicitly test how different types of claims are processed and utilized.

Since expenditure share can take values from 0 to 1, we follow Papke and Wooldridge (1996) and estimate a Generalized Linear Model (GLM). Specifically, we estimate GLM specifying the binomial family and a logit link function with robust standard errors.

An issue with estimating equation 3 is the potential endogeneity of several of the demographic variables, particularly nutrition consciousness and the nutrition label consciousness. If there are factors that are unobserved to the econometrician in the error term that are correlated with either of these variables, then our estimates of these terms will be biased. There are several factors which may limit the impact of endogeneity. First, the treatments are randomly assigned to the participants. As such, any omitted variables in the error term associated with a self-selection process are mitigated. Additionally, any unobserved exogenous market effects are unlikely to impact this analysis since the data was generated using a survey experiment approach. That is, other forms of marketing that may influence an individual's nutrition label consciousness *and* their choice of healthy products are not likely to be in the error term because our data is collected in a semi-controlled environment. There still could be exogenous marketing factors that impact survey participant choices. However, our inclusion of many individual level demographic variables should help control for unobserved factors in the error term. Given all this, we consider endogeneity to be a minor issue for our particular analysis, but recognize that it is an important consideration to this type of research in general.

Salad Dressings

We estimate four different models in which define healthy salad dressings as having at least one nutrition claim, two claims, three claims and then four claims. In all four cases, both the low and high prominence nutrition labels, moderated by individual nutrition label consciousness score, has an impact on an individual's expenditure share of healthy salad dressings (Table 3, columns

1-4). The moderation effect of the nutrition label consciousness score demonstrates the heterogeneous effect of the treatment across individuals. For example, with three nutrition claims, the base effect of the high prominence nutrition label is negative (-0.864) but increases with the nutrition label consciousness score by a factor of 0.0723. This suggests that the high prominence nutrition label has a positive effect on individuals with a nutrition label consciousness score above 12 (0.864 / 0.0723 = 11.95) and that these shoppers select a larger proportion of healthy salad dressings. Alternatively, there is a negative effect for those with a lower nutrition label consciousness score. The threshold is even higher for the low prominence nutrition label. Individuals with a nutrition label consciousness score above 16 (1.276 / 0.0803 = 15.89) select a greater proportion of healthy salad dressings.

The maximum value for the nutrition label consciousness score is 21 and the average is 15.4. However, the distribution is skewed to the left, with most people reporting a higher score. As such, both the low and high prominence nutrition labels have an impact on selecting more healthy salad dressings. Further, those shoppers who pay attention to labels are more likely to be effected by their presence, an expected result.

Table 3. Model of Expenditure Share for Healthy Salad Dressings

DV= Healthy Salad Dressing Expenditure Share				
Variable	*1 claim*	*2 claims*	*3 claims*	*4 claims*
Age	0.0119***	0.00205	-0.000473	-0.00155
	-0.00456	-0.00378	-0.00467	-0.0059
Gender (female = 1)	-0.0789	-0.018	0.171	-0.158
	-0.152	-0.125	-0.157	-0.198
Household size	-0.0915**	-0.131***	-0.0973*	0.0228
	-0.0456	-0.0422	-0.0515	-0.0613
Education	-0.0623	0.0503	0.0505	0.0677
	-0.0424	-0.0353	-0.0415	-0.0571
Unit price treatment	0.208	0.0327	0.543	0.106
	-0.371	-0.286	-0.341	-0.439
Unit price treatment	-0.00246	0.00975	-0.0132	0.0132
X price consciousness	-0.0139	-0.0111	-0.0134	-0.017
Low prominence nutrition	-1.032**	-0.695**	-1.276***	-1.786**
label treatment	-0.401	-0.337	-0.489	-0.71
High prominence nutrition	-0.716*	-0.959**	-0.864*	-1.644***
label treatment	-0.407	-0.384	-0.501	-0.602
Low prominence nutrition label treatment X nutrition label	0.0735***	0.0513***	0.0803***	0.0991**
consciousness	-0.0234	-0.019	-0.0273	-0.0386
High prominence nutrition label treatment X nutrition label	0.0615***	0.0724***	0.0723**	0.108***
consciousness	-0.0232	-0.0219	-0.0281	-0.0333
Nutrition consciousness score	-0.00013	-0.00175	0.000922	0.00288
	-0.00623	-0.00497	-0.0063	-0.0076
Shopping percentage	-0.00828	-0.177	-0.348	-0.705**
	-0.252	-0.2	-0.237	-0.301
Constant	0.787	-0.133	-0.974	-1.618**
	-0.594	-0.481	-0.599	-0.727
Observations	790	790	790	790

Robust standard error below estimates
***p<0.01, **p<0.05, *p<0.1

Mayonnaise

Mayonnaise products are defined as healthy if they have at least three, four, then five nutrition claims (Table 4, columns 1-3)[4]. The low prominence nutrition label has a modest effect on the expenditure share for healthy mayonnaise, moderated by the nutrition label consciousness score. The threshold for the nutrition label consciousness score is much higher, however, than with the salad dressings. For example, with 3 nutrition claims the low prominence nutrition label has a positive effect on expenditure shares of healthy mayonnaise for individuals with a nutrition label consciousness score greater than 19 (0.963 / .0507 = 18.99). This is a much higher value, suggesting the effect of the nutrition label only impacts individuals who are highly interested in nutrition labels. The high prominence nutrition label has no significant effect on behavior. The unit price label, moderated by price consciousness score, also has an impact on the selection of more healthy mayonnaise. This could suggest that unit price is an important consideration when purchasing healthy mayonnaise, however this is only speculation.

Table 4. Model of Expenditure Share for Healthy Mayonnaise

DV= Healthy Mayonnaise Expenditure Share			
Variable	*3 claims*	*4 claims*	*5 claims*
Age	0.0156***	0.0118**	0.00763
	-0.00455	-0.00467	-0.00765
Gender (female = 1)	-0.184	-0.226	-0.585***
	-0.148	-0.151	-0.226
Household size	0.00321	0.0494	0.0111
	-0.043	-0.0437	-0.071
Education	0.0431	-0.00189	0.0918
	-0.0407	-0.0423	-0.0716
Unit price treatment	-0.548	-0.635*	-1.469**
	-0.354	-0.365	-0.688
Unit price treatment	0.0245*	0.0254*	0.0494*
X price consciousness	-0.0137	-0.014	-0.0259
Low prominence nutrition	-0.963**	-0.774*	-1.513**
label treatment	-0.434	-0.428	-0.756
High prominence nutrition	0.237	0.52	0.617
label treatment	-0.43	-0.433	-0.743
Low prominence nutrition label treatment X nutrition label	0.0507**	0.0334	0.0801*
consciousness	-0.0244	-0.0242	-0.0414
High prominence nutrition label treatment X nutrition label	-0.00492	-0.0327	-0.0382
consciousness	-0.0246	-0.025	-0.0429
Nutrition consciousness score	0.00814	0.00465	0.0177*
	-0.00607	-0.0062	-0.0107
Shopping percentage	-0.326	-0.25	-0.842**
	-0.239	-0.243	-0.411
Constant	-1.134*	-0.971	-3.390***
	-0.612	-0.622	-1.002
Observations	788	788	788

Robust standard error below estimates
***p<0.01, **p<0.05, *p<0.1

[4] The minimum number of claims on any mayonnaise in our sample is three; therefore it is the cutoff for classifying a product as healthy.

Popcorn

Healthy popcorn is defined as having at least three nutrition claims and then at least five nutrition claims (Table 5, columns 1 and 2)[5]. The high prominence nutrition label moderated by the nutrition label consciousness score has an effect with both three and five claims. The threshold of the nutrition label consciousness is 15 for 3 claims (1.343 / 0.089 = 15.089) and 19 for 5 claims (3.424 / 0.182 = 18.81). Based on this, it appears that only individuals with high nutrition label consciousness scores are affected by nutrition labels with a lot of nutrition claims. This result is interesting in contrast to Berning et al (2011) who found using a field experiment that nutrition labels for microwave popcorn lead to a decrease in purchases of labeled popcorn. Their suggestion was that nutrition labels might signal less-preferred taste. While this finding seems to be at odds with their field experiment results, there are important differences in the analyses. First, this research is able to capture greater individual heterogeneity and account for an individual's propensity to use nutrition information. Additionally, this analysis identifies stated preference results, whereas Berning et al (2011) explores actual purchasing behavior.

Table 5. Model of Expenditure Share for Healthy Popcorn

DV= Healthy Popcorn Expenditure Share		
Variable	*3claims*	*5 claims*
Age	0.000409	0.0023
	-0.00488	-0.0128
Gender (female = 1)	0.11	-0.364
	-0.151	-0.42
Household size	-0.0506	-0.317**
	-0.0473	-0.134
Education	0.000468	-0.107
	-0.0435	-0.141
Unit price treatment	-0.0491	-1.261
	-0.351	-0.92
Unit price treatment	0.00584	-0.0223
X price consciousness	-0.0136	-0.0315
Low prominence nutrition	-0.56	0.622
label treatment	-0.404	-0.843
High prominence nutrition	-1.343***	-3.424**
label treatment	-0.483	-1.606
Low prominence nutrition label	0.0291	-0.028
treatment X nutrition label consciousness	-0.0231	-0.0548
High prominence nutrition label	0.0890***	0.182**
treatment X nutrition label consciousness	-0.0274	-0.0914
Nutrition consciousness score	0.0171***	-0.021
	-0.00655	-0.016
Shopping percentage	0.211	0.308
	-0.243	-0.688
Constant	-0.992*	-15.22***
	-0.581	-1.393
Observations	788	788

Robust standard error below estimates
***p<0.01, **p<0.05, *p<0.1

[5] There were not enough popcorn products in our sample with four claims; therefore a natural jump was from three to five claims.

Peanut Butter

Healthy peanut butter is defined as having at least two nutrition claims and then at least three nutrition claims (Table 6, columns 1 and 2). The high prominence nutrition label moderated by the nutrition label consciousness score has an effect on the expenditure share of healthy peanut butter. The threshold of the nutrition label consciousness score is roughly 13.5 for 2 claims (1.568 / 0.116 = 13.517) and 16 for 3 claims (3.308 / .205 = 16.13). The low prominence nutrition label moderated by the nutrition label consciousness score has an effect on the expenditure share of healthy peanut butter with 3 or more nutrition claims.

Table 6. Model of Expenditure Share for Healthy Peanut Butter

DV= Healthy Peanut Butter Expenditure Share		
Variable	*2 claims*	*3 claims*
Age	0.00298	0.0106
	-0.0054	-0.00929
Gender (female = 1)	0.0464	0.529*
	-0.18	-0.313
Household size	-0.0921*	-0.152
	-0.0532	-0.099
Education	0.115**	0.162*
	-0.051	-0.0831
Unit price treatment	0.162	-0.517
	-0.446	-0.851
Unit price treatment	-6.62E-05	0.0221
X price consciousness	-0.017	-0.0329
Low prominence nutrition	-1.574**	-0.336
label treatment	-0.653	-0.859
High prominence nutrition	-1.568**	-3.308**
label treatment	-0.726	-1.363
Low prominence nutrition label	0.0761**	0.0141
treatment X nutrition label consciousness	-0.0355	-0.0416
High prominence nutrition label	0.116***	0.205***
treatment X nutrition label consciousness	-0.0393	-0.0732
Nutrition consciousness score	0.0295***	0.00821
	-0.00837	-0.0117
Shopping percentage	-0.272	-0.77
	-0.284	-0.482
Constant	-2.408***	-3.903***
	-0.732	-1.207
Observations	784	784

Robust standard error below estimates
***p<0.01, **p<0.05, *p<0.1

Summary of Results

In this experiment, we find that shelf label nutrition information provided on grocery store shelf labels has an affect on shopper behavior and that the effect is moderated by the likelihood to use nutrition labels, as measured by the nutrition label consciousness score. Specifically, we find that shoppers with a high nutrition label consciousness score are more likely to select healthy products, where healthy products are identified by the number of nutrition claims presented on their shelf label.

The effect we identify is consistent across four different product groups. Additionally, the effect is consistent across different definitions of healthy based on the number of nutrition claims. This suggests that the presence of any nutrition claim has an impact on behavior rather than the number of nutrition claims. We also find that the effect of nutrition labels is stronger for certain products. With salad dressing and peanut butter, the effects appear to be strongest. This may be because these are common products that are consumed more regularly. Further, salad dressing is a complement to an inherently health product, salad.

The limited effects found with mayonnaise products point to the strong brand influence among shoppers. Shoppers ultimately purchase these items according to experience and taste and are generally loyal to a specific type of mayonnaise product[6]. With microwave popcorn, the limited effect may be due to the consumption of popcorn as a snack item. Shoppers purchase popcorn as a treat to be consumed more sparingly than vegetables and therefore are less concerned with the nutritional content. The differences in the effect of nutrition labels based on product function needs to be further examined.

Conclusions

In response to growing health concerns and shopper demand, more grocery stores and manufacturers are beginning to offer their own nutrition information. We attempt to examine the effectiveness of this type of nutrition information offered on grocery store shelf labels. Based on our first measure of label effectiveness, attention, it appears that shelf label nutrition information does attract the attention of shoppers when it is in bold text and highlighted. In terms of behavioral compliance, we find that the nutrition label treatments affect shopper behavior for certain products and this behavior is moderated by our measure of nutrition consciousness.

Shoppers are inundated with advertisements and product displays in grocery stores. Consequently, the effect of shelf label information may become swamped by an excess of information. The moderating effect of the individual nutrition label consciousness score may provide useful insight into how to improve consumers' use of nutrition labels. To help improve the use of nutrition information, it may be beneficial to help shoppers identify nutrition information provided to them by grocery stores, thereby raising their nutrition consciousness. For example, grocery stores may create value for shoppers by providing specific, well-placed and well-designed nutrition information, thereby making the information easier to locate. Additionally, stores may engage in educating their shoppers about the nutrition labels they provide. For example, the NuVal nutrition label is a shelf label nutrition scoring system being used extensively across the country. Its promotion has been accompanied by an awareness campaign documenting the interpretation of the nutrition score. Additional information regarding their labels is available at their website as well (http://www.nuval.com/). While providing

[6] Many survey participants were upset that *Best Foods* brand mayonnaise was not an available choice in the experiment, citing it as "their brand".

nutrition information can be beneficial to shoppers, it is also important to find ways to help shoppers both use and interpret the information provided.

There are several limitations to this research as well that should be considered. First, as pointed out by a reviewer, evaluating nutritional quality is a complex procedure. Effectively communicating such information can be very difficult. This study does not measure comprehension of nutritional information being communicated. Instead, this analyses focuses on the impact of visual cues. That is, as shoppers see nutrition label claims, they behave differently. Clearly more research is necessary to evaluate consumer comprehension of this information as well. Second, there is considerable heterogeneity in consumer ability. We attempt to capture this to an extent using measures of individual nutrition consciousness and nutrition label consciousness. This provides only a limited picture of consumer differences, however. Again, further research into assessing consumer types and abilities would enhance this research area.

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A Spatial Analysis of Supplemental Nutrition Assistance Program in the Appalachian Region

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Abstract

Supplemental Nutrition Assistance Program (SNAP) helps low income people and households buy food for proper health. This study seeks to examine the effects of changes in economic conditions and welfare on SNAP participation in the Appalachian region. Using county level data, the Spatial Durbin (SDM) Model was used to examine the effect of economic conditions, demographic attributes and institutional factors on SNAP participation. Empirical results from the marginal effects indicate that poverty had the greatest influence on SNAP participation. Findings from this study could be helpful in improving welfare programs in this region.

Keywords: Supplemental Nutrition Assistance Program, Spatial Durbin Model, Appalachia

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Introduction

The poverty rate in the United States (U.S.) has been increasing since the 1970's, particularly during recessions. The 2009 poverty rate of 14.3 percent was substantially higher than the 11.1 percent level reported in 1973, showing that a significant portion of families and children in the U.S. live in poverty today, and that the portion is more than three and a half decades ago. The U.S. government has an obligation in implementing appropriate welfare and effective food assistance programs to its people (USDA 2010).

The Supplemental Nutrition Assistance Program (SNAP), formerly known as the Food Stamp Program, is a federal assistance program that provides assistance to low and no-income people and families living in the U.S. It is the largest food assistance program and the cornerstone of the federal government's efforts to alleviate hunger and food insecurity among low income households. The federal government and states share authority over the assistance program. The federal government sets the program's income eligibility limits and benefit levels, both of which are uniform across most states. It also pays the full costs of benefits, all administrative costs at the national level, and half of the administrative costs at the state level. The states administer the program, pay the other half of administrative costs and choose policy options that affect eligibility in their state (Finegold 2008). The SNAP is an integral component of the social safety net in the U.S. and accounts for a total of $53.6 billion in fiscal year 2009 compared to $17.1 billion in fiscal year 2000 (USDA 2010).

Past studies on SNAP participation attributed its dynamics to a region's economic conditions along with changes in welfare reform. They indicated that SNAP participation is positively correlated with unemployment and poverty (Kornfeld and Wilde 2002). Recent trends show that SNAP participation has grown from 17.2 million in 2000 to 35.8 million people in 2009 (USDA 2010). Given these trends, it is important to analyze what has caused SNAP participation to undergo changes since 2000. The most recent recession which started in December 2007 and lasted 18 months indicated a jump in individual monthly participation in SNAP (NBER 2008; NBER 2010).

Past studies have focused on these dynamics at the national level, with little research done at the regional level. In general, there is lack of adequate information about the factors affecting SNAP participation which need to be addressed in a wider perspective within a policy context. In addition, little has been done with regards to spatial analysis of SNAP participation. With the exception of Goetz, Rapusingha et al. (2004), early work on the SNAP program ignored the fact that latent variables can vary over geographical regions, thereby creating spatial interdependence on counties (Lacombe 2004). This paper examines the influence of economic activity, administrative and institutional policies, transaction costs, demographic factors, and welfare policy on SNAP program participation. This paper attempts to answer the following questions: (1) What results do we obtain when we run an OLS model and how do they change when we employ spatial econometric techniques? (2) Which spatial model do we employ for making inferences? This paper attempts to answer these questions using secondary data together with spatial models.
At the macroeconomic level, individual income and employment opportunities are expected to influence households' decisions to participate in the SNAP program. For example, the recent economic downturn between 2008 and 2009 caused a rise in unemployment levels, perhaps

increasing SNAP participation by eligible households. Conversely, policies aimed at promoting employment may lower SNAP participation, while a reduction in transaction costs may cause an increase in participation. Measures to increase awareness among low income households are also likely to increase SNAP participation rates. By analyzing these trends, we can examine how the economy has affected low income households in the Appalachian region. The results from the empirical analysis will assist in drawing appropriate policy implications for improving the program to reach the desired goals. Research findings are anticipated to guide future development of welfare and SNAP policy measures, and aid policy makers to develop appropriate programs. This study is unique in the sense that the results calculate the marginal effects estimated in many spatial econometric models. These effects estimates differ from the standard regression interpretation of coefficient estimates. Models that contain spatial lags of the dependent variable must account for the fact that changes to an explanatory variable in all regions can occur through changes in its own dependent variable. The paper is also unique in the sense that it is the primary study to cover the Appalachian region with regard to SNAP participation.

The paper is organized as follows: Section 2 provides an overview of past literature and explains the factors that affect SNAP participation. Section 3 covers the methodology where the spatial models are developed. Section 4 presents the empirical results and analysis. Section 5 presents the conclusions and limitations of the study.

Literature Review

There are eight factors that affect SNAP participation dynamics: participation trends, poverty and unemployment, administrative measures, demographic factors, institutional factors, theoretical explanations, empirical models applied and other welfare changes. The role and effectiveness of SNAP can be better understood by observing participation patterns and trends. Participation patterns look at those individuals who have enrolled in the program and received benefits. Lately, policymakers have been concerned with individuals who meet eligibility requirements but do not receive benefits. According to USDA (2010) there were 33.7 million SNAP participants in 2009 compared to the 25.7 million reported in 2005. On a monthly basis, 26 out of the 39 million eligible individuals participated for the SNAP program in 2007, which was one percent lower than the total reported in 2006. Participation trends varied among individuals and households. The number of participating individuals has been rising steadily since 2001, while household participation has been non-uniform. This relationship is illustrated in Figure 1.

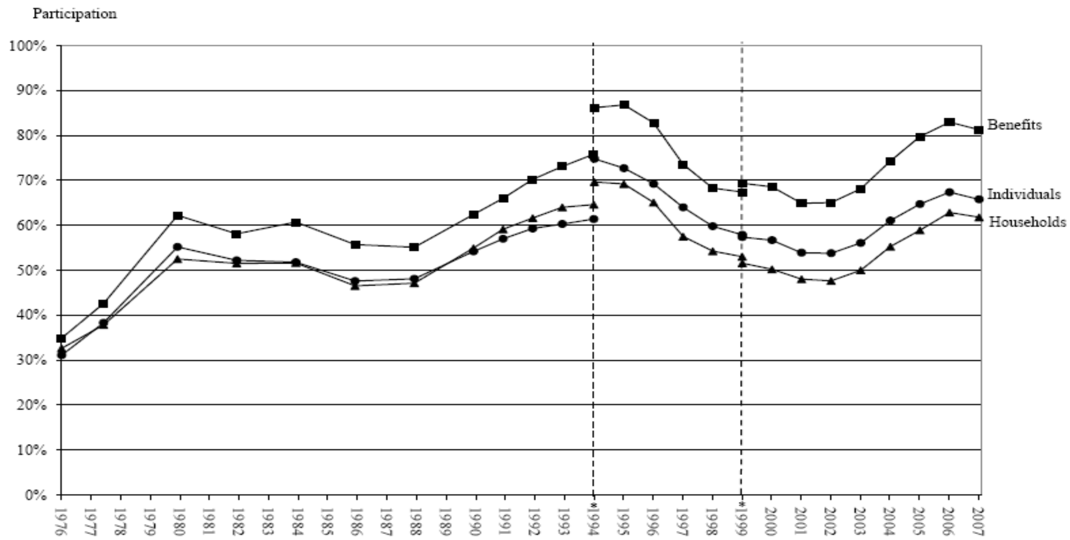

Figure 1. Trends in SNAP participation rates (1976-2007)[1]

Source. Wolkwitz, 2008. SNAP Program Operations data, SNAP QC data, and March CPS data. There are breaks in the time series in 1994 and 1999 due to revisions in the methodology for determining eligibility.

Unemployment levels and SNAP participation have followed parallel patterns over the last two decades. They rise and fall together over the same periods as shown in Figure 2. However, this is not always the case. Some deviation between the two has been observed, suggesting that SNAP participation is not only affected solely by economic factors but also by non-economic ones. This can be shown in Figure 2 where the two patterns were different, with SNAP participation declining as unemployment peaked as observed in the early 1980's or mid 1990's (Wilde, Cook et al. 2000).

A study by Kabbani and Wilde (2003) also attempted to explain the fact that administrative measures may have a significant effect on SNAP participation dynamics. The federal government requires that states recertify participants at least once a year. States vary recertification periods in a bid to lower error rates by keeping up-to-date information on users. Varying the recertification periods has an influence on SNAP participation. Past studies found that using shorter recertification periods lowered SNAP participation either because ineligible participants were unable to participate or eligible participants failing to participate in the program (Currie and Grogger 2001; Kornfeld and Wilde 2002; Kabbani and Wilde 2003).

[1]There are breaks in the time series in 1994 and 1999due to revisions in the methodology for determining eligibility.

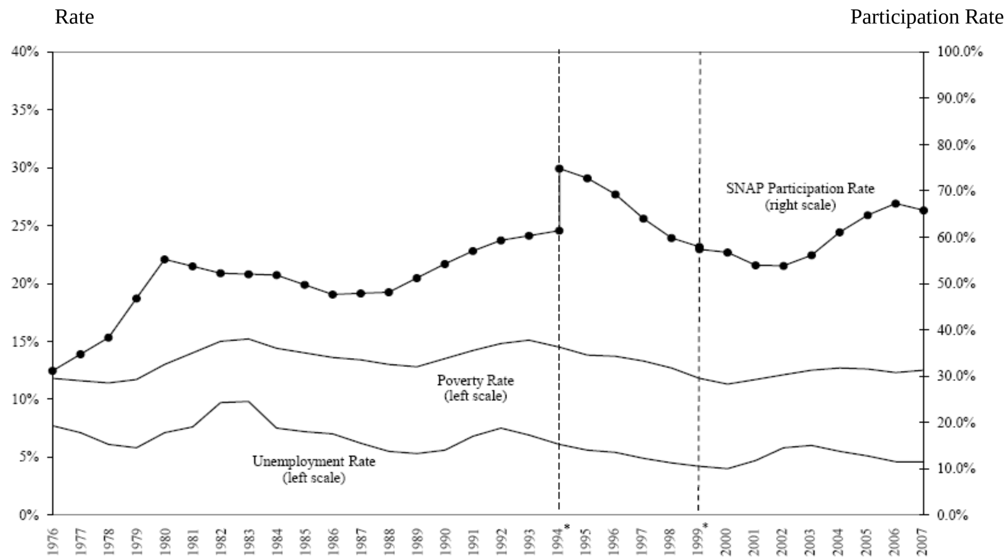

Figure 2. Trends in SNAP participation rates, Poverty Rates, and Unemployment Rate (1976- 2007)[2]

Sources. Wolkwitz, 2008. Participation rates from SNAP Program Operations data, SNAP QC data, and March CPS data for the years shown. Poverty rates from U.S. Bureau of the Census, Poverty in the United States. Unemployment rates from Department of Labor, Bureau of Labor Statistics.

A state based study by Finegold (2008) elaborates on the issue of recertification periods. Participants are required to report changes in income and employment within recertification periods. With different reporting requirements, states that had lenient requirements had higher participation rates compared to those that had stricter rules. The same study found that states that had face to face interviews with individuals had lower participation rates. This task proved onerous because participants had to schedule the interviews during hours in which they were supposed to be working. The realization of this has led to the adoption of interviews by telephones in a bid to ease the reporting process (Finegold 2008).

Hanratty (2006) reported that demographic factors can cause changes in SNAP participation. His study showed that participation is highly correlated with a person's age, parental race, educational attainment, and disability status. Kim (1997) argued that individuals who are older, male, have higher income, higher education, fewer children, and fewer jobs are less likely to participate in SNAP.

Welfare reform may have indirectly reduced the rate of SNAP participation by reducing the number of people receiving welfare (McConnell 2001). Most people receiving welfare were almost automatically eligible to benefit from SNAP. The Personal Responsibility and Work Opportunity Reconciliation Act of 1996 (PRWORA) changed welfare and altered eligibility requirements for the poor. Welfare reform seeks to move people from welfare to work by

[2]There are breaks in the time series in 1994 and 1999due to revisions in the methodology for determining eligibility.

imposing time limits on receiving benefits and penalizing states that have too few welfare recipients at jobs. The legislation reduced SNAP (food stamps at the time) participants by limiting able bodied adults without dependents (ABAWD) to face a 3-month limit on receiving food stamps unless they were working. The program made it more difficult for single mothers to receive cash welfare, and may have had the largely unintended consequence of making it more difficult for them to access food stamps. Non-citizens could not receive food stamps until they became citizens or worked for ten years or more (Wilde 2001). However, the 2002 Farm Bill made many legal immigrants eligible for benefits of the SNAP program by allowing those residing in the US for at least 5 years and those less than 18 years old eligible to receive benefits (FRAC 2004). These issues show how the influences of institutional factors affect the success of the program.

Other factors such as lack of information and high psychological costs or stigma can cause SNAP participation to decline. McConnell (2001) suggested that the stigma of getting food stamps in rural areas is lower compared to that in urban areas. According to their study, SNAP participation in urban areas dropped from 72 percent to 63 percent while rising from 71 percent to 73 percent in rural areas between 1996 and 1998, a period that witnessed a strong economy. The Electronic Benefit Transfer (EBT) system helps to encourage participation by reducing stigma in the use of food stamps, but EBT may make it harder for people unfamiliar with debit card to get benefits (Currie and Grogger 2001; Kabbani and Wilde 2003). This system was introduced to lower administrative costs and deter fraud. Even so, recipients of the EBT card perceived less stigma in using it in comparison to the more visible coupons. On the downside, the card can only be used in certain stores which have EBT conversion technology.

Clarke, Levedahl et al. (2004) argue that the variations of Temporary Assistance for Needy Families (TANF), formerly Aid to Families with Dependent Children (AFDC) caseloads are important in explaining the movements of SNAP participation caseloads. Households made up entirely of AFDC/TANF recipients are automatically eligible for food stamps (Currie and Grogger 2001). Caseload levels in the two programs are indirectly linked through their implementation at the state level. Any shared approach would imply that states' practices in one program might affect implementation of both programs (US GAO 1999). Therefore, caseloads track the general pattern of per capita SNAP participants fairly well. Fluctuations in per capita SNAP participants are consistently tracked by concomitant rise and drop predicted by per capita AFDC/TANF caseloads (Clarke, Levedahl et al. 2004). This may raise the issues of simultaneity but studies get around this problem by employing proxies (Currie and Grogger 2001).

There is a growing literature concerning the factors associated with SNAP participation. Economists and researchers have attempted to examine the factors and causes for changes in participation, and found that trends varied over the years due to various reasons such as unemployment, income, poverty, recertification periods and so on.

Figlio, Gunderson et al. (2000) found that unemployment rate was statistically significant and had countercyclical impact movement of SNAP participation. They also reported that nearly six percent of the food stamp caseload declines were observed in states that implemented Electronic Benefit Transfers (EBT). Some researchers attributed the current rise in SNAP participation to increasing poverty levels (Smeeding 2009). Other studies by Currie and Grogger (2001), Kornfeld and Wilde (2002) and Kabbani and Wilde (2003) attempted to investigate the role of recertification periods in SNAP participation. The studies above employed econometric models for empirical analysis. Clarke, Levedahl et al. (2004) employed time series analysis of the SNAP program and found that poor economic conditions increased caseloads.

Goetz, Rapusingha et al. (2004) used spatial econometric methods to investigate factors affecting SNAP participation dynamics in U.S. counties and states. Using the Spatial Error Model (SEM), they found that individual and community level factors affected SNAP participation. They also found that controlling spatial dependence bias in such studies was important. This study builds on that conducted by Goetz, Rapusingha et al. (2004) where the focus is on the Appalachian region using a different spatial model.

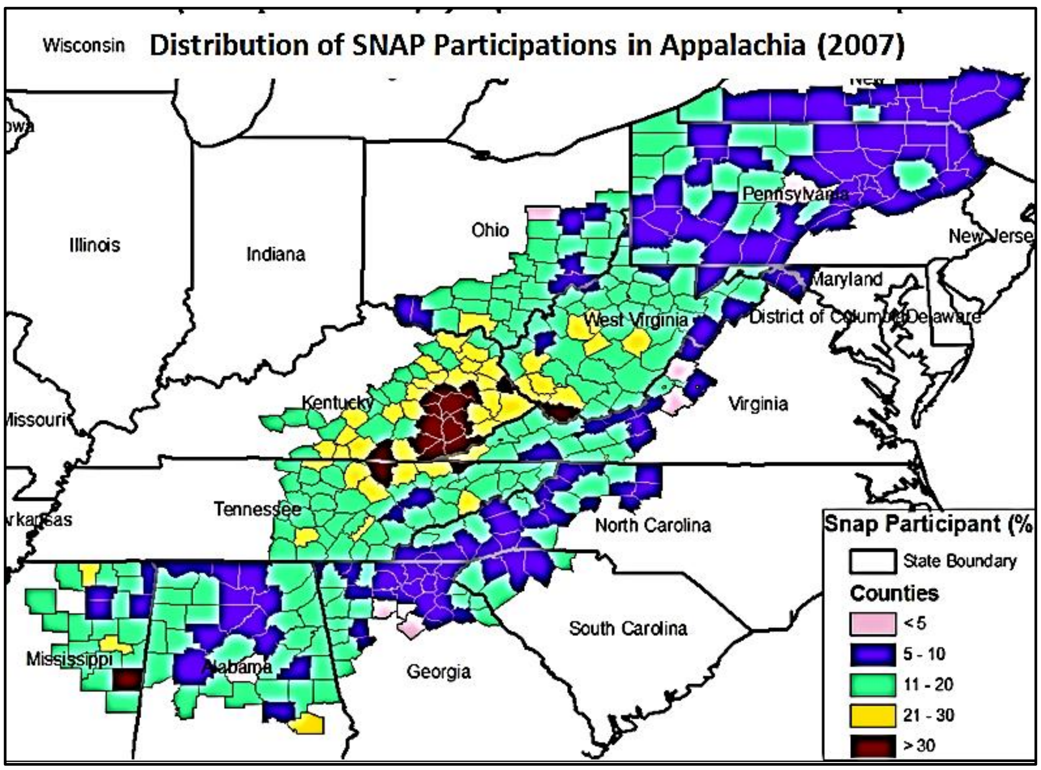

Figure 3. SNAP Participants Distribution in Appalachian Counties (2007)

Methodology

LeSage (1997) found that practitioners engaged in statistical work with regional data samples should try considering spatial configuration in their work. It has also been realized that geographical factors play an important role in determining the effects of public policy (Lacombe 2004). Spatial autocorrelation in SNAP studies can occur in many contexts, but this study aims to address the common issues that lead to the suspicion that variables are measured with errors.
It is known that poverty occurs in clusters, especially where inner cities are located. Also, state level policies may cause clustering to occur in SNAP caseloads (Goetz, Rupasingha et al. 2004). Not surprisingly, participation is clustered in a spatial sense in the Appalachian region as shown in Figure 3. The diagram shows "pockets" of high participation numbers located around the south eastern part of Kentucky.

Populations possessing unobservable characteristics such as culture and attitude are likely to cluster around certain areas in communities. These groups may possess attitudes towards government assistance programs that may be uniform within certain geographical areas. Studies wishing to account for unobservable qualities require the use of proxies to capture these unobservable characteristics. To make the proxies operational, a set of geographic boundaries must be assumed where clustering of the behaviors occur. However, these boundaries may not be the same boundaries used by data collectors. These two problems, unobservability and boundaries, make it virtually certain that SNAP variables will be measured with error, with the result that the regression error terms will be autocorrelated. Overall, ignoring the spatial configuration of sample observations in regression analysis is known to contribute to spatial autocorrelation (Dubin 1998). Overlooking this information may produce inferences that are qualitatively and quantitatively different from models that contain these relations due to the biasedness and inconsistency of OLS estimates.

The spatial model proposed in this study includes three specifications. The first is the Spatial Error Model (SEM), the second is the Spatial Autoregressive Model (SAR) and the third is the Spatial Durbin Model (SDM). The models are useful for analyzing the effects of all the independent factors responsible for changes in SNAP participation over time *t* and space. These models are employed to capture the level of interdependence among regions in the independent variables (LeSage 1997). The study is built on past models developed by Goetz, Rapusingha et al. (2004), Figlio, Gunderson et al. (2000), Currie and Grogger (2001), Kornfeld and Wilde (2002), Kabbani and Wilde (2003) and Clarke, Levedahl et al. (2004). The model is unique because it addresses the issue of marginal effects in SNAP participation within the Appalachian region. The models focus on four major groups of independent variables representing: economic conditions, business cycle, welfare policy changes, demographic variables, and institutional factors.

SNAP participation rate is assumed to be a function of economic and business cycle conditions, changes in welfare reforms, demographic and household attributes, and institutional factors. The available data is a panel dataset which is more informative, provides more variability, has less collinearity among the variables, results in more degrees of freedom, and gives more efficient estimates (Baltagi 1995). This approach controls for individual unobserved heterogeneity which is not easily detectable in cross-section or time-series data. The general form of this model is expressed as follows:

$$SNAP = f\,(UNEM, EMPGR, POVRTY, NLINC, RECERT, ERRT, IMMIG) \quad (1)$$

where: *SNAP* is SNAP participation rate, *UNEM* is unemployment per capita, *EMPGR* employment growth rate is the rate of change of employment, *POVRTY* poverty per capita, *NLINC* non labor income as a fraction of total income, *RECERT* recertification interval, *ERRT* the state error rate, and *IMMIG* the immigrant population per capita (as shown in Table 1).

Table 1. Data Types and Sources

Variable	Description	Source
SNAP	Supplemental Nutrition Analysis Caseloads	U.S. Census Bureau
UNEMP	Unemployment rate	Bureau of Labor Statistics
EMPGR	Employment growth rate	Bureau of Labor Statistics
POVRTY	Poverty rate	U.S. Census Bureau
NLINC	Non labor sources of income	Bureau of Economic Analysis
RECERT	Recertification interval[3]	United States Department of Agriculture
ERRT	State SNAP Participation error rate	United States Government Accountability Office
IMMIG	Percentage of immigrants population	U.S. Census Bureau

Given the geographic nature of the data, it is reasonable to suspect that spatial autocorrelation may be an issue. Spatial autocorrelation is formally defined as follows (Anselin and Bera 1998):

$$(2)\quad \operatorname{cov}(y_i, y_j) = E(y_i, y_j) - E(y_i)E(y_j) \neq 0 \;\; for \;\; i \neq j$$

where y_i and y_j are observations on a random variable at locations i and j in space. The subscripts i and j can refer to any geographic designation and the equation implies non-independence of the random variable across space. Spatial autocorrelation can pose problems when using standard econometric techniques, such as OLS.

The Spatial Error Model (SEM) is used to account for the possibility of residual spatial autocorrelation as justified by Anselin and Bera (1998) and implied in their model as the most relevant for applied empirical work on cross sectional data. The SEM model can be expressed as follows:

$$(3)\quad Y_{it} = \beta X'_{it} + u_{it} \qquad i = 1,.....N; \;\; t = 1,....T$$

$$(4)\quad u_{it} = \lambda \mathrm{W} \mu_i + \varepsilon_{it}$$

$$(5)\quad \varepsilon_{it} = N(0, \sigma^2 I_n)$$

where Y is the dependent variable (SNAP participation rate), ε is the error term, X is the vector of independent variables, λ is the spatial error parameter to be estimated which measures the degree of spatial error independence across neighboring counties. W is a 417 X 417 first order contiguity weight matrix. It is used to incorporate the spatial configuration information about the

[3]The federal government requires households be recertified for SNAP eligibility at least once a year, or at least every two years if they contain an elderly person. Recertification describes the process where households are required to prove eligibility in receiving SNAP benefits by periodically reporting their levels of incomes and assets. Based on reported figures and state requirements, SNAP officials decide whether or not to issue benefits to the households. This exercise enables states to keep up to date information on participants and households, so as to issue benefits to intended people and reduce errors. States believed that they could reduce their risk of errors by imposing shorter recertification periods, especially for households whose incomes were likely to fluctuate (Kabbani and Wilde, 2003).

points in space at which our data observations gathered, and is therefore a convenient way to summarize the spatial configuration of the Appalachian counties. The subscript i denotes the cross-section dimension and t denotes the time-series dimension. In this model i represents counties and t represents years.
We also employed the Spatial Autoregressive Model (SAR) which is specified as:

$$(6) \qquad Y_{it} = \rho WY_{it} + \beta X'_{it} + \varepsilon_{it} \qquad i = 1,.....N; \; t = 1,....T$$

where ρ is the spatial autoregressive coefficient for the SAR model, ε is the vector of error terms and the other notation is as indicated before (Anselin 1999). Finally, the Spatial Durbin Model (SDM) is specified as:

$$(7) \qquad \rho WY_{it} + \beta X'_{it} + \mathrm{W}X'_{it}\theta + \varepsilon_{it} \qquad i = 1,.....N; \; t = 1,....T$$

$$(8) \qquad Y_{it} = (I_n - \rho W)^{-1}(\beta X'_{it} + \mathrm{W}X'_{it}\theta + \varepsilon_{it})$$

$$(9) \qquad \varepsilon_{it} \sim N(0, \sigma^2 I_n)$$

We can further simplify the equation (8) or the Data Generating Process (DGP) such that

$$(10) \qquad Y_{it} = P^{-1}\left[(\beta X'_{it} + \mathrm{W}X'_{it}\theta + \varepsilon_{it})\right]$$

where P^{-1} is a 417 X 417 matrix. Assuming that the β's do not vary over time, the matrix of the marginal effects changes in the X_r variable at time t is given by $(I_n - \rho W)^{-1}(I_n\beta_r + W\theta_r)$. The diagonal elements of this matrix are the effects on region i from changing X_r in the region at time t plus feedback effects. In the presence of spatial dependence, these "own derivatives" account for higher-order neighbor effects. This follows from the fact that: $(I_n - \rho W)^{-1} = (I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 ... + \rho^\infty W^\infty)$ which are the direct plus feedback effects. The infinite series expansion shows that if a region is influenced by its neighbors, and those neighbors are influenced by their neighbors, then every region is influenced by higher order neighbors. Similarly, the off-diagonals of this matrix represent the indirect effects (LeSage and Pace 2009).

The data for the 417 Appalachian counties used for empirical analysis was collected from various sources for the period between 2000 and 2007. Data on the number of SNAP participants was collected from the data sets contained in the Economic Research Service under the United States Department of Agriculture. Poverty rates and immigrant population data was obtained from the U.S. Census Bureau. Data on employment and unemployment are obtained from the Bureau of Labor Statistics. The Bureau of Economic Analysis (BEA) provided data on non-labor sources of income while the Government Accountability Office (US GAO) provided data on error rates. Table 1 provides a description of variables and sources.

The dependent variable used in the empirical analysis is the SNAP participation rate. SNAP participation rate is the ratio of people who participate in the program divided by the total county population. It is a measure that has been used in previous studies to see how well the program is reaching its target population (Castner and Schirm 2004). Not all of those who are eligible participate in the program; some choose not to participate while others are unaware that they are eligible (Finegold 2008). The SNAP participation rate may rise or drop depending on economic conditions or institutional factors which affect eligibility rules. Relaxing these regulations affects the participation rate by expanding or shrinking the number of people eligible for benefits. Past studies have used estimates of participation rates to assess the programs performance (Castner and Schirm 2004; Cunnyngham and Castner 2009).This paper assumes that participation rates change due to a number of reasons, hence its use as a dependent variable. SNAP participation rate is specifically affected by eight factors: participation trends, poverty and unemployment, administrative measures, demographic factors, institutional factors, theoretical explanations, empirical models applied and other welfare changes.

Like other studies, Figlio, Gunderson et al. (2000) concluded that macroeconomic conditions had a significant effect on a person's decision whether or not to be a SNAP participant. For this reason, we included unemployment rate (UNEMP) and employment growth rates (EMPGR) in the model in order to capture the effects of business cycle conditions on SNAP caseloads. The model also included poverty (POVRTY) and non-labor income (NLINC) variables to capture the effects of the individual's economic condition.

High transaction costs are likely to reduce SNAP participation rate. This effect can be captured by the use of a variable that includes the individual states' recertification rates (RECERT), which also acts as a variable measuring the state-level policy differences. SNAP participants do not receive supplemental nutrition assistance continuously; they are eligible only for a certain period. They need to reapply to receive continued assistance when their certification period expires. Mostly, reapplying for the assistance involves face-to-face interviews. We assume that higher recertification rates add expenses to the SNAP participants because they have to make repeated trips to agency offices to prove that they are eligible to receive benefits (Kabbani and Wilde 2003). These repeated trips tend to lower participation rates. The variable is also used to capture the effects of the stigma associated with SNAP participation. The state error rate (ERRT) is also useful in explaining the caseload dynamics. Error rates are used to report state's overpayment and underpayment, and vary across states. The percentage of immigrants in each county is the variable used to capture the effect of demographics in our model. This variable is expected to capture the households' participation decision in being a SNAP participant. Since individual county level recertification intervals were not available, we divided the states' recertification intervals with each county's SNAP participants to capture the magnitude of the interval at the county level. The same procedure was conducted for the state error rates. Finally, we employed a log-linear model where all the variables we used were natural logs for all the variables except the employment growth rate and non-labor income because some values had zeros.

Results and Analysis

To estimate the results, MATLAB 9.1 is used together with the Spatial Econometric Toolbox developed by James LeSage. The results obtained from the SEM and SAR models are estimated using maximum likelihood techniques. However, model specification needs to be carried out to enable us to select one of the models for inference. To do the estimation, as shown in Table 4 (see Appendix), the Panel Lagrange Multiplier (LM) test for specification was employed (Elhorst 2010). According to the test, the SAR model had a Lagrange Multiplier value of 905.80 while the SEM had a value of 1073.32. These results obtained through the classical approach were confirmed by the powerful robust test which found that the SEM model was preferred because the SAR tests were not significant. The results of the Likelihood ratio tests point to the SEM model as the preferred one of the two. This outcome requires reporting the SEM estimates of the model.

Theory indicates that the OLS and SEM estimates should be the same, if the true Data Generating Process (DGP) is OLS, SEM or any other error model (LeSage and Pace 2009). However, our results reported in Table 2 show otherwise. Although estimates exert similar signage and significance, the point estimates differ in magnitude. The OLS estimates of most variables tend to underestimate the coefficients of the SEM, where the largest differences in variables are observed in the immigration and poverty variables. Discrepancies in these two variables are 0.57 and 0.31 percentage points, respectively. With the exception of the error rate and non-labor income variables, all coefficients in the OLS are an underestimate of the SEM

Table 2. Empirical Results of Spatial Econometric Model Estimation

Variables	**SEM Model** *(spatial and time period fixed effects)*	**Fixed Effect Model** *(spatial and time period fixed effects)*
log_unemp	0.5299***	0.2235***
	(26.2300)	(16.5661)
empgr	0.0029*	0.0007*
	(3.0925)	(1.7913)
log_povrty	1.2387***	0.9258***
	(54.4005)	(14.6276)
log_errt	-0.1105***	-0.0752***
	(-7.7467)	(-11.3319)
nlinc	0.0102***	0.0261***
	(6.5636)	(7.3079)
log_immig	-0.025***	-0.5921***
	(-4.5546)	(-10.4690)
log_recert	0.1921***	0.1767***
	(7.1150)	(8.1159)
spat.aut.	0.4320***	
	(18.9203)	
R^2	0.8419	0.9801
Log-Likelihood	181.5067	3696.107

Note. ***, ** and * denotes level statistical significance at 1%, 5% and 10%, respectively. Number in brackets represents t-stat.

coefficients. Nevertheless, the spatial error correlation parameter, $\boldsymbol{\rho}$, is significant at the 99% confidence level and displays a moderate level of spatial error correlation, with a value of 0.4320. Also of note is that the overall fit of the SEM model is very good with approximately 84.19% of the variation in the dependent variable explained by the set of independent variables.

This mismatch in values of estimates could be attributed to the omission of variables that are spatially dependent. The DGP associated with spatially omitted variables matches the SDM

DGP. Using this model shrinks the bias relative to OLS estimates, which provides a good econometric motivation for its use in this analysis (LeSage and Pace 2009). This also adds to the richness of our results because we cater for spatial dependence in the dependent variable and error terms, thereby avoiding bias in estimates of coefficients. Consequently, we estimated SDM with spatial and time fixed effects to control for place-and-time-specific variations resulting from additional variable omission not captured in traditional panel-data analysis. Ignoring these effects in our study may lead to biased estimates (Elhorst and Fréret 2009).

Table 3 shows the direct, indirect and total effects estimates of the SDM. The second column presents the direct effect estimates which relay the impacts of the variables on their own-county's SNAP participation rate plus feedback effects. The indirect effect estimates presented in the third column reflect the effects of the variables on SNAP participation rate in neighboring counties. The sum of the direct and indirect effects give the total effects estimates. These estimates reflect the variable's effect on its own-county plus the (average) cumulative sum of impacts on all other counties as well (Kirby and LeSage 2009).

Table 3. Empirical Results of Spatial Durbin Model with Spatial and Time Fixed Effects

Variables	Direct	Indirect	Total
log_unemp	0.5247***	-0.1298*	0.3948***
	(25.4974)	(-2.2092)	(6.1832)
empgr	0.0019**	-0.0067**	-0.0047
	(1.9038)	(-1.8671)	(-1.1607)
log_povrty	1.3611***	0.3167***	1.6777***
	(31.5060)	(3.9325)	(21.1792)
log_errt	-0.1007***	0.2204***	0.1197***
	(-6.7430)	(5.7666)	(2.9125)
nlinc	0.0102***	-0.0137***	-0.0035
	(5.6250)	(-4.1499)	(-1.1398)
log_immig	-0.1768***	0.0886	-0.0881
	(-4.4393)	(1.2636)	(-1.3585)
log_recert	0.2528***	-0.3597***	-0.1070*
	(7.5904)	(-6.8254)	(-2.3748)
W*dep.var.	0.3280***		
	(13.2273)		
R^2	0.8480		
Log-Likelihood	273.1215		

Note. ***, ** and * denotes level statistical significance at 1%, 5% and 10%, respectively. Number in brackets represents t-stat.

The degree of spatial dependence is 0.33 and statistically significant indicating a level of spatial autocorrelation in the regression relationship. The direct and indirect effects estimates of the unemployment variable are significant at the 1% and 10% levels of significance respectively. A 10% point increase in unemployment rate increases the SNAP participation rate by 5.25% within the county whereas the indirect effects cause a 1.29% decrease. The total effect is a 3.90% increase in SNAP participation rate in the Appalachian region. The direct and indirect effects of the employment growth rate are significant at the 5% level of significance. A one unit increase in the employment growth rate increases SNAP participation by 0.19% due to direct effects but the indirect effects reduces it by 0.67%. The covariate for the total effect is not significant hence implying that the employment growth rate exhibits no effect on SNAP participation in the Appalachian region.

The poverty variable exerts the greatest influence on the SNAP participation rate in Appalachia based on the characteristics and magnitudes of the marginal effects. A 10% increase in poverty rate exerts a 13.6% increase in participation due to the direct effects and a 3.17% increase due to the indirect effects. The total effect on participation due to the 10% increase in poverty rate is a 16.77% rise in participation rate. The direct effect estimates for the error rate reveals that a 10% increase in the error rate reduces SNAP participation by 1.01%, whereas the indirect effects impart a 2.20% increase in participation rate. The overall effect for the error rate on the county is an increase of 1.16% in participation rate. This came as no surprise, as higher error rates could signify an increase in participation rates. The direct and indirect effects estimates for the non-labor income falls within the 99% confidence level but that of the total effect is not significant. The impact of a one unit increase in the direct effect increases SNAP participation by 1% whereas the indirect effects exerted a 1.30% decrease in participation. The total effects did not impact participation rates in the region. Only the direct effects of the immigrant numbers affected SNAP participation in the region, where a 10% increase in the immigrant numbers causes a 1.70% decrease in SNAP participation in the county. Finally, increasing the recertification intervals by 10% causes SNAP participation to rise by 2.53% due to the direct effects but the indirect effects cause a reduction of 3.60. The overall effect decreases SNAP participation in the Appalachian region by 1.07%. The overall fit of the SDM is good, with approximately 84.8% of the variation in the dependent variable being explained by the variation within the set of independent variables.

Concluding Summary

This study employs county level data to capture variation in SNAP participation rates in the Appalachian region. The Spatial Durbin Model is employed to examine the effects between economic and business cycle conditions, changes in welfare reforms, demographic and household attributes, and institutional factors upon SNAP participation rates. The results from the marginal effects estimates presented new findings on how participation rates in counties are affected by factors within their counties. They also shed light on how factors in neighboring counties affect their participation. All the covariates of the direct effects yielded an influence in participation rate in the Appalachian region. They also suggested that poverty exerted the greatest influence on SNAP participation in Appalachia. The results from the indirect effects estimates produced similar results in terms of significance, except for the demographic factor which indicated that immigration numbers did not influence SNAP participation in the region. The total effects produced mixed results. The economic variables namely unemployment and poverty exerted a positive influence on SNAP participation, while the institutional factors namely error rate and recertification interval produced negative effects. Surprisingly, the employment growth rate showed no effect on SNAP participation rates in the region. One possible explanation for this could be that the jobs created might not match the skills of the SNAP participants. It is also possible that jobs might not pay enough for those employed to still be eligible for SNAP participation. The total effects also relayed that longer recertification intervals were found to reduce participation in the region. This result differs with Kabbani and

Wilde (2003) who found that shorter recertification intervals reduced participation. The reason for this could not be immediately inferred because different states were in the process of adopting new techniques for recertification. Most of the Appalachian counties were conducting recertification through telephone interviews thereby reducing the burden of participants to go to state agencies to recertify (Finegold 2008). Although the impact was present in the direct and indirect effects, the demographic factors showed no impact on SNAP participation in the total effects estimates. These results could give an insight to the progress of the 2002 Farm Bill, which sought to ease regulations regarding immigrants' eligibility for SNAP programs. Then again, the Bill was introduced during the study period and as such it would not be suitable to assess its' progress at this time.

The findings from this study could be helpful in designing welfare programs in this region. The SNAP program helps low income individuals and families to obtain a more nutritious diet by supplementing their income with SNAP benefits. However, not all eligible individuals participate because of various challenges they face in obtaining benefits. Policy makers need to be concerned about the situation because they want all affected individuals to participate in the program and receive benefits. This study looked at factors that induce individuals to participate in the program. Understanding these factors can give policy makers a better ability to forecast demands on federal and state funds during periods of economic downturns. They can concentrate on formulating policies that encourage participation or save costs incurred in running the program. As an example, if high unemployment rate increases participation numbers, the government can introduce policies that create more jobs, or those that provide education and training. This can reduce unemployment rates, lower poverty numbers and reduce the number of SNAP participants, thereby making government spending more cost effective. Finally, the analysis of such studies can help in measuring and comparing the effectiveness and impacts of alternative programs.

This study analyses various factors affecting SNAP participation rates in the Appalachian region using spatial analysis. However, there are limitations in this study that should be improved in future work. The first limitation is related to data sets. Some of the data sets for the study area were only available for the period 2000 to 2007, precluding conducting the analysis for extended time period. Some data were not easily accessible at the county level. For example, policy variables for the error rate and recertification interval are collected at the state level and we had to manipulate the state variable to represent the county effect which affected the accuracy of the results. Future work in this area would involve assessing the relationship between the SNAP program and the overall health of the participants. It would also be interesting to carry out an analysis of the program where the effect of welfare programs such as TANF/AFDC or ABAWD were taken into consideration.

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Appendix

Table 4. Model Specification: Lagrange Multiplier Test

LM Lag Test for Omitted Spatial Autoregressive Model (SAR)	
LM value	905.8021
Marginal Probability	0.0000
Chi(1) .01 value	6.6400
LM Error Test for Omitted Spatial Error Model (SEM)	
LM value	1073.3237
Marginal Probability	0.0000
Chi(1) .01 value	6.6400
Robust LM Spatial Autoregressive Model (SAR)	
LM value	104.2275
Marginal Probability	0.0000
Chi(1) .01 value	6.6400
Robust LM Spatial Error Model (SEM)	
LM value	271.7491
Marginal Probability	0.0000
Chi(1) .01 value	6.6400

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Determinants of Meat Purchasing Behavior by Ethnic Groups

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Abstract

The decision to purchase meat products is investigated across ethnic groups with data from the Consumer Expenditure Survey. Particularly, we emphasize the U.S. Hispanics markets since its population increased 43% in the 2000-2010 period. The determinants included socio-economic factors in Probit regressions. Income and household composition were characterized as the most significant determinants, however, the effects varied across ethnic groups. As such, ethnicity can be considered as a major factor influencing the decisions to purchase meat products. The findings can be used to develop marketing tactics to influence the purchasing behavior of ethnic groups.

Keywords: ethnicity, expenditures, allocation decisions, market segmentation, consumer behavior

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Introduction

The Hispanic market is one of the faster growing ethnic groups in the United States. This demographic change presents challenges and opportunities for the food industry. From 1990 to 2000, the U.S. population grew by 33 million for an overall change of 13% while the Hispanic population grew by 12.9 million that represented a 58% increase (U.S. Census Bureau, 2001). This growing trend was also observed in the 2010 census that exposed 50 million Hispanics which comprised 16.3% of the total population; a positive change from the 2000 census that counted 35 million Hispanics which amounted to 12.5% of the total population (U.S. Census Bureau, 2001, 2011). In other words, there was one Hispanic person for every eight individuals in 2000 whereas in 2010 there was one person of Hispanic descendancy for every six individuals—making the U.S. the third largest Spanish speaking country in the world (Humphreys, 2003).

Furthermore, according to population projections by the U.S. Census Bureau (2010), the Hispanic population by 2030 is likely to represent almost 20% of the total population, and by 2050—this market may comprise 25% of the U.S. population. These projections imply that food retailers and wholesalers may have latent business opportunities due to the coincidental increase in the purchasing ability of U.S. Hispanics.

However, consumer behavior studies have shown that Hispanics exhibit different consumption patterns compared to the rest of the U.S. population (Fan and Solis, 1994, 1998; Paulin, 2003). Moreover, Hispanic consumer segments may have their own preferences toward foods since the Hispanic population is not a homogeneous market (Nevaer, 2004; Korzenny and Korzenny, 2011). Such diversity in consumption patterns affect the demand for goods and services provided by companies operating in the United States. Hence, it is expected that consumers will make purchase decisions based on their preferences, income, economic behavior as well as their own culture, traditions and food consumption habits. Thus, it is imperative to understand the consumption patterns of households across ethnic groups.

These conditions altogether with the emergence of consumer market fragments will direct production and marketing strategies, specifically, ethnic foods that tie consumers to their country of origin and/or descendancy. Lanfranco (2001) has documented that Hispanics commit a higher percentage of their expenditures to total food relative to other population groups. Thus, if Hispanics consume more beef products than other ethnic groups, then, a rise in Hispanic population would signal an increase in beef demand, *ceteris paribus*; this change may create future opportunities for farmers. Similarly, food companies may change their marketing and advertising strategies not only to deliver their message directed toward the Hispanic population but also for discovering new market opportunities for bringing healthier foods to the marketplace.

As such, it is important to evaluate the meat purchasing behavior of U.S. Hispanics in relation to White, African American, and households of other minorities. Consequently, the aim of this study is to evaluate the determinants of meat purchasing behavior among various ethnic groups in the United States. The focus of inquiry is centered on answering the following question: is the purchasing behavior for meat products across ethnic groups equally responsive to household composition and income?

Methods

The meats included in the analysis were ground beef, roast beef, beef steak, other beef, bacon, pork chops, ham, other pork, poultry, and seafood products. The dependent variable, for a particular meat item, takes the value of 1 if the household purchased it and 0 otherwise. The variables evaluated as determinants of purchase decisions of meat products were: prices, income, expenditures on other goods, household size, number of persons less than 18 years old, number of persons over 64 years old, age, sex, food stamp status, urban status, and education of the household head.

The estimation of a Probit regression for each meat product facilitated the analysis of the determinants of the purchasing behavior; multivariate analyses were limited due to differences in sample size across meat items and ethnic groups. A probit model was defined as

$$(1)\ \Pr(y_j \neq 0 \mid x_j) = \Phi(b_j x_j),$$

where $\Phi(b_j x_j)$ corresponds to the cumulative normal distribution function. Thus, marginal effects are estimated as

$$(2)\ \frac{\partial \Phi}{\partial x_1} = \varphi(b_j \bar{x})\mathrm{b}_1,$$

which corresponds to the height of the probability density function of the normal distribution (estimated at average values of the remaining variables) multiplied by the corresponding coefficient. Thus, the marginal effect is the infinitesimal change in probability when the independent variable of interest is increased by one unit (Stata, 2005).

The composition of the household is measured by the size of the household in the Amsterdam scale. It represents members of the household by summing a scaled value that gives reference to males 18 years and over with the value of 1; males and females under 14 years are valued as 0.52 equivalent scale; females above 14 years are valued as 0.90 equivalent scale; and males between 14-17 years old are valued as 0.98 equivalent scale (Deaton and Muellbauer, 1980). The use of this scale is common in applied consumer behavior research (Lanfranco, 2001).

Data

The data for the analysis was obtained from the 2003 Consumer Expenditure Survey (CES) released by the U.S. Bureau of Labor Statistics. Information about prices was obtained from the same bureau. Average monthly prices were matched with surveyed households in the CES by geographic region. The sample contained information of 5,919 households; 821 households of

Hispanic origin (HISP), 4,118 Non-Hispanic White households (WHIT), 664 African American households (AFAM), and 316 households belonged to other minorities (OTEM) that corresponded to 14%, 70%, 11%, and 5% of the sample, respectively (Table 1). In the CES, Hispanics are identified following the guidelines from the U.S. Census Bureau, asking for self-identification of the origin or descendancy. The options included Mexican-American, Chicano, Mexican, Mexicano, Puerto Rican, Cuban, Central or South American, and other Hispanic. Households that belonged to other minorities included Asian, Asian-Pacific, Native Americans and other groups (U.S. Census Bureau, 1993).

Table 1. Socio-Economic Characteristics by Ethnic Groups.

Characteristic	**HISP**	**WHIT**	**AFAM**	**OTEM**
Number of households	821	4118	664	316
Percentage of households	13.87	69.57	11.22	5.34
Average number of persons/household	3.49	2.52	2.90	2.86
Household size (Amsterdam scale)	2.89	2.18	2.39	2.50
Average number of persons under 18 years old	1.22	0.61	1.10	0.66
Average number of persons over 64 years old	0.22	0.42	0.23	0.30
Average age of household head	43.79	51.63	47.38	47.67
Average annual household income ($/year)	36310.02	45209.14	33906.59	42758.62
Average number of earners	1.60	1.34	1.25	1.52
Average weekly income per earner ($/week)	435.62	650.95	522.27	541.34
Average weekly household income per adult	241.32	398.70	272.79	329.28
Number of households under poverty threshold	168	340	160	45
Percentage of households under poverty	20.61	8.26	24.10	14.24
Number of food stamps recipients	125	500	133	57
Percentage of food stamps recipients	15.34	12.14	20.03	18.04

[a]The poverty threshold for a household of four members (including two children) was $18,859.00/year.

The average annual income was $36,310, $45,209, $33,906, and $42,758 for HISP, WHIT, AFAM and OTEM households, respectively. Hispanic households had the lowest average weekly income per earner and average weekly income per adult equivalent scale, even when they had—on average—more earners. More than 20% of African American households were below the poverty threshold. The same proportion of households was recipient of food stamps. There were more White households below the poverty threshold compared to other groups (Table 1).

The average weekly expenditures on total food was $131.00, $127.00, $104.00, $120.00 for Hispanic, White, African American and households of other minorities, respectively. Those expenditures corresponded to approximated average weekly budget shares on food of 19%, 15%, 16%, and 15%, respectively. Hispanic households lead on average weekly expenditures on total food and food at home—with an average spending of about $131.00 and $94.00, respectively. But, White households lead on food away from home spending—with a $40.00 average weekly expenditure (Table 2). Hispanics had the highest average weekly expenditures on meats followed by other minorities and trailed by African American households. Hispanic households allocated

Table 2. Income, Expenditures, and Purchasing Decisions by Ethnic Groups.

Category	Decisions*	HISP	WHIT	AFAM	OTEM
Average weekly income[a]		698.27	869.41	652.05	822.28
Total Food	Expenditure	130.66	127.04	103.74	120.49
Food at Home	Expenditure	93.61	86.63	77.58	84.75
Food away from Home	Expenditure	37.06	40.41	26.16	35.74
Meat Expenditures	Expenditure	24.60	19.31	22.61	23.27
Ground beef	Non-Purchase[b]	443	2266	353	204
	Purchase[b]	378	1852	311	112
	Expenditure	3.02	2.96	3.01	2.19
Roast beef	Non-Purchase	699	3588	583	284
	Purchase	122	530	81	32
	Expenditure	1.63	1.24	1.31	0.97
Beef steak	Non-Purchase	552	3187	515	242
	Purchase	269	931	149	74
	Expenditure	4.19	2.84	2.76	2.43
Other beef	Non-Purchase	742	3829	612	296
	Purchase	79	289	52	20
	Expenditure	0.95	0.73	0.60	0.46
Bacon	Non-Purchase	652	3178	483	258
	Purchase	169	940	181	58
	Expenditure	0.84	0.95	1.15	0.73
Pork chops	Non-Purchase	665	3548	516	268
	Purchase	156	570	148	48
	Expenditure	1.41	0.91	1.57	1.23
Ham	Non-Purchase	609	3420	563	274
	Purchase	212	698	101	42
	Expenditure	1.36	1.12	1.08	0.70
Other pork	Non-Purchase	664	3530	535	239
	Purchase	157	588	129	77
	Expenditure	1.50	1.25	1.59	2.10
Poultry	Non-Purchase	313	2076	250	138
	Purchase	508	2042	414	178
	Expenditure	5.45	4.08	5.35	4.95
Seafood	Non-Purchase	501	2552	386	122
	Purchase	320	1566	278	194
	Expenditure	4.25	3.23	4.19	7.52

[a]Income and expenditures are measured in U.S. Dollars/week at the household level.
[b]Number of households.

on average 3.5% of the average weekly income on meat expenditures which represented 19% of total food expenditures. Hispanics allocated 22%, 17.3% and 17% of meat expenditures on poultry, seafood products and beef steak products respectively (Table 2).

Overall, the highest non-purchase behavior (zero expenditure) was found in other beef products, followed by roast beef and trailed by pork chops and other pork. In the case of Hispanic households, non-purchase behavior above 80% was found in other beef, roast beef and other pork; for White households such level was found in pork chops. African Americans were similar to White households; in addition, they had high zero-expenditure in ham products (Table 2).

Results

Across ethnic groups, most of the price variables, in nominal and real values, were insignificant factors on the decision to purchase meat products. Different ways of scaling the price variables were evaluated, but, the same results were obtained. Likewise, across ethnic groups, a few socio-economic variables had significant effects on the decision to purchase different meat products; in part, due to the prevailing effects of household size and income.

The inclusion of demographic variables did not produce significant differences in the average probability to consume. The practice of including only household's weekly income and household size as explanatory variables was favored since it produced less insignificant likelihood ratio (LR) tests in which the combined estimated coefficients were hypothesized to be equal to zero. Furthermore, surprisingly, those explanatory variables produced very slight changes in the classification tables of the predicted purchase decisions in comparison with the results from models that included greater number of explanatory variables. Henceforth, the regressions only included household size in Amsterdam scale and logarithm of the household weekly income, such approach is also followed by Lanfranco (2001) in the study of meat purchase decisions.

After the estimation of the coefficients in the Probit regressions, marginal effects were also calculated. They measure the infinitesimal change in probability when the independent variable is increased by one unit, evaluated at the means. For example, the marginal effect of logarithm weekly income for the purchase of a particular meat item is interpreted as the change in probability that occurs when the logarithm of weekly income is increased by one unit; in the same fashion, the household size marginal effect corresponds to the change in probability when the household is increased by one unit (Amsterdam scale) while holding other factors constant.
Hispanic households were less likely to be influenced by income in their purchase decisions in comparison to African American and households of other minorities. Income had a significant effect on purchase decisions of beef steak and other beef products at the 95% level of confidence. Consequently, as weekly income of Hispanics increases from \$700 to \$1900[1], they are 5% more likely to purchase beef steaks and 3% less likely to purchase other beef products.

[1] The difference between \$1900 and \$700 corresponds to an increase of one unit of logarithm of weekly income, the lower limit \$700 corresponds to the average weekly income of Hispanic households.

Table 3. Marginal Effects to Purchase Meat Products by Ethnic Groups.

Product	**Hispanics**	**White**	**AFAM**	**OTEM**
Weekly Income				
Ground beef	-0.024	-0.017	-0.054**	-0.068*
Roast beef	-0.014	-0.009	-0.001	0.001
Beef steak	0.051**	0.032***	0.027	0.087**
Other beef	-0.029**	0.008	0.010	0.044**
Bacon	0.027	-0.011	-0.013	-0.022
Pork chops	0.010	-0.015*	0.002	0.002
Ham	0.024	0.004	-0.040**	0.038
Other pork	-0.005	0.004	0.013	-0.020
Poultry	0.047	0.002	-0.063**	0.062
Seafood	0.022	0.014	0.051**	0.008
Household Size				
Ground beef	0.047***	0.084***	0.061***	0.051**
Roast beef	0.010	0.027***	0.007	0.034**
Beef steak	0.016	0.016*	0.011	-0.008
Other beef	0.021***	0.012***	0.012	0.000
Bacon	-0.010	0.032***	0.020	0.037**
Pork chops	0.012	0.029***	0.035***	-0.006
Ham	0.036***	0.005	0.017	-0.005
Other pork	0.028***	0.029***	0.007	0.091***
Poultry	0.067***	0.054***	0.054***	0.026
Seafood	-0.002	0.015*	-0.002	0.045*

Levels of significance: *=0.10, **=0.05, ***=.01

Unlike income, household size among Hispanic households played a more important role in their decisions to purchase meat products. At the 5% level of significance, significant positive marginal effects of household size were found in ground beef, ham, poultry, and other pork products (Table 3). Thus, an additional household size unit in the Amsterdam scale results in the probability to purchase ground beef to increase by 5%, ham by 4%, other pork by 3%, and poultry products by 7%. So, Hispanics are more likely to consume meat products as household size increases. This finding is noteworthy, since Hispanics tend to live in much bigger households than Whites, African Americans, and households of other minorities (Table 1).

In the case of White households, in general, meat purchase decisions were less influenced by income—implying that it is an irrelevant factor—thus, it is deducted that household size is the major determinant, *ceteris paribus*. Only beef steaks and pork chops were significantly affected by income. Holding household size constant, as weekly income increases from $869 to $2,363, the probability to purchase beef steaks increases by 3% and decreases 2% for pork chops; the effects are statistically different from zero at the 5% and 10% level of significance, respectively. The purchase decisions of meat products were consistently influenced by Household size among White households—the marginal effects were significantly positive at the 90% confidence level—with the exception of ham products (Table 3).

African American households, at the 95% confidence level, had significant and negative effects of income on ground beef, ham, and poultry products. In contrast, purchase decisions of seafood products were positively and significantly affected by income. As AFAM households increase the household size by one unit in the Amsterdam scale, there is a significant positive change in the probability to purchase ground beef by 6%, pork chops by 3%, and poultry products by 5%. On the whole, African Americans were less likely to be influenced by household size in comparison to HISP, WHIT, and OTEM households (Table 3).

Households of other minorities presented significant and negative marginal effect of income effect on the purchase decisions of ground beef products at the 90% confidence level. On the contrary, significant and positive marginal effects of income were found on beef steak and other beef products at the 95% confidence level. Thus, as the weekly income of OTEM households changed from $822 to $2235, the probability to purchase meat products changed by -7% for ground beef, 9% for beef steak and 4% for other beef products. As such, it can be inferred that as OTEM households increase their income, they are more likely to consume beef steak compared to other meat products like chicken, pork and seafood products (Table 3).

As household size increases by one unit, at the 95% confidence level, OTEM households had significant positive changes in the probability to purchase meat products; for instance, the likelihood to purchase ground beef increased by 5% while roast beef, bacon, and other pork products increased by 3%, 4%, and 9%, respectively (Table 3). Moreover, at the 90% confidence level, OTEM households significantly increased the likelihood to purchase seafood products by 4%.

Discussion and Conclusions

The marginal effects from Probit regressions showed that Hispanic households are more likely to purchase beef steaks as income increases and less likely to purchase other beef products as their income increases. These results contrast with those of Lanfranco (2001) who found that Hispanics had positive marginal effects of income in almost all meat products, with the exception of other pork. Moreover, the results of Lanfranco also showed that most of the household size marginal effects were significant at the 10% level of significance.

Our results indicate that White households were more likely to purchase beef steaks and less likely to purchase pork chops as income increased. But, in general, their decisions to purchase meat products were more influenced by the size of the household whereas the influence of income was irrelevant in comparison with African Americans and households of other minorities. These results contrast those of Stegling (2001) who found that regardless of the ethnic origin, household size was more important than income on the decision to purchase meat products.

As a general result, the empirical evidence shows that different ethnic groups are more likely to purchase meat products as the household size increases. Surprisingly, however, some ethnic groups presented insignificant-negative marginal effects of household size. The influence of income on meat purchase decisions was mixed. For instance, it influenced positively the purchase decisions of beef steaks among Hispanic, White, and households of other minorities; but, higher income decreased the likelihood to purchase ground beef among African American and households of other minorities.

As the U.S. consumer market for food is faced with a growing population composed of many ethnic minorities from around the world, the food industry cannot ignore this structural change since the demand for products will be influenced by the purchasing behavior of consumers. Thus, in this paper the purchasing decisions of meat products by different ethnic groups is analyzed, finding that household composition and income were the most important determinants, but, the importance of the effects varied across ethnic groups and meat products.

This result implies that targeting ethnic markets is justified since U.S. food consumers' decisions to purchase meats are not homogeneously responsive to socio-economic factors. As such, when possible, we recommend that future consumer behavior research studies should report the influence of ethnicity along with their major findings since it is at the core of individuals' conduct. All in all, the reported findings may be used to strategically develop marketing campaigns with the aim of encouraging meat demand across ethnic groups, specifically, on tactics focused at motivating the decision to purchase.

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