INFORMATION PRICING AND THE ROLE OF SELF-COMMITMENT DEVICES IN CONSUMER FOOD PURCHASING DECISIONS

by

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I dedicate this dissertation to my late father, Preston Rash, who would have loved watching my PhD journey.

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ABSTRACT

In this dissertation, I investigate the value of information to consumers, the pricing of chicken, and the value of shopping lists to consumers. My first essay finds that across 14 different product categories and seven types of information, information about price and origin are the most important and information about social and environmental impacts are the least important. Our estimates also suggest consumers are willing to wait a large amount of time to obtain the most vs. least desirable types of information prior to making a non-hypothetical product choice. My second essay relates to price indices used to value chicken in the United States. There were two main price indices commonly used by the industry in recent history: the USDA 12-City Price Index and the Georgia Dock Price. We find that there was a long standing equilibrium relationship between these two price indices that shifted across time. Additionally, our analysis shows that there was a structural break between these two price indices around 2000. After this structural break, the analysis suggests Georgia Dock prices were about $0.047/lb higher than they would have been without the break. Last, my third essay aims to determine the impact of shopping lists on consumer spending and healthy shopping behaviors. We find that after controlling for conscientiousness, consumers willingness-to-accept to give up their shopping list is $5.05, while the equivalent gain to write a shopping list is $3.87. We did not find a significant difference in the healthiness of the purchases made by consumers using a shopping list versus those who shopped without a list.

1. INTRODUCTION

In this dissertation, comprised of three separate essays, I study the value of information to consumers, the pricing of chicken, and the value of shopping lists to consumers. Each of these areas of study are not only of particular interest to me as a researcher, but they are also opportunities to meaningfully contribute to the literature and fill important knowledge gaps.

Today's consumers make food choices in an information-rich environment, and yet there are often calls for even more information in the form of new labels and standards. How valuable is information to food consumers, and which types of information do they most desire? My first essay introduces a new approach to valuing multiple types of information in a non-hypothetical environment, which imposes a time cost on the selection of additional information. Across 14 different product categories and seven types of information, we find that information about price and origin are the most important and information about social and environmental impacts are the least important among our sample of almost 1,000 French consumers. Estimates suggest consumers are willing to wait a large amount of time to obtain the most vs. least desirable types of information prior to making a non-hypothetical product choice, primarily because they were not particularly sensitive to wait times in the context of our experiment.

My second essay relates to price indices used to value chicken in the United States; these are indices upon which millions of dollars of contractual relationships between chicken producers, wholesalers, and retailers are founded. Chicken is the number one consumed meat product in the United States; however, the pricing practices of the industry are not well understood. There were two main price indices commonly used by the industry in recent history: the USDA 12-City Price Index and the Georgia Dock Price. My second essay uses time series econometrics to investigate the statistical properties of these two price indices. There was a long standing equilibrium relationship between these two price indices that shifted across time. The analysis shows that there was in fact a structural break between these two price indices around 2000. After this structural break, the analysis suggests Georgia Dock prices were about \$0.047/lb higher than they would have been without the break.

Last, my third essay aims to determine the impact of shopping lists on consumer spending and healthy shopping behaviors. A non-hypothetical field experiment was conducted to determine the value consumers place on these self commitment devices via their willingness-to-accept (to give up their list) or equivalent gain (to write a list) for a shopping list during a grocery shopping trip. By randomly determining who kept and who gave up shopping lists, we are able to explore causal effects of lists on food spending and the healthiness of food purchases. We find that after controlling for conscientiousness, consumers willingness-to-accept to give up their shopping list is \$5.05, while the equivalent gain to write a shopping list is \$3.87. We did not find a significant difference in the healthiness of the purchases made by consumers using a shopping list versus those without. While previous studies have explored correlations between shopping list use and spending, this study provides an estimate of the value of list use, utilizes a credible approach to determine impact of list use disentangled from unobserved confounds, and provides insights on impact of shopping lists on healthy eating.

The three essays will be in the corresponding sections that follow: *Valuing Multiple Types of Information: A Non-Hypothetical Information Display Matrix*, *A Tale of Two Chicken Prices*, and *The Causal Impact of Grocery Shopping Lists on Consumer Shopping Behavior*.

2. VALUING MULTIPLE TYPES OF INFORMATION: A NON-HYPOTHETICAL INFORMATION DISPLAY MATRIX

2.1 Introduction

Consumers are confronted with a dizzying array of information when grocery shopping ([1]). Yet, consumers often say they want even more information about country of origin, GMO content, gluten, added sugars, and more ([2]; [3]); however, package space and consumer attention is limited. How can retailers and policy makers prioritize which information is most valuable to consumers?

A number of papers have estimated the value of information for food consumers. Conventional approaches use consumers' choices before and after being exposed to information to infer the information's value. Examples include using scanner data to determine the value of nutritional labels ([4]), lab experiments valuing information about GMOs, irradiation, and nutrition ([5]; [6]; [7]), and field experiments on calorie labels in restaurants ([8]). In these studies, the value of information is directly related to the size of the demand shift after the provision of information. A downside of these approaches is that it requires observing behavior before and after information, or comparing one group of people exposed to information to another group that has not been provided information. Moreover, these approaches tend to focus on a single attribute or a few information shocks, making it difficult to know which type of information might be more or less valuable. Other approaches have emerged that use attribute-based, random utility models to indirectly infer the value of providing information about particular attributes (e.g., [9]; [10]). One challenge is that these approaches are indirect, inferring the value of information from attribute-based preferences, rather than looking at behavioral change after the provision of information per se. Other studies have proposed directly eliciting consumer's willingness-to-pay for information, such as field experiments valuing information about origin ([11]); however, their approach is limited to single or small number of attributes and information.

This paper introduces a new approach to value information that directly elicits consumer preferences for multiple types of information. The approach bears some similarity to an "information display matrix" (IDM) approach, that has experienced limited use in studying information processing in marketing research ([12]; [13]; [14]). We adapt this approach to make it non-hypothetical by imposing a cost on the selection of additional information; moreover, we modify the approach by having consumers subsequently make actual purchasing decisions between different products given whatever information they have acquired. We also show how data from this approach can be used to estimate relative preferences for different types of information.

In a typical IDM, respondents are presented with a matrix, where the first column shows a list of product attributes and the remaining columns denote specific choice options, somewhat akin to discrete choice experiments. Columns denoting the choice options have corresponding cells that denote the attributes describing the choices. However, the precise level of each attribute associated with each product is initially hidden from the respondent. The respondent is given the task of uncovering attribute information. Analysis typically focuses on the sequence with which respondents choose to uncover information, and when the respondent decides to make a choice.

The contribution of this paper is to show how these methods can be made non-hypothetical, and to show that the method reveals more than just insights about the psychology of information processing. It also provides economic measures of consumers' relative preferences for different types of information. One of the approaches we use to incentive responses, that may be widely applicable in online surveys, is to use waiting time as a "currency." In our application, individuals choose to obtain information for a "price" equal to the number of seconds he/she had to wait before moving on to the next task. We further incentive responses by delivering, to a randomly selected set of respondents, some of the products they actually chose, and deducing the monetary price from their participation fee. We apply this method to seven different types of information for 14 different sets of food products, allowing us to explore how the value of different types of information might change across product categories.

2.2 Methods

The sections that follow detail the data collection, filtering, and modeling techniques that were used in this paper.

2.2.1 Data Collection

Just under 1,000 French participants were recruited, via a large French consumer association, the Confédération Locale du Cadre de Vie (CLCV) website and blog, to participate in an online study. The study was made non-hypothetical by (as described in the subjects' instructions), randomly selecting a subset of individual's choices as binding. For the randomly selected individuals, the random subset of the products they chose were actually delivered, and the cost was subtracted from their participation fee.

Our analysis primarily focuses on a series of information display tasks. Respondents were first shown three food options in a particular product category, such as cookies or rice. Respondents were told the three options differed from each other along seven dimensions or attributes, but they didn't yet know which attribute-levels each product actually contained. The seven product attributes were: price, nutrition, environment, corporate social responsibility, origin, brand, and organic label. This set of attributes have been found, in the literature, to be among the most important to consumers ([15]).

Respondents could learn the product specific levels of each of the attributes by selecting to reveal the information by clicking the respective cell with their mouse. However, in order to see the specific attribute level, the respondent had to incur a specific wait time, or cost as previously mentioned. Waiting times varied from 0 to 30 seconds.[1] As seen in Figure 2.1, the respondent could select as many attributes as she would like, then after the prescribed waiting time had elapsed, the selected attributes appeared underneath the corresponding product, facilitating her decision making. Respondents were able to select as many or as few attributes as they would like during this part of the experiment. This process was carried out for 14 different product categories: Biscuit, Rice, Raisin, Pineapple, Milk, Cream, Corn,

[1]↑There were two different time treatments in this experiment. Half of the products were assigned a continuous time variable and half were assigned either 1 or 15 seconds as their time variable. These treatments allowed for the use of an econometric model or, in the latter case, application of descriptive statistics.

Ratatouille, Salmon, Mackerel, Cereal, Chocolate, Ravioli, and Casserole. To incentivize participants, one out of ten randomly selected participants were given a subset of the items he/she chose, with a value up to 20 euros worth of products.

Only seven products had continuous variable "time costs" that varied across information alternatives, and as a results the time variable was only included in the models for these products. The other seven products also imposed a wait time, but there was no variations across information types. For example, the biscuit product had a time value of 1 second or 15 seconds randomly assigned to all information attributes. Because there was no within subject variance, we could not associate a willingness-to-wait value for these products' attributes. On the other hand, the rice product had waiting times associated with each attribute on a continuous scale from 0 to 30 seconds, and for these products we can estimate a willingness-to-wait value, for each respondent. As indicated, there were seven distinct attributes for which respondents could seek information. The descriptions of these attributes can be found in Table 2.1.

Data from 989 participants was used in this study. The average age of participants was 51.2 years old, with 41% being under the age of 51. 72.5% of respondents were women, and 72.7% reported that they are always in charge of food shopping for the household. The average income was 19,681 euros, and only 5.2% reported living in a rural area.

2.2.2 Data Filtering

In order to ensure that the data set used for analysis was the most robust, we employed the following filtering process. First, we filtered by respondents who did not rank any attributes for a product. From that subset of individuals, the respondents who did not ultimately choose a final product were removed from the data. The respondents falling into the aforementioned category were removed across all products in order to have a consistent sample size for the analysis. This data cleaning process guaranteed that the 771 remaining respondents selected attributes and made a product decision after ranking attributes for each product in the experiment.

Table 2.1.
Attribute Descriptions

Attribute	Description
Price	Amount Paid
Process	How the product was made (organic vs. GMO)
Nutrition+	Rating from 1-10 taking into account health benefits and risks
Environment+	Rating from 1-10 accounting for greenhouse gas emissions, biodiversity, soil/water pollution from production
Social+	Rating from 1-10 regarding corporate behavior of production company
Origin	Country of origin or region of processing
Brand	Brand name of product

+ Ratings were determined using, *Noteo*, a French smartphone application used to inform consumer decision making.

2.2.3 Econometric Model

A random utility framework was used to analyze the information choice data. We define the utility function for individual i, product j, and information t as:

$$U_{\mathrm{ij}t} = V_{\mathrm{ij}t} + \epsilon_{\mathrm{ij}t} \tag{2.1}$$

where $V_{\mathrm{ij}t}$ is the deterministic portion of the random utility function associated with individual i, product j, and information t and $\epsilon_{\mathrm{ij}t}$ is the unobserved error term. We can define $V_{\mathrm{ij}t}$ as:

$$V_{\mathrm{ij}t} = \beta_{\mathrm{j}t} + \alpha_{\mathrm{j}} time_{\mathrm{ij}t} \tag{2.2}$$

where $\beta_{\mathrm{j}t}$ is the marginal utility for information type t (nutrition, brand, process, origin, social, environment, or price) and product j; $time_{\mathrm{ij}t}$ is the number of seconds respondent i

has to wait to get information t for product j; and, $\alpha_{\rm j}$ is the marginal disutility to wait for product j. In other words, individual i derives utility $U_{{\rm ij}t}$ from information t for product j. For identification purposes, the coefficient associated with the value of receiving price information was normalized to zero, meaning the estimated effects associated with the other types of information are relative to receiving price information.

A random parameter logit (RPL) model was used to analyze the information choice data. Estimates include alternative specific constants for each information type and the marginal disutility of time. This model allows us to investigate if there is any heterogeneity by consumer. Each of the parameters were estimated assuming $\beta_{{\rm ij}t}$ is normally distributed. Time parameters,$-\alpha_{\rm ij}$, were assumed to follow a log-normal distribution to ensure that the time estimates were positive ([16]). We will estimate the relative value of each type of information, for each specific product, and to determine the amount of time people are willing to wait (akin to willingness-to-pay but in units of time rather than dollars) to have different types of information. Fourteen RPL models were estimated - one for each product category.

Assuming $\epsilon_{{\rm ij}t}$ are distributed iid type I extreme value, the probability of choosing information type k first among the seven types of information is and v is a vector of individual draws from the random parameter distributions:

$$\boldsymbol{\pi}_{{\rm ij}k|v} = \frac{{\rm e}xp(V_{{\rm ij}k})}{\sum_{t=1}^{7} {\rm e}xp(V_{{\rm ij}t})}. \tag{2.3}$$

Equation 2.3 is the probability of choosing the next most preferred information out of the remaining options conditional on an individual's preferences. In order to estimate the RPL, one must integrate over all of the individual preferences in the sample.

Often consumers chose only one or two types of information, in which case there is a tie for last among the remaining information alternatives. We used only observations from the first two ranked attributes in this study, as previous studies have shown the more attributes a respondent ranks, the less accurate the rankings become ([17]). In other words, the later ranked attributes are less informative than the initial rankings. Moreover, a majority of participants ranked only one or two product attributes[2]. All types information not selected are effectively tied for last.

Willingness-to-Wait (WTW) values were calculated using the RPL estimates. Because the RPL time estimates were distributed log-normal, we used a simulation to calculate the estimates to use in the WTW calculations. Taking 1,000 draws from the distribution function for each product-attribute combination, and likewise 1,000 draws from the exponential of the normal distribution function for the time coefficient provided the estimates to use for the calculation. The median value was used to calculate WTW for an attribute, relative to price information, using equation 2.4. Where $\beta_{\mathrm{ij}t}$ is the simulated median coefficient for individual i, product j, and information t, and α_{ij} is the simulated median coefficient for the waiting time for individual i and product j. Equation 2.4 reports the WTW for information t versus information v, where v equals information about price.

$$WTW_{\mathrm{ij}t} = -\frac{\beta_{\mathrm{ij}t} - \beta_{\mathrm{ij}v}}{\alpha_{\mathrm{ij}}} \tag{2.4}$$

The willingness-to-wait is the difference in waiting times that makes an individual indifferent between receiving two different information options.

2.3 Results

The results of this study showed that consumers did not select a high number of product attributes, on average. Table 2.2 shows the ranking of price for each of the 14 product categories in the experiment. More than 100 respondents selected price as their most preferred attribute for more than half of the products in the experiment. For three of the products, 90 or more respondents ranked price as the first attribute label they would like to see before making a purchasing decision, leaving only three products with less than 75 respondents choosing price first. It is possible that for the three products in the last category, prices are relatively similar for all brands or types chosen, or this is a non explanatory. Price information is most often selected first by participants. Price information is more important to

[2]↑Both the multinomial logit (MNL) and RPL results using the full attribute rankings for the rice product are found in table 2.7 in the appendix.

consumers than information about nutrition, environment, corporate social responsibility, origin, brand, and process, for a majority of products observed in this data.

We can look at these estimates using an importance score, which is calculated using Equation 2.3. The results of these ratios, for all products, can be found in Table 2.3. Once again, looking at the biscuit product, on average, respondents were most likely to choose price as their most preferred attribute 32.3% of the time. Comparing this importance score to the lowest ranked attribute, social, we see that, on average, respondents would select this attribute 4.7% of the time. The product with the highest probability of choosing price above all other attributes was ratatouille (37.9%). As previously observed, the social and environmental attributes have the lowest probabilities of being selected first across all product types. Figure 2.2 shows the importance scores for the seven attributes for the biscuit product. For four of the products included in this study, we find that the origin attribute was selected first before attributes such as price or brand. It is possible that among the representative consumers participating in the experiment, there is a niche of consumers who are most interested in the origin attribute.

The estimates from the random parameter logit model (RPL) are shown in table 2.4. The statistically significant standard deviations for attributes, indicate that there are heterogeneous preferences for information for certain products. Across products we find that consumers were homogeneous in their ranking for the social product attribute; however, the brand and process attributes display heterogeneity in consumer ranking. The same can also be said for the origin attribute for all products except casserole and cereal.

If we look at the nutrition attribute for the rice product (column 8), the standard deviation is not significant, which suggests that the ranking coefficient of nutrition should be represented by one value (-0.83) for the entire sample population. In other words, there is not any heterogeneity on the individual level when it comes to the ranking of the nutrition attribute for the rice product. On the other hand, this would mean that for the attributes that have significant standard deviations, we cannot statistically represent the entire sample population with one coefficient and therefore we would want to use a distribution to represent the population for the brand and process attributes for all products and the origin attribute for all products except casserole and cereal.

The Willingness-to-Wait (WTW) estimates in Table 2.5, show that the median consumer would be willing to wait about 23 minutes (-23.47) to see price information instead of nutrition information, for the rice product. On average, participants were willing to wait at least as long as the maximum time that was used in the experiment (30 seconds). This indicates consumers were not very sensitive to time, as shown in the rank-ordered logit estimates[3].

2.4 Conclusion

Using a new approach to elicit consumer preferences for multiple types of information, this study implements a variation on the information design matrix to uncover which product attributes are most valuable to consumers. The results of this experiment show that price was the most frequently selected product attribute for a majority of products in the study. We also found that, on average, the time-price that respondents "paid" did not significantly impact their attribute choices. In other words, waiting to see an attribute, such as price or nutrition, did not hinder a respondent's desire to see these attributes, in this experiment. These results not only provide us with information about what attributes are important to consumers but also information on consumers preferences across various types of information.

A critique of our analysis is that the waiting times were not long enough to have a significant impact, and as a result, we see that consumers were relatively insensitive to time. Future work might consider how to make waiting time more salient. One way to do this would be do have participants complete a series of monotonous tasks (counting items, stuffing envelopes, etc.) in order to reveal attribute information. Additionally, we could include analysis related to the consumers specific product choice. We know the final product chosen by the consumer; however, consumers were given the opportunity to change their product selection after the specific product was revealed. Using this product choice data, we could better understand the attributes associated with a consumers choice to switch products.

Previous research has found that more product information does not always increase consumer welfare ([18]), and consumers do not always want more information ([19]); therefore,

[3]↑The results for this analysis were converted from seconds to minutes for easier interpretation. Additionally, we note that these estimates are quite large relative to the 0-30 seconds presented to the participants.

it is important for retailers and policy makers to carefully consider which new information to introduce. These results would be aid marketing teams working for food production companies, making and designing product labels, by informing them of not only what information consumers are really using when making purchasing decisions but which pieces of information they find most valuable and are willing to pay for when making a purchasing decision.

Additionally, these results would be helpful for policy makers who make decisions about product labeling legislation. It helps them make informed decisions about what information consumers are really using when making purchasing decisions. This information combined with specific product/brand information could reveal more information about consumer brand preferences to be used by food production companies.

In conclusion, this research has presented a new approach to elicit preferences for multiple types of information using an Information Display Matrix. We have also expanded on the use of the Information Display Matrix by adding a way that incentivize consumers to use it, while also making it non-hypothetical. Additionally, we determined consumers' relative value amongst seven different product attributes.

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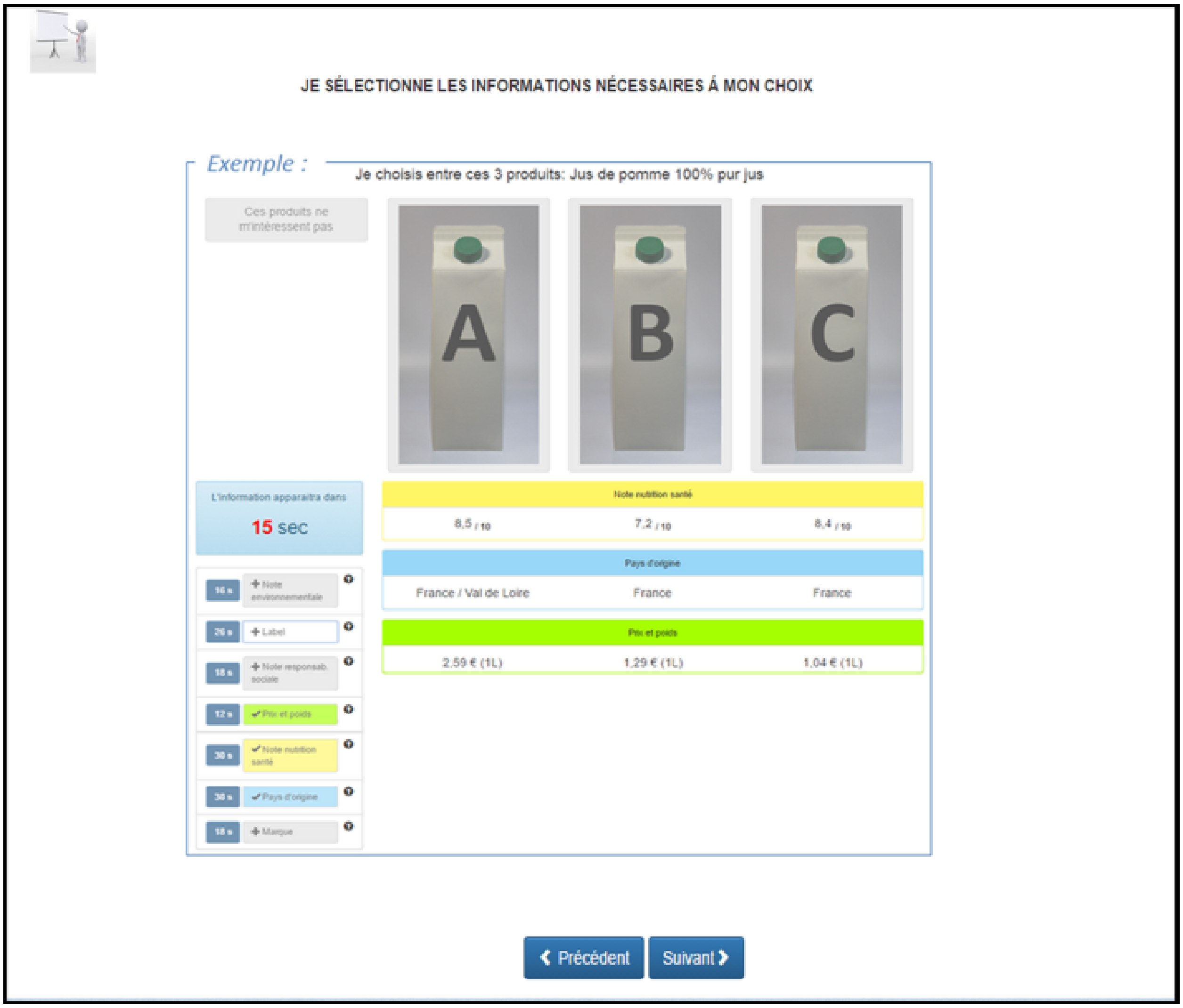

Figure 2.1. Sample of Information Display Matrix

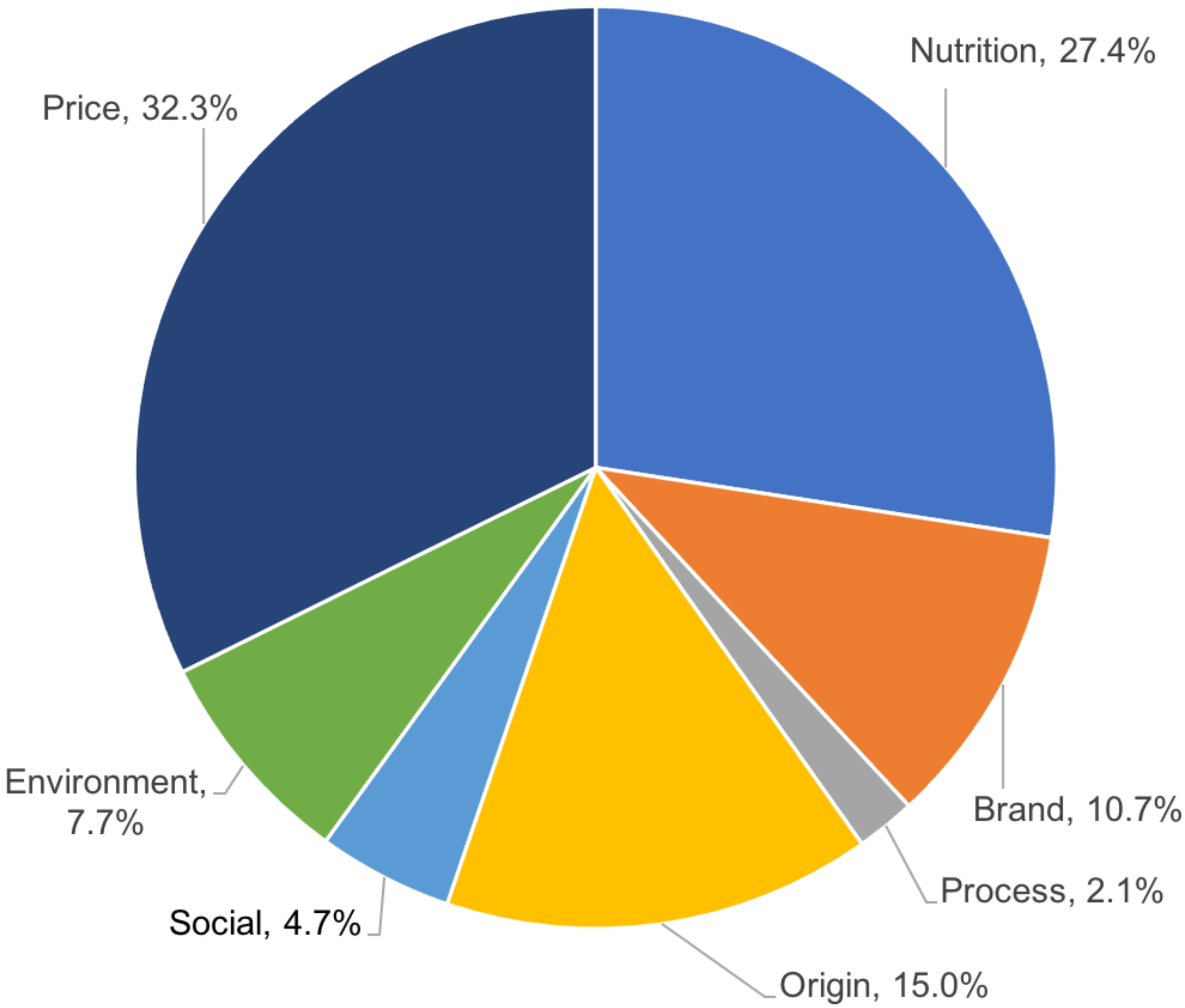

Figure 2.2. Probability of Selecting an Information Type First for Biscuit Product

Table 2.2.
Number of People Ranking Price Attribute by Product

Rank	Biscuit	Rice	Raisin	Pineapple	Milk	Cream	Corn	Ratatouille	Salmon	Mackerel	Cereal	Chocolate	Ravioli	Casserole
1	102	127	105	100	92	127	109	90	93	113	73	117	54	64
2	86	98	85	78	85	79	71	59	65	73	58	97	47	52
3	43	53	38	50	50	40	54	19	50	37	41	52	24	30
4	22	27	21	22	26	23	31	10	34	22	8	26	7	13
5	8	21	13	7	7	8	15	9	18	15	8	24	5	11
6	8	10	9	2	14	6	13	6	5	8	4	11	5	4
7	4	0	6	2	3	3	3	4	4	3	2	4	4	2
8	498	435	494	510	494	485	475	574	502	500	577	440	625	595

Table 2.3.

Probability of Selecting Each Attribute First by Product

	Biscuit	Raisin	Milk	Corn	Salmon	Cereal	Raviolis	Rice	Pineapple	Cream	Ratatouille	Mackerel	Chocolate	Casserole
Nutrition	27.4%	14.7%	9.2%	14.0%	17.2%	39.0%	22.4%	12.3%	14.8%	16.5%	18.6%	13.6%	22.0%	18.5%
Brand	10.7%	2.3%	7.0%	10.9%	8.5%	13.5%	13.0%	5.7%	7.3%	11.1%	9.1%	13.8%	13.8%	8.4%
Process	2.1%	5.7%	13.6%	12.7%	9.1%	1.1%	5.8%	8.1%	7.9%	5.4%	0.7%	6.6%	10.6%	6.1%
Origin	15.0%	35.7%	42.0%	24.8%	27.6%	12.3%	21.1%	32.8%	22.3%	31.1%	24.6%	26.7%	10.9%	28.1%
Social	4.7%	5.6%	3.0%	3.1%	2.8%	0.7%	1.6%	5.3%	7.4%	3.3%	3.2%	4.2%	9.3%	4.0%
Environment	7.7%	6.9%	3.4%	9.5%	10.4%	4.1%	1.5%	7.5%	8.2%	1.0%	5.8%	8.2%	6.2%	5.9%
Price	32.3%	29.2%	21.8%	24.9%	24.5%	29.2%	34.6%	28.3%	32.1%	31.5%	37.9%	26.9%	27.2%	28.9%

Table 2.4.
Random Parameter Logit Model

	(1) Biscuit	(2) Raisin	(3) Milk	(4) Corn	(5) Salmon	(6) Cereal	(7) Ravioli	(8) Rice	(9) Pineapple	(10) Cream	(11) Ratatouille	(12) Mackerel	(13) Chocolate	(14) Casserole
Nutrition	-0.16	-0.68***	-0.89**	-0.57***	-0.35**	0.31**	-0.42**	-0.83**	-0.70**	-0.64***	-0.71***	-0.71**	-0.21	-0.44**
	(0.11)	(0.15)	(0.36)	(0.15)	(0.15)	(0.13)	(0.21)	(0.40)	(0.33)	(0.13)	(0.27)	(0.32)	(0.16)	(0.20)
Nutrition - SD	0.04	0.26	0.96	0.20	0.26	0.51	0.45	0.60	1.16*	0	1.15*	0.93	0.05	0.04
	(0.50)	(0.59)	(0.71)	(0.83)	(0.58)	(0.57)	(0.83)	(1.14)	(0.67)	(4.97)	(0.64)	(0.71)	(4.32)	(8.43)
Brand	-1.08***	-2.51***	-1.18***	-0.80***	-1.02***	-0.71**	-0.89**	-1.58***	-1.36***	-1.10***	-1.43***	-0.73**	-0.69***	-1.26**
	(0.34)	(0.68)	(0.37)	(0.29)	(0.38)	(0.30)	(0.40)	(0.47)	(0.46)	(0.31)	(0.44)	(0.28)	(0.26)	(0.51)
Brand - SD	3.14***	2.78***	2.06***	1.53***	1.89***	1.61***	2.30***	2.25***	1.95***	1.78***	2.25***	1.91***	1.60***	2.79***
	(0.61)	(0.76)	(0.55)	(0.52)	(0.62)	(0.61)	(0.76)	(0.65)	(0.67)	(0.51)	(0.70)	(0.52)	(0.48)	(0.81)
Process	-2.71***	-1.60***	-0.52**	-0.65**	-0.95***	-3.13***	-1.71**	-1.23***	-1.30***	-1.85***	-3.93***	-1.45***	-0.96***	-1.57**
	(0.73)	(0.44)	(0.25)	(0.27)	(0.36)	(1.11)	(0.79)	(0.36)	(0.47)	(0.48)	(1.26)	(0.53)	(0.30)	(0.61)
Process - SD	3.72***	2.66***	2.16***	1.23**	1.96***	3.47***	1.96*	2.36***	1.55**	2.96***	4.52***	1.38*	1.80***	1.85**
	(0.87)	(0.64)	(0.51)	(0.54)	(0.59)	(1.17)	(1.07)	(0.58)	(0.74)	(0.69)	(1.39)	(0.77)	(0.52)	(0.86)
Origin	-0.75***	0.22	0.63***	0.02	0.14	-0.82**	-0.41	0.16	-0.25	-0.04	-0.43*	-0.04	-0.94***	-0.03
	(0.27)	(0.14)	(0.13)	(0.15)	(0.15)	(0.35)	(0.33)	(0.13)	(0.22)	(0.13)	(0.23)	(0.16)	(0.30)	(0.15)
Origin - SD	2.03***	1.48***	1.21***	1.02**	0.90*	1.00	2.18***	1.04**	1.81***	0.91**	1.39**	0.93*	1.99***	0.00
	(0.49)	(0.39)	(0.38)	(0.42)	(0.48)	(0.72)	(0.84)	(0.43)	(0.53)	(0.42)	(0.57)	(0.50)	(0.51)	(7.92)
Social	-1.92***	-1.65***	-1.99***	-2.06***	-2.16***	-3.66**	-3.00*	-1.67	-1.46*	-2.26**	-2.47***	-1.86***	-1.07***	-1.97**
	(0.37)	(0.40)	(0.21)	(0.59)	(0.50)	(1.78)	(1.78)	(1.03)	(0.75)	(1.09)	(0.64)	(0.21)	(0.19)	(0.79)
Social - SD	0.40	0.49	0.03	0.62	0.51	1.98	1.91	0.19	0.14	0.18	0.16	0	0.02	0.03
	(0.94)	(0.96)	(1.14)	(1.03)	(1.00)	(1.40)	(1.62)	(6.87)	(6.34)	(6.33)	(4.25)	(8.32)	(6.08)	(18.26)
Environment	-1.43***	-1.44***	-1.88***	-0.96***	-0.85***	-1.93**	-3.10**	-1.32**	-1.34	-3.49***	-1.88***	-1.19***	-1.49*	-1.59
	(0.18)	(0.30)	(0.63)	(0.15)	(0.26)	(0.99)	(1.57)	(0.58)	(0.89)	(1.33)	(0.66)	(0.36)	(0.79)	(1.46)
Environment - SD	0.14	0.54	0.93	0.09	0.44	0.71	1.61	1.09	0.50	2.29**	0.15	0.05	0.83	0.13
	(0.85)	(0.66)	(0.87)	(0.68)	(0.78)	(1.72)	(1.39)	(0.98)	(2.71)	(1.15)	(4.97)	(7.35)	(1.37)	(12.19)
Time^{+}	-	-	-	-	-	-	-	-7.68	-14.00	-5.50***	-5.80***	-5.68***	-11.33***	-12.30
								(6.84)	(17.63)	(1.29)	(1.56)	(1.90)	(3.96)	(13.12)
Time - SD	-	-	-	-	-	-	-	1.81	5.80	1.86**	2.41**	1.55	4.79***	4.94
								(3.35)	(8.12)	(0.89)	(1.04)	(1.32)	(1.62)	(5.90)
N	871	826	913	860	811	596	442	1040	778	896	598	855	1041	493
AIC	3015.6	2836.7	3017.1	3035.2	2860.6	1975.8	1514.3	3648	2767.6	3031.8	2033.4	2984.4	3780	1708.6

+ log-normally distributed
t statistics in parentheses
* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 2.5.
Median Willingness-to-Wait Values Relative to Price (Minutes)

	Rice	Pineapple	Casserole	Chocolate	Cream	Mackerel	Ratatouille
Nutrition	-23.47	-1555.16	-1437.24	-236.05	-2.67	-1.94	-1.50
Brand	-31.88	-3,118.15	-287.14	-25.89	-2.32	-1.74	-2.57
Process	-21.37	-8581.92	-1225.51	-77.63	-4.56	-5.35	-11.12
Origin	1.75	-9.37	-96.35	-71.37	-0.03	0.06	-0.75
Social	-63.38	-48110.65	-6508.38	-1289.08	-9.37	-8.77	-13.62
Environment	-36.34	-39535.64	-5021.33	-1253.79	-11.80	-5.57	-10.50

2.A Appendix

Table 2.7 shows the MNL and RPL results for the full attribute ranking for the rice product. We found that the difference in results using the full product ranking (versus using only the first two attribute ranks) did not add to the analysis. As a result, we chose to use only the first two attribute rankings in the analysis.

Tables 2.8, 2.9, 2.10, 2.11, 2.12, 2.13, and 2.14 show regressed demographic variables against each of the individual specific preference estimates for each of the attributes from the random parameter models. We analyzed only the products with variable waiting time across attributes, and we found that there is not a significant difference in the estimates across age, income, or gender. It is important to note that the attributes (dependent variables) are measured in thousands.

Table 2.6.

Multinomial Logit Model

	(1) Biscuit	(2) Raisin	(3) Milk	(4) Corn	(5) Salmon	(6) Cereal	(7) Raviolis	(8) Rice	(9) Pineapple	(10) Cream	(11) Ratatouille	(12) Mackerel	(13) Chocolate	(14) Casserole
Nutrition	-0.15	-0.64***	-0.62***	-0.55***	-0.32***	0.30**	-0.34**	-0.71***	-0.43***	-0.56***	-0.45***	-0.49***	-0.20**	-0.43***
	(0.11)	(0.12)	(0.13)	(0.12)	(0.12)	(0.12)	(0.15)	(0.11)	(0.12)	(0.11)	(0.13)	(0.12)	(0.10)	(0.15)
Brand	-0.15	-0.92***	-0.40***	-0.35***	-0.35***	-0.29**	-0.23	-0.61***	-0.60***	-0.49***	-0.59***	-0.23**	-0.26**	-0.33**
	(0.11)	(0.13)	(0.12)	(0.12)	(0.12)	(0.13)	(0.15)	(0.11)	(0.12)	(0.11)	(0.13)	(0.11)	(0.10)	(0.14)
Process	-0.66***	-0.51***	-0.01	-0.34***	-0.29**	-0.90***	-0.81***	-0.37***	-0.72***	-0.54***	-0.97***	-0.89***	-0.36***	-0.79***
	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.16)	(0.18)	(0.11)	(0.13)	(0.11)	(0.15)	(0.13)	(0.11)	(0.16)
Origin	-0.23**	0.27***	0.59***	0.11	0.21*	-0.57***	-0.01	0.21**	0.02	0.04	-0.21*	0.05	-0.29***	-0.04
	(0.11)	(0.10)	(0.10)	(0.11)	(0.11)	(0.14)	(0.15)	(0.09)	(0.11)	(0.10)	(0.12)	(0.10)	(0.11)	(0.14)
Social	-1.80***	-1.51***	-1.96***	-1.87***	-2.03***	-2.17***	-1.73***	-1.62***	-1.37***	-2.11***	-2.18***	-1.81***	-1.02***	-1.92***
	(0.18)	(0.16)	(0.21)	(0.19)	(0.22)	(0.26)	(0.25)	(0.16)	(0.16)	(0.20)	(0.24)	(0.18)	(0.13)	(0.25)
Environment	-1.37***	-1.29***	-1.50***	-0.94***	-0.77***	-1.70***	-2.02***	-0.95***	-1.20***	-1.79***	-1.67***	-1.14***	-1.18***	-1.52***
	(0.16)	(0.15)	(0.17)	(0.14)	(0.14)	(0.21)	(0.28)	(0.12)	(0.15)	(0.17)	(0.19)	(0.14)	(0.14)	(0.21)
Time	-	-	-	-	-	-	-	0.00	0.00	0.01**	0.01**	0.01**	0.00	0.00
								(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
N	871	826	913	860	811	596	422	1040	778	896	598	855	1041	493
AIC	3053	2847	3024	3029	2858	1977	1514	3650	2769	3036.4	2042	2979	3784	1708

t statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

Table 2.7.
MPL & RPL Full Ranking Results

	Rice	
	MNL	RPL
Nutrition	-0.58***	-0.61***
	(0.09)	(0.11)
Nutrition - SD	-	0.32
		(0.55)
Brand	-0.69***	-0.97***
	(0.09)	(0.16)
Brand - SD	-	1.46***
		(0.25)
Process	-0.46***	-0.66***
	(0.09)	(0.14)
Process - SD	-	1.48***
		(0.26)
Origin	0.15*	0.25**
	(0.08)	(0.1)
Origin - SD	-	1.01***
		(0.18)
Social	-1.18***	-1.26***
	(0.01)	(0.12)
Social - SD	-	0.09
		(1.09)
Environment	-0.78***	-0.83***
	(0.10)	(0.11)
Environment - SD	-	0.25
		(0.57)
Time	0.00	-6.80
	(0.00)	(8.46)
Time - SD	-	1.09
		(8.05)
N	1691	1691
AIC	5379	5350

Table 2.8.
Pineapple

	Nutrition	Brand	Process	Origin	Social	Environment	Time
Age	-3.75	1.47	2.67	14.72***	0.05**	2.56***	0.61
	(-1.81)	(-0.36)	(-0.91)	(-3.61)	(-2.74)	(-3.55)	(-1.18)
Income	-0.01	-0.02	0.01	-0.02	0.00	0.02**	0.00
	(-0.48)	(-0.38)	(-0.15)	(-0.38)	(-0.78)	(-2.63)	(-0.81)
Gender	63.55	-46.63	9.53	102.90	0.56	10.67	4.10
	(-0.96)	(-0.36)	(-0.10)	(-0.79)	(-1.05)	(-0.46)	(-0.25)
Constant	-624.10***	-1339.00***	-1503.10***	-1175.10**	-1479.20***	-1682.40***	-17.37
	(-3.40)	(-3.69)	(-5.78)	(-3.25)	(-999.13)	(-26.27)	(-0.38)
N	380	380	380	380	380	380	380

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Table 2.9.
Casserole

	Nutrition	Brand	Process	Origin	Social	Environment	Time
Age	-0.00	-10.75	-6.79	0.00	-0.00	0.07*	0.36
	(-0.93)	(-1.21)	(-1.44)	-0.32	(-0.45)	(-2.33)	(-1.04)
Income	-0.00	0.05	0.07	0.00	-0.00	-0.00	-0.00
	(-0.56)	(-0.45)	(-1.33)	(-0.82)	(-0.28)	(-0.51)	(-0.49)
Gender	-0.03	172.20	-375.80**	-0.01	0.16	0.04	-22.06*
	(-0.18)	(-0.66)	(-2.71)	(-0.94)	(-1.78)	(-0.05)	(-2.15)
Constant	-444.30***	-1165.00	-707.80	-28.30***	-1974.10***	-1589.90***	42.16
	(-1157.04)	(-1.60)	(-1.83)	(-834.51)	(-8132.40)	(-641.29)	(-1.48)
N	233	233	233	233	233	233	233

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Table 2.10.

Chocolate

	Nutrition	Brand	Process	Origin	Social	Environment	Time
Age	0.01	-4.52	-1.38	12.13**	0.15	0.80	-0.17
	(-0.56)	(-1.69)	(-0.42)	(-3.24)	(-1.31)	(-1.43)	(-0.45)
Income	-0.00	0.03	0.03	-0.00	0.00	0.01	0.00
	(-0.74)	(-1.01)	(-0.67)	(-0.05)	(-0.66)	(-1.70)	(-0.46)
Gender	0.31	12.97	25.36	59.36	0.44	-14.17	1.67
	(-0.72)	(-0.15)	(-0.24)	(-0.50)	(-0.12)	(-0.79)	(-0.14)
Constant	-219.00***	-536.50*	-999.20***	-1629.90***	-1109.20***	-1482.60***	30.08
	(-190.62)	(-2.31)	(-3.49)	(-5.02)	(-115.24)	(-30.52)	(-0.91)
N	493	493	493	493	493	493	493

t statistics in parentheses

* p<0.05 ** p<0.01 *** p<0.001

Table 2.11.

Cream

	Nutrition	Brand	Process	Origin	Social	Environment	Time
Age	-0.00	0.21	-5.68	3.36**	0.13**	6.35	0.10
	(-0.80)	(-0.06)	(-0.84)	(-2.61)	(-2.65)	(-1.74)	(-1.21)
Income	0.00	0.03	0.06	-0.01	0.00	-0.03	0.00
	(-0.12)	(-0.73)	(-0.77)	(-0.60)	(-0.82)	(-0.74)	(-0.94)
Gender	0.22	96.70	-130.40	-45.39	-1.03	-134.00	-2.80
	(-1.20)	(-0.91)	(-0.61)	(-1.12)	(-0.66)	(-1.16)	(-1.13)
Constant	-646.50***	-1406.40***	-1479.70*	-119.80	-2273.30***	-3628.70***	18.84**
	(-1290.75)	(-4.83)	(-2.53)	(-1.07)	(-531.93)	(-11.42)	(-2.76)
N	435	435	435	435	435	435	435

t statistics in parentheses

* p<0.05 ** p<0.01 *** p<0.001

Table 2.12.
Rice

	Nutrition	Brand	Process	Origin	Social	Environment	Time
Age	-0.49	-0.22	-1.67	5.69***	0.16*	-0.80	0.00
	(-0.61)	(-0.05)	(-0.35)	(-3.95)	(-2.13)	(-0.71)	(-0.29)
Income	-0.01	-0.01	0.02	0.01	-0.00	0.02	-0.00
	(-0.81)	(-0.12)	(-0.37)	(-0.38)	(-0.04)	(-1.50)	(-0.50)
Gender	34.82	-213.60	158.90	44.16	2.16	-11.25	-0.30
	(-1.35)	(-1.62)	(-1.04)	(-0.96)	(-0.92)	(-0.31)	(-1.53)
Constant	-940.00***	-1220.50***	-1536.50***	-208.60	-1681.00***	-1303.10***	2.78***
	(-13.23)	(-3.35)	(-3.66)	(-1.64)	(-259.89)	(-13.17)	(-5.16)
N	509	509	509	509	509	509	509

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Table 2.13.
Ratatouille

	Nutrition	Brand	Process	Origin	Social	Environment	Time
Age	0.05	-4.12	-0.97	5.79***	0.14	-0.00	0.04
	(0.05)	(-0.55)	(-0.10)	(3.50)	(0.56)	(-0.03)	(0.10)
Income	-0.01	0.07	0.15	0.03	-0.00	0.00*	0.00
	(-0.95)	(0.73)	(1.23)	(1.46)	(-0.59)	(2.33)	(0.12)
Gender	74.91*	40.09	174.80	-169.90**	-4.82	0.57	-11.33
	(2.29)	(0.16)	(0.55)	(-3.12)	(-0.57)	(0.64)	(-0.79)
Constant	-835.70***	-1953.30**	-3813.40***	-379.00*	-2711.30***	-1850.40***	62.36
	(-9.27)	(-2.85)	(-4.39)	(-2.53)	(-116.39)	(-755.95)	(1.58)
N	289	289	289	289	289	289	289

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

Table 2.14.
Mackerel

	Nutrition	Brand	Process	Origin	Social	Environment	Time
Age	0.05	-5.18	-0.26	4.52**	0.00	0.03	-0.03
	(-0.04)	(-1.27)	(-0.13)	(-3.14)	(-0.28)	(-0.35)	(-0.61)
Income	0.00	-0.03	-0.01	0.02	0.00	0.00	0.00*
	(-0.13)	(-0.69)	(-0.52)	(-0.88)	(-0.68)	(-0.73)	(-2.32)
Gender	64.93	98.32	-21.08	-16.26	-0.05	-2.20	0.74
	(-1.82)	(-0.78)	(-0.34)	(-0.37)	(-0.10)	(-0.74)	(-0.56)
Constant	-820.30***	-576.70	-1358.20***	-269.40*	-1872.60***	-1220.00***	10.09**
	(-8.20)	(-1.63)	(-7.93)	(-2.17)	(-1348.80)	(-146.80)	(-2.73)
N	416	416	416	416	416	416	416

t statistics in parentheses
* p<0.05 ** p<0.01 *** p<0.001

3. A TALE OF TWO CHICKEN PRICES

3.1 Introduction

In the United States, there were 58.259 billion pounds of chicken produced in 2019 ([1]). Additionally, the chicken industry has long been known for its vertical coordination and opaque pricing practices, which means that access to information about the industry could be worth billions. The past seventy years have shown a significant increase in the per capita consumption of chicken in the United States (see figure 3.1) due in part to lower prices brought about by greater vertical coordination and efficiency. According to the USDA, in 1996 chicken became the second most consumed meat product - a title previously held by pork, as shown in figure 3.1. Then around 2010, chicken overtook beef as the most consumed meat product and remains in that number one spot to this day. Additionally, the genetic makeup of broilers across the last fifty years has increased not only the size of each individual animal but the meat yield per animal ([2]). This dramatic increase in chicken consumption and animal size in America leads us to further investigate the measures that the industry is using to price this commodity that continues to increase in popularity among US consumers.

The chicken industry is vertically integrated, and large chicken integrators control most, if not all, parts of the downstream production process ([3]). According to WattAgNet.com, the top five integrators in the United States/North America are: Tyson Foods, Pilgrim's Pride, Koch Foods, Perdue Farms, and Sanderson Farms. One way to define vertical coordination is that these large chicken processors can control adjacent parts of the production process and it has been argued that they have significant control of the prices received by the growers and paid by consumers ([4]; [5]; [6]). The type of vertical coordination that these chicken processors participate in can be called Ownership Integration because these large firms own almost all the production process ([7]).

There are two main sources of information about chicken prices. The United States Department of Agriculture reports prices (daily, weekly, monthly, etc.) for many agriculture commodities. As stated on the National Agricultural Statistics Service (NASS) website, their objective is to provide accurate, unbiased statistics to individuals involved in agriculture in order to further the work of the industry. The data produced by the USDA and NASS are used for pricing in the chicken industry; however, historically there is another price index that has been relied on more heavily by the industry ... that is the Georgia Dock Price. In addition to being one of the top chicken producing states in the US, Georgia was also home to the Georgia Dock Price. Due to the size of the chicken industry in Georgia, over time, this became one of the main price indices used to price chicken all over the country.

The Georgia Dock Price has been reported, alongside the USDA data, since March of 1990. This report was issued monthly, by the Georgia Department of Agriculture, until December of 2016 when the Georgia Department of Agriculture discontinued the report. On November 3rd, 2016, an article in the New York Times reported that there was something questionable happening regarding the Georgia Dock Price. The allegations were coming from various Wall Street investors who began to wonder why the Georgia Dock Price was staying relatively constant while the other indices for chicken were declining ([8]).

These lawsuits included claims that the chicken producers worked together to coordinate meat production and supply ([9]; [10]). The lawyers representing the chicken buyers claim that these large processors were in communication to keep the price of chicken inflated, and as a result hurt the chicken buyers ([11]). It was later discovered that the agency was no longer using the formula historically used when calculating the Georgia Dock Price, which was concerning because this is the price index primarily used by food distributors to price the chicken they were purchasing from these large chicken companies ([9]; [10]). This controversy eventually led to the Georgia Department of Agriculture discontinuing the price index ([8]).

The lawsuits regarding allegations of collusion have been brought by the Justice Department over the past four years. They claim that the price fixing took place between 2012 and 2017. However, a closer look at the data from the Georgia Department of Agriculture and the USDA, reveal that there was actually a change in this price relationship much earlier than 2012. In fact, we see that something fundamentally changed around 2000.

Looking at figure 3.2, the percentage of days that the Georgia Dock Price Index was higher than the USDA 12-City Price Index for each year that we have data available. We can see that for the years prior to 2000, the Georgia Dock price is higher than the 12-City price only about 30% of the time; however, after 2000 we see that it is higher than the USDA price index much more often, almost 100% of the time. While it is hard to say specifically what happened to these price indices around the year 2000, it appears that something changed in the Georgia Dock Price index during this time period.

January 2021 began to bring resolution to the years of litigation. As of January 12, 2021 the *Wall Street Journal* reported that Tyson Foods, Inc. and Pilgrim's Pride Corp. both reached a settlement with select poultry buyers while not admitting their claims are factual ([11]). This settlement was reported by Pilgrim's to be $75 million, while no value was reported by Tyson. As we previously mentioned, the data seems to show that there was a divergence from the established relationship around the year 2000, which is about 12 years prior to the dates claimed in the lawsuit (see figure 3.3). The analysis in this paper aims to understand how the relationship between these two price indices shifted throughout history.

This begs the question did the Georgia Dock Price diverge from the long-established equilibrium between it and the competing price indices? This paper will investigate the statistical properties of the price index and determine its effect on other chicken price indices commonly used by the industry. We will use time series econometrics to examine two different measures of chicken prices in the United States: the Georgia Dock Price and the USDA 12-City Composite Price Index. The objective of this paper is to determine if and when there was any divergence between the Georgia Dock Price and the 12-City Composite Wholesale price, reported by the USDA, and if so, understand how the relationship between these two price indices changed over time.

3.2 Data

There are three main indices used for pricing chicken in the United States, all of which are shown in Figure 3.3. This chart shows the historical data for the USDA National Composite Weighted Average, Georgia Dock Price, and the USDA 12-City Composite Wholesale Price. In 2012, the 12-City Composite Wholesale price was discontinued but then the USDA started reporting the National Weighted Composite Average. As a result, we will be using the complete data, for the Georgia Dock Price and the USDA 12-City Composite price index for this analysis.

Looking further at Figure 3.3, the Georgia Dock Price and the USDA 12-City price seem to move almost in perfect harmony until the early 2000s. At this point, the Georgia Dock Price starts to slightly differ from the USDA data but follows the same general pattern. In the beginning of 2013, the Georgia Dock Price started to differ from the volatility of the USDA price until it was discontinued. This volatility pattern was also observed and recorded in the legal documents filed, by distributors, for violations of antitrust laws by the chicken producers.

This paper will use data on the Georgia Dock Price for whole birds, obtained from the Livestock Marketing Information Center (LMIC) as well as the 12-City Composite Wholesale Price, reported by the USDA. Because of the lawsuit with the Georgia Dock Price, the last piece of data recorded from the Georgia Dock Price was in November of 2016. For our summary statistics and high level analysis, we will use the entire time period that is available for each index; however, when performing the economic price analyses on this data, we will only use time periods that are available for both indices. [1]

In order to better understand the movement between the Georgia Dock Price and the USDA 12-City Composite Index specifically, we will begin by looking at the high level graph of this time series data. Figure 3.4 shows the price index data for 2000 to 2011 - this is the time period when we hypothesize the Georgia Dock Prices started to differ considerably from the 12-City USDA reported values. It is easy to see that the Georgia Dock Price does not have the same amount of variation over this time period compared to the USDA data; however, the USDA 12-City composite price fluctuated and at some points significantly decreased during this time period.

This leads to the question: is there cointegration between these two series' that was not present prior to 2000 but appeared as time passed? Which leads to our hypothesis that the prices from the 12-City Composite Index and the Georgia Dock Price are not cointegrated before 2000 but are cointegrated after 2000.

[1] ↑The statistical analyses was performed using R Studio version 3.5.1.

3.3 Methods

The main goal of this paper is to determine if the Georgia Dock Price and the 12-City Composite Price Index are cointegrated and if so, when did the cointegration begin. To do this, we model the data using either a VAR or a VECM model depending on if there is cointegration present in the data.

The VAR model was used when the model is specified as not cointegrated and can be written as follows, where "GP" represents the Georgia Dock Price and "City" represents the 12-City Price Index:

$$\begin{aligned} GP_t = \beta_0^{GP} + \beta_1^{GP} GP_{t-1} + \beta_2^{GP} GP_{t-2} \\ + \beta_3^{GP} City_{t-1} + \beta_4^{GP} City_{t-2} + \epsilon_t^{GP} \end{aligned} \tag{3.1}$$

$$\begin{aligned} City_t = \beta_0^{City} + \beta_1^{City} City_{t-1} + \beta_2^{City} City_{t-2} \\ + \beta_3^{City} GP_{t-1} + \beta_4^{City} GP_{t-2} + \epsilon_t^{City} \end{aligned} \tag{3.2}$$

We used a first differences of prices when the data was found to be not stationary, which can be written as follows using the same notation previously used in the VAR models. Where k indicates the selected lag length chosen to minimize Bayesian information criterion.

$$\Delta GP_t = \gamma_0^{GP} + \alpha_1(\beta_0 + \beta_1 GP_{t-1} + \beta_2 City_{t-1}) + \sum_{\mathrm{i}=1}^{k} \gamma_{\mathrm{i}}^{GP} \Delta GP_{t-\mathrm{i}} + \sum_{\mathrm{i}=1}^{k} \gamma_{\mathrm{i}}^{GP} \Delta City_{t-\mathrm{i}} + \epsilon_t^{GP} \tag{3.3}$$

$$\Delta City_t = \gamma_0^{City} + \alpha_2(\beta_0 + \beta_1 GP_{t-1} + \beta_2 City_{t-1}) + \sum_{\mathrm{i}=1}^{k} \gamma_{\mathrm{i}}^{City} \Delta City_{t-\mathrm{i}} + \sum_{\mathrm{i}=1}^{k} \gamma_{\mathrm{i}}^{City} \Delta GP_{t-\mathrm{i}} + \epsilon_t^{City} \tag{3.4}$$

In order to determine the precise point in time when the data became cointegrated, we performed structural break tests with both price indices. These structural break tests were done following the work of Bai and Perron (1998). This algorithm allows for multiple break points by selecting the one that minimizes the sum of squared residuals for a model using the individual time series data sets as the outcome variables ([12]).

We used the results from the structural break tests to complete a difference in differences estimation using equation 3.5. We stacked the data and created dummy variable indicating to which price index each value belonged. The structural break dates were used as a binary variables in the model denoted by $Break_{\mathrm{i}}$ with each i representing a different date range. These variables are defined as equal to 1 until the next break point and then goes back to zero. The intercept, β_0, represents the 12-City price, with *Georgia* indicating the Georgia Dock price.

$$\begin{aligned} Price = \beta_0 + \beta_1 Georgia + \beta_2 Break_1 + \beta_3 Break_2 + \beta_4 Break_3 + \beta_5 Break_1 * Georgia \\ + \beta_6 Break_2 * Georgia + \beta_7 Break_3 * Georgia + \epsilon \end{aligned} \tag{3.5}$$

The main variable of interest in the difference in differences estimation are the interaction variables. These variables will compare the change in price between the 12-City price index to the Georgia Dock Price after each of the structural break dates. We found that there were 3 structural break dates; therefore, we included binary variables in the model to indicate each of the respective time periods.

3.4 Results

3.4.1 Unit Root & Stationarity Tests

In order to test our hypothesis, we looked at three different subsets of data: the full sample, pre-2000, and post-2000. We began the analysis by checking both price indices for stationarity. In order to do this, we ran an Augmented Dickey-Fuller Test (ADF), Phillips-Perron Test (PP), and a KPSS Test for both price indices prior to 2000, after 2000, and the full sample. The results can be found in table 3.1. We used the results of these tests to determine using levels or differences for the rest of the data analysis.

Based on these tests, we conclude that the data prior to 2000 is stationary and consequently not cointegrated. That is because two of the three unit root tests point us toward this same conclusion (ADF and PP tests). As a result we will use price levels and a Vector Autoregressive Regression (VAR) model for this subset of the data.

VAR Results: Pre-2000

During our analysis of the data prior to 2000, we estimated a Vector Autoregressive Regression (VAR) model. We used price levels for our analysis due to the stationarity of the data. The results of this model can be seen in the first two columns of table 3.4.

Looking at the VAR model results, we see that in the Georgia Dock Price equation only the first lag of the Georgia Dock Price (GP) and the constant are statistically significant. In the 12-City equation, we see that the the first lag of the 12-City price is statistically significant as well as both lags for the Georgia Dock Price; however, the lags for the Georgia Dock Price are only significant at the 10% level while the first lag of the 12-City price is significant at the 1% level. The analysis of the VAR model helps us have a broad picture about what is happening with the data, but it is important to perform a couple of additional causality tests to make sure we have a complete understanding of the data.

In order to get a more complete understanding of the implications of the VAR model, we looked into the Granger Causality implied by this model. Using the results from the VAR, we performed a Granger Causality test. The results of these tests are found in Table 3.3. Based on this analysis, we fail to reject both that the Georgia Dock Price does not Granger-cause the 12-City price and that the 12-City price does not Granger-cause the Georgia Dock Price, prior to 2000.

Additionally, we looked at the Forecast Error Variance Decomposition (FEVD). The results of the FEVD are found in figure 3.5. From the FEVD, we find that there is evidence to support our decision to conclude that 12-City prices do not Granger-cause the Georgia Dock Prices; however, we do find evidence that the Georgia Dock Price makes up over half of the forecast error variance for the 12-City prices, which can be seen in the lower half of figure 3.5.

VECM Results: Post-2000

Looking at the unit root tests for the data after 2000, we conclude that this time series is non-stationary. We see this conclusion as a result of the stationarity tests in table 3.1. Due to the non-stationarity of this subset of data, we know that we will either be using a VAR in differences model or a VECM in price levels model to analyze the data between the Georgia Dock Price the 12-City price data reported by the USDA after 2000. The model selection will be determined by the Johansen cointegration test. If we find that there is evidence of cointegration, we will analyze their effects on one another using a VECM model; however, if we find that there is no cointegration, we will use a VAR in differences model to perform our analysis.

For the post 2000 time series, we ran a Johansen cointegration test using price levels, to determine if any cointegration existed in this data. The results of this test can be found in table 3.2 below. Looking at the results from the cointegration test, we observe the null hypothesis test statistic is equal to 20.84, which is larger than the 5% critical value. Therefore, we can reject the null hypothesis that the matrix is equal to zero. The next hypothesis we will test is that the rank of the matrix is less than or equal to one. For this hypothesis, we see the test statistic is equal to 3.87, which is much smaller than the critical value at all levels. As a result, we determine that the rank of the matrix is equal to one, which means that taking one difference in the data will provide us with a stationary data set. In other words, we know that there exists a cointegrating relationship in this data and we should use the VECM model in price levels to analyze these two time series after 2000 ([13]; [14]; [15]).

The results of our VECM model, using price levels for the post 2000 data, is found in columns 3 and 4 of table 3.4. We see the value of α for Georgia Dock Price is 0.033 and α for 12-City is 0.301***. These α values tell us the speed with which these price indices respond to disequilibrium. The larger speed of adjustment parameter (α) for the 12-City price index indicates that this price index responds more strongly to restore equilibrium, which indicates that the Georgia Dock Price is the price leader. The rest of the variables in columns 3 and 4 of table 3.4 represent the coefficients on the lagged return variables, which are represented by γ values in equations 3.3 and 3.4.

The error correction term in table 3.5 is the portion of the VECM model that differs from the previously used VAR model. It is represented by the following equation: $\beta_0 + \beta_1 GP_{t-1} + \beta_2 City_{t-1}$. These β values tell us the equilibrium relationship between these two price indices.

Given that we know the values of the β coefficients, we can look at how shifts in the Georgia Dock Price would impact the 12-City Price Index, in the long run and vice versa, using the following equation $0 = 7.283 + GP_{t-1} - 1.154City_{t-1}$. Rearranging the equation, we get $GP_{t-1} = -7.283 + 1.154City_{t-1}$, the positive coefficient on $City_{t-1}$ indicates to us that as the 12-City Price Index increases so does the Georgia Dock Price. This follows our economic intuition that these prices are cointegrated after 2000.

VECM Results: Full Sample

The results of the stationarity test, for the full sample, indicate that there is the presence of a unit root in the data. Additionally, the unit root tests for the 12-City Price Index and the Georgia Dock Price across the full sample, indicate that this time series is non-stationary. We see this conclusion as a result of the stationarity tests in Table 3.1.

Because we have non-stationary, time series data sets, we know that we will either be using a VAR in differences model or a VECM in price levels model to analyze the data between the Georgia Dock Price the 12-City price data reported by the USDA. The model selection was determined using the Johansen cointegration test.

We ran a Johansen cointegration test using price levels, to determine if any cointegration existed in this data. The results of this test can be found in table 3.2 below. Looking at the results, we observe the null hypothesis test statistic is equal to 43.70, which is higher than all critical values. Therefore, we can reject the null hypothesis that the matrix is equal to zero. The next hypothesis we will test is that the rank of the matrix is less than or equal to one. For this hypothesis, we see the test statistic is equal to 2.75, which is much smaller than the critical value at all levels. As a result, we determine that the rank of the matrix is equal to one, which means that taking one difference in the data will provide us with a stationary data set. In other words, we know that there exists a cointegrating relationship in this data and we should use the VECM model in price levels to analyze these two time series ([13]; [14]; [15]).

In table 3.4, we see the value of α for the Georgia Dock Price VECM equation is 0.001 and α for the 12-City is 0.153^{***}. The rest of the variables in table 3.4 represent the coefficients on the lagged return variables, which are represented by γ values in equations 3.3 and 3.4.

Given that we know the values of the β coefficients, we can look at how shifts in the Georgia Dock Price would impact the 12-City Price Index, in the long run and vice versa, using the following equation $0 = 15.486 + GP_{t-1} - 1.262City_{t-1}$. Rearranging the equation, we get $GP_{t-1} = -15.486 + 1.262City_{t-1}$, the positive coefficient on $City_{t-1}$ indicates to us that as the 12-City Price Index increases so does the Georgia Dock Price. This equilibrium relationship is shown in figure 3.6. The black arrow in figure 3.6 indicates the Georgia Dock Price premium over the 12-City Price Index. In other words, if the 12-City price is 96 then the model indicates that the Georgia Dock Price will be 105.621.

3.4.2 Structural Break Tests

The structural break tests were performed using the cointegration residuals to determine the point when the two data series' cointegration began. A Quandt-Andrews Breakpoint test, an extension of the Chow Breakpoint test, was performed to find the breaks across time. The results of these structural break tests can be found in figures 3.7 and 3.8. We see in figure 3.7 that there are three break points: July 1982, September 1989, and October 1997. Looking at the structural break test the other way around (figure 3.8), we also see three break points: July 1982, October 1997, and January 2003. Regardless which time series was the dependent variable, we observe a structural break around 2000.

3.4.3 Difference-in-Differences Estimation

After observing the structural break dates, we used these dates to estimate a difference-in-differences model. In order to apply the difference-in-differences model, we must address the parallel trends assumption. This assumption implies that the Georgia Dock Price would have followed the same pattern as the 12-City Price index, if there was no treatment effect present. In order to test this assumption, we follow the work of Mullally & Lusk (2018) by testing the stationarity of the data prior to the structural breaks ([16]). We can use the results from table 3.1, which show that the data is stationary prior to 2000. As a result, we can say that these price indices showed parallel trends prior to the structural breaks.

The results of the difference-in-differences model can be found in table 3.6. The coefficients we are most interested in are the interaction terms in this model. These tell us the level of the Georgia Dock Price for each structural break range. We see that during the first structural break dates (July 1982 - August 1989) the Georgia Dock Price was, on average, -$0.02 lower than the 12-City Price Index. Similarly, for the second structural break (September 1989 - October 1997) the Georgia Dock Price is less than a penny lower than the 12-City Price Index; however, we find that both of these values are not statistically significant. This follows our intuition that these price indices are trending the same until around 2000. The third break date (November 1997 - December 2011) shows that the Georgia Dock Price is higher than the 12-City Price Index by a statistically significant $0.05.

Using the results from the difference-in-differences model, we can calculate the total amount overpaid by consumers after the November 1997 structural break date. Taking the difference between the Georgia Dock Price and the unobserved counterfactual price and multiplying by the total monthly chicken production ($/pound) indicates that from November 1997 - November 1998 consumers over payed by approximately $1.52 billion. This trend of increasing prices continues to cost consumers for the next 17 years. Results from November 2015 - November 2016 show over payment of more than $2.22 billion over this time period.

3.5 Conclusions

In conclusion, we analyzed the former Georgia Dock Price and the USDA 12-City price index in order to better understand the price fixing allegations brought against the Georgia Department of Agriculture and the Georgia Dock Price. Using time series analysis, we found that there was, in fact, a point in time when the Georgia Dock Price and the 12-City price index had a fundamental relationship change. This is an important finding that will help economists better understand the dynamic pricing factors that affected sales of the most widely consumed animal protein in the US.

The objective of this paper was to better understand the relationship between the Georgia Dock Price and the USDA 12-City Price Index. It was hypothesized that there was no cointegration prior to 2000, but a cointegrating relationship did exist between these price indices after 2000. We are unable to reject this hypothesis. A structural change in the data set was found around 2003. This is much earlier than the claims in the lawsuit regarding these price indices, which claim the price fixing took place between 2012 and 2017. We have shown that there was a change in this price relationship much earlier. While there have been a few settlements reached regarding the price fixing allegations, additional lawsuits have surfaced as more and more retailers take action against these producers ([17]).

Many formula contracts were created, industry wide, based on these price indices. Because we have shown that these indices diverged from their equilibrium relationship, future research on the contracting framework would benefit chicken producers and buyers alike. It would be interesting to determine if there was any arbitrage happening while this price relationship was fluctuating. Additionally, these results could help growers, integrators and retailers better understand the factors that are influencing their most used price indices. It could be that the Georgia Dock price began to diverge from the USDA price because of a shift in the way that chickens have been marketed over time. For example, if these prices were determined historically by referencing chickens of a certain weight, if that weight were to change this would lead to a fundamental change in the price index.

Lastly, they would benefit policy makers who are working on policies to make the agriculture industry fair for all participants. This could provide insight for policy makers about antitrust laws related to the meat industry in the United States. As the number of meat processors in the US continues to decrease due to consolidation, understanding how the price indices interact will continue to be increasingly important

One potential downfall of our analysis is the length of the time series data. While we are using the entire set of data available for these two indices, it is not nearly the volume of many other time series analyses, and therefore we do not have the same robustness that is usually found in the price analysis literature. Our results would be more robust if we had a longer time series to work with; however, since the Georgia Dock Price was discontinued when the allegations started to rise, this is the data series that is available to answer this particular research question.

These findings will hopefully provide insight into a better understanding of the potential impact the Georgia Dock Price was having on national chicken prices. It is possible that economists will be able to incorporate results from this paper into their analysis of commodity pricing in the future. Specifically, for analyses related to the historical welfare gains or losses in the industry, economists should use these results to adjust their welfare calculations, using the Georgia Dock Price, accordingly. They must at minimum acknowledge the fact that this price index diverged from the long established market equilibrium.

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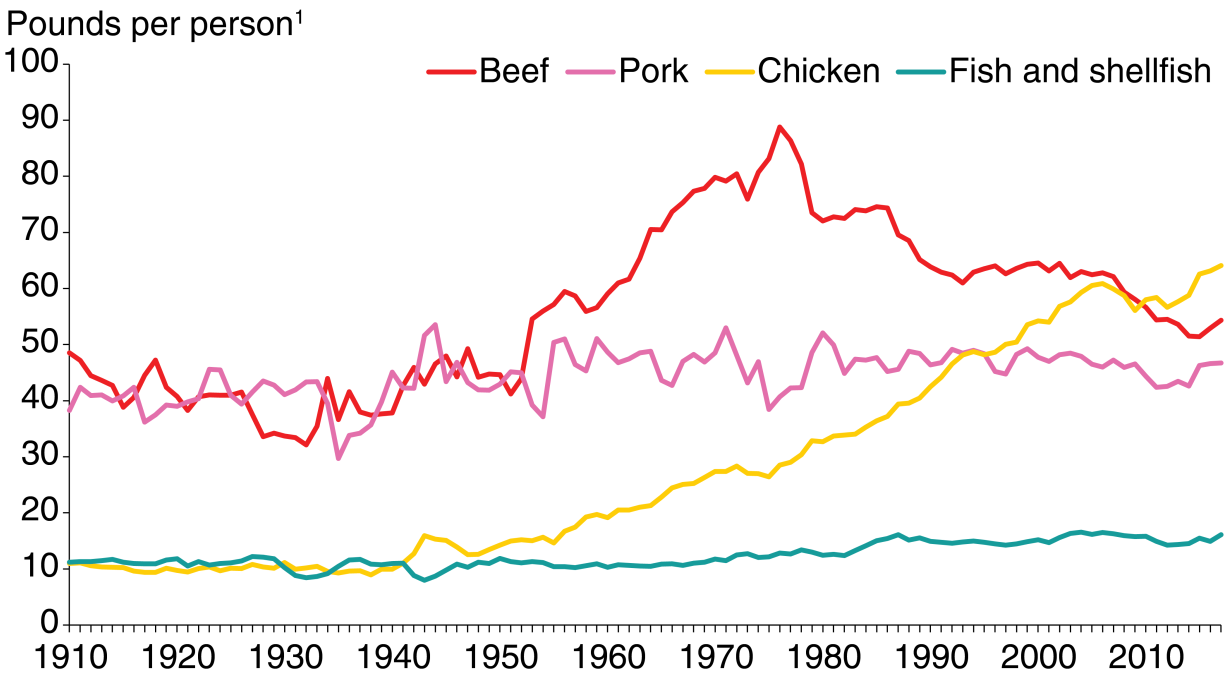
U.S. per capita availability of beef, pork, chicken, and fish/shellfish, 1910-2017



[1]Calculated on the basis of raw and edible meat in boneless, trimmed (edible) weight. Excludes edible offals, bones, viscera, and game from red meat. Includes skin, neck, and giblets from chicken. Excludes use of chicken for commercially prepared pet food.
Source: USDA, Economic Research Service, Food Availability Data.

Figure 3.1. Source: USDA ERS

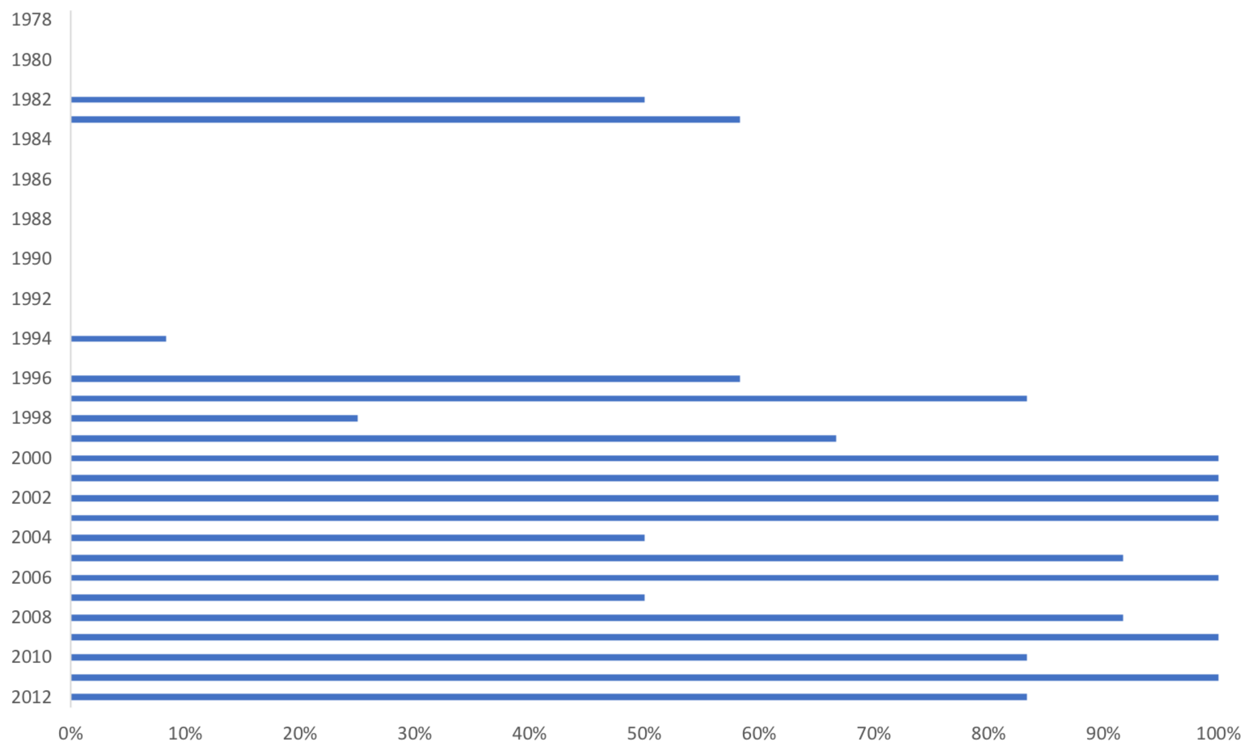


Figure 3.2. Percentage of Months where Georgia Dock Price is greater than USDA 12-City Price

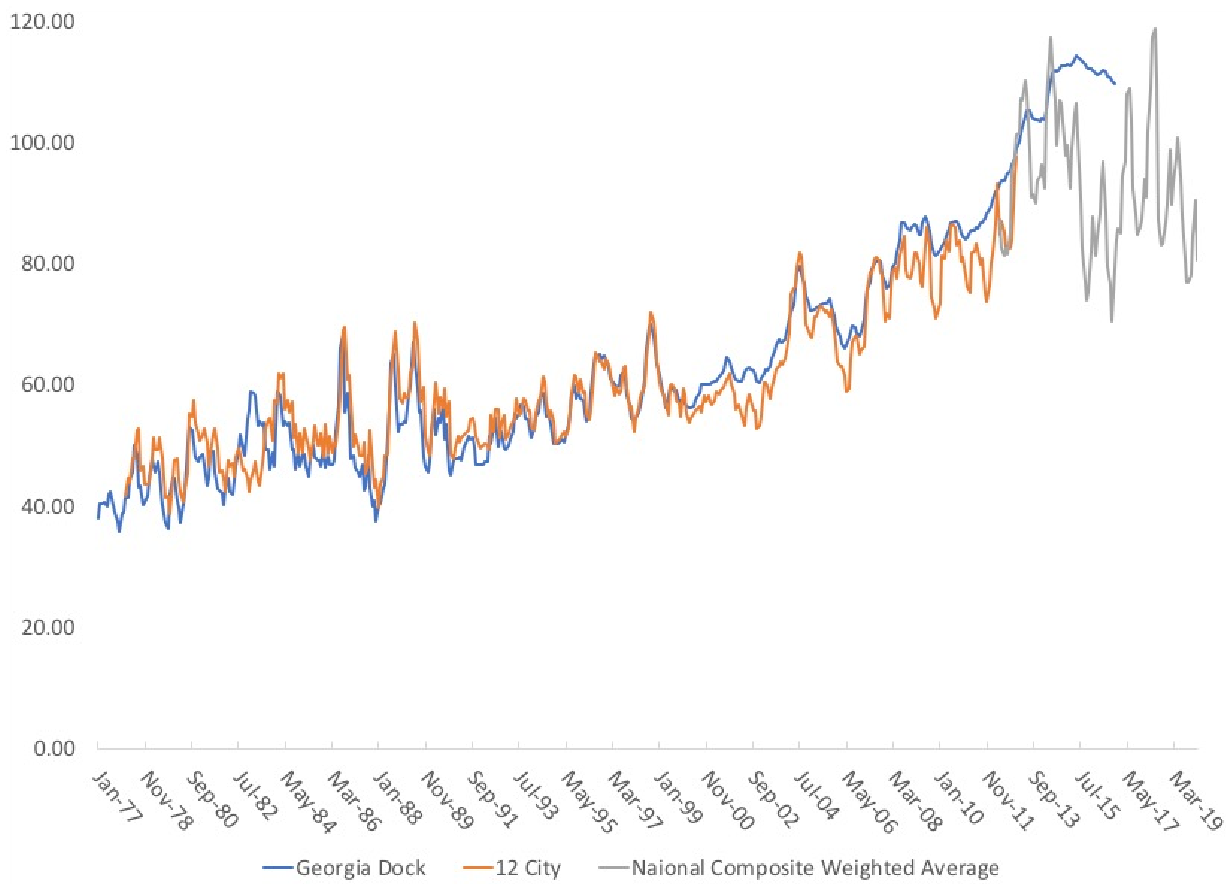


Figure 3.3. Historical Graph of Chicken Price Indices
Source: Livestock Marketing Information Center (LMIC) and USDA

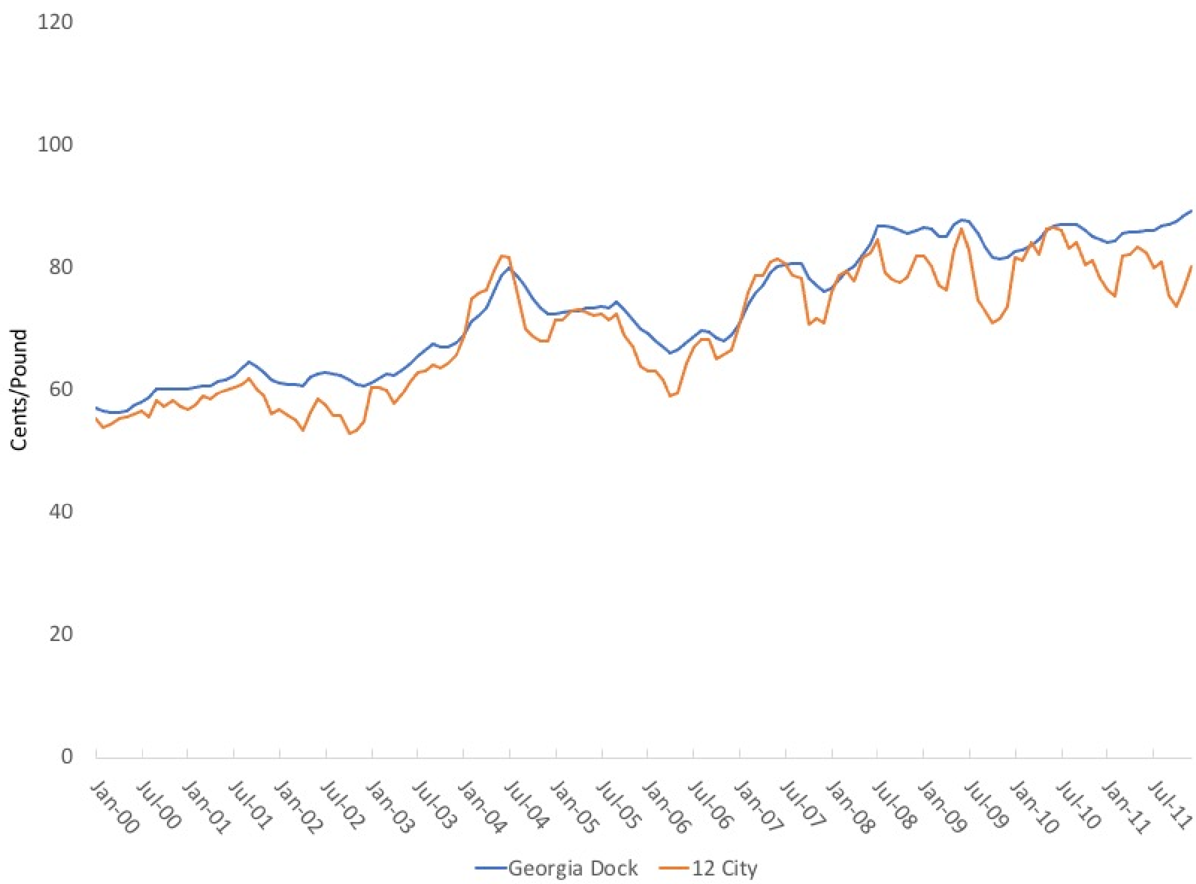


Figure 3.4. Georgia Dock Price and 12-City Price Index: 2000 - 2011
Source: Livestock Marketing Information Center (LMIC) and USDA

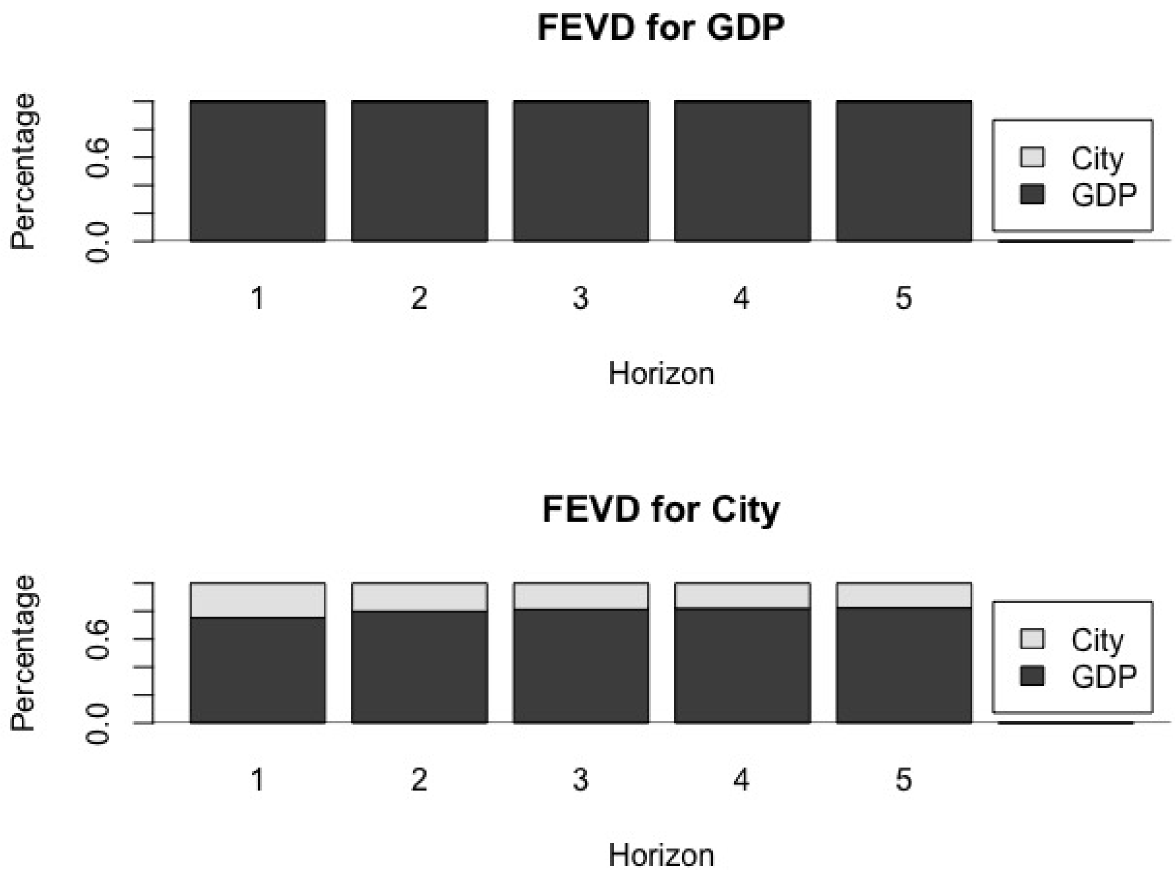


Figure 3.5. Forecast Error Variance Decomposition Plot

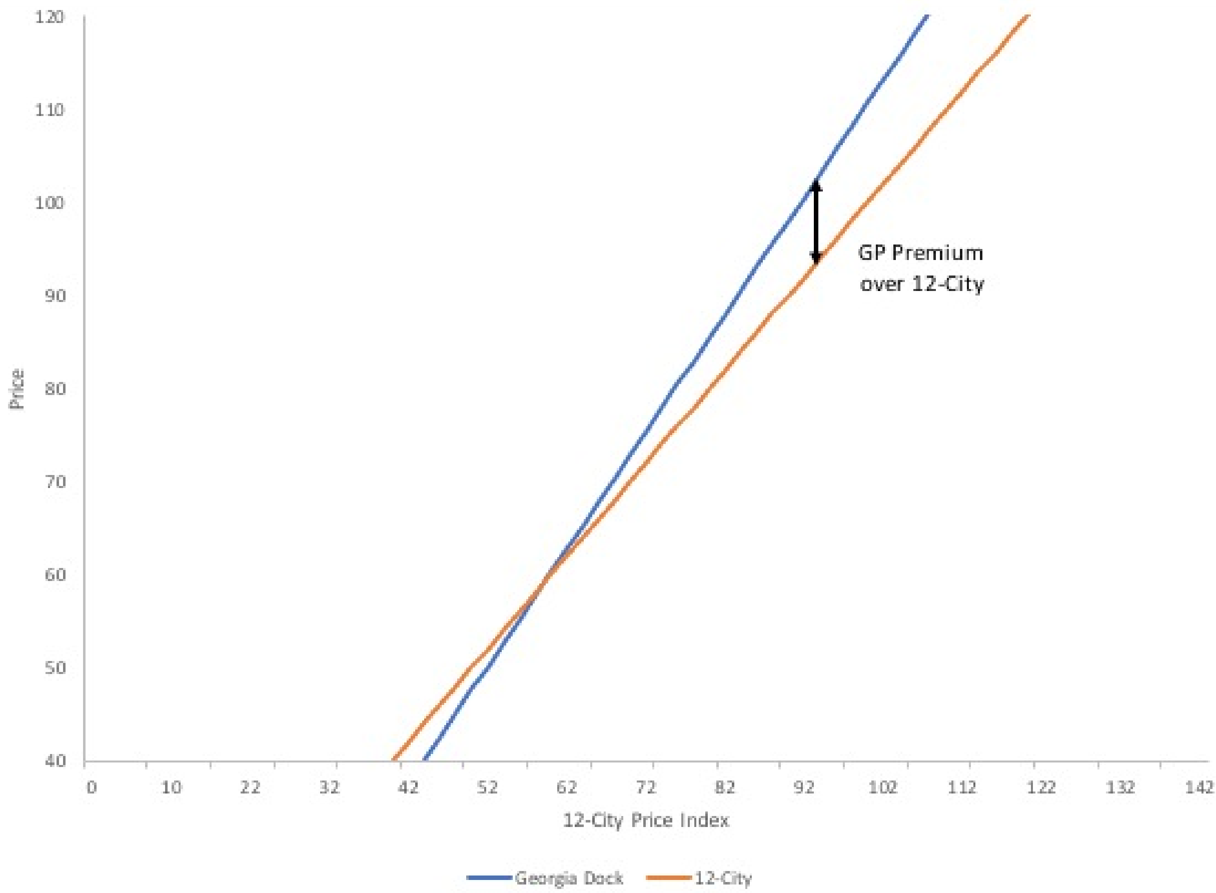


Figure 3.6. Equilibrium Premium: Full Sample Georgia Dock Price over 12-City Composite Price Index

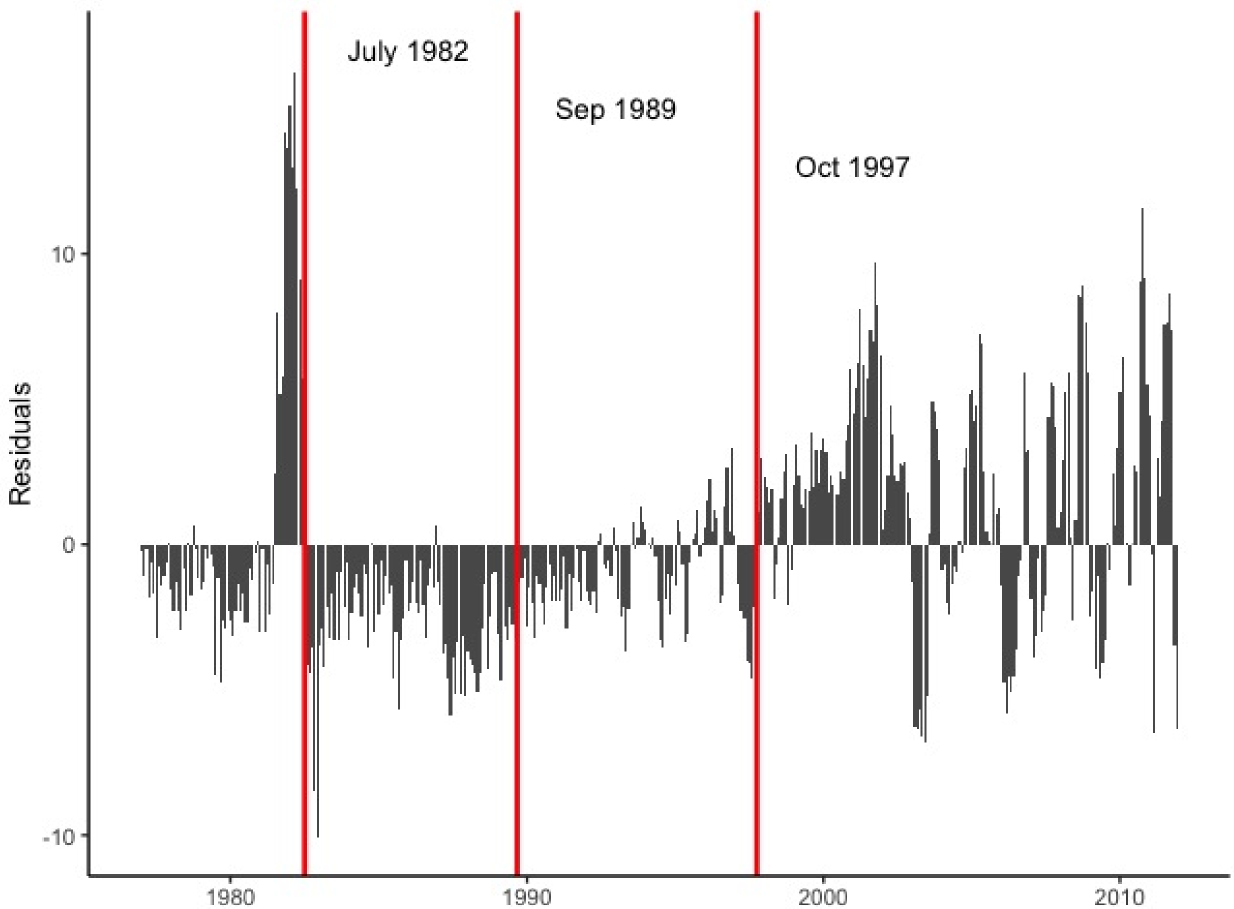


Figure 3.7. Georgia Dock Price Structural Break Test

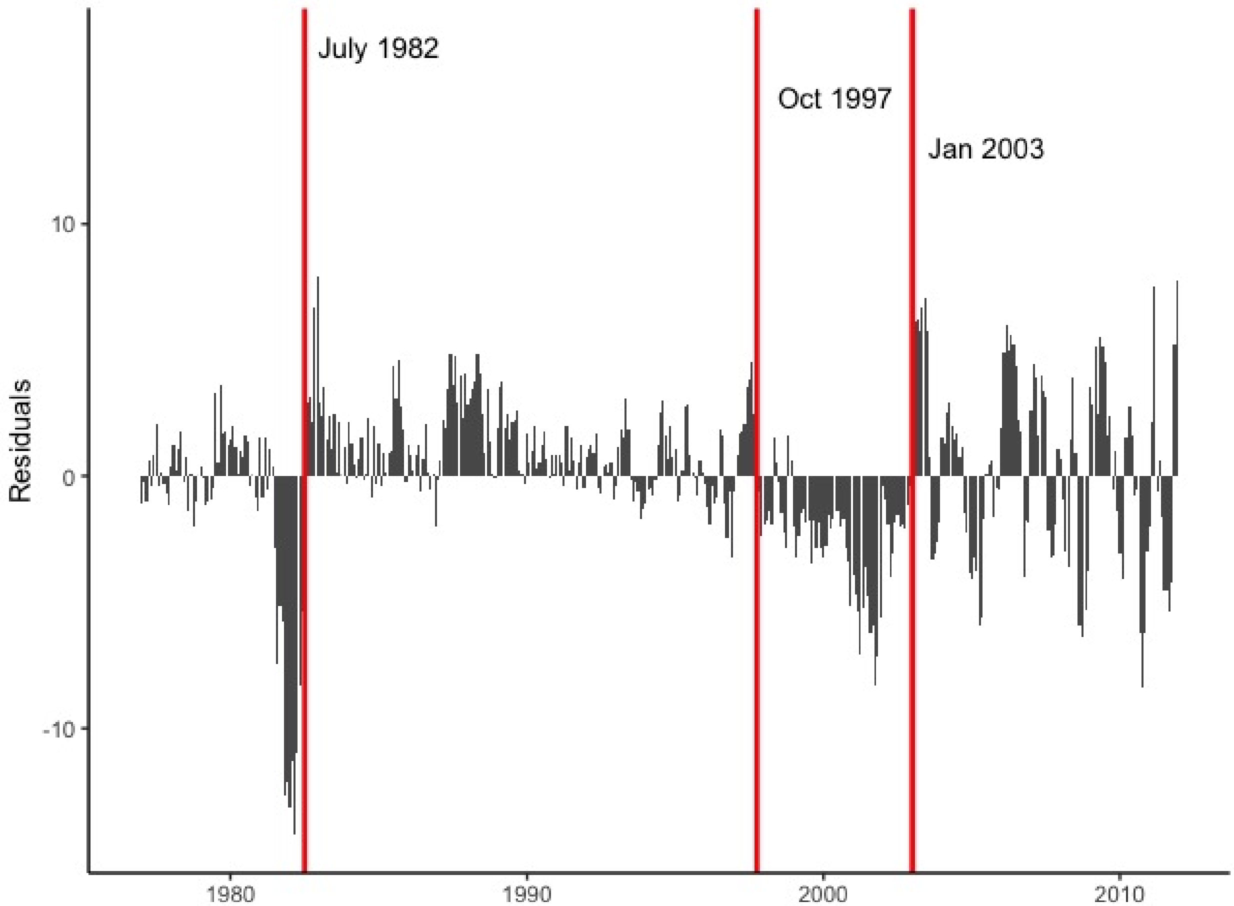


Figure 3.8. 12-City Composite Price Index Structural Break Test

Table 3.1.
Stationarity Tests

	Price Index	Statistic	P-Value	Method	Alternative
Full Sample	12-City	-3.218	0.084	Augmented Dickey-Fuller Test	stationary
		-47.224	0.010	Phillips-Perron Unit Root Test	stationary
		5.366	0.010	KPSS Test for Level Stationarity	unit root
	Georgia Dock	-2.567	0.337	Augmented Dickey-Fuller Test	stationary
		-33.180	0.010	Phillips-Perron Unit Root Test	stationary
		5.874	0.010	KPSS Test for Level Stationarity	unit root
Pre-2000	12-City	-5.253	0.010	Augmented Dickey-Fuller Test	stationary
		-60.341	0.010	Phillips-Perron Unit Root Test	stationary
		2.409	0.010	KPSS Test for Level Stationarity	unit root
	Georgia Dock	-5.181	0.010	Augmented Dickey-Fuller Test	stationary
		-54.961	0.010	Phillips-Perron Unit Root Test	stationary
		2.906	0.010	KPSS Test for Level Stationarity	unit root
Post-2000	12-City	-2.934	0.187	Augmented Dickey-Fuller Test	stationary
		-23.418	0.027	Phillips-Perron Unit Root Test	stationary
		2.016	0.010	KPSS Test for Level Stationarity	unit root
	Georgia Dock	-2.659	0.302	Augmented Dickey-Fuller Test	stationary
		-12.947	0.368	Phillips-Perron Unit Root Test	stationary
		2.402	0.010	KPSS Test for Level Stationarity	unit root

Table 3.2.

Johansen Cointegration Tests

			Critical Value		
	H_0	Test Statistic	10%	5%	1%
Full Sample	$r \leq 1$	2.75	7.52	9.24	12.97
	$r = 0$	43.70	17.85	19.96	24.60
Post-2000	$r \leq 1$	3.87	7.52	9.24	12.97
	$r = 0$	20.84	17.85	19.96	24.60

Table 3.3.

Granger Causality Test

	Test Statistic	P-Value	Null Hypothesis
Pre-2000	1.871	0.155	H_0: GP does not Granger-cause City
	0.224	0.799	H_0: City does not Granger-cause GP

Table 3.4.
VAR and VECM Models

	Dependent variable:					
	GP:VAR (Pre-2000)	12-City:VAR (Pre-2000)	GP:VECM (Post-2000)	12-City:VECM (Post-2000)	GP:VECM (Full Sample)	12-City:VECM (Full Sample)
	(1)	(2)	(3)	(4)	(5)	(6)
α	–	–	0.033	0.301***	0.001	0.153***
			(0.023)	(0.083)	(0.031)	(0.039)
GP lag1	1.035***	0.246+	1.066***	1.780***	0.066	0.150
	(0.118)	(0.127)	(0.138)	(0.497)	(0.081)	(0.103)
City lag1	0.039	0.741***	−0.0814*	−0.282*	0.091	−0.057
	(0.110)	(0.119)	(0.038)	(0.138)	(0.065)	(0.082)
GP lag2	−0.103	−0.221+	−0.342+	−0.644	–	–
	(0.117)	(0.126)	(0.175)	(0.629)		
City lag2	−0.066	0.106	0.027	−0.106	–	–
	(0.109)	(0.118)	(0.041)	(0.147)		
GP lag3	–	–	0.010	0.136	–	–
			(0.135)	(0.484)		
City lag3	–	–	−0.030	−0.383**	–	–
			(0.037)	(0.132)		
Constant	5.091***	7.020***	–	–	–	–
	(1.426)	(1.539)				
R^2	0.856	0.788	0.544	0.241	0.030	0.041
Adjusted R^2	0.854	0.785	0.517	0.197	0.023	0.034
Residual Std. Error	2.703	2.918	0.763	2.742	2.347	2.961
F Statistic	416,521***	261.120***	20.58***	5.473***	4.235**	5.925***

Note: $^{+}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$
Numbers in parentheses are standard errors.

Table 3.5.

VECM Model Error Correction Terms

		Error Correction Term
Full Sample	Georgia Dock Price (β_1)	1
	12-City Price (β_2)	-1.262
	Constant (β_0)	15.486
Post-2000	Georgia Dock Price (β_1)	1
	12-City Price (β_2)	-1.154
	Constant (β_0)	7.283

Table 3.6.

Difference in Differences Estimation

	Price (cents/pound)
12-City Price	47.344***
	(1.012)
Georgia Dock Price	-1.174
	(1.442)
July 1982 - August 1989	7.234***
	(1.363)
September 1989 - October 1997	9.194***
	(1.323)
November 1997 - December 2011	22.762***
	(1.204)
GP * July '82 - Aug '89	-2.315
	(1.928)
GP * Sept '89 - Oct '97	-0.213
	(1.871)
GP * Nov '97 - Dec '11	4.688**
	(1.702)
R^2	0.595

Note: **$p<0.01$; ***$p<0.001$.

Standard Errors appear in parentheses.

3.A Appendix

As a robustness check, we used the *CausalImpact* package in R to verify the difference-in-differences estimates using the structural break dates ([1]). This packages creates a Bayesian structural time-series model, which is then used to predict the counterfactual values after the structural break date that was given to the model. For full model assumptions see [1]. Figure 3.9 shows the counterfactual prediction for the Georgia Dock Price after the November 1997 structural break date. The solid black line represents the actual Georgia Dock Price Index, while the dashed line represents the counterfactual data. The results from the Bayesian model indicate that the average causal effect of the structural break date was 5.1, which is similar to the results we found using the difference-in-differences model.

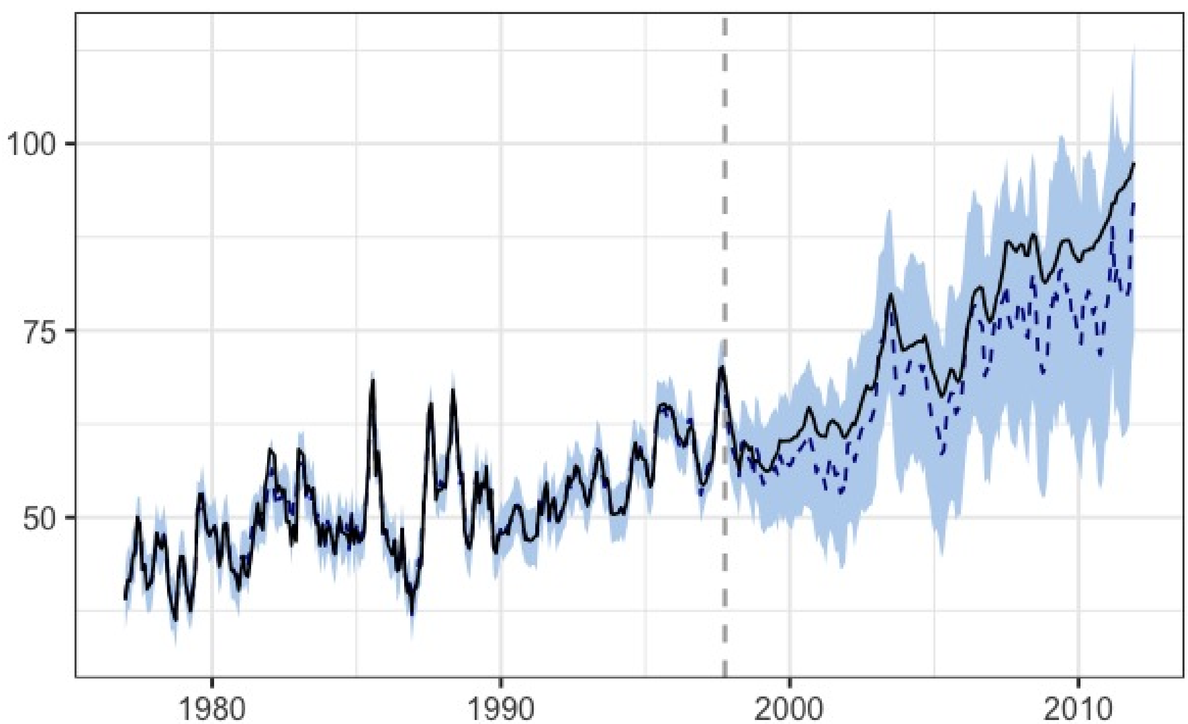


Figure 3.9. Counterfactual Prediction after November 1997

4. KEEP FORGETTING TO MAKE A SHOPPING LIST? DON'T BEAT YOURSELF UP OVER IT!

4.1 Introduction

Every day consumers make decisions that not only impact their present self but also their future self. During that decision-making process, they must make trade-offs between their utility now and their utility in the future ([1]; [2]). This begs the question: what tactics do consumers employ to benefit their future selves?

Many consumers use a shopping list or memory aides during grocery shopping. Creating a shopping list has an immediate cost to the consumer, but is generally thought to have payoffs in the form of decreasing impulse purchases during the shopping trip, time spent in the store, and reduced opportunistic decision-making ([3]; [4]). Some consumers look for self-commitment devices, perhaps by using a grocery shopping list, knowing that adhering to this strategy means the benefits might not be immediately realized ([5]; [1]). For example, healthier grocery store purchases could lead to better eating habits and as a result weight loss and improved lifestyle.

While there have been a number of studies that have looked at the impact of shopping list use on spending and number of items purchased (e.g. [6], [3], [7], [8]), it is likely that there are many unobservable factors associated with list use (e.g., conscientiousness, patience, risk avoidance) that also affect food spending. Moreover, while previous studies have looked at correlations between spending and list use, few have attempted to estimate the value consumers place on having the list (i.e., the value of the self commitment device) for those that use lists or estimate the value of the transaction costs of creating a list among those consumers who do not typically use lists.

This research will determine the importance of the self-made contract of a shopping list to consumers, how a shopping list impacts the health level of products they purchase, and the willingness-to-accept of consumers to shop without a list or equivalent gain of consumers to shop with a shopping list. Additionally, we will use an experimental design in order to determine the causal impact that shopping lists have on consumer shopping behavior.

The overall objective of this paper is to determine the difference in grocery expenditures between consumers using a shopping list and consumers not using a shopping list. Additionally, we will identify differences in the actual purchases of those consumers who shop with and without a shopping list in order to determine the impact shopping lists have on expenditure and the healthiness purchases. Lastly, we will determine the value of shopping list to consumers.

4.2 Literature Review

There is a wide array of literature surrounding the idea of self-commitment devices. Bryan et al. define self-commitment devices as "an arrangement entered into by an individual with the aim of helping fulfill a plan for future behavior" when such a plan would be difficult to achieve without the particular arrangement (i.e. - self-commitment device) ([9]). In other words, this device will help an individual make a plan and stick to it to help control for a possible lack of self-control. There are many types of actions or plans that would benefit from the use of a self-commitment device. For example: healthier eating, saving money, or quitting a bad habit just to name a few ([9]).

There are numerous ways to conceptualize and implement self-commitment devices. A significant portion of the literature on self-commitment devices is dedicated to soft commitments, which relates mainly to the psychological costs associated with certain decisions. One way to model soft commitment devices is to account for the cost of performing a particular activity now by exerting a certain amount of willpower or delaying the activity and bearing the related cost ([10]). Previous research has studied the internal, personal rules that individuals create and follow in order to make their decisions. Additionally, by studying the impulse control of consumers at the grocery store, using scanner data, they found that there exist time preference differences that depend on the type of product that is being purchased ([11]). In other words, consumers respond differently to price changes depending on if they plan to consume the product now or later ([11]).

Another form of self-commitment device is to use goal-setting as a means to achieve ones goals. The "Rubicon Model" of action phases tells us that there are four different phases of action an individual will face when individuals decide to set a goal and work to achieve it. These phases are: "pre-decision, pre-action, action, and post-action" ([12]; [13]). We can separate consumer grocery shopping into these four phases. The pre-decision phase, as it relates to grocery shopping, would be defined as the consumer decision to begin eating healthier. Then in the pre-action stage, the consumer will begin implementing the goal achieving behavior by making an actual shopping list (a phase in which some consumers might not participate). The pre-action stage is followed by the action stage, which in this case is the act of purchasing their groceries, possibly while using a shopping list. Lastly, the consumer will enter the post-action phase where he/she decides if the original goal was met. These phases of action help us to better understand at which point in the grocery shopping process a consumer is most likely to commit to and keep to their desire to eat healthier, and as a result, when a grocery shopping list is most likely to be influential. It is during the pre-action stage of goal-setting in which we are most interested as this is the phase where consumers implement the ways they believe they will be able to achieve their goals - i.e. write a shopping list ([12]).

Another way in which previous research has tried to determine the impact of goal-setting was to study the impact of task-based goals versus performance-based goals in college students. This research found that when the students were asked to write down a task-based goal at the beginning of a semester, they received a higher total points score in the class and performed better throughout the course than students who were asked to write a performance-based goal ([14]). This research helps inform our study because the act of creating a shopping list serves as a task-based goal rather than a performance-based goal.

Previous research has shown that most consumers see obesity as a personal responsibility, and looking at obesity levels in the United States it has been found that 71% of Americans over the age of 20 are overweight or obese ([15]; CDC, 2018). This begs the question, what can Americans do themselves to improve their decision-making related to food purchases? One possible solution to this problem is to use self-commitment devices to help individuals make a plan for healthier grocery shopping and follow through with that plan.

There are a number of papers that look at the impact that having a shopping list has on consumers in a grocery shopping environment. One experiment looked at the impact of shopping lists as memory aids to measure the percentage of items purchased that were on the list versus items purchased not on the list, and found that consumers purchase over 80% of the items they write on their shopping list ([16]). Specifically, the Block & Morwitz (1999) study found that 78% of consumers added items to their shopping list because they were out of the item at home. On the other hand, they found that 44% of people purchased items not on their list because the items were on sale ([16]). Additional researchers have studied the impact having a shopping list (or conversely not having a shopping list) has on the number of items purchased and found similar results ([3]; [7]; [8]).

Another experiment studied the impact of coupons and in-store marketing on planned versus unplanned purchases. They found that for fill-in grocery trips versus major grocery shopping trips consumers were more likely to be influenced by in-store marketing, whereas during a major shopping trip the influence would come primarily from coupons ([17]). Kollat and Willett (1967) found that consumers shopping with a list make unplanned purchases less frequently than those shopping without a list ([6]).

Fernandes et al. (2016) studied how memory-based versus stimulus-based memory aides impact consumer decision making in an online grocery store setting. They found that consumers who use a memory-based shopping strategy will be less likely to forget items that they regularly purchase ([18]). This study also found that the consumers who believed that they would remember the items they intended to purchase were less likely to say they would use a shopping list ([18]). Conversely, consumers that indicated that they would be less likely to remember items in the store also indicated they would be more likely to shop with a list ([18]).

Previous research based on the use of a variety of external memory aids found that external memory aids are more often used than internal memory aids to help individuals with tasks involving future memory recall ([19]). This study also found that using an external memory aid increases an individual's ability to recall information in the future ([19]). However, these studies do not include consumers who complete a grocery shopping trip without the use of a shopping list. There are conflicting results about the impact of shopping with or without a list on dollars spent at the grocery store. For example, Kollat and Willett (1967) did not find significant evidence that dollars spent was impacted by use of a shopping list;

however, Thomas and Garland (1993) found that consumers shopping with a list spent $13 less, on average.

These studies are focused on the impact of the shopping list on number of items purchased and overall spending. In other words, the main focus is related to dollars spent and unplanned versus planned purchases not to the actual food products purchased. Additionally, the previous studies were focused on consumers who already shop using a shopping list during their grocery shopping trips. The objective of this paper aims to close the literature gap by providing an experimental framework to not only study the shopping behavior and purchasing patterns of consumers shopping both with and without a shopping list, but also to examine the actual basket of goods purchased.

We hypothesize that individuals shopping with a grocery list will be more focused and able to make more intentional decisions in the grocery store because the shopping list will act as a self-commitment device ([6]). It is logical to believe that consumers who are prepared before going to the grocery store will make healthier, less impulsive shopping decisions, which is why we hypothesize as follows:

Hypothesis 1 (H1)**.** *Consumers shopping with a shopping list will have a higher "healthy foods" score than consumers shopping without a shopping list.*

Hypothesis 2 (H2)**.** *Consumers with a shopping list will spend less money on a grocery shopping trip than consumers shopping without a shopping list.*

We believe that these hypotheses are testable using the methods explained in the following sections.

4.3 Methods and Procedures

4.3.1 Data Collection

In order to test these objectives, we launched a two wave online survey. This survey was administered using Amazon Mechanical Turks (referred to as MTurk) web-based crowdsourcing marketplace designed to elicit wide online participation in a variety of tasks. Previous work has been done to determine the differences, if any, in behavior of MTurk participants versus participants recruited via more traditional means. These studies found that results from MTurk participants, on average, were not statistically different than traditional survey recruits and in fact are often a better representation of the United States population ([20]; [21]). Paolacci et al. replicated a survey using samples from MTurk, a Midwest University, and a traditional internet survey discussion board often used in psychology research. They found that the MTurk survey method strongly decreases the possibility of non-response error that is typically found in traditional online experiments ([20]). There was no difference found between the samples regarding attention given to the survey, and found no overall significant differences between samples from MTurk and the Midwest University ([20]).

The first wave of our survey was delivered to 500 participants and consisted of questions about their *next* shopping trip. Questions included what the type of shopping trip is (fill-in shopping trip, full shopping trip, small shopping trip), questions about how they plan to pay for their groceries, and basic demographic questions (race, age, etc.). These questions help us to better understand the motivation for this specific grocery shopping trip. The participants earned $5 for successfully completing the first wave of the survey.

There is likely heterogeneity in how consumers plan for shopping trips. For example, we expect some consumers to plan to shop without a shopping list, others will plan to shop with a small shopping list of things they must purchase while they plan to purchase other items, and some consumers will plan to shop with a complete list of every item they plan to purchase. Therefore, as a part of the first wave of the survey, we used a Multiple Price List (MPL) to determine if consumers who arrive with a shopping list kept their list or if consumers who arrive without a shopping list were asked to write a list ([22]).

The participants completed a multiple price list indicating their preferences for "Keep" or "Without - Receive $" for a series of choices - see the tables 4.1 & 4.2 below for two example MPL. Figure 4.1 shows the possible categories that could represent each consumer before and after the MPL. A random number was generated to determine which row was selected as binding for that consumer - indicating if the consumer completed her shopping trip as originally planned, if she was asked to shop without a list, or if she was asked to create a list.

Table 4.1.
Multiple Price List: Consumers with a Shopping List

Payoff Alternative	A	B	Choice
1	Keep	Without - Receive $2	A or B
2	Keep	Without - Receive $2.50	A or B
3	Keep	Without - Receive $3	A or B
4	Keep	Without - Receive $3.50	A or B
5	Keep	Without - Receive $4	A or B
6	Keep	Without - Receive $4.50	A or B
7	Keep	Without - Receive $5	A or B
8	Keep	Without - Receive $5.50	A or B

Table 4.2.
Multiple Price List: Consumers without a Shopping List

Payoff Alternative	A	B	Choice
1	No List	Write - Receive $2	A or B
2	No List	Write - Receive $2.50	A or B
3	No List	Write - Receive $3	A or B
4	No List	Write - Receive $3.50	A or B
5	No List	Write - Receive $4	A or B
6	No List	Write - Receive $4.50	A or B
7	No List	Write - Receive $5	A or B
8	No List	Write - Receive $5.50	A or B

After completing wave 1 of the survey, we asked the participants to complete their grocery shopping trip and return, within a week, to complete wave 2 of the survey using the MTurk platform. The second wave of the survey asked all participants to attach a picture of their grocery shopping receipt, and if they were asked to complete their shopping trip with a list they were also asked to attach a picture of their list. This wave of the survey asked specific questions about the shopping trip they just completed.

At the end of wave 2, participants were asked to make a series of non-hypothetical decisions to determine their risk preferences following the work of Holt & Laury (2002) and time discounting following the work of Anderson et al. (2008)([23];[24]). To determine their risk preferences, consumers were presented with a series of paired lotteries (see [23]) and asked to choose between a safe and a risky option. We would expect a risk-neutral consumer to choose the "safe" option four times, a risk-seeking consumer would choose the "safe" option less than four times, and a risk-averse consumer greater than four times. Using this data, we counted the number of "safe choices" made by each consumer to indicate their risk preferences, which we called their *risk score* to use in our analysis. Additionally, participants were asked a series of personality questions compiled by Saucier (1994) ([25]). The responses from the personality questions was aggregated to create a score for each of the big 5 personality types for each consumer.

Upon completion of the second wave of the survey, all participants earned $5. There were a total of 228 consumers who successfully completed wave 2 of the survey. The data collected from the both waves of the survey was used to address the objectives of the paper.[1]

4.3.2 Econometric Model

The shopping lists and receipts were manually re-coded and each food item was assigned a Ratio of Recommended to Restricted (RRR) value ([26]).[2] These scores indicate the relative health level of each of the food products on a shopping list or receipt. In order to calculate the appropriate RRR, the nutrition information for each food item was taken from the USDA FoodData Central database ([27]). In general, if the food item from the receipt/list was only broadly specified by the consumer, we used the "NS" or "NFS" classification of the product. These are defined as "Not Specified" or "Not Further Specified" and indicate the average nutrients for each product.[3]

The RRR is calculated using the following formula:

$$RRR = \frac{\begin{array}{r}(\%DV protein + \%DV dietary fiber + \%DV calcium \\ + \%DV iron + \%DV vitaminA + \%DV vitaminC)/6\end{array}}{\begin{array}{r}(\%DV calories + \%DV sugars + \%DV cholesterol \\ + \%DV saturatedfat + \%DV sodium)/5\end{array}} \tag{4.1}$$

[1]↑Survey available from authors upon request.

[2]↑Original receipt/list data available upon request. Receipts or lists that were unreadable, incomplete, or stock photos were not included in the analysis. Items on receipts/lists that were unidentifiable were not included in the analysis.

[3]↑For example, if "chicken" was on a shopping list, then "Chicken - NS" was chosen from the FoodData database because the piece of the chicken was not specified. If "chicken breast" was on a shopping list, then "Chicken Breast - NFS" was chosen from the FoodData database.

The percent daily value recommended for each nutrient are based off the 2,000 calorie diet standard amounts and found in table 4.4. Using the calculated RRR scores for each food product, we calculated an overall healthy foods score for both the reported shopping lists and receipts. This was calculated by taking the simple average of all the food items' RRR scores. We used this score to test hypothesis 1. Equation 4.2 was used to determine whether consumers shopping with a grocery list have a larger RRR score than consumers shopping without a grocery list. Additionally, equation 4.2 was used to analyze the impact that different types of shopping trips have on consumers' purchases:

$$\begin{aligned} RRR_{\mathrm{i}} = \beta_0 + \beta_1 list_{\mathrm{i}} + \beta_2 nolist_{\mathrm{i}} + \beta_3 list/nolist_{\mathrm{i}} + \beta_4 gender_{\mathrm{i}} \\ + \beta_5 age_{\mathrm{i}} + \beta_6 numhouse_{\mathrm{i}} + \beta_7 middleincome_{\mathrm{i}} + \beta_8 highincome_{\mathrm{i}} \\ + \beta_9 items_{\mathrm{i}} + \beta_{10} smalltrip_{\mathrm{i}} + \beta_{11} majortrip_{\mathrm{i}} + \beta_{12} child_{\mathrm{i}} + \epsilon_{\mathrm{i}} \end{aligned} \tag{4.2}$$

The variable for *list* is a dummy variable indicating if the individual planned to shop with a list and kept their list for their shopping trip, *nolist* indicates consumers planning to shop without a list who were paid to write one, and *list/nolist* represents consumers planning to shop with a shopping list that were paid to shop without their list. These are all estimated relative to the reference category which is an individual who planned to shop without a list and actually shopped without a list. *Gender* is a binary variables such that a 1 indicates a female consumer; *age* is a categorical variable defined as follows: 1=18-24 years old, 2=25-34 years old, 3=35-44 years old, 4=45-54 years old, 5=55-64 years old, 6=65-74 years old, and 7=74+ years old; *numhouse* is the number of people in the household;*middleincome* is a binary variable representing consumers making between $60,000 and $79,999; *highincome* is also a binary variable representing consumers making $80,000+; *items* is the number of items the consumer purchased on his/her shopping trip; *child* is a binary variable controlling for if the consumer was shopping with children present or not. The variables, related to the type of shopping trip, are dummy variables indicating the type of shopping trip (*smalltrip* & *majortrip*), relative to what we are defining to be a fill-in shopping trip. For the dependent variable, RRR_i, we have the healthy foods score that was calculated for each consumer using their receipt purchase data.

In order to understand the impact that shopping with or without a shopping list has on expenditure and test hypothesis 2, we analyzed the following equation:

$$\begin{aligned} expenditure_i = \beta_0 + \beta_1 list_i + \beta_2 nolist_i + \beta_3 list/nolist_i + \beta_4 gender_i \\ + \beta_5 age_i + \beta_6 numhouse_i + \beta_7 middleincome_i + \beta_8 highincome_i + \beta_9 items_i \\ + \beta_{10} smalltrip_i + \beta_{11} majortrip_i + \beta_{12} child_i + \beta_{13} RRR_i + \epsilon_i \end{aligned} \quad (4.3)$$

The dependent variable, $expenditure_i$, is the actual dollar amount spent by each consumer. The right side of the equation is comprised of the same variables from the first equation with the addition of the RRR_i, defined as above.

Using the results from the multiple price list elicitation (MPL), we know a range for the consumer willingness-to-accept (WTA) or willingness-to-pay (WTP). To be precise, consumers were not asked to pay anything in this experiment, and as such what we call "willingness-to-pay" has a different meaning in this study than in others. Rather, both valuation exercises entail the researchers paying participants to undertake a certain activity (give up a list or write a list). Thus, our valuation measures would be more accurately defined as willingness-to-accept (the minimum amount people must be paid to give up a list) and equivalent gain (the minimum amount people must be paid to write a list), as described in Bateman et. al (1997) [28]. We will henceforth refer to these measures as willingness-to-accept (WTA) and equivalent gain (EG).

The switching point in the MPL determines the WTA/EG range values ([22]). The exact WTA_i or EG_i value for each consumer is found in equation 4.4, where β is a constant, X_i is a vector of explanatory variables including demographic and personality related questions, and ϵ_i is the error term ([29]).

$$WTA_i^* = \beta + X_i\rho + \epsilon_i \quad (4.4)$$

Following the work of Klain et al. (2014), we estimate an interval censored regression using the coefficients from equation 4.4([30]). From the MPL, we know that $P_{\mathrm{i},low}$ and $P_{\mathrm{i},high}$ are the boundaries the consumer is willing to receive in order to write a list or keep their list. Equation 4.5 is the likelihood function used to estimate an interval censored regression where Φ is the cumulative standard normal distribution function ([31]; [30]).

$$LF = \Phi((P_{\mathrm{i},high} - \beta - X_{\mathrm{i}}\rho)/\sigma) - \Phi((P_{\mathrm{i},low} - \beta - X_{\mathrm{i}}\rho)/\sigma) \quad (4.5)$$

We estimated two separate interval censored regression models. The dependent variable in our first analysis is the willingness-to-accept (WTA) for consumers planning to shop with a shopping list to be compensated to give up their list, and the dependent variable for the second model estimates equivalent gain (EG) for consumers planning to shop without a shopping list to be compensated to create a shopping list. Bateman et. al (1995) find that WTA and EG should be equal under Hicksian theory; however, for Reference Dependent theory EG and the corresponding EL (equivalent loss) will fall between WTP and WTA ([28]).

The personality questions asked at the end of wave 2 were used to form a scale of contentiousness (along with the other calculated personality types) to incorporate into our analysis to better understand the way personality impacts the WTA/EG values revealed by consumers. As previously mentioned, following the work of Holt & Laury (2002), consumers were asked to make a series of decisions indicating their risk preferences ([23]). We counted the number of safe choices made by a consumer and used this as a risk score in a logistic regression analysis.

4.4 Results

Table 4.5 shows the mean demographic and personality summary statistics for the full sample as well as by shopping list classification. Only 14% of consumers who planned to shop with no list and actually shopped with no list were female; however, 60% of consumers who planned to shop with a list and actually shopped with a list were female. The average number of items purchased by consumers who were shopping with a list was higher than those consumers shopping without a list. Additionally, the average receipt RRR was higher (2.10 & 2.21 versus 1.91 & 1.93), for consumers who *planned* to shop using a shopping list, indicating healthier purchases for this category of consumers. Consumers who planned to shop with a list have higher average conscientiousness scores than consumers who planned to shop without a list.

Figure 4.1 shows how the 228 consumers who successfully completed wave 2 of the survey were classified after the MPL elicitation. 53 consumers planned to shop with a list and after the MPL elicitation were asked to shop using their list; 141 consumers planned to shop with a list and were asked to shop without a list; 19 consumers planned to shop with no list and were asked to write a list to use on their shopping trip; 15 consumers planned to shop with no list and after the MPL elicitation were asked to shop without a list.

On a scale from 1 - 10, with 1 being very unhealthy and 10 being very healthy, 228 consumers ranked their basket of purchases at a 6.5, on average. Additionally, these same customers were asked what percentage of their grocery bill was spent on fruits & vegetables. On average, consumers reported that 25.25% of their total spending was on fruits & vegetables with a standard deviation of 27.55%. Excluding those consumers who said that 0% of their spending was on fruits and vegetables, 75% of consumers reported spending 50% or less on fruits and vegetables, as shown in figure 4.2. The summary statistics for the RRR scores for the receipts and shopping lists that were collected and analyzed are found in table 4.6. The average RRR score was about 0.22 higher for consumer receipts than it was for shopping lists, which implies that consumers actual purchases were, on average, healthier than what they planned to purchase.

4.4.1 Ratio of Recommended to Restricted (RRR)

In order to determine the impact a shopping list has on the healthiness of food items purchased (using the previously defined Ratio of Recommended to Restricted score), we estimated a model using equation 4.2. The results from this analysis are found in column 1 of table 4.7. We do not see a statically significant impact on the RRR score as a result of using a shopping list or not; however, we do see that the RRR score for females is, on average, higher than for males. The RRR score for consumers shopping with their children present is, a statistically significant, 0.91 higher.

The causal impacts of a shopping list are seen by comparing coefficients from column 1 of table 4.7. Comparing consumers planning to shop with a list who actually shopped *with* a list ($List$) and consumers who planned to shop with a list but actually shopped *without* a list ($List/NoList$) we see that consumers shopping without a list had, on average, higher RRR scores. This indicates that there is clear evidence the list is *not* the causal impact behind healthier food purchases. We also see that consumers who planned to shop with a list, regardless of how they actually completed their shopping trip, had higher RRR scores than consumers who planned to shop without a list. While these differences are not statistically significant, they do suggest that there is a selection effect for the type of consumers who make grocery shopping lists.

4.4.2 Expenditure

To determine the impact of a shopping list on expenditure, we modeled equation 4.3 and the results are found in column 2 of table 4.7. As we would expect the most significant predictor of expenditure on a shopping trip is number of items purchased. For each additional item purchased, we expect expenditure to increase by an average of $2.72. This finding follows our basic intuition that the more items you purchase, the more money you will spend on a particular shopping trip. Additionally, while not statistically significant, each of the binary variables included in the analysis related to if the consumer was shopping with a list - are negative. Indicating that relative to consumers planning to shop without a list who *actually* shopped without a list, all other consumers spent less on their shopping trip, on average. We also find that a 1 unit increase in the receipt RRR score corresponds to a $1.35 decrease in expenditure, indicating that, while not statistically significant, that purchasing healthier foods does not increase total expenditure.

4.4.3 Expenditure on Fruits & Vegetables and Healthiness Rating

The results using the self-reported percentage of the grocery bill spent on fruits and vegetables as the dependent variable are in column 3 of table 4.7. For a 1 unit increase in the receipt RRR, we expect expenditure on fruits and vegetables to increase by 6.56%. This makes intuitive sense - the higher the RRR score, the more money a consumer will spend on healthier foods (i.e. - fruits and vegetables). Shopping with children present increases expenditure on fruits and vegetables by an average of 10.51%.

Examining the impact of the self-reported healthiness rating of their purchases, we find a positive, statistically significant coefficient for the receipt RRR. The healthiness rating ranges from 1-10, and we find that a 1 unit increase in the receipt RRR corresponds to a 0.71 increase in the healthiness rating as reported by consumers (column 4 of table 4.7).

4.4.4 Willingness-to-Accept & Equivalent Gain

The results from our interval censored regression analysis using data from only wave 1 of the survey are found in table 4.8. The interval censored regression analysis using the combined data from waves 1 & 2 is found in table 4.9, which includes the personality marker scores. As previously mentioned, we estimated separate models depending on whether a consumer arrived with or without a shopping list. This indicates if he/she was paid to give up his/her list or paid to write a list to use on the upcoming shopping trip.

Columns 1-4 in table 4.8 correspond to consumers indicating they plan to shop with a list (WTA to give up their list), while columns 5-8 correspond to consumers indicating they do not plan to shop with a list (EG to write a shopping list). The first model (column 1) indicates an average WTA of $5.29 to give up a shopping list, across all consumers indicating they planned to shop with a list. For consumers who indicated they do not plan to shop with a list, their average EG to write a list to use on their trip was $5.54. After controlling for age, number of people in the household, and trip type, we see in column 4 that relative to a fill-in trip, the WTA for a consumer on a small or major shopping trip decreases by \$0.40 and \$0.51 respectively.[4]

As previously mentioned, we utilized Saucier's measures of the Big Five personality types (extraversion, agreeableness, conscientiousness, emotional stability, and intellect/openness) ([25]). These personality markers and associated personality types can be found in table 4.3. Using the average of these personality markers, as reported by consumers in wave 2, we calculated a score to control for conscientiousness of a consumer - in other words, are you just the type of person who will remember what you wanted to purchase with or without your shopping list in hand. Additionally, we calculated personality scores for the other four personality types as defined by Saucier and included these in our willingness-to-pay analysis to help determine the extent to which the selection effect is a problem if people are not randomly assigned to a list category ([25]).

Our results for the WTA/EG analysis, controlling for personality type, are found in table 4.9. It is important to note that there are less observations than in table 4.8 because the personality questions were only asked in wave 2 of the survey. When conscientiousness is the only personality type included in the WTA model (column 7), the results show that a 1 unit increase in conscientiousness is associated with an \$0.11 increase in WTA; however, when controlling for all of the big five personality types, there is a shift in the significance of these coefficients. Consumers planning to shop with a list show that a 1 unit increase in extroversion is associated with a \$0.16 reduction in WTA for a list (column 8). We found a statistically significant \$1.68 reduction in EG for consumers who did not plan to shop with a list when shopping with their children present (column 14). Our analysis showed that including personality types did not have a significant impact on EG for consumers planning to shop without a list.

4.4.5 Logistic Regression Analysis

Table 4.10 shows the results of the logistic regression analysis where the outcome variable is a binary variable equal to one if the consumer planned to shop with a list. The model

[4]↑Additional demographic characteristics related to income and children were not asked in wave 1 of the survey, and therefore were not included in this portion of the analysis.

was estimated using data from only wave 1 of the survey as well as wave 1 & wave 2 data combined. Both sets of estimates are presented in table 4.10. The wave 1 analysis, columns 1-4, shows that the log odds of shopping with a list increase by 0.813 (column 4) for a consumer on a major shopping trip relative to a fill-in shopping trip.

When we combine the data for waves 1 & 2, we have only consumers who actually completed a shopping trip as part of the experiment (reflected in the decrease in number of observations). While the estimates are not statistically significant, we do find that a one unit increase in conscientiousness score increases the log odds of shopping with a list by 0.205, and a one unit increase in risk score increases the log odds of shopping with a list by 0.089 (column 6).

4.5 Conclusion

The objective of this paper was to determine the difference in grocery expenditures between consumers shopping with a list and consumers shopping without list. We were also seeking to determine the value of the shopping list to consumers and to better understand what factors influence their decision to shop with or without a shopping list.

There was not a significant impact on healthiness of items purchased or dollars spent by using a shopping list; however, we were able to determine the value consumers place on their shopping list and better understand what factors influence their decision to shop with or without a list. Our analysis was able to elicit willingness-to-pay and equivalent gain range estimates for consumers in our experiment. We found that consumers planning to shop with a list were willing to shop without their list for \$5.56, while consumers planning to shop without a list had an average equivalent gain of \$5.69 to shop with a list when controlling for personality type.

These results would be useful to economists in helping understand the impact that shopping lists have on expenditure. Previous research has found that it is more expensive to purchase healthier foods. We do not find a significant relationship between expenditure and RRR score (our healthiness indicator).

Additionally, nutritionists could use our findings when helping consumers make food purchasing choices. We did not find evidence to suggest that shopping with a list has a significant impact on the healthiness of purchases; however, our findings do indicate that higher self-reported healthiness scores of purchases correspond to higher calculated RRR scores. This implies that, on average, consumers are able to make fairly accurate predictions about the healthiness of their purchases.

One critique of this analysis is that our ways of verifying that the participating consumers were shopping with (or without) their shopping lists, as directed in the survey, was imperfect. Additionally, since the randomization of consumers shopping with or without a list was done using the multiple price list format, we did not have direct control over the number of observations in each group. As a result, the number of consumers in the group shopping with a list was smaller than those shopping without a list.

In conclusion, this paper was able to observe the grocery shopping patterns of consumers and estimate the value of a grocery shopping list. We hope our findings will provide useful contributions to the future of research related to consumer shopping behaviors.

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Figure 4.1. Categories of Consumers before and after Multiple Price List (MPL) elicitation

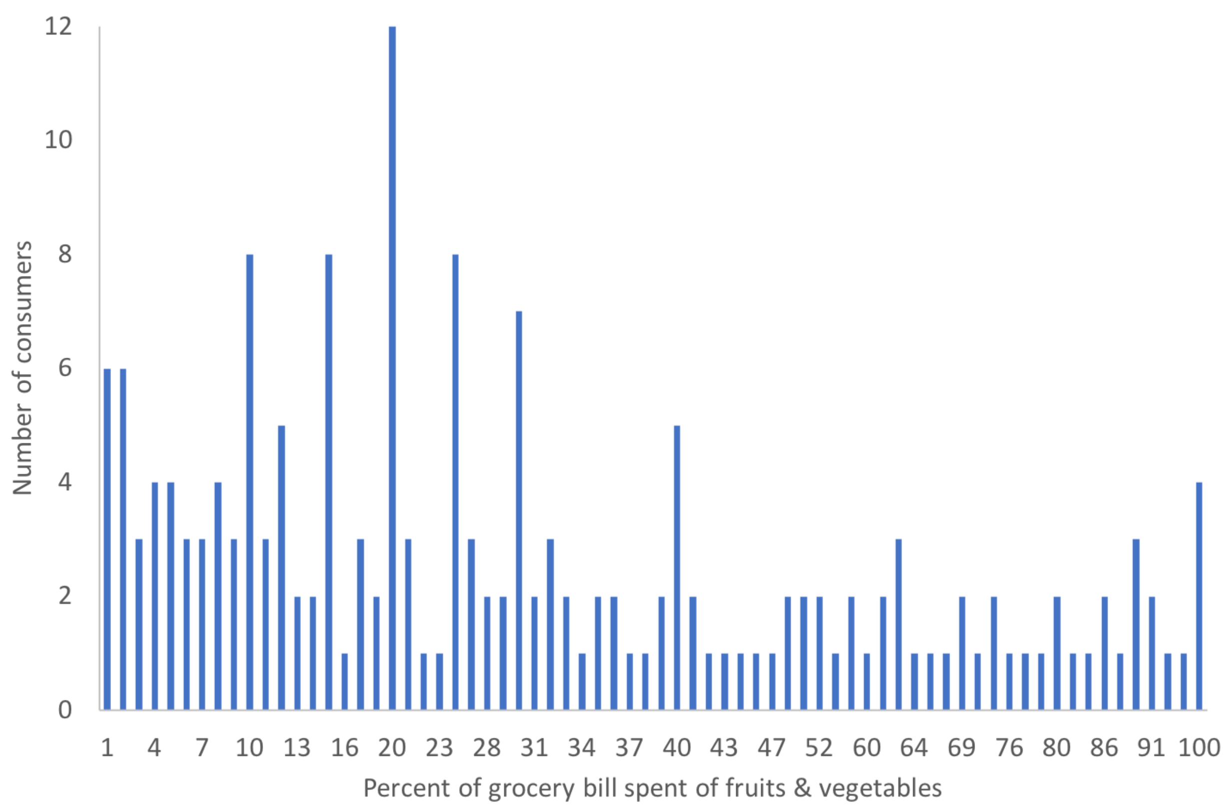

Figure 4.2. Percent of Total Spending on Fruits and Vegetables

Table 4.3.
Big-Five Personality Markers

Personality Factor	Positive Trait	Negative Trait
Extraversion	Talkative Extroverted Bold Energetic	Shy Quiet Bashful Withdrawn
Agreeableness	Sympathetic Warm Kind Cooperative	Cold Unsympathetic Rude Harsh
Conscientiousness	Organized Efficient Systematic Practical	Disorganized Sloppy Inefficient Careless
Emotional Stability	Unenvious Relaxed	Moody Jealous Temperamental Envious Touchy Fretful
Intellect/Openness	Creative Imaginative Philosophical Intellectual Complex Deep	Uncreative Unintellectual

Source: [2]

Table 4.4.
% Daily Value of Recommended and Restricted Nutrients

	Nutrient	% DV
Recommended	Protein	60g
	Dietary Fiber	25g
	Calcium	1000mg
	Iron	18mg
	Vitamin A	5000 IU/900 mcg
	Vitamin C	60mg
Restricted	kcal	2000
	Sugar	50g
	Cholesteral	300mg
	Saturated Fat	20g
	Sodium	2400mg

Source: [3]

Table 4.5.
Mean Demographic and Personality Type Summary Statistics

		No List/No List	No List/List	List/No List	List/List	Full Sample
Demographics	Female	0.14	0.37	0.34	0.60	0.39
	Age	2.64	3.00	2.79	2.98	2.84
	Low income	0.60	0.42	0.47	0.49	0.48
	Middle income	0.20	0.11	0.23	0.17	0.21
	High income	0.13	0.47	0.29	0.32	0.30
	Number of items	13.21	21.00	20.99	21.94	20.73
	Fill-in Trip	0.20	0.26	0.15	0.21	0.18
	Small Trip	0.53	0.21	0.38	0.26	0.35
	Major Trip	0.27	0.53	0.47	0.53	0.47
	Child	0.33	0.21	0.26	0.36	0.29
	Receipt RRR	1.91	1.93	2.10	2.21	2.11
Personality	Conscientiousness	5.96	6.57	6.69	6.85	6.67
	Extraversion	5.21	5.01	5.06	5.41	5.14
	Agreeableness	6.11	7.20	6.63	6.64	6.65
	Emotional Stability	5.64	6.04	5.73	5.63	5.73
	Intellect/Openness	5.81	6.40	6.46	6.24	6.36

Table 4.6.
RRR Score Summary Statistics

	# of Observations	Mean	St. Dev.	Min	Max
List RRR Score	52	1.880	1.278	0.309	5.119
Receipt RRR Score	137	2.106	1.596	0.087	8.393

Table 4.7.
Regression Results

	(1)	(2)	(3)	(4)
	Receipt RRR	Expenditure	Expenditure on Fruits & Vegetables	Healthiness Rating
Constant	2.052*	4.879	23.770*	4.868***
	(2.52)	(0.27)	(2.36)	(4.17)
List	0.005	-5.186	-9.364	-0.411
	(0.01)	(-0.36)	(-1.18)	(-0.45)
No List	-0.126	-30.070	-0.095	-1.254
	(-0.16)	(-1.74)	(-0.01)	(-1.14)
List/No List	0.061	-10.990	-12.400	-0.655
	(0.10)	(-0.84)	(-1.71)	(-0.78)
Female[1]	0.702*	-2.939	-0.022	-0.746
	(2.26)	(-0.43)	(-0.01)	(-1.69)
Age[2]	-0.238	2.828	-3.514	0.204
	(-1.50)	(0.81)	(-1.82)	(0.92)
Number in Household[3]	-0.181	2.594	-0.213	0.121
	(-1.49)	(0.97)	(-0.14)	(0.70)
Middle Income[4]	0.319	-2.255	8.420	0.790
	(0.80)	(-0.26)	(1.76)	(1.42)
High Income[5]	0.464	9.988	4.498	-0.049
	(1.41)	(1.38)	(1.12)	(-0.11)
Number of Items	0.007	2.718***	-0.070	-0.002
	(0.76)	(13.37)	(-0.62)	(-0.18)
Small Trip[6]	0.743	0.171	-3.107	-0.794
	(1.83)	(0.02)	(-0.63)	(-1.38)
Major Trip[7]	0.430	-0.040	-2.742	-0.709
	(1.03)	(-0.00)	(-0.54)	(-1.21)
Child[8]	0.908*	7.621	10.510*	0.701
	(2.17)	(0.82)	(2.04)	(1.18)
Receipt RRR		-1.345	6.555***	0.709***
		(-0.68)	(6.01)	(5.61)
N	135	135	135	135

t-statistics in parentheses

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.01$

[1] Effect of females relative to males
[2] Defined as (1) 18-24 years old, (2) 25-34 years old, (3) 35-44 years old, (4) 45-54 years old, (5) 55-64 years old, (6) 65-74 years old, and (7) 74 years or older
[3] Defined as (1) 1 person (including yourself) in household, (2) 2 people in household, (3) 3 people in household, (4) 4 people in household, and (5) 5 or more people in household
[4] Defined as consumers making between $60,000 and $79,999
[5] Defined as consumers making $80,000+
[6] Effect of a Small trip relative to a Fill-In trip
[7] Effect of a Major trip relative to a Fill-In trip
[8] Effect of shopping with children present

Table 4.8.
Willingness-to-Accept and Equivalent Gain for a Shopping List

	"Yes" Shopping with List (WTA - to give up list)				"No" Shopping without List (EG - to write a list)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	5.286***	5.254***	5.685***	6.161***	5.535***	5.233***	4.704***	5.289***
	(102.02)	(73.65)	(25.57)	(21.68)	(31.84)	(23.58)	(6.78)	(7.38)
Female[1]		0.0710	0.0931	0.0428		0.513	0.573	0.510
		(0.63)	(0.81)	(0.37)		(1.42)	(1.55)	(1.44)
Age[2]			-0.0432	-0.0585			0.268	0.264
			(-0.80)	(-1.07)			(1.59)	(1.63)
Number in Household[3]			-0.103*	-0.105*			-0.0859	-0.0817
			(-2.22)	(-2.29)			(-0.56)	(-0.56)
Small Shopping Trip[4]				-0.402*				-0.919
				(-2.19)				(-1.95)
Major Shopping Trip[5]				-0.508**				-0.529
				(-2.91)				(-1.16)
σ	0.930	0.966	0.959	0.947	1.132	1.119	1.080	1.011
N	456	432	432	432	68	60	60	60

t-statistics in parentheses

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.01$

[1] Effect of females relative to males

[2] Defined as (1) 18-24 years old, (2) 25-34 years old, (3) 35-44 years old, (4) 45-54 years old, (5) 55-64 years old, (6) 65-74 years old, and (7) 74 years or older

[3] Defined as (1) 1 person (including yourself) in household, (2) 2 people in household, (3) 3 people in household, (4) 4 people in household, and (5) 5 or more people in household

[4] Effect of a Small trip relative to a Fill-In trip

[5] Effect of a Major trip relative to a Fill-In trip

Table 4.9.

Willingness-to-Accept and Equivalent Gain for Shopping List with Personality Types

	"Yes" Shopping with List (WTA - to give up list)								"No" Shopping without List (EG - to write a list)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Constant	5.556***	5.585***	5.426***	5.404***	5.644***	5.621***	5.048***	4.901***	5.693***	5.216***	4.609***	4.777***	5.492***	4.659***	3.872***	1.877
	(74.09)	(57.60)	(20.27)	(19.71)	(16.12)	(16.00)	(11.89)	(10.47)	(19.19)	(19.31)	(5.46)	(5.57)	(5.98)	(8.14)	(3.71)	(0.87)
Female[1]		-0.0571	-0.0930	-0.100	-0.135	-0.141	-0.164	-0.174		1.685*	1.440*	1.388*	1.009	0.672	0.615	2.394
		(-0.39)	(-0.62)	(-0.66)	(-0.86)	(-0.90)	(-1.07)	(-1.10)		(2.21)	(2.08)	(2.05)	(1.55)	(1.55)	(1.58)	(1.43)
Age[2]			0.0764	0.0875	0.0698	0.0594	0.0226	0.0535			0.400	0.353	0.398	0.549*	0.530*	0.465
			(1.03)	(1.14)	(0.90)	(0.76)	(0.29)	(0.70)			(1.53)	(1.32)	(1.54)	(2.05)	(2.54)	(1.66)
Number in Household[3]			-0.0150	-0.00986	-0.00517	0.0297	0.0160	0.0109			-0.162	-0.135	-0.126	-0.0453	-0.0614	0.112
			(-0.26)	(-0.17)	(-0.09)	(0.44)	(0.25)	(0.17)			(-0.74)	(-0.62)	(-0.62)	(-0.26)	(-0.43)	(0.57)
Middle Income[4]				0.0309	0.0442	0.0437	0.0396	0.0481				-0.596	-0.491	-0.579	-0.629	-1.196
				(0.17)	(0.24)	(0.24)	(0.22)	(0.27)				(-0.89)	(-0.76)	(-1.30)	(-1.53)	(-1.38)
High Income[5]				-0.0955	-0.0906	-0.124	-0.171	-0.162				-0.0271	-0.0522	0.182	0.163	-0.198
				(-0.56)	(-0.53)	(-0.71)	(-1.00)	(-0.95)				(-0.05)	(-0.11)	(0.51)	(0.51)	(-0.29)
Small Trip[6]					-0.262	-0.225	-0.244	-0.196					-1.171	-0.544	-0.355	0.285
					(-1.16)	(-0.98)	(-1.10)	(-0.88)					(-1.56)	(-1.16)	(-0.76)	(0.38)
Major Trip[7]					-0.211	-0.179	-0.204	-0.173					-0.838	-0.0888	0.0809	0.965
					(-0.99)	(-0.83)	(-0.97)	(-0.83)					(-1.18)	(-0.21)	(0.20)	(1.51)
Child[8]						-0.215	-0.122	0.00359						-1.683***	-1.593***	-1.356**
						(-1.20)	(-0.68)	(0.02)						(-3.58)	(-3.78)	(-2.58)
Conscientiousness Score							0.108*	0.0932							0.109	0.373
							(2.15)	(1.30)							(0.90)	(0.96)
Extraversion Score								-0.161**								0.0354
								(-2.76)								(0.17)
Agreeableness Score								-0.0219								-0.587
								(-0.29)								(-1.22)
Emotional Stability Score								0.0708								0.360
								(1.22)								(1.00)
Intellect/Openness Score								0.108								0.150
								(1.54)								(0.93)
σ	0.798	0.801	0.797	0.798	0.798	0.799	0.770	0.749	1.241	1.075	1.012	0.990	0.899	0.471	0.417	0.346
N	188	187	187	187	187	187	187	187	32	31	31	31	31	31	31	31

t-statistics in parentheses
Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.01$

[1] Effect of females relative to males
[2] Defined as (1) 18-24 years old, (2) 25-34 years old, (3) 35-44 years old, (4) 45-54 years old, (5) 55-64 years old, (6) 65-74 years old, and (7) 74 years or older
[3] Defined as (1) 1 person (including yourself) in household, (2) 2 people in household, (3) 3 people in household, (4) 4 people in household, and (5) 5 or more people in household
[4] Defined as consumers making between $60,000 and $79,999
[5] Defined as consumers making $80,000+
[6] Effect of a Small trip relative to a Fill-In trip
[7] Effect of a Major trip relative to a Fill-In trip
[8] Effect of shopping with children present

Table 4.10.

Logistic Regression Model

	Wave 1				Wave 1 & Wave 2					
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)	(6)
Constant	1.386***	1.283**	1.232**	1.134	1.583	1.468	1.376	1.376	0.215	-0.272
	(4.96)	(2.88)	(2.60)	(1.78)	(1.76)	(1.60)	(1.50)	(1.50)	(0.18)	(-0.21)
Small Trip[1]	0.357	0.451	0.470	0.481	0.597	0.646	0.618	0.617	0.687	0.715
	(1.03)	(1.21)	(1.25)	(1.27)	(1.11)	(1.15)	(1.10)	(1.07)	(1.18)	(1.22)
Major Trip[2]	0.838*	0.784*	0.805*	0.813*	0.673	0.593	0.589	0.588	0.606	0.635
	(2.44)	(2.15)	(2.17)	(2.19)	(1.31)	(1.08)	(1.07)	(1.05)	(1.08)	(1.12)
Number in Household[3]		0.057	0.057	0.059	-0.030	-0.064	-0.071	-0.071	-0.101	-0.079
		(0.51)	(0.51)	(0.53)	(-0.19)	(-0.40)	(-0.44)	(-0.42)	(-0.58)	(-0.45)
Female[4]			0.089	0.076	0.805	0.708	0.745	0.745	0.724	0.723
			(0.31)	(0.26)	(1.79)	(1.54)	(1.60)	(1.60)	(1.55)	(1.54)
Age[5]				0.031	-0.174	-0.112	-0.113	-0.113	-0.157	-0.158
				(0.23)	(-0.91)	(-0.57)	(-0.56)	(-0.56)	(-0.76)	(-0.76)
Number of Items						0.006	0.005	0.005	0.002	0.001
						(0.45)	(0.41)	(0.41)	(0.12)	(0.08)
Middle Income[6]							0.449	0.449	0.404	0.381
							(0.81)	(0.81)	(0.73)	(0.68)
High Income[7]							0.131	0.131	0.022	-0.038
							(0.29)	(0.29)	(0.05)	(-0.08)
Child[8]								0.004	0.162	0.168
								(0.01)	(0.33)	(0.35)
Conscientiousness Score									0.218	0.205
									(1.61)	(1.49)
Risk Score										0.089
										(0.91)
N	555	512	512	512	227	226	226	226	226	226

t-statistics in parentheses

Note: $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.01$

[1] Effect of a Small trip relative to a Fill-In trip
[2] Effect of a Major trip relative to a Fill-In trip
[3] Defined as (1) 1 person (including yourself) in household, (2) 2 people in household, (3) 3 people in household, (4) 4 people in household, and (5) 5 or more people in household
[4] Effect of females relative to males
[5] Defined as (1) 18-24 years old, (2) 25-34 years old, (3) 35-44 years old, (4) 45-54 years old, (5) 55-64 years old, (6) 65-74 years old, and (7) 74 years or older
[6] Defined as consumers making between $60,000 and $79,999
[7] Defined as consumers making $80,000+
[8] Effect of shopping with children present

5. CONCLUSION

My three dissertation essays aimed to fill specific gaps in the literature related to consumer food purchasing.

My first essay introduced a new approach to value multiple types of information in a non-hypothetical environment. We imposed a time cost on the consumer for the selection of additional information. This time cost was the analyzed to determine willingness-to-wait to see specific product attributes. We found that, across 14 different products and seven different types of information, both the price and origin attribute are the most important to consumers, while attributes related to the social and environmental impacts of a product are least important.

In my second essay, sought to better understand the relationship between different wholesale chicken price indices that were once commonly used in the United States. We found that there was a divergence from the long standing equilibrium price relationship between the USDA 12-City Composite Price Index and the Georgia Dock Price - both indices used, at one time, to price chicken in the United States. Our difference-in-differences analysis suggests that after a structural break in the data around November 1997, the prices reported by the Georgia Department of Agriculture were about \$0.047/lb higher than prior to the break.

Using a non-hypothetical field experiment, my third essay aimed to determine the value consumers place on a grocery shopping list by eliciting their willingness-to-accept or equivalent gain for a shopping list during an upcoming grocery shopping trip. Using a Multiple Price List, we were able to randomly determine who kept or gave up their shopping list, and as a result explore the causal effect of a shopping list on food spending and healthiness of food purchases. While we did not find a significant difference in the healthiness of purchases made by consumers using a shopping list versus those without, we did find that consumers willingness-to-accept to give up their list was \$5.05 while the equivalent gain to write a shopping list was \$3.87.