WILLINGNESS TO PAY FOR FOOD SAFETY ASSURANCE: AN ANALYSIS OF THE CASE OF TIME-TEMPERATURE INDICATORS AND UNCOOKED CHICKEN

by

VICTORIA WRIGHT

(Under the Direction of Jeffrey Dorfman)

ABSTRACT

With widespread worry of outbreaks and panic over food-borne pathogens, a potential niche has been created within the market for uncooked chicken. New technology allows monitoring of time-temperature abuse to hold suppliers accountable whilst increasing the information the consumer has before purchase. Indicators change color if there are any abnormally high temperatures during the supply chain for an extended period of time. The question therefore follows concerning whether these indicators would be an economically viable addition to the supply chain. A double-bounded dichotomous choice model was used to find the willingness to pay for these sensors. These values were then compared to the price of the sensors and found to be economically viable within the poultry market.

INDEX WORDS: WTP, willingness to pay, poultry, time-temperature indicators, food safety, profitability, chicken, dichotomous choice

ANALYZING THE WILLINGNESS TO PAY OF TIME-TEMPERATURE INDICATORS IN UNCOOKED CHICKEN

by

VICTORIA WRIGHT

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VICTORIA WRIGHT

Major Professor:	Jeffrey Dorfman
Committee:	Ellen McCullough
	Gregory Colson

Electronic Version Approved:

Suzanne Barbour
Dean of the Graduate School
The University of Georgia
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CHAPTER 1

INTRODUCTION

Poultry market research is not a new field of interest. A relatively untapped source of interest in this market, however, is poultry's relationship with food safety. New technologies in the food sector have the potential to dramatically lessen the concerns of consumers. Of course, this relies on a few factors. Consumers must believe that a new technology is helpful. They must also have an understanding of the technology and how it relates to food safety. Finally, consumers must be willing to pay an extra cost for this technology. The specific technology that we seek to evaluate regards time-temperature indication. This is a relatively new technology that could be implemented through the supply-chain to hold producers and retailers accountable for refrigeration throughout the chain. The question lies, however, in whether this market is one in which this technology is an economically viable addition.

The supply chain of the poultry industry is almost entirely dominated by large processing firms (Epple and McCallum, 2006). Discovering what affects willingness to pay for technological changes in this industry will allow these firms to see the potential gains from enacting these types of changes within their section of the supply chain. Another economically viable option would be for large store chains to see the willingness to pay and fill an untapped source of potential consumer satisfaction. This would put pressure on the major producers in the industry to accomplish any technological changes in that way. Of course, this would only be viable if consumers are found to be willing to pay more than the cost of an additional technology.

The specific technology we are analyzing is an up and coming one. Time-temperature indicators are sensors that change color if they are outside a set temperature zone. The factor of how long they are in this zone is also taken into consideration (3M Microbiology, 2006). The idea is that these sensors could be added to consumer-ready poultry packages. This would alert the consumer of the safety of their poultry throughout the supply chain before reaching the shelf. Ideally, there would never be activated sensors on the shelf for sale. Having these indicators could then serve as an extra level of assurance of safe traveling temperatures during the distribution process.

The United States Department of Agriculture notes the importance of refrigeration. Notably, pathogenic bacteria is able to grow rapidly in unsafe temperature zones. This is problematic since these bacteria do not change the taste, smell, or physical state of the food (United States Department of Agriculture [USDA], 2015). Unfortunately for a consumer, this makes it nearly impossible to discern the treatment of refrigerated products before they reached the shelf. While indicators would not be able to ensure that there are no pathogens present at all, they can provide an extra level of assurance. Consumers would have to believe in this assurance, however, for the indicators to make economic sense. Further, consumers must be willing to pay for this assurance for the indicators to be economically viable.

The purpose of this study is therefore to calculate the willingness to pay for an indicator. Further, we aim to be able to determine factors that are likely to affect the willingness to pay of a given group. We use a survey to collect data within a double-bounded dichotomous choice model so that we may find willingness to pay [WTP] for the sample as a whole as well as for individual sub-groups. Our study therefore aims to see if the addition of this technology is economically viable through WTP analysis.

CHAPTER 2

LITERATURE

The poultry market has historically been studied through many different lenses. Its relationship with food safety has specifically been examined. Further, the market's demand and its relationship with changing prices has been investigated. This prior research informs our understanding of the current market for uncooked chicken.

There has been an increase in consumer understanding of food safety issues in relation to different meat varieties. Notably, in 2004, Piggott and Marsh investigated food safety's relationship to poultry. They sorted through English newspapers to find articles related to food safety. For example, some articles included words such as "*e.coli*" and "outbreak of *salmonella*." The poultry-based reporting on food safety mostly had to do with *salmonella* (Piggott and Marsh, 2004).

There is a common research question concerning how much food safety awareness and/or publicity affects the demand of poultry and other meats. Piggott and Marsh found that in the period from 1982 to 1999, there were an average of 153.04 articles per quarter about poultry. While beef had a higher article average, poultry had a more consistent number of articles regarding food safety (Piggott and Marsh, 2004). Poultry reporting with regard to safety has therefore existed for decades. This informs our understanding of the way the average consumer looks at poultry in the context of food safety.

This reporting would not matter to market research, however, if it was found that it does not affect demand. Piggott and Marsh actually found that the response to food safety concerns could be as high as -1.64 pounds per person (a consumption decrease). This would be a 6.9% decline in demand. They express that this decrease corresponds with the food safety index maximum. Times with the highest food safety reporting on poultry were therefore correlated with times of increased demand (Piggott and Marsh, 2004). This study utilized data from the 1990s. It can perhaps be assumed that more recent data would show a much higher knowledge of food safety issues. The internet and all of its offspring through social media and instant news notifications can alert consumers of any problems in food safety almost immediately. There are still questions of how the current levels of food safety knowledge impact poultry demand.

Demand in meat markets have also been investigated to find elasticities. Poultry in Australia was shown to have a pretty inelastic demand curve in 1985 by Bhati (Bhati, 1987). This was found before further analyses included food safety as a factor on demand changes. An inelastic demand somewhat conflicts with the findings of Piggott and Marsh. In their more recent study, poultry demand did indeed respond to food safety reporting (Piggott and Marsh, 2004).

The popularity of poultry may influence the changing elasticities. A more recent 2010 study by Tonsor, Mintert, and Schroeder also used a media-based analysis with data including media analysis from the early 2000s. They note that the average quarterly poultry consumption per person stood at 21.3 pounds per person. This was higher than the demand for pork or beef. They also found that there was an average of 2.6 poultry food safety recalls in the quarterly data from 1982-2007. This was a smaller average than pork or beef (Tonsor, Mintert, and Schroeder, 2010). Perhaps the popularity of chicken consumption adds to its relative inelasticity in respect to price, but elasticity in response to negative food safety reports.

Interestingly, media attention does not just cause a negative impact on demand. It can sometimes have a positive effect on poultry demand. In the early 2000s, there were a lot of publications about the benefits of poultry. These coincided with the popularity of high-protein diets that praised the minerals within meat (Tonsor, Mintert, and Schroeder, 2010). The general trend of increased food recalls through their study period led to their conclusion about the effects of these recalls. These effects, of course, need to be measured in comparison to price and the relationship between health/diet and household demographics, for example (Tonsor, Mintert, and Schroeder, 2010). The research on food safety impacts on demand brings a sense of authentication to furthering research on how much consumers really care about food safety. It will be especially useful to add to this body of research with a more recent understanding of how much people care about food safety based on current chicken prices.

Rivera-Ferre (2009) argues, however, that the producers are the ones driving the shifts in production. This conflicts with a more traditional assumption that consumer demand drives market shifts. Regardless of the specific role producers play in marketing food-safety instruments with regard to international meat markets, their addition of technology potentially has an ability to influence demand.

Chicken prices do indeed change with changes in productivity. In their 2006 study, Epple and Mccallum brought up the intense productivity growth that accompanied a falling price for poultry (Epple and McCallum, 2006). This dramatic productivity increase is relevant to the impacts that food safety has on this market. There are a wide-range of consumers who purchase poultry due to its hold on the market and its production. The importance of cost to these consumers is key since food safety alert technologies implicitly add cost. The importance can be somewhat estimated by the elasticity estimates explained previously.

On the producer side, Okpukpara’s 2016 study notes that producers are more likely to have a lower WTP if they are smaller (Okpukpara, 2016). It is important to note the importance of the production side and their level of openness to adopting new technologies. It can be assumed that even if they are not the ones paying for an increase in price, they would likely have supply-related initial costs with any implementation. For firms to be willing to implement any additional technology, we can assume that they would want to be able to pass increased costs to the consumer. Firms and consumers therefore both have roles in determining economic viability.

In prior studies, food safety has specifically been investigated through consumer-based willingness to pay analyses. Researchers have worked to see if there was a relationship between technologies, methods, and/or labeling and the value a consumer puts onto a product. The applications of these types of studies are threefold: 1) Are consumers willing to pay for food safety increases? 2) Do specific technologies represent higher food safety to consumers? 3) Are these technologies viable based on their price? Lewis, Grebitus, Colson, and Hu (2017) note that certain labels on beef in the European Union serve as a signal. The labels serve as an assurance for food safety. They also state that other labels (i.e. quality assurance and gourmet labels) do not necessarily make consumers feel more comfortable with their food. There is evidence to suggest that the effect of labeling depends on how much consumers trust the label/technology itself. The results can therefore seem to coincide with the explanation of the technology and the information given to consumers.

The “believability” factor can be looked at by many systems. Perhaps the ranking of important food-related factors by consumers can help add validity to this factor. The OECD notes that the agreement with statements about the relationship between labels and actual real-world problem-solving plays a major role in consumer faith (Organization for Economic Cooperation and Development [OECD], 2014). Consumers need to trust in the relationship between a label and a real-world problem (which they must believe exists) so that they will be willing to pay for a new technology that claims to solve or help solve a problem.

Further, slow growth chicken has specifically been analyzed from a willingness to pay (WTP) standpoint. Lusk (2018) uses a choice model to try to figure out the demand changes based on labels of slow-growth chicken. His main conclusion is the importance of the information given to consumers. He notes that labels could have a strong effect on demand. This is limited, however, by the consumers' level of understanding (Lusk, 2018). Consumers will perhaps have a higher WTP for poultry innovations if they understand them. This is why we seek to thoroughly explain the time-temperature technology which we are working to evaluate.

The final connection of willingness to pay [WTP], food safety, and poultry is that of WTP analysis and poultry. Previous WTP analyses with regard to the poultry market have looked at changes in demand based on certain factors and/or signals to consumers. Anwar, Aziz, and Ali (2012) found that chicken is pretty price responsive when compared to other common Pakistani staples and when using real income. While, as noted previously, there have been differing opinions on the elasticity of poultry, it can be assumed that, relative to other less-expensive, commodities, chicken price does affect demand. These technologies implicitly add cost to the product. This yields an increase in price that needs to be paid by some agent in market. The clearest choice would be for it to add to the cost paid by the final consumer in a supermarket. If we account for wholesale markets, however, the price may be inherited by supermarkets themselves. This would likely be for an indirect reason of wanting to increase profit by marketing their products differently to consumers. The likely response to this would be an increase in the price for final consumers anyway.

CHAPTER 3

RESEARCH JUSTIFICATION AND INSTRUMENT

The research question addressed here is: How much are people willing to pay for the assurance of food safety? What is the potential change in consumer willingness to pay based on the characteristics of consumers? Is any potential change greater than the cost of these indicators?

We want to figure out the viability of adding these sensors to the market based on what we know about the prices of the sensors.

Our goal is to add evidence to answer the question of whether participants would be willing to pay for these sensors at all. This goes along with the question of why some participants are willing to pay while others do not. This will help to provide clarity to the viability of this technology at its current price.

There are many varieties of time-temperature indicators. For this research, we are focused on the WarmMark models distributed by DeltaTrak. We assume that using this model will serve as an accurate presentation of time-temperature indicators as a product. Based on a product specification table by DeltaTrak, most of the differences among the WarmMark models involve the temperature zones in which the sensor will change colors. When outside of the listed temperature range, the indicator will turn red. It has three separate areas that can turn red. These each correspond with the amount of time in which the product is not in the proper zone. There are brief, moderate, and prolonged potential indicator spots. The specific one we would look at for poultry would be the model 51014 (DeltaTrak).

According to DeltaTrak's sale team, the best price for their sensors is the price for a 25,000 pack. This price is $11.25 per 10. Each sensor would therefore be $1.125 which we round to $1.13 (Schumpp, 2018). This serves as a pretty good price estimate. Although it only represents one brand in the market, it allows us to have a baseline from which to evaluate willingness to pay. This gives us a way to see the economic feasibility of these sensors in the market we are looking for. It allows us to predict the potential willingness to pay [WTP] from the consumer standpoint.

Appendix A has our full survey that was created with a goal of finding the WTP. For the options within the pictures included on the survey, the best and most recent available price for chicken (noted by the Bureau of Labor Statistics) at the time of survey creation was used. This was $2.896 per pound (which was then rounded to $2.90). This was based on the non-seasonally adjusted city average price per pound of chicken breast in the U.S. in September of 2018 (Bureau of Labor Statistics [BLS]). We used this price within the survey to edit pictures and form a dichotomous choice model based on choices between a package with a sensor and one without. Each choice (and related price) was for 2 pounds of chicken.

In addition to demographic information, we used this dichotomous choice model to frame our choice questions. This model used pictures with differing prices. The double-bounded dichotomous model sorted the participants into four groups based on their choices. We also included a ranking question in which participants had to rank how important five properties were to them. These categories were Food Safety, Animal Welfare, Cost, Health, and Taste. This survey was edited into Qualtrics for the University of Georgia and paired with a consent form. After receiving IRB approval from the University of Georgia, we began our collaboration to receive survey observations. Research Now SSI (now renamed Dynata) then spread out the survey with a hard launch after testing of the questions with a soft launch. Research Now SSI recruited 1000 participants that that took the survey and yielded viable observations (i.e. not incomplete or within an excluded population category (i.e. under 18 or non-chicken purchasers)).

The pictures that made up the survey options regarding willingness to pay for the sensor were based on an edited picture of purchased chicken breast. The picture was edited within Photoshop to include no identifying information of store location. Also, Deltatrak's WarmMark time temperature indicator was used for the options that included the sensor (DeltaTrak). Price differences between the chicken breast including the sensor and the chicken breast not including the sensor were chosen based on the approximate prices of individual sensors. Participants were each asked 3 different willingness to pay questions. The first one was given to everyone. It included a price difference of \$.565 per pound, or \$1.13 total. The second question was different based on the participant's answer to the previous question. If a participant answered no to the first question (i.e. chose the package without the sensor), the participant was given a price difference of \$.39 per pound, or \$.78 total. If a participant answered yes to the first question (i.e. chose the package with the sensor), the participant was given a price difference of \$.74 per pound, or \$1.48 total. A third question sought to see if people cared about the sensor in general by showing both options as the same price.

CHAPTER 4

DATA

This study identifies a set of observations based on a series of criteria. Variables were then defined to allow for ease in modeling and analysis. Data sensibility checks and population comparisons were also completed to ensure that the sample was a random representation of the population.

Collection and Sample Creation

Research Now SSI (now renamed Dynata) aimed to give us at least 1000 responses following a hard launch of our survey. These observations were then cleaned based on requirements for the survey as well as completeness and answer sensibility.

1410 total observations were exported from the main outreach resulting from the hard launch. We then deleted observations from respondents under age 18. This cut 23 observations. This was due to the initial exclusion in which the participants had to be 18 or older. Those who do not ever purchase uncooked chicken were then excluded. This involved 39 observations. This was due to the second exclusion for participation. This exclusion followed from the requirement that participants had to be purchasers of uncooked chicken.

The incompletes were then removed. This included 348 observations. After these exclusions, 1000 total observations were left. This corresponded with the promised viable observations from Research Now SSI.

For the household size question, participants were required to type in their household size. While they were limited to only two characters, they could type in any two characters (numerical or not). There were five observations that were excluded with noted household sizes of 0. 18 observations were excluded because they had answers over 10 or non-numerical values in their answers.

This resulted in 977 observations going into the deeper stage of data cleaning and sensibility checks before analysis.

Variable Creation and Redefinition

From the original data export and initial cleaning of observations, an excel sheet was made. This sheet included only potentially relevant and needed variables. For the additional data cleaning and eventual analysis, all (potentially) identifying features were erased. This included 977 observations and 17 variables before additional variable creation/changes. The variables were labeled for SAS (9.4) analysis as the following: age, purchases, education, income, hhsize, store, vegetarian, mealkit, original, less, no, food, animalwelfare, cost, health, and taste.

The five ranked variables that ended the survey were changed. Filtering was used to create a ranking system 1(least)-5(most) based on responses to each of the 5 variables. This was done for increased ease during analysis.

Categorical variables were then created in an effort to increase the ease of analysis and interpretation based on our model.

An education categorical variable was defined from education results based on the following key: 1: less than high school; 2: high school/equivalent; 3: some college, no degree; 4: associate’s degree; 5: bachelor’s degree; 6: master’s degree or higher

An age categorical variable was added. This variable was created based on the following key: 1: 18-24; 2: 25-34; 3: 35-44; 4: 45-54; 5: 55-64; 6: 65-74; 7:75-84; 8: 85+. Notably, the categories increase in numerical value as age increases. For the education variable, the categories also increase in numerical value as education level increases.

A category for purchase frequency was created based on the following key: 1: Less than once a month; 2: once per month; 3: once every two weeks; 4: once per week; 5: two times per week; 6: three times per week. Notably, the categorical value increases as participants make purchases more often.

An income categorical variable was redefined from the income results based on the following key: 1: <10,000; 2: 10,000-24,999; 3: 25,000-49,999; 4: 50,000-69,999; 5: 70,000-99,999; 6: 100,000+.

The categorical meal kit variable was defined based on the following key: 0: never; 1: less than once/month; 2: 1-2 times per month; 3: 3-4 times per month.

For a dependent variable, a group category variable was created based on the following key: 1=A; 2=B; 3=C; 4=D. This divided the participants based on their choices within the picture-based dichotomous choice model. These groups are based on a participant's answers to the first and second choice questions respectively. These groups were therefore defined as: A: yes, yes to sensor; B: yes, no to sensor; C: no, yes to sensor; D: no, no to sensor.

Two additional variables were added to replace the store variable. An original variable asked participants to choose what store type they consider their usual store from a list of store categories. The replacement variables identified a consumer's store-use diversity as well as their self-identification as an organic and/or local shopper. The store diversity dummy variable took a value of 1 for any observation with 3 or more options chosen and a 0 otherwise. This was created to test the potential effect of store diversity on willingness to pay. For the variable on organic/local shopping, anyone that chose the organic option and/or the local/co-op option (see appendix A for wording of questions and examples given) was given a value of 1 for this dummy variable. Everyone without either or both of those options chosen was given a value of 0. This was done to see the potential relationship between people who shop at these stores and willingness to pay for more expensive chicken per pound.

The supercenter and/or dollar store dummy variable was made for those who only shop at one and/or both of these store types. A one indicates them fitting this description.

We then created a variable to represent if participants were ever willing to pay when there was a cost for the sensor. This dummy variable was created by assigning a 1 if the observation fell into group a, b, or c and a 0 if they were within group d. Group D included those who said no, no and were therefore not willing to pay for the sensor at any price.

A vegetarian dummy was created in which 1 represented not eating chicken (vegetarian).

After the creation of all the variables, the newly created variables were compared to the original variables. The SAS output using the frequency procedure was compared to the Microsoft Excel-based counts generated after the sorting and filtering features. This was done for age, purchasing frequency, education, income, household size, store diversity, organic and/or local purchasing, the vegetarian categories, meal kit participation, the supercenter/dollar variable, the choice response variables, and each of the importance variables (i.e. food safety, animal welfare, cost, healthiness, and taste). The original variables were therefore matched with the created dummy variables and categorical variables to ensure accurate frequencies of the created variables. After this assurance of correct variables, we completed sensibility checks.

Sensibility and Representation Checks

One conducted sensibility test involved the use of the frequency feature in SAS to create cross tabulation tables. We compared these tables to the expectations of the relationship between education and income and between age and education. It was expected that more education would generally be correlated with more income. It was also expected that age would somewhat increase alongside education. This is because of the sensibility of someone 18-24 having a master's degree or above. This is possible, but we want to be sure that there is not an unbelievable amount of people in this category.

The SAS frequency procedure was used to look at the relationship in a cross tabulation of each of the expected variable pairs above. We used the categorical versions because it was easier to see the general relationship and check for sensibility. This check yielded results that we deemed to be sensible.

As far as the cross tabulation of the income category and education category variables, there were few outliers from the trend of low income and low education and vice versa. The middle category variable pairs follow trends that seem approximately normal at a glance. For the most part, it seems that as education increases in this sample, income increases as well. This proved to match our expectations.

Table 1. Cross Tabulation of Education and Income Categorical Values

		Income Categorical Values					
Education Categorical Values		1	2	3	4	5	6
1		2	3	6	0	2	0
2		14	46	67	30	15	16
3		14	43	57	48	24	21
4		2	9	37	35	20	14
5		3	13	45	60	79	86
6		2	2	12	19	56	75

As far as the cross tabulation of the age category and the education category variables, there are very few participants aged 18-24 who also are in the category with the highest level of education.

Table 2. Cross Tabulation of Age and Education Categorical Variables

		Education Categorical Values					
Age Categorical Values		1	2	3	4	5	6
1		1	15	20	4	7	2
2		3	39	33	26	65	36
3		3	23	34	16	53	26
4		2	24	27	16	42	28
5		3	42	41	33	52	28
6		1	38	45	18	57	38
7		0	6	7	4	9	7
8		1	0	0	0	1	1

The general frequency results yielded a few questions and led to a few assumptions about the category creations. In our data cleaning, there were 14 individuals who identified as vegetarians that do not eat chicken. In our initial requirements for taking the survey, we excluded those who never purchase chicken. There was therefore an assumption made that they are purchasing or other people. These observations were therefore not excluded.

We also made a decision about the willingness to pay categories. 76 people were in the willingness to pay at all group, but were not willing to pay when there was no price difference between the choices with or without a sensor. This means they were willing to pay for the sensor when the prices were different (when the sensor added an additional price on the chicken), but not when the prices were even. An assumption was made that these people see the price differences as a measure of worth for the sensors and would not trust them if they were the same price as chicken without the sensor

We made sure to check that the age demographics were approximately reflective of those of the U.S. According to the U.S. Census Bureau's 2010 Summary, 24% of citizens in the U.S. are under 18 (Howden and Meyer, 2011). This means that persons aged 18 and older (the target survey population for our study) constitute 76 percent of the population. Using proportional math, we can figure out what the values "should" be if our survey perfectly aligned with the population of the U.S. We must note, however, that this survey was not restricted to the U.S. so some of the participants recruited by ResearchNow SSI (now Dynata) may have taken the survey from outside of the U.S. (This, however, is not likely to have been the case for the vast majority of the participants.) Below is the math (rounded to two decimal places) that we used to find the proportions of each group for our comparison.

9.9*/76 =x/100 x=13.02

26.6*/76=x/100 x=35

26.4*/76=x/100 x=34.74

13*/76=x/100 x=17.11

We could then compare the above xs to the values in our survey to see the following percentage comparisons.

Table 3. Ages: percentage comparisons between U.S. and Survey Populations

Below is a comparison between the percentages within our survey sample and those of the U.S. age population distribution.* retrieved from 2010 U.S. Census Bureau data for Age and Sex Composition (Howden and Meyer, 2011).		
Age Group	2010 Percentages *	Survey Percentages
18 to 24	13.02%	5.02%
25 to 44	35%	36.54%
45 to 64	34.74%	34.6%
65+	17.11%	23.85%

The percentages here about match the expected ones. Our sample is somewhat skewed towards the 65+ population and away from the 18-24 population.

We then moved on to checking for accuracy within the household income distribution. For this comparison, the note within the age section still stands regarding the potential international participants.

Table 4. Income: percentage comparisons between U.S. and Survey Populations

This shows a comparison between the percentages within our survey sample and those of the U.S. income population distribution.* retrieved from DQYDJ U.S. income distribution calculator from 2017: This used data from the University of Minnesota to make a calculator for ease in comparison (PK, 2019).		
Income Group	2017 Percentages*	Survey Percentages
Less than 10,000	6%	3.79%
10,000-24,999	14%	11.87%
25,000-49,999	21%	22.93%
50,000-69,999	13%	19.65%
70,000-99,999	16%	20.06%
100,000+	30%	21.70%

The demographics of our participants closely matched that of the true population. We had fewer high income households then the population estimates, but the deviations are acceptable.

We then moved on to checking for accuracy within the education distribution. For this comparison, the note within the age section still stands regarding the potential international participants.

Table 5. Education: percentage comparisons between U.S. and Survey Populations

This shows a comparison between the percentages within our survey sample and those of the U.S. education population distribution.*From charts published on statisticalatlas.com and based on data from the U.S. Census Bureau (U.S. Census Bureau).		
Education Group	2017 Percentages*	Survey Percentages
Less than a high school diploma	5.6%	1.33%
High school diploma or equivalent (e.g., GED)	27.5%	19.24%
Some college, no degree	21.0%	21.19%
Associate's degree	8.2%	11.98%
Bachelor's degree	18.8%	29.27%
Master's degree or higher	11.5%	16.99%

These values align approximately to the expected ones. Our sample was slightly skewed towards a more educated population. We can assume that any difference is due to access to the survey, random sampling, and/or the self-selection into taking the survey through Research Now.

The means procedure was used for variables that were numerical originally. These included the household size variable and all five of the ranked variables (food safety, animal welfare, cost, health, and taste).

Overall, no additional observations were excluded. This decision was made due to the above sensibility checks as well as an analysis of the means of the numerical variables. Notably, we deemed that our sample had a sensible spread for household size and a sensible average with a mean of 2.60. The means given in the SAS output of the final five ranked variables were as follows (with the means rounded to two decimals).

Table 6. Original Quantitative Variables: Means

Food Safety	4.85
Animal Welfare	4.14
Cost	4.53
Health	4.65
Taste	4.76

The decision that these were sensible means was made in addition to the decisions made from the age and income checks as well as the assumptions from the frequency results. It was decided to move forward with the analysis with the 977 observations.

CHAPTER 5

METHODS

In addition to finding the WTPs for our sample and sub-groups, we developed the following hypotheses/predictions alongside our methodology development:

Hypothesis 1) Willingness to pay for these sensors is affected positively by income, and the importance of food safety and health.

Prediction 1) Participants who shop at organic and local stores will be more willing to pay than others (i.e. more likely to be in group A as noted below).

Prediction 2) Participants who only shop at supercenters and/or dollar stores will be less willing to pay than others (i.e. more likely to be in group D as noted below).

Other included potential explanatory variables are ones that we believe could have a potential effect on the likelihood of being in one of these groups resulting from our dichotomous choice model. These include purchasing frequency, age, education, household size, store diversity, meal kit purchases, and whether someone is a vegetarian. There is strong justification for the variables of household income and family size based on Fathelrahman, Hussein, Muhammad, and Sherif (2015). They found that WTP (willingness to pay) is affected by these two variables in the poultry market. Other notable variables that are included as potentially explanatory are taste and animal welfare.

In 2012, Lopez-Feldman developed a method in Stata that could be used to estimate willingness to pay from double-bounded dichotomous choice survey data. Previously, there were not any commands that could be used to estimate a double bounded model with such efficiency

(Lopez-Feldman, 2012). Please see Appendix E for the WTP probability estimation models based on utility estimations. These models formulated by Lopez-Feldman were used as the basis for our analysis as well (Lopez-Feldman, 2012).

Our dichotomous choice model needed to be based on two levels of bounds as we estimated the willingness to pay. Lopez-Feldman's command and model estimation uses an approach that programs in bids to find the coefficients for each explanatory variable. These can then be programed into an nlcom command that finds the willingness to pay based on the average of each explanatory variable (Lopez-Feldman, 2012). We therefore had to redefine the groups by instead listing the response variables (i.e. yes or no) as dummy variables and the difference between the two packages (i.e. the price of the sensor in each choice) as the bid. Since this was a dichotomous choice model with two choice options, we had two response variables (yes1 and yes2) and two bid variables (bid1 and bid2). Bid1 was defined as 1.13 since that was the difference that every participant had between their first two choices. Bid2 was defined as either 1.48 or .78. 1.48 was the larger difference in price that was given to anyone who said yes to bid1, while .78 (i.e. 78 cents) was the bid price for the group that said no to the first choice.

After redefining these variables, we used Stata to estimate the general WTP based on a model with no explanatory variables (Lopez-Feldman, 2012). In essence, this model shows the WTP of our sample when the explanatory elements are not controlled for. We then found the estimate of WTP with the control variables using the doubleb command. These coefficients are useful in estimating the overall willingness to pay using all the explanatory variable betas. We could use these coefficients alongside the means of each explanatory variable to find the WTP using the nlcom Stata command based on the maximum likelihood formula defined by Lopez-Feldman (Lopez-Feldman, 2012).

After finding the WTP of the average of the sample, we were able to break down individual WTPs for each category/section within the data. This kept everything else constant except for the value of the explanatory variable we were looking into. For example, we replaced the mean of the age category variable with 1 to estimate the WTP of the first group (ages 18-24). Since the categorical versions of the variables were used, we could simply replace the mean with the category to find the WTP of that group (Lopez-Feldman, 2012).

We then ran a probit model with the dependent variable as the dummy variable of whether a participant was ever willing to pay for the sensor at an additional cost. This worked to see how the explanatory variables affected a participant saying yes to the sensor at all (i.e. at any difference in price).

We used the mfx Stata command to find the marginal effects based on the results from the probit analysis. We decided that this was the correct command since this command is noted by Stata to model the effects of the averages rather than the average effect. We made the decision that the mfx command aligns better with our modeling than the other commands to find marginal effects. We deemed that this is a good reflection of the doubleb command in which we use the averages to estimate WTP in the nlcom command.

As a side note, we ran the WTP models as well as the probit and marginal effect commands using two different model specifications. Our first one included the explanatory variables that we deemed to be important in affecting our bid responses. The second one includes all of the explanatory variables in our sample. As shown in our results, both of these specifications yielded approximately the same WTPs. This gives us some evidence that our original specification has approximately the same level of explanatory power as the expanded model.

As a final check, we ran a probit model with a specification of income as categories. This required us using the same doubleb command, but putting in i. before incomecat. This divided up our incomecat into individual dummy variables for each category (excluding one). The purpose of this was to evaluate our initial negative income coefficient and see if there was less precision with using the categorical version of the income variable. We had to do this to use the Stata commands and find full WTP, but we wanted to see how the probit would change if we divided income into dummy variables. No discernable effect was found between these two probit models. We came to the conclusion that our methodology did not yield incorrect income results since this second probit (using i.) yielded all negative income coefficients as well.

CHAPTER 6

RESULTS AND DISCUSSION

A majority of respondents were willing to pay for the sensor. As noted in tables 7 and 8, there were few participants (relative to our sample as a whole) who were unwilling to pay for a sensor at any price.

Table 7. Willing to Pay for the Sensor at any Price

This is a summary of frequencies from Stata. The variable in question is a dummy variable that represents whether a certain participant ever was willing to pay for the sensor.		
Willing to Pay for the Sensor at any Price	Freq.	Percent
0	383	39.20
1	594	60.80
Total	977	100.00

Table 8. Group Frequencies

This is a summary of frequencies from Stata. The variables in question are ones that represent the participants in each of our four different response categories.		
Group Frequencies	Frequency	Percent
1: Group A (yes, yes)	419	42.89
2: Group B (yes, no)	80	8.19
3: Group C (no, yes)	95	9.72
4: Group D (no, no)	383	39.20
Total	977	100.00

These results were promising in supporting that consumers are potentially willing to pay for these sensors at the market price.

We ran basic probit models to see the relationship between saying yes to the chicken with the sensor (at any additional price displayed) and our explanatory variables. The results of these analyses are displayed in tables 11 and 13 within Appendix C. The significant variables from the first probit regression (displayed in table 11) include the age categorical variable, the purchasing frequency categorical variable, household size, animal welfare importance, cost importance, and healthiness importance. These are all significant at a significance level of .10 (although all the variables except for household size are significant at a significance level of .05). As age increases, the probability of being willing to pay for the sensor decreases. The same inverse relationship was found with an increase in cost. As purchasing frequency, household size, animal welfare importance, and healthiness importance increase, the probability of being willing to pay for the sensor increases. While the same signs on significant variables are observed for the expanded probit regression, the coefficient on household size was no longer significant. The coefficients are relatively the same for the significant variables in both models.

We used the probit analysis results to find marginal effects. These are displayed in tables 12 and 14 in Appendix C. The same significant variables were observed to have significant marginal effect coefficients in these tables. The vegetarian dummy variable also had a significant positive marginal effect coefficient.

Our main goal was to determine if the willingness to pay for these sensors made them an economically viable addition to poultry. Tables 9 and 10 show WTPs as we look at the models in their entirety. We can interpret the coefficients in these tables as representing the price that consumers would be willing to pay based on the designated specification (Lopez-Feldman, 2012). With no control variables, there is a willingness to pay of just under $1.20. Further, when we add in our explanatory variables, we also get statistically significant results. We got willingness to pay values of $1.20 and $1.21 respectively.

Table 9. Willingness to Pay with No Explanatory Variables

This table shows a summary of Stata output of the WTP before the explanatory variables were added. The coefficient can be interpreted as the WTP estimate in dollars. Note: For all tables, one star represents a significance level of .1, two stars represents one of .05 and three stars represents one of .01.	
Coefficient	Std. Error
1.199***	.058

Table 10. Overall Willingness to Pay

This table shows a summary of Stata output of our willingness to pay values when we took our explanatory variables into account. This shows the comparison between our original and expanded specifications as referenced above.			
Coefficient (Original Specification)	Std. Error (Original Specification)	Coefficient (Expanded Specification)	Std. Error (Expanded Specification)
1.201***	.055	1.206***	.055

These WTP estimates displayed in table 9 and 10 represent the sample as a whole. We also wanted to see, however, how sub-groups of our sample behave. The tables with these WTP estimates for each sub-group can be found in Appendix D. As shown in table 20, the purchasing frequency category as well as the animal welfare, cost, and healthiness importance variables all had significant coefficients. This means they had significant effects on the overall willingness to pay estimates. Age and cost each share an inverse relationship with WTP and animal welfare and healthiness importance are both directly related to WTP. Our hypothesis 1 is mostly not supported since income did not affect WTP positively and both income and food safety did not have a significant effect. Our hypothesis predicting that healthiness positively affects WTP was correct.

Tables 16-24 all show significant WTP estimates for sub-groups. Table 16 shows how people who are store diverse have a lower WTP than those who are not. This makes sense since you can assume that people who are store diverse may be searching for the lowest costs. As shown in table 17, the purchasing sub-groups' WTPs vary from $1.02 for the consumers with the lowest frequency of purchases and $1.41 for those with the highest purchasing frequency. The education sub-groups displayed in table 18 show a similar trend. They vary from $1.17 to $1.22 and increase alongside education. For age groups, younger shoppers have a higher WTP than older shoppers. The WTP varies from a WTP of $1.36 to $0.98 respectively. Table 19 shows these coefficients. The income subgroups show WTP estimates that decrease alongside increasing income. This did not support our first hypothesis.

Tables 21-24 reflect the additional variables that were included in the expanded model. Vegetarians notably were only found to be willing to pay $0.94 compared to non-vegetarians' $1.21. Supercenter/dollar store shoppers were willing to pay less than those that did not list these store types as their only grocery stores. They had WTPs of $1.13 and $1.22 respectively. This supports what we predicted in prediction 2. Our first prediction was also supported. Those who listed themselves as organic and/or local shoppers had a higher WTP estimate than those who did not. They had WTPs of $1.31 and $1.18 respectively. WTP estimates for the meal kit groups decreased as people purchased meal kits more often. This may be due to a lower store-bought chicken purchasing frequency

CHAPTER 7

CONCLUSION

Our research yielded results that could be applied for further food safety research and food technological advancement as a whole. We found evidence to suggest that consumers are willing to pay for sensors that can better assure them of food safety. While we cannot be sure that these results would be reflective of other food safety technologies, this study provides justification for more research within this element of the food sector. Our results show support for the idea that consumers value food safety or at least value this specific technology that can add assurance to the assumption of food being safe. We found that the WTP values reflect economic viability when compared to the prices of these sensors. These sensors could be integrated into the supply chain. Adopting this technology is economically viable as long as we can assume that the cost of sensor placement is not too high. There is even an opportunity here for potential profit for a participant in the supply chain who integrates these sensors. Recall that the price is just under $1.13 per sensor (Schumpp, 2018). This is less than the WTP of $1.20 found in table 10. Based on this research, we have strong evidence that processors and/or retailers would be able to pass the costs of these sensors onto the consumer.

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APPENDIX A

Appendix A: Survey: Below is the Qualtrics survey that was inputted into the University of Georgia's Qualtrics system. Please note that it was combined with a survey about antibiotic-free chicken that included questions after our dichotomous choice questions. These questions that are unrelated to our study are not included below.

UNIVERSITY OF GEORGIA CONSENT FORM
How do time-temperature indicators and antibiotic-free labels affect consumers' views on chicken?
Researcher's Statement
We are asking you to take part in a research study. Before you decide to participate in this study, it is important that you understand why the research is being done and what it will involve. This form is designed to give you the information about the study so you can decide whether to be in the study or not. Please take the time to read the following information carefully. If you need more information, you may contact the investigator listed below. When all your questions have been answered, you can decide if you want to be in the study or not. This process is called "in- formed consent." You may print this form for your records.
Principal Investigators: Jeffrey H. Dorfman University of Georgia
Agricultural & Applied Economics
Phone: 706-542-0754 Email: jdorfman@uga.edu
Purpose of the Study
This study is looking to discover how much are people are willing to pay for the assurance of food safety. It is looking to discover the potential usefulness of these new technologies and/or methods in the food sector whilst pinpointing what consumers find important in making purchasing deci- sions.
Study Procedures
If you agree to participate, you will be asked to provide some basic demographic information and then asked your preferred choices to a few questions. Your time commitment should be only 5-10 minutes. All individual data will be kept anonymous; we will never collect your name, address, or any other identifying characteristics.
Risks and discomforts
We do not anticipate any risks from participating in this research.
Benefits
We anticipate that this survey will help identify what aspects of the food sector consumers find most important and what consumers seek to know when making purchasing decisions. Likewise, it will work to pinpoint the willingness-to-pay for potential new elements of the poultry sector. This information can help inform both the supply chain and consumers so product-related advances for the poultry sector may occur with a better understanding for demand.

Incentives for participation
None.
Privacy/Confidentiality
Your data will be identified in our dataset only by an ID number. No identifying information will ever be collected. Every reasonable effort has been taken to ensure the effective use of available technology; however, confidentiality during online communication cannot be guaranteed.
Taking part is voluntary
Your involvement in the study is voluntary, and you may choose not to participate or to stop at any time without penalty or loss of benefits to which you are otherwise entitled.
If you have questions
The main researcher conducting this study is:
Jeffrey Dorfman, a professor at the University of Georgia. If you have questions, you may contact Jeffrey Dorfman at 706-542-0754 or jdorfman@uga.edu. If you have any questions or concerns re- garding your rights as a research participant in this study, you may contact the Institutional Review Board (IRB) Chairperson at 706.542.3199 or irb@uga.edu.
Research Subject's Consent to Participate in Research:
Your completion of the survey will be taken as your consent to participate in this research.

What is your age?

- Under 18
- 18 - 24
- 25 - 34
- 35 - 44
- 45 - 54
- 55 - 64
- 65 - 74
- 75 - 84
- 85 or older

How often do you purchase uncooked chicken on average?

- I don't ever purchase uncooked chicken
- Less than once a month
- One package every month
- One package every two weeks
- One package a week
- Two packages a week
- Three+ packages a week

What is the highest degree or level of school you have completed?

- Less than a high school diploma
- High school diploma or equivalent (e.g., GED)

- Some college, no degree
- Associate's degree
- Bachelor's degree
- Master's degree or higher

Which of the following best match your household income?

- Less than 10,000
- 10,000-24,999
- 25,000-49,999
- 50,000-69,999
- 70,000-99,999
- 100,000+

How many people currently live in your household (i.e. How many people do you share grocery items with?) ?

Where do you typically purchase food for your household? (Select all that apply)

- Convenience store/Gas station (e.g., 7/11, Circle K)
- Supercenter (e.g., Walmart, Target)
- Supermarket (e.g., Kroger, Safeway)
- Club store (e.g. Sam's Club, Costco)
- Co-ops/local stores
- Organic specialty stores (e.g., Whole Foods)
- Ethnic Grocery Stores
- Dollar Store (e.g., Dollar General, Dollar Tree)
- Drug Store (e.g., Walgreens, CVS)

Are you a vegetarian/vegan?

- Yes, but I eat chicken
- Yes, and I do not eat chicken
- No, I am not a vegetarian or a vegan

How often do you receive a meal kit delivery service?

- 3-4 times a month
- 1-2 times a month
- Less than once a month
- Never

Time-Temperature Indicators are used to measure whether meat has been in a potentially unsafe temperature zone for part of its transport. They change color when there has been exposure to a potentially unsafe, high temperature. Some brands (such as DeltaTrak's WarmMark) have differing sensors that show how long the meat was exposed to a potentially unsafe temperature. High temperatures can allow the growth of dangerous pathogens that can grow on raw chicken and potentially cause sickness. Purchasing a package with a sensor on it would show you that that specific chicken package did not reach a dangerous temperature during transport.

If you were going to purchase one 2 lb. package of chicken, which of the following would you purchase?

Option A: One two pound package of uncooked chicken for $2.90 per pound ***without*** a time-temperature indicator.

Option B: One two pound package of uncooked chicken for $3.465 per pound ***with*** a time-temperature indicator.

If you were going to purchase one 2 lb. package of chicken, which of the following would you purchase?

Option A: One two pound package of uncooked chicken for $2.90 per pound ***without*** a time-temperature indicator.

Option B: One two pound package of uncooked chicken for $3.29 per pound ***with*** a time-temperature indicator.

If you were going to purchase one 2 lb. package of chicken, which of the following would you purchase?

Option A: One two pound package of uncooked chicken for $2.90 per pound ***without*** a time-temperature indicator.

Option B: One two pound package of uncooked chicken for $3.64 per pound ***with*** a time-temperature indicator.

If you were going to purchase one 2 lb. package of chicken, which of the following would you purchase?

Option A: One two pound package of uncooked chicken for $2.90 per pound ***without*** a time-temperature indicator.

Option B: One two pound package of uncooked chicken for $2.90 per pound ***with*** a time-temperature indicator.

How important are the following to you when buying chicken?

	Importance				
	Very Important	Somewhat Important	Neither Important Nor Unimportant	Not Very Important	Not At All Important
Food Safety	○	○	○	○	○
Animal Welfare	○	○	○	○	○
Cost	○	○	○	○	○
Healthiness	○	○	○	○	○
Taste	○	○	○	○	○

APPENDIX B

Appendix B: Code: Below is the SAS and Stata codes that were used for analysis.

```
%let directory=%str(F:\tti);

PROC IMPORT OUT= WORK.tti

            DATAFILE= "&directory\ttidata.xlsx"

            DBMS=XLSX REPLACE;

            GETNAMES=YES;

RUN;

data tti;

set tti;

age= age; purchases= purchases;

education= education; income= income;

hhsize= hhsize; storediversity= storediversity;

org= orgorlocal; store= store;

vegetarian= vegetarian; mealkit= mealkit;

originaldif= original; lessdif= less; moredif=more;

nodif=no; foodsafety=foodsafety; awelfare=animalwelfare;

cost=cost; health=healthiness; taste=taste;

run;

title 'Frequences';

proc freq data = tti;
```

```
tables age purchases education income hhsize storediversity org store vegetarian mealkit
originaldif lessdif moredif nodif foodsafety awelfare cost health taste;
run;
proc means data = tti;
var hhsize foodsafety awelfare cost health taste;
run;
data tti;
set tti;
incomecat= incomecat; educcat= educcat; agecat= agecat;
run;
title "Sensibility checks";
proc freq data = tti;
tables agecat incomecat educcat;
run;
title "Cross-Tabulation Table Education (Categorical and Income (Categorical)";
proc freq data=tti;
tables educcat * incomecat ;
run;
title "Cross-Tabulation Table Age (Categorical) and Education (Categorical)";
proc freq data=tti;
tables agecat * educcat;
run;
%let directory=%str(F:\tti);
```

```
PROC IMPORT OUT= WORK.tti
            DATAFILE= "&directory\ttifinalclean3.3.xlsx"
            DBMS=XLSX REPLACE;
            GETNAMES=YES;
RUN;
data tti;
set tti;
age= agemid;
dummylessmonth= dummy_lessmonth; dummymonth= dummy_oncemonth; dummy2weeks=
dummy_2weeks; dummy1week= dummy_oneweek; dummy2week; dummy_2week
dummy3week; Dummy_3+;
dummyless= dummy_less; dummyhigh= dummy_high; dummysome= dummy_some;
dummyassoc= dummy_assoc; dummybach= Dummy_bach; dummymast= Dummy_mast;
income= incomemedian;
hhsize= hhsize; storediversity= storediversity;
orglocal= orgorlocal; superordol= supercenter/Dollaronly;
vegetarian= vegetariancat; mealkit= mealkitcat;
foodsafety=foodsafety; awelfare=animalwelfare; cost=cost; health=healthiness; taste=taste;
run;
import excel "F:\TTI\tti.xlsx", sheet("Sheet1") firstrow
doubleb bid1 bid2 yes1 yes2
doubleb bid1 bid2 yes1 yes2 agecat purchcat educcat incomecat hhsize storediversity foodsafety
animalwelfare cost healthiness taste
```

```
gen age_m=4.0

generate purch_m= 3.32

generate educ_m = 4.0

generate mean_hh=2.60

generate mean_store=.34

generate food_m=4.85

generate animal_m=4.14

gen cost_m=4.53

gen health=4.65

gen taste_m=4.76

gen income_m=4.05

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+inco
me_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsa
fety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste)
)

probit Willingtopayatall agecat purchcat educcat incomecat hhsize storediversity foodsafety
animalwelfare cost healthiness taste

mfx, predict (p)

probit Willingtopayatall agecat purchcat educcat incomecat hhsize storediversity orgorlocal
SupercenterDollaronly vegetariancat mealkitcat foodsafety animalwelfare cost healthiness taste

mfx, predict (p)

doubleb bid1 bid2 yes1 yes2 agecat purchcat educcat incomecat hhsize storediversity foodsafety
animalwelfare cost healthiness taste
```

```
nlcom(WTP:(_b[_cons]+1*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+2*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+3*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+4*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+5*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+6*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+7*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
```

```
nlcom(WTP:(_b[_cons]+8*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+0*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+1*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+1*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+2*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+3*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+4*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
```

```
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+5*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+6*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+1*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+2*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+3*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+4*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+5*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
```

```
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+6*_b[educcat]+income_m*
_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+a
nimal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+1*_b
[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+ani
mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+2*_b
[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+ani
mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+3*_b
[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+ani
mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+4*_b
[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+ani
mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+5*_b
[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+ani
mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+6*_b
[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+ani
mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
gen orgorlocal_m=.19
gen Supercenter_m=.12
```

```
gen vegonly_m=.01
gen meal_m=.49
doubleb bid1 bid2 yes1 yes2 agecat purchcat educcat incomecat hhsize storediversity orgorlocal
SupercenterDollaronly vegetariancat mealkitcat foodsafety animalwelfare cost healthiness taste
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+inco
me_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsa
fety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]
+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vege
tariancat]+ meal_m*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+inco
me_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsa
fety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]
+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vege
tariancat]+ 0*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+inco
me_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsa
fety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]
+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vege
tariancat]+ 1*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+inco
me_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsa
fety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]
```

+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ 2*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ 3*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+ 0*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+ 1*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+ orgorlocal_m*_b[orgorlocal]+0*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+meal_m*_b[mealkitcat]))

```
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+inco
me_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsa
fety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]
+ orgorlocal_m*_b[orgorlocal]+1*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+
meal_m*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+inco
me_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsa
fety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]
+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+1*_b[vegetariancat]
+ meal_m*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+inco
me_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsa
fety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]
+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+0*_b[vegetariancat]
+ meal_m*_b[mealkitcat]))


tab groupcat
tab Willingtopayatall
import excel "F:\TTI\tti.xlsx", sheet("Sheet1") firstrow
doubleb bid1 bid2 yes1 yes2 agecat purchcat educcat incomecat hhsize storediversity orgorlocal
SupercenterDollaronly vegetariancat mealkitcat foodsafety animalwelfare cost healthiness taste
gen age_m=4.0
generate purch_m= 3.32
```

```
generate educ_m = 4.0

generate mean_hh=2.60

generate mean_store=.34

generate food_m=4.85

generate animal_m=4.14

gen cost_m=4.53

gen health=4.65

gen taste_m=4.76

gen income_m=4.05

gen orgorlocal_m=.19

gen Supercenter_m=.12

gen vegonly_m=.01

gen meal_m=.49

nlcom(WTP:(_b[_cons]+1*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+2*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))
```

```
nlcom(WTP:(_b[_cons]+3*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgo
rlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetarian
cat]+ meal_m*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+4*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgo
rlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetarian
cat]+ meal_m*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+5*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgo
rlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetarian
cat]+ meal_m*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+6*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgo
rlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetarian
cat]+ meal_m*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+7*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m
*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+
animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgo
```

rlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetarian

cat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+8*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+income_m

*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+

animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgo

rlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetarian

cat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+inco

me_m*_b[incomecat]+mean_hh*_b[hhsize]+0*_b[storediversity]+food_m*_b[foodsafety]+ani

mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlo

cal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat

]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+inco

me_m*_b[incomecat]+mean_hh*_b[hhsize]+1*_b[storediversity]+food_m*_b[foodsafety]+ani

mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlo

cal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat

]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+1*_b[purchcat]+educ_m*_b[educcat]+income_m*_

b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+ani

mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlo

cal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat

]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+2*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+3*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+4*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+5*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+6*_b[purchcat]+educ_m*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlo cal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+1*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+2*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+3*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+4*_b[educcat]+income_m*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

```
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+5*_b[educcat]+income_m*
_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+a
nimal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorl
ocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetarianc
at]+ meal_m*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+6*_b[educcat]+income_m*
_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+a
nimal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+1*_b
[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+ani
mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlo
cal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat
]+ meal_m*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+2*_b
[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+ani
mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlo
cal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat
]+ meal_m*_b[mealkitcat]))
nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+3*_b
[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+ani
mal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlo
cal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat
]+ meal_m*_b[mealkitcat]))
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nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+4*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+5*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

nlcom(WTP:(_b[_cons]+age_m*_b[agecat]+purch_m*_b[purchcat]+educ_m*_b[educcat]+6*_b[incomecat]+mean_hh*_b[hhsize]+mean_store*_b[storediversity]+food_m*_b[foodsafety]+animal_m*_b[animalwelfare]+cost_m*_b[cost]+health*_b[healthiness]+taste_m*_b[taste]+orgorlocal_m*_b[orgorlocal]+Supercenter_m*_b[SupercenterDollaronly]+vegonly_m*_b[vegetariancat]+ meal_m*_b[mealkitcat]))

probit Willingtopayatall agecat purchcat educcat i.incomecat hhsize storediversity foodsafety animalwelfare cost healthiness taste

probit Willingtopayatall agecat purchcat educcat i.incomecat hhsize storediversity orgorlocal SupercenterDollaronly vegetariancat mealkitcat foodsafety animalwelfare cost healthiness taste

APPENDIX C

Appendix C: Probit and Marginal Effects Tables: These are tables summarizing the Stata output for our probit and marginal effect regressions referenced above.

Table 11. Original Probit Regression

Variable	Variable
Age Category	-.082 (.029)***
Purchasing Frequency Category	.071 (.033)**
Education Category	.004 (.034)
Income Category	-.038 (.034)
Household Size	.061 (.037)*
Store Diversity	-.098 (.092)
Food Safety Importance	.109 (.114)
Animal Welfare Importance	.166 (.050)***
Cost Importance	-.459 (.070)***
Healthiness Importance	.210 (.089)**
Taste Importance	.029 (.097)
Intercept	.146 (.578)

Table 12. Original Marginal Effects

Variable	dy/dx
Age Category	-.031 (.011)***
Purchasing Frequency Category	.027 (.013)**
Education Category	.002 (.013)
Income Category	-.014 (.013)
Household Size	.023 (.014)*
Store Diversity	-.037 (.035)
Food Safety Importance	.041 (.043)
Animal Welfare Importance	.063 (.019)***
Cost Importance	-.175 (.027)***
Healthiness Importance	.080 (.034)**
Taste Importance	.011 (.037)

Table 13. Expanded Probit Regression

Variable	Coefficient
Age Category	-.066 (.031)**
Purchasing Frequency Category	.069 (.033)**
Education Category	-.005 (.034)
Income Category	-.048 (.035)
Household Size	.061 (.037)
Store Diversity	-.169 (.103)
Food Safety Importance	.091 (.115)
Animal Welfare Importance	.152 (.051)***
Cost Importance	-.451 (.071)***
Healthiness Importance	.213 (.090)**
Taste Importance	.065 (.099)
Intercept	.062 (.586)
Organic or Local Shopper	.139 (.126)
Supercenter or Dollar Store Only Shopper	-.063 (.140)
Vegetarian Dummy Variable	.631 (.437)
Meal Kit Category	.057 (.055)

Table 14. Expanded Marginal Effects

Variable	dy/dx
Age Category	-.025 (.012)**
Purchasing Frequency Category	.026 (.123)**
Education Category	-.002 (.013)
Income Category	-.018 (.013)
Household Size	.023 (.014)
Store Diversity	-.065 (.040)
Food Safety Importance	.035 (.044)
Animal Welfare Importance	.058 (.019)***
Cost Importance	-.172 (.027)***
Healthiness Importance	.081 (.034)**
Taste Importance	.025 (.038)
Organic or Local Shopper	.052 (.047)
Supercenter or Dollar Store Only Shopper	-.024 (.054)
Vegetarian Dummy Variable	.207 (.115)*
Meal Kit Category	.022 (.021)

APPENDIX D

Appendix D: WTP tables: These are Stata Output tables for our WTP analyses as referenced above.

Table 15. Willingness to Pay Coefficients

Variable	Coefficient (Original Specification)	Coefficient (Expanded Specification)
Age Category	-.054 (.038)	-.073* (.040)
Purchasing Frequency Category	.077* (.043)	.084* (.043)
Education Category	.009 (.044)	.013 (.045)
Income Category	-.054 (.044)	-.052 (.045)
Household Size	.064 (.047)	.069 (.047)
Store Diversity	-.124 (.120)	-.167 (.134)
Food Safety Importance	.211 (.144)	.224 (.144)
Animal Welfare Importance	.246*** (.067)	.254*** (.068)
Cost Importance	-.665*** (.099)	-.661*** (.099)
Healthiness Importance	.346*** (.116)	.339*** (.116)
Taste Importance	.189 (.123)	.151 (.124)
Intercept	-.319(.727)	-.151 (.732)
Organic or Local Shopper	—	.134 (.161)
Supercenter or Dollar Store Only Shopper	—	-.088 (.180)
Vegetarian Dummy Variable	—	-.268 (.419)
Meal Kit Category	—	-.096 (.067)

Table 16. Willingness to Pay of Store Diversity Subgroups

This table shows the store diversity dummy variable and the WTP coefficients for the subgroups of those who have a value of 0 and 1 respectively.		
Sub-Store Diversity Groups	Coefficient (Original Specification)	Coefficient (Expanded Specification)
Less than 3 store types chosen	1.243*** (.068)	1.262*** (.071)
Store Diverse: 3 or more types chosen	1.119*** (.097)	1.096*** (.105)

Table 17. Willingness to Pay of Purchase Subgroups

Sub-Purchase Frequency Groups	Coefficient (Original Specification)	Coefficient (Expanded Specification)
Purchase Group 1 (Less than once a month)	1.021*** (.113)	1.011*** (.113)
Purchase Group 2 (One package every month)	1.099*** (.078)	1.095*** (.079)
Purchase Group 3 (One package every two weeks)	1.176*** (.056)	1.179*** (.056)
Purchase Group 4 (One package a week)	1.253*** (.062)	1.263*** (.062)
Purchase Group 5 (Two packages a week)	1.331*** (.090	1.347*** (.091)
Purchase Group 6 (Three+ packages a week)	1.408*** (.127)	1.431*** (.128)

Table 18. Willingness to Pay of Education Subgroups

Sub-Education Frequency Groups	Coefficient (Original Specification)	Coefficient (Expanded Specification)
Education Group 1 (Less than a high school diploma)	1.175*** (.143)	1.167*** (.144)
Education Group 2 (High school diploma or equivalent (e.g., GED))	1.183*** (.104)	1.180*** (.104)
Education Group 3 (Some college, no degree)	1.192*** (.070)	1.193*** (.070)
Education Group 4 (Bachelor’s degree)	1.201*** (.055)	1.206*** (.055)
Education Group 5 (Associate’s degree)	1.210*** (.071)	1.218*** (.071)
Education Group 6 (Master’s degree or higher)	1.218*** (.104)	1.266*** (.119)

Table 19. Willingness to Pay of Age Subgroups

Sub-Age Groups	Coefficient (Original Specification)	Coefficient (Expanded Specification)
Age Group 1 (18-24)	1.364*** (.125)	1.423*** (.133)
Age Group 2 (25-34)	1.310*** (.092)	1.351*** (.097)
Age Group 3 (35-44)	1.255*** (.066)	1.278*** (.068)
Age Group 4 (45-54)	1.201*** (.055)	1.206*** (.055)
Age Group 5 (55-64)	1.146*** (.067)	1.133*** (.068)
Age Group 6 (65-74)	1.092*** (.094)	1.060*** (.097)
Age Group 7 (75-84)	1.038*** (.127)	.988*** (.133)
Age Group 8 (85+)	.983*** (.162)	.915*** (.170)

Table 20. Willingness to Pay of Income Subgroups

Sub-Income Frequency Groups	Coefficient (Original Specification)	Coefficient (Expanded Specification)
Income Group 1 (Less than 10,000)	1.364*** (.147)	1.364*** (.148)
Income Group 2 (10,000-24,999)	1.311*** (.107)	1.312*** (.108)
Income Group 3 (25,000-49,999)	1.257*** (.072)	1.260111*** (.072)
Income Group 4 (50,000-69,999)	1.203*** (.058)	1.208*** (.055)
Income Group 5 (70,000-99,999)	1.150*** (.069)	1.156*** (.070)
Income Group 6 (100,000+)	1.096*** (.102)	1.104*** (.104

Table 21. Willingness to Pay of Vegetarian Subgroups

This shows a summary of Stata output for the dummy variable that takes on a value of 1 if a participant self-identified as a chicken-eater and 0 otherwise.	
Sub-Vegetarians Groups	Coefficient (Expanded Specification)
Not Vegetarians	1.208***(.055)
Vegetarians	.940**(.415)

Table 22. Willingness to Pay of Supercenter/Dollar Store Subgroups

This shows a summary of Stata output for the dummy variable that takes on a value of 1 if a participant self-identified as shopping only at supercenters and/or dollar stores and 0 otherwise.	
Sub- Supercenter/Dollar Store Groups	Coefficient (Expanded Specification)
Not Supercenter/Dollar only shoppers	1.216***(.059)
Supercenter/Dollar only shoppers	1.129***(.169)

Table 23. Willingness to Pay of Organic/Local Subgroups

This shows a summary of Stata output for the dummy variable that takes on a value of 1 if a participant self-identified as an organic and/or local shopper and 0 otherwise.	
Sub-Organic or Local Groups	Coefficient (Expanded Specification)
Not Organic and/or Local Shoppers (Did not select these store types)	1.180*** (.059)
Organic and/or Local Shoppers	1.314*** (.141)

Table 24. Willingness to Pay of Meal Kit Subgroups

Sub-Meal Kit Groups	Coefficient (Expanded Specification)
Never	1.253*** (.065)
Less than once a month	1.157*** (.063)
1-2 times a month	1.060*** (.113)
3-4 times a month	.964*** (.174)

APPENDIX E

Appendix E: WTP Model: Below is a model reprinted from Lopez-Feldman's study on Contingent Valuation. This represents the relationship between the doubleb command, willingness to pay, and utility.

$y_i^1 = 1$ and $y_i^2 = 0$.

$$\begin{aligned}
Pr(s,n) &= Pr(t^1 \leq WTP < t^2) \\
&= Pr(t^1 \leq z_i'\beta + u_i < t^2) \\
&= Pr\left(\frac{t^1 - z_i'\beta}{\sigma} \leq \frac{u_i}{\sigma} < \frac{t^2 - z_i'\beta}{\sigma}\right) \\
&= \Phi\left(\frac{t^2 - z_i'\beta}{\sigma}\right) - \Phi\left(\frac{t^1 - z_i'\beta}{\sigma}\right)
\end{aligned}$$

where the last expression follows from $Pr(a \leq X < b) = F(b) - F(a)$. Therefore, using symmetry of the normal distribution we have that:

$$Pr(s,n) = \Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^1}{\sigma}\right) - \Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^2}{\sigma}\right)$$

$y_i^1 = 1$ and $y_i^2 = 1$.

$$\begin{aligned}
Pr(s,s) &= Pr(WTP > t^1, WTP \geq t^2) \\
&= Pr(z_i'\beta + u_i > t^1, z_i'\beta + u_i \geq t^2)
\end{aligned}$$

Using Bayes rule, which says that $Pr(A,B) = Pr(A|B) * Pr(B)$, we have:

$$Pr(s,s) = Pr(z_i'\beta + u_i > t^1 | z_i'\beta + u_i \geq t^2) * Pr(z_i'\beta + u_i \geq t^2)$$

Here by definition $t^2 > t^1$ and then $Pr(z_i'\beta + u_i > t^1 | z_i'\beta + u_i \geq t^2) = 1$ which implies:

$$\begin{aligned}
Pr(s,s) &= Pr(u_i \geq t^2 - z_i'\beta) \\
&= 1 - \Phi\left(\frac{t^2 - z_i'\beta}{\sigma}\right)
\end{aligned}$$

so by symmetry we have:

$$Pr(s,s) = \Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^2}{\sigma}\right)$$

$y_i^1 = 0$ and $y_i^2 = 1$.

$$\begin{aligned} Pr(s,n) &= Pr(t^2 \le WTP < t^1) \\ &= Pr(t^2 \le z_i'\beta + u_i < t^1) \\ &= Pr\left(\frac{t^2 - z_i'\beta}{\sigma} \le \frac{u_i}{\sigma} < \frac{t^1 - z_i'\beta}{\sigma}\right) \\ &= \Phi\left(\frac{t^1 - z_i'\beta}{\sigma}\right) - \Phi\left(\frac{t^2 - z_i'\beta}{\sigma}\right) \end{aligned}$$

$$Pr(s,n) = \Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^2}{\sigma}\right) - \Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^1}{\sigma}\right)$$

$y_i^1 = 0$ and $y_i^2 = 0$.

$$\begin{aligned} Pr(n,n) &= Pr(WTP < t^1, WTP < t^2) \\ &= Pr(z_i'\beta + u_i < t^1, z_i'\beta + u_i < t^2) \\ &= Pr(z_i'\beta + u_i < t^2) \\ &= \Phi\left(\frac{t^2 - z_i'\beta}{\sigma}\right) \end{aligned}$$

$$Pr(n,n) = 1 - \Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^2}{\sigma}\right)$$

$$\sum_{i=1}^{N}\Bigg[d_i^{sn}\ln\left(\Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^1}{\sigma}\right) - \Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^2}{\sigma}\right)\right) + d_i^{ss}\ln\left(\Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^2}{\sigma}\right)\right) \\ + d_i^{ns}\ln\left(\Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^2}{\sigma}\right) - \Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^1}{\sigma}\right)\right) + d_i^{nn}\ln\left(1 - \Phi\left(z_i'\frac{\beta}{\sigma} - \frac{t^2}{\sigma}\right)\right)\Bigg]$$

(Lopez-Feldman, 2012).