Demand for Food Attributes During COVID-19:

Evidence from a Large Sample of U.S. Carrot Buyers

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ABSTRACT. This paper explores empirically the WTPs for the organic attribute and the baby-cut attribute (a fresh-cut attribute) of carrot products and focuses on how the WTP responded to the massive economic shock and market disruptions caused by the COVID-19 pandemic. A series of on-line survey responses were collected from hundreds of thousands of U.S. carrot buyers before and during the COVID-19 pandemic and lockdowns. We estimate that the median estimate of the WTP for an organic attribute rose from $0.05 before COVID-19 to $0.07 per pound during COVID-19. The median estimate of the WTP for the baby-cut attribute fell from $0.56 before COVID-19 to $0.51 per pound during COVID-19. The estimates of changes in WTP were not statistically significant for either attribute even with quite large national samples.

Key Words: organic, fresh-cut, willingness to pay, carrots, and COVID-19

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Introduction

Foods have attributes, some of which are tied to farm production methods (such as GMO free or organic, or pasture raised) and some tied to processing method (fresh cuts carrots, bagged salads or humanely slaughtered meat. Estimating willingness to pay (WTP) for food attributes helps us understand demand for attributes and evaluate impacts of technology developments, product regulations, taxes, and private standards.

Many scholars have explored economics of food product attributes. Perhaps the most robust literature, which dates back several decades, relates to wine attributes such as grape variety, where the grapes are grown, the year the grapes were harvested, reputation of the wine among experts, and reputation of the climate (Oczkowski 1994; Lecocq and Visser 2006; Storchmann 2012). Several scholars have explored other farm-production attributes (See, for example, Rausser, Sexton, and Zilberman 2019)

This paper explores willingness to pay for attributes of carrots using a large set of repeated representative cross sections data sets. This data design feature allows us to consider an aspect of WTP that has received less attention in the literature. That is, to what extent are estimates of WTP robust over time and robust to large exogenous shocks to the market. Of course, economists have understood that WTPs for food attributes may differ across samples from different periods, places, demographics, and other market features. Nonetheless, relatively little evidence has been presented on what drives difference in WTP estimates. This paper explores estimation of WTP for attributes of a common food exploiting COVID-19 as a significant exogenous shock on food market experiences and conditions.

COVID-19 has caused uniquely deep and far ranging shocks to food markets in the United States, including shocks to income, employment, where meals are consumed, and choice of grocery shopping channels. To our knowledge, however, those factors have rarely been controlled in estimating WTPs for food attributes. This paper explores the importance of changes in those factors on the WTP estimation using COVID-19.

To explore the impacts of COVID-19 on the WTP estimates, we used a large and especially relevant on-line survey approach to efficiently collect data from hundreds of thousands of carrot consumers. Carrots are a useful and important case for study for at least three reasons. First, carrots are one of the most frequently consumed vegetables. Second, organic carrots are widely consumed and represent an attribute based on farm production practices. Third, baby-cut carrots are also popular in the market and represent an attribute related to food processing and packaging.

U.S. Carrot Industry: Organic Carrots and Baby Carrots

Carrots have been a popular vegetable and are frequently used in soups, salads, snacks, and desserts. The domestic production was about 4,756 million pounds (or about $860 million of farm revenue) in 2019 (Table 1). Considering the net import of carrot products, the per capita availability, obtained from the formula, (domestic production + net import) / U.S. population, was about 16.6 pounds per year in 2019.[4] The per capita availability likely underestimates the per capita consumption of carrots among U.S. carrot buyers because part of the U.S. population may not consume carrots because of allergy or other reasons. Based on our surveys, slightly less

[4] USDA-ERS (2020) has reported the per capita availability across 20 main agricultural commodities. Based on the 2019 values (pounds per year), among those commodities, only sweet corn (18.9), lettuce (25.1), onions (22.1), tomatoes (88.3), and potatoes (118.8) have a higher per capita availability than carrots (16.6).

than 15% of the U.S. population may not consume carrots.[5] Hence, among U.S. carrot buyers, the per capita consumption of carrots would be slightly bigger than 16.6 pounds per year.

Organic carrots are widely available at retail in the U.S. However, in terms of quantity, organic carrots' share at retail would be small, considering that organic carrots accounted for about 7.4% of domestic production in 2019 (USDA, 2020).[6] Organic carrots are generally priced higher than regular (that is, non-organic) carrots. According to USDA Agricultural Marketing Service (AMS), the average price of organic full-sized carrots was about $1.39 per pound in the U.S., while the average price of regular full-sized carrots was about $0.81 per pound in 2019 (Table 2).

One important feature in the U.S. carrot industry is the popularity of fresh-cut products. In the U.S., "baby carrots," also called "petite" or "baby-cut," generally refer to full-sized carrots cut into small, peeled, washed, and bite-sized pieces. Baby carrots are commonly sold in one-pound packages, 12-ounce packages, or small one-serving snack packages. Like other fresh-cut vegetable products such as celery sticks or peeled garlic cloves, baby carrots save consumers' time and effort in cooking or snacking versus uncut, unpeeled, and unwashed full-sized carrots. Baby carrots account for about 54% of retail, according to Winsight Grocery Business (2019), which is a company that provides information about U.S. food retail industries (Table 1). The carrot share information originally came from IRI retail data, and the value (54%) would represent the U.S. carrot retail market under the assumption that the IRI retail data represent it. Baby carrots are generally priced higher than full-sized carrots. According to USDA AMS, the

[5] To our knowledge, there is no publicly available information about carrot consumers' share in the U.S. population. Instead, we allowed respondent to opt out of the WTP questions by including the response "I don't buy carrots.".
[6] "Organic" carrots used in this calculation only include those labeled as USDA certified. To our knowledge, there is no direct information about the retail share of organic carrots. We expect that the organic carrot share in the domestic production is a good proxy because carrot trade is a small share of production or consumption.

average price of regular baby carrots was about $1.23 per pound in the U.S. in 2019, which implies an average premium of $0.42 per pound over regular full-sized carrots (Table 2).

Survey Design: A Large Sample from U.S. Carrot Buyers

For our research purpose, we used on-line surveys for several reasons. First, our on-line survey approach allowed us to collect information from many consumers about product variants quickly and cheaply. Second, our on-line surveys allowed us to repeat the data collection several times throughout the year. Third, since survey data has been often used, we have a good sense of the weaknesses of this method and how to try to avoid the worst of those. Finally, observed purchase data (for example, retail scanner data) usually comes with a lag and would not allow evaluation of COVID-19 impacts quickly. When such data become available, we plan to compare our current results with estimates from purchase data. Finally, in a next step in our research program, we will evaluate WTP for attributes that are not yet in the market, and our current results with already observed product attributes can serve as a benchmark.

We conducted a series of surveys six times before and during COVID-19: December 2019 and January 2020, March and April 2020, June 2020, August 2020, October 2020, and January 2021. The first periods, December 2019 and January 2020, constructed the dataset without the impacts of COVID-19. The other five periods included impacts of COVID-19, and it evolved in economic and market impacts. Regardless of periods, the survey administration and questionnaire were identical. In each case, the target population was U.S. carrot consumers. The repeated surveys help us identify the impacts of COVID-19 on the WTP estimates.

To distribute surveys, we used Google Surveys, which is an on-line platform that distributes surveys through more than 1,500 websites that feature topics, including news, arts, and entertainment. The Google process partially blocks the contents of a website, and visitors to that website must answer a very short set of questions to access the blocked content. Google Surveys selects respondents randomly within demographic groups, including geography. For more information about how Google Surveys distribute surveys and collect responses, see Sostek and Slatkin (2017).

One important feature of Google Surveys is that it provides inferred respondent characteristics (age, gender, and region) rather than reported demographics by respondents. Google Surveys infers those characteristics from the respondent's internet use history. Inferring respondent characteristics reduces the number of questions in a survey, avoids dishonest responses, and reduces survey costs.

Google Surveys have been used in economics, marketing, and other fields to elicit consumer preferences and political attitudes (Frederick, Lee, and Baskin, 2014; Stephens-Davidowitz, and Varian, 2015). In a prominent recent article, Brynjolfsson, Collis, and Eggers (2019) used data from Google Surveys to estimate the economic welfare effects of digital services such as Facebook and YouTube. Several papers have found evidence that Google Surveys provide representative samples of the U.S. population and reliable estimation results (McDonald, Mohebbi, and Slatkin, 2013; Hulland and Miller, 2018). Although many studies over the past decade have used online surveys to explore food demand (Gao and Schroeder, 2009; Waterfield, Kaplan, and Zilberman, 2020), we know of no other food demand papers that have used Google Surveys to elicit preferences or willingness to pay.

We used Google Surveys for several reasons. First, it is cheap. Second, it is quick. Third, it provides random samples. Fourth, by using an anonymous survey with no personal interactions conducted in private, we avoid implicit bias from respondent reactions to survey personnel. In a face-to-face or even telephone interviews, respondents may be more likely to say what they think the surveyor would like to hear (about, for example, organic or some other similar attribute that has been lauded as better by food advocates and influencers). A disadvantage, of course, is that people are not devoting real resources to their choice. In that sense, a controlled experiment would be better, if we could have done this without sacrificing other benefits of our survey, such as anonymity and large sample size.

Question Design to Elicit WTP for Carrot Attributes

To estimate demand parameters, we used both a single binary hypothetical choice question and, for different groups of respondents, a direct willingness to pay question about a single product. This approach ameliorates some of the concerns raised in the early environmental economics literature (Bishop and Heberlein 1979; Arrow et al. 1993; Carson and Groves 2007; Magat, Viscusi, and Huber 1988; Hanemann, Loomis, and Kanninen 1991).

We considered two forms of survey questions, which we call Multiple Choice and Yes-No. For the Multiple Choice, we provided respondents with a picture of one of four realistic packages of carrots: organic full-sized, organic baby, conventional baby, and conventional full-sized. With the package on the screen, we asked respondents the following single question: *Imagine you're shopping for carrots, and you see this 1-pound package. What's the most you would be willing to pay for it?* After first allowing the response, "I don't buy carrots," we offered respondents four payment intervals: *Less than $1.00, Between $1.00 and $1.99, Between $2.00 and $2.99, and $3.00 or more.* In another iteration of the survey, we also offered the payment intervals: *Less than $1.00, Between $1.00 and $1.49, Between $1.50 and $1.99, and $2.00 or more.*

For the Yes-No surveys, we showed respondents a pair of pictures of two realistic carrot packages and asked the following question: *Imagine you're shopping for carrots, and you see these two 1-pound packages. Which package, if any, would you buy?* After first allowing the response, "I don't buy carrots," respondents faced three potential answers: Package A for $Z, Package B for $X, and Neither of these packages.

The "Z" or "X" prices in the offered responses were: $1.00, $1.50, and $2.00 to reflect the common range of carrot prices in the U.S. market. We used a higher or equal price for baby versus conventional and organic versus conventional.

This paper provides only the results based on the Yes-No surveys. The descriptive statistics on responses (Tables 3) consider only responses from Yes-No questions. The econometric strategy for estimating the WTPs for carrot attributes is based on only the responses from Yes-No questions.

Descriptive Statistics on Survey Data

Table 3 shows the sample demographics before and during COVID-19. As noted earlier, Google Surveys provides demographics inferred based on internet use history. Some respondents' demographics are not reported because of limited information about internet use, and those respondents are not considered in the calculation of descriptive statistics. Overall, regardless of COVID-19, the sample demographics are similar to those in the U.S. Census population. The demographics in our sample are similar but slightly different from those in the U.S. population. Therefore, to improve the representativeness of the U.S. population, we used sampling weights in regressions. The sampling weights are the inverse of the probability that the observation is included to represent the U.S. population in demographics (gender, age, and region).

The share of the option, “I don’t buy carrots,” is slightly less than 15% of the total respondents. We may interpret the share of the option as a proxy of the share of non-carrot consumers. Based on those results, we used this option, “I don’t buy carrots,” to exclude non-carrot consumers in estimating the WTPs for carrot attributes.

The option “Neither of these packages” corresponds to a no-answer option, and the share is about 8.6%. We included this option to the Yes-No question (a dichotomous choice question) based on the recommendation of Arrow et al. (1993). In general, the estimation results are not statistically affected by the no-answer option, so we excluded those responses in the WTP estimation.

The variations in responses by different prices are consistent with our expectations and consistent with carrot market observations (Tables 4 for organic carrots and Table 5 for baby carrots). First, the share of each product is decreasing as its relative price is increasing. Second, given the same price, the organic product share is bigger than that of the corresponding regular product. Third, given the same price, the baby-cut product’s share is bigger than that of the corresponding full-sized product.

It is noticeable that the share of respondents choosing organic carrots over regular carrots is significantly more than half when the prices of the two products are identical, but the share does not approach 1.0. The results imply that many consumers do not consider organic carrots superior to non-organic carrots, although many existing studies have often assumed that all consumers would prefer organic products to non-organic ones (for example, Giannakas 2002). We found a similar result in the choice between baby carrots and full-sized carrots. Many respondents prefer full-sized carrots to baby carrots, although baby carrots can save time and effort to cook and consume carrots and are typically more expensive in the market. Based on this result, our econometric strategy allows surveyed respondents to have a non-positive WTP for carrots attributes.

Econometric Strategy for Estimating WTPs for Carrot Attributes

Our econometric strategy follows the approach of Hanemann (1984) who used a dichotomous choice survey to estimate WTP as a Hicksian welfare measure. The dichotomous choice was modeled under the random utility framework. For all respondents who participated in the survey, each respondent is assumed to know his utility function and maximize it. However, there is a part of utility that is stochastic to researchers because researchers cannot observe it. As noted earlier, we consider two carrot attributes: the organic attribute and the baby-cut attribute. Because modeling the organic attribute is analogous to the baby-cut attribute, without loss of generality, we describe only the model for the organic attribute in this section.

Consider a population of respondents, denoted by I. Individual respondents face two carrot products, denoted by $j \in \{0,1\}$. Product 1 is organic, but product 0 is non-organic. Under the random utility framework, the indirect utility, U, for respondent $i \in I$ from product j is represented as

$$(1)\ U_{i,j} = V\left(Z_j, Inc_i - P_j; Q_j, X_i\right) + \epsilon_{i,j}.$$

The indirect utility is decomposed into a systematic part, V, and a stochastic part, ϵ. The systematic part is a function of the organic attribute, Z_j, the price, P_j, other product attributes, Q_j, income, Inc_i, and other respondent characteristics, X_i. The variable, Z_j, is one for product 1 and zero for product 0. The stochastic part is the utility determined by product attributes and respondent characteristics that respondent i perceives but researchers cannot observe. Because of the utility maximization assumption, respondent i chooses product 1 rather than product 0 if the following condition holds:

$$(2)\ V(Z_1, Inc_i - P_1; Q_1, X_i) + \epsilon_{i,1} \geq V(Z_0, Inc_i - P_0; Q_0, X_i) + \epsilon_{i,0}.$$

Because the error terms are random, the response is also random. The probability of choosing product 1, denoted by $Prob(Yes_i)$, is as follows:

$$(3)\ Prob(Yes_i) = Prob(\eta_i \leq \Delta V_i),$$

where $\eta_i \equiv \epsilon_{i,0} - \epsilon_{i,1}$ and $\Delta V_i \equiv V(Z_1, Inc_i - P_1; Q_1, X_i) - V(Z_0, Inc_i - P_0; Q_0, X_i)$. Let $F_\eta(\cdot)$ denote the cumulative density function of η_i. Then, the probability of choosing product 1 can be written as

$$(4)\ Prob(Yes_i) = F_\eta(\Delta V_i).$$

According to Hanemann (1984), the utility is specified as a linear in variables: For all i, j,

$$(5)\ V_{i,j} = \alpha_{i,j} + \beta\big(Inc_i - P_j\big).$$

For simplicity, the other variables except for income are suppressed (that is, the term $\alpha_{i,j}$ is a linear function of other variables). Then,

$$(6)\ \Delta V_i = \Delta\alpha_i + \beta Bid_i,$$

where $\Delta\alpha_i \equiv \alpha_{1,i} - \alpha_{0,i}$ and the term $Bid_i \equiv P_1 - P_0$.

Notice that respondent i chooses product 1 if Bid_i is less than the WTP premium (WTP_i) for product 1 over product 0. Hence, $F_\eta(\Delta V_i)$ is identical as the probability when $Bid_i \leq WTP_i$. Furthermore, assume that, for all $i \in I$, respondent i faces two products identical except for the organic attribute, which is $Z_{j=1} \neq Z_{j=0}$ and $Q \equiv Q_{j=1} = Q_{j=0}$. Then, the term WTP_i becomes the WTP for the organic attribute.

To complete the econometric specification, the distributional assumption on F_η is required. Consistent with prior work (for example, Hanemann 1984; Hanemann and Kanninen

1996), we assumed a logistic distribution on F_η. According to the properties of the logit specification, we obtain the following econometric specification:

$$(7)\ \ln\left(\frac{Prob(Yes_i)}{1-Prob(Yes_i)}\right) = \Delta V_i = \Delta\alpha_i + \beta Bid_i$$

$$= \beta Bid_i + \alpha_0 + \alpha_1 March2020_i + \alpha_2 June2020_i + \alpha_3 August2020_i$$

$$+ \alpha_4 October2020_i + \alpha_5 January2021 + \alpha_6 X_i.$$

The left-hand side is the log-odd ratio of the probability of choosing the treated carrots over the probability of choosing the base (that is, non-treated) carrots. The treatment is either organic or baby-cut, depending on respondents. The variable Bid_i is the price difference between the two products given to respondent i. The variables, March 2020 to January 2021, are dummy variables that capture the heterogeneous impacts of COVID-19 over periods. The term X_i is a vector of demographics and survey environment. The demographics include gender (male or female), age (18 – 24, 25 – 34, 35 – 44, 45 – 54, 55 – 64, and 65+), and region (North East, Midwest, South and West). The survey environment variables include reference product picture location (left or right), time of day of the answer (0 AM – 6 AM, 6 AM – 12 PM, 12 PM – 6 PM, and 6 PM – 0 AM), and how long the respondent took to complete response.

Most importantly, the X_i set of explanatory variables also includes the reference price variable and the reference product attribute variable. The reference price variable is either \$1.00 or \$1.50 per pound. The reference product attribute variable reflects one of the two products full-sized carrots or baby carrots when respondents choose between organic and non-organic carrots. However, when respondents choose between baby carrots and full-sized carrots, the variable now reflects whether two products are organic or non-organic carrots.

We used the median WTP as a measure to represent the welfare of surveyed respondents. The median is statistically preferred because we expect that it is less sensitive to a small portion of respondents who value the targeted carrot attribute as very high or very low. The calculation of the median WTP in a logit model was computed as the following formula (Hanemann, 1984):

$$(8)\ median(WTP_i) = -\frac{\widehat{\Delta\alpha}}{\hat{\beta}}.$$

The numerator $\widehat{\Delta\alpha}$ represents the sum of the products of the means of the explanatory variables times their associated coefficient estimates. The denominator $\hat{\beta}$ is the coefficient estimate of the bid amount. The 95% confidence intervals were computed by a bootstrapping technique with 1,000 random draws.

Econometric Results

Tables 6 and 7 reports the logit results. For both attributes, overall, the regressions are significant. The bid negatively affects the probability of purchase of the treated products. The probability of buying organic carrots is decreasing as the relative price of organic carrots is increasing. Also, the probability of buying baby carrots decreases as the relative price of baby carrots increases.

The period dummies capture the impacts of COVID-19. For the organic attribute, the coefficients of the period dummies are estimated to be positive. Those non-zero coefficients are precisely estimated from June 2020 to October 2020 but are not in March 2020 and January 2021. The results imply that the probability of buying organic carrots rose during COVID-19 but was recently coming back to the probability before COVID-19.

For the baby-cut attribute, the coefficients of the period dummies are estimated to be negative. Those coefficients are precisely estimated in March 2020, October 2020, and January 2021 but are not in June 2020 and August 2020. The results imply that the probability of buying baby carrots fell in an early period (March 2020) and a recent period (October 2020 and January 2021) of COVID-19.

Estimates of WTPs for Carrot Attributes before and during COVID-19

The median WTP estimates are computed from their corresponding logit coefficient estimates in Tables 6 and 7, using equation (8). Table 8 shows that the median WTP estimate of the organic attribute was about $0.04 per pound before COVID-19. This low median WTP estimate is consistent with a low market share and a high retail price premium of organic carrots (Tables 1 and 2). The median WTP estimate of the baby-cut attribute was about $0.56 before COVID-19. The median WTP estimate of the baby-cut attribute is slightly bigger than the retail price difference ($0.40 per pound), which is consistent with the data that baby carrots accounted for more than half of the retail total (Tables 1 and 2).

Now let us consider the median WTP estimates during COVID-19 (Table 8). The median WTP estimate of the organic attribute ranges from $0.07 to $0.08 per pound between March 2020 to October 2021. However, the median WTP estimate comes back to $0.04 per pound in January 2021. In terms of the baby-cut attribute, during COVID-19, the median WTP ranges from $0.47 to $0.53 per pound, which is slightly less than the median WTP estimate ($0.56 per pound) before COVID-19. However, according to 95% confidence intervals, the reduction in the median WTP estimate is not statistically significant for both attributes.

Summary and Discussion

We explored the impacts of COVID-19 on the WTPs for the organic attribute and the baby-cut attribute in carrot products. A series of surveys were collected from U.S. carrot buyers before and during COVID-19. The median WTP for the organic attribute was estimated to be about $0.04 per pound before COVID-19. In terms of the baby-cut attribute, the median WTP estimate was about $0.56 per pound before COVID-19. The median WTP for the organic attribute slightly rose during COVID-19, but the changes are not statistically significant. The median WTP for the baby-cut attribute slightly fell in several periods during COVID-19, but the changes are also not statistically significant.

The econometric results imply that the WTP estimates for carrot attributes may be robust to COVID-19. The impacts of COVID-19 may occur mainly through changes in time use at home and grocery shopping places. Under the assumption that those impact channels are prominent, this paper provides evidence that average WTP estimates of food attributes may be robust to changes in time use and grocery shopping places. We acknowledge the limitation of survey methods in the WTP estimation. Our analysis could be more valid if observed purchase data (for example, retail scanner data) were used in the estimation. When such data become available, we plan to compare our current results with estimates from purchase data.

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Table 1. 2019 U.S. Carrot Production, Availability, Organic Share in Production, and Baby-Cut Share at Retail

	Units	Values	Sources
Domestic production	Million lbs.	4,745	USDA, *Vegetables and Pulses Yearbook* (2020)
	Million $	860	
Domestic availability[1]	Million lbs.	5,061	
	Million $	927	
Per capita availability	lbs.	15.4	
Organic share in production[2]	%	7.4%	USDA, *2019 Organic Survey* (2020)
Baby-cut share at retail[3]	%	54.0%	Winsight Grocery Business (2019)

[1]Domestic availability is domestic production minus net export.
[2]Includes only certified organic operations in the U.S. The share at retail may differ from 7.4% due to net export.
[3]According to Winsight Grocery Business (2019), the value originally came from IRI retail data. The value represents the share of baby-cut products on average over the period from July 2018 to June 2019 and all the U.S. retail channels contracted with IRI.

Table 2. 2019 Average Carrot Retail Prices by Organic and Baby-Cut Attributes

	Regular	Organic	Total
	Unit: $/lb.		
Full-sized	0.81	1.39	0.98
Baby-cut	1.23	1.80	1.41
Total	1.18	1.75	1.36

Source: USDA-AMS (2020), *Weekly Advertised Fruits & Vegetables Retail Prices*.
Note: Carrots considered in the calculation include only packaged carrots.

Table 3. Demographics of Survey Sample

Demographics	All respondents (aged 18 or more only)		U.S. Census data
	Before COVID-19	After COVID-19	(2010)
Gender			
Male	50.1%	47.6%	49.1%
Female	49.9%	52.4%	50.1%
Age			
18 – 24	11.3%	9.0%	12.8%
25 – 34	17.5%	17.7%	17.9%
35 – 44	17.7%	18.2%	17.6%
45 – 54	18.2%	18.4%	19.4%
55 – 64	18.3%	19.4%	15.4%
65 +	16.9%	17.2%	16.8%
Region			
North East	15.4%	12.8%	17.9%
Midwest	27.3%	31.1%	21.7%
South	34.5%	34.3%	37.1%
West	22.8%	21.8%	23.3%
Number of observations	40,047	164,497	-

Note. Google Surveys infer respondents' demographics based on individuals' internet use history. Google Surveys fail to infer some respondents' demographics if the information about internet use is not enough. Those respondents without inferred demographics are not included in the calculation of the descriptive statistics of demographics.

Table 4. Response Share of Organic Relative to Regular

Price of organic carrots	$1.00	$1.50	$1.50	$2.00	$2.00
Price of regular carrots	$1.00	$1.50	$1.00	$1.50	$1.00
Price difference	$0.00	$0.00	$0.50	$0.50	$1.00
Survey periods					
December 2019 – January 2020	61.8	63.8	28.9	30.6	23.2
March/April 2020	62.9	64.6	27.2	28.3	23.5
June 2020	63.7	64.4	31.1	30.3	22.9
August 2020	64.6	65.5	29.2	29.3	23.1
October 2020	62.2	65.2	28.8	29.9	23.5
January 2021	63.2	63.7	29.3	29.5	22.5

Note. The share of organic carrots is calculated after dropping "I don't buy carrots" and "Neither of these packages."

Table 5. Response Share of Baby Relative to Full-Sized

Price of baby carrots	$1.00	$1.50	$1.50	$2.00	$2.00
Price of full-sized carrots	$1.00	$1.50	$1.00	$1.50	$1.00
Price difference	$0.00	$0.00	$0.50	$0.50	$1.00
Survey periods					
December 2019 – January 2020	70.2	71.1	52.6	52.9	44.7
March/April 2020	68.8	70.0	50.4	50.2	42.4
June 2020	68.9	69.8	53.6	50.9	43.9
August 2020	69.9	68.9	54.0	53.5	44.9
October 2020	69.4	68.8	51.6	51.6	43.4
January 2021	68.0	68.5	50.3	50.2	41.5

Note. The share of baby carrots is calculated after dropping "I don't buy carrots" and "Neither of these packages."

Table 6. Logit Regression Results: Organic Attribute

Variable		Coefficient	Standard Error
Bid		-2.1	0.026
Reference: baby carrots		0.070	0.0163
Reference price: $1.50		-0.22	0.034
Reference picture location: Right		0.086	0.0168
Female		0.086	0.0169
Age	18 – 24	Base	Base
	25 – 34	0.14	0.036
	35 – 44	0.18	0.035
	45 – 54	0.077	0.0352
	55 – 64	0.044	0.0350
	64+	-0.025	0.0359
Region	North East	Base	Base
	Midwest	-0.36	0.028
	South	-0.19	0.027
	West	0.081	0.0291
Time within a day	0 AM – 6 AM	-0.029	0.0273
	6 AM – 12 PM	0.023	0.0238
	12 PM – 6 PM	Base	Base
	6 PM – 0 AM	0.018	0.0222
Response time length (100 seconds)		0.59	0.094
Periods	Dec 2019 – Jan 2020	Base	Base
	March 2020	0.043	0.0284
	June 2020	0.090	0.0286
	August 2020	0.078	0.0275
	October 2020	0.080	0.0273
	January 2021	0.014	0.0295
Constant		0.40	0.069

Log pseudolikelihood	-50250.9
Chi squared	6882.3
(P-value)	0.000
Number of observations	72,953

Table 7. Logit Regression Results: Baby-Cut Attribute

Variable		Coefficient	Standard Error
Bid		-1.2	0.023
Reference: organic carrots		0.084	0.0160
Reference price: $1.50		-0.12	0.035
Reference picture location: Right		0.023	0.0164
Female		-0.024	0.0166
Age	18 – 24	Base	Base
	25 – 34	-0.075	0.0349
	35 – 44	-0.073	0.0344
	45 – 54	-0.11	0.034
	55 – 64	-0.18	0.034
	64+	-0.30	0.035
Region	North East	Base	Base
	Midwest	0.20	0.027
	South	0.32	0.027
	West	-0.092	0.0285
Time within a day	0 AM – 6 AM	0.023	0.0269
	6 AM – 12 PM	-0.020	0.0238
	12 PM – 6 PM	Base	Base
	6 PM – 0 AM	0.016	0.0220
Response time length (100 seconds)		-1.28	0.089
Periods	Dec 2019 – Jan 2020	Base	Base
	March 2020	-0.056	0.0274
	June 2020	-0.045	0.0274
	August 2020	-0.0077	0.0268
	October 2020	-0.063	0.0265
	January 2021	-0.095	0.0287
Constant		0.93	0.086

Log pseudolikelihood	-52483.9
Chi squared	3586.1
(P-value)	0.000
Number of observations	70,351

Table 8. Median WTP estimates with 95% Confidence Intervals

Period	Organic attribute		Baby-cut attribute	
	Median WTP	C.I.	Median WTP	C.I.
Dec 2019 – Jan 2020	\$0.04	(\$0.02, \$0.08)	\$0.56	(\$0.47, \$0.65)
March 2020	\$0.07	(\$0.04, \$0.10)	\$0.52	(\$0.43, \$0.62)
June 2020	\$0.08	(\$0.05, \$0.11)	\$0.51	(\$0.42, \$0.60)
August 2020	\$0.07	(\$0.05, \$0.10)	\$0.53	(\$0.44, \$0.62)
October 2020	\$0.07	(\$0.04, \$0.10)	\$0.50	(\$0.41, \$0.59)
January 2021	\$0.04	(\$0.01, \$0.07)	\$0.47	(\$0.38, \$0.57)

Note. The margins of error are constructed based on a bootstrapping technique, with 1,000 draws.