



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Demand for Food Attributes: Evidence from a Large Sample of Carrot Buyers

Hanbin Lee, Department of Agricultural and Resource Economics, University of California at Davis, hblee@ucdavis.edu; Robin Goldstein, University of California Agricultural Issues Center, robin.s.goldstein@gmail.com; Daniel A. Sumner, Department of Agricultural and Resource Economics, University of California at Davis, dasumner@ucdavis.edu

*Selected Paper prepared for presentation at the 2020 Agricultural & Applied Economics Association
Annual Meeting, Kansas City, MO
July 26-28, 2020*

Copyright 2020 by Hanbin Lee, Robin Goldstein, and Daniel A. Sumner. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Demand for Food Attributes:

Evidence from a Large Sample of Carrot Buyers

Hanbin Lee, Robin Goldstein, and Daniel A. Sumner

July 1, 2020

I. Introduction

Organic farming practices have been widely certified and labeled on food products, and, recently, organic food products are universally available across food categories. As organic products become widely available, the heterogeneity in attributes among organic products becomes higher. For example, within the organic vegetable category, some products are fresh vegetables (for example, a bunch of organic carrots), but some other products are further processed (for example, cut, peeled, washed organic carrots). Hence, food suppliers would get benefit from the information about the relationship between the organic attribute and other food attributes in food demand. Such information would be crucial for farms who consider adopting organic farming practices because it is costly to adopt them.

Among food attributes that possibly associate with the organic attribute, this paper focuses on the convenience attribute. Here convenience means ease in cooking and consuming food products. In the literature, studies have provided evidence that substantial consumers are willing to pay more for organic claims on food products (for example, Thompson and Kidwell, 1998; Meas et al., 2015). Also, as a growing literature, several studies have provided evidence that at least substantial consumers value the convenience attribute in food consumption (Lusk and Briggeman, 2009; Bazzani et al., 2018). However, little evidence has been accumulated on

the role of convenience for organic food demand. To fill in this gap in the literature, this paper provides evidence on the relationship between the two attributes.

The role of convenience for organic food is not apparent. The convenience attribute may raise organic food demand if the following three conditions hold: (1) The convenience attribute can be obtained through further processing (for example, cutting, peeling, and washing). (2) Consumers concern about food safety more on processed products than fresh products. (3) Consumers use the organic attribute as a signal for safe food products. Combining the three conditions, the value of the organic attribute would be higher in processed products than fresh products. However, the convenience attribute may also interfere with the perception of full-sizedness, healthfulness, authenticity, or environmental sustainability that underlies some of the demand for organic food.

For studying the role of convenience for organic food, this paper uses carrots. In the United States, “baby carrots,” also called “petite” or “baby-cut,” generally refers 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. Also, we expect that carrots would be useful to identify the role of convenience for organic food demand. Often, further processing provides not just the convenience attribute but also other attributes that potentially affect food demand. Those additional attributes would make it difficult to identify the relationship between the organic attribute and the convenience attribute in empirical analysis. Baby carrots are processed just enough for the ease in cooking or consuming carrots, which would help the identification in econometrics.

To obtain data, we used an online survey. In the survey, respondents faced a pair of carrot products and chose the preferred one between the two products. The paired carrot products were identical except for one attribute (either the organic attribute or the baby-cut attribute). We provided different pairs of carrot products in terms of attributes randomly across respondents, which allowed us to identify the relationship between the two attributes in carrot demand. Although observing actual food consumption behaviors may be preferred especially if the research purpose is an accurate estimation of the magnitude of demand for the organic attribute, our research purpose is a comparison of organic demand with the convenience attribute.

As one way to see the robustness of the inference, we consider the potential effects of a transient exogenous shock on income (food budget). Of interest is a long-run demand rather than the corresponding short-run demand. Using the survey data, if we succeed in estimating a long-run demand, the inference results would be robust to a transient exogenous shock on income. To explore such robustness, we exploit COVID-19 in 2020. Because of COVID-19, in the United States, substantial people suffered from transient income loss. We conducted surveys before and after people widely perceived COVID-19 in the United States, and we exploit this time interval to explore the potential effects of a transient income shock on carrot demand.

The remainder of this paper is organized as follows. Section II describes the survey data. Section III reports the regression results on the relationship between the organic attribute and the convenience attribute. Section IV explores the relationship between the two attributes again, additionally considering the potential effects of COVID-19. Section V reports conclusions.

II. Data: A National Survey of Carrot Consumers in the United States

A national survey of carrot consumers was conducted. The survey was designed by the authors and distributed in December 2019, January 2020, March 2020, and June 2020 by Google Surveys, an online survey platform (for more discussion on Google Surveys, see the following subsection). In total, about 132,000 completed responses were obtained. Table 1 shows that, overall, the sample demographics are similar to those in the U.S. Census population.

Google Surveys

To gather survey responses, we used Google Surveys, an online platform that distributes surveys through more than 1,500 websites across different topics, including news, arts, and entertainment. Surveys partially block the contents of each website, and visitors to those websites must answer short questions to access the blocked contents. Google Surveys selects respondents randomly within demographic groups. For more information about how Google Surveys distribute surveys and collect responses, see Sostek and Slatkin (2017).

Google Surveys have been used in economics, marketing, and other fields to elicit consumer preferences, and political attitudes (Frederick, Lee, 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 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.

Survey design

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. For an example of the survey design, see Figure 1.

III. Exploring the Interaction Effects between Organic Attribute and Convenience

Attribute

Descriptive statistics

Tables 2 to 5 report the response proportions by options, pairs of carrot products, and pairs of prices. Most combinations have about 8,000 observations, but some combinations have about 6,000 observations because those combinations were not collected in either December 2019 or January 2020.

The share of the option, “I don't buy carrots,” is about 15% across the cases. We may interpret the share of the option as a proxy of the share of non-carrot consumers. Based on those results, we use this option, “I don't buy carrots,” to exclude non-carrot consumers in inferring demand for carrot attributes.

The variations in responses by different prices are consistent with our expectations (Tables 2 to 5). First, the share of each product is decreasing as its relative price is increasing. Second, given the same price, the share of the organic product is bigger than that of the corresponding regular product. Third, given the same price, the share of the baby-cut product is bigger than that of the corresponding full-sized product. We will see the price effects using the regressions after controlling demographics and survey characteristics below.

Identifying the interaction between organic attribute and baby-cut attribute

We consider four groups of respondents in terms of pairs of carrot products: (1) organic full-sized carrots and regular full-sized carrots, (2) organic baby-cut carrots and regular baby-cut carrots, (3) regular baby-cut carrots and regular full-sized carrots, and (4) organic baby-cut carrots and organic full-sized carrots. Here the term, “regular” means “non-organic.”

Among the four groups, two groups face a pair of identical carrots except for the organic attribute. The difference in the two groups is that one group faces a pair of full-sized carrots, while the other group faces a pair of baby-cut carrots. For these two groups, we specify the following linear probability model: For all i ,

$$(1) y_i = \alpha_0 + \alpha_1 Bid_i + \alpha_2 Baby_i + \alpha_3 X_i + v_i.$$

The subscript i indicates either a respondent or a survey question because each respondent receives only one question. The dependent variable, y_i , is a binary variable whose value is either one or zero. Specifically, if an organic product is compared to the corresponding regular product, then the dependent variable is one if the organic product is chosen, otherwise zero. The term, Bid_i , is the price difference between the two products that each respondent faces in his survey question. The price difference can be \$0.00, \$0.50, and \$1.00, depending on the surveys. The

term, $Baby_i$, is a dummy variable whose value is one if respondent i faces a pair of baby-cut carrots, otherwise zero. The term, X_i , is a vector of control variables. The control variables include demographics and survey characteristics. The demographics include gender, age (18 – 24, 25 – 34, 35 – 44, 45 – 54, 55 – 64, and 65+), and region (North East, Midwest, South, and West). The survey characteristics include response time within a day (midnight to 6 AM, 6 AM to noon, noon to 6 PM, and 6 PM to midnight), the price of the regular product and the picture location of the regular product. The price of the regular product is for checking which one matters in demand between relative price difference and relative price ratio. If the coefficient of the price of the regular product is zero, then relative price difference matters in demand rather than the relative price ratio. The picture location of regular product is for checking whether respondents are more likely to choose the product on the left-hand side (or on the right-hand side).

The demographics in our sample are similar but slightly different from those in the U.S. population (Table 1). To improve the representativeness of the U.S. population, we use 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 terms of demographics (gender, age, and region).

The parameter, α_1 , is the coefficient of the relative price difference. According to the law of demand, the coefficient is expected to be negative. That is, the probability of choosing an organic product is expected to be decreasing as the relative price of the organic product is increasing. Because we explore the demand characteristics, the law of demand must hold to proceed to infer the relationship between the organic attribute and the convenience attribute in carrot demand.

Of our interest is the parameter, α_2 , which indicates the relationship between the organic attribute and the convenience attribute. If the parameter is positive, the organic attribute positively relates to the convenience attribute in carrot demand. However, if the parameter is negative, the organic attribute negatively relates to the convenience attribute in carrot demand. If the parameter is zero, two attributes are independent in carrot demand.

As mentioned above, we have four groups of respondents in terms of the pairs of carrot products, and only two groups among them are used to specify Equation 1. To identify the relationship between the two attributes, we can use the remaining two other groups: One group of respondents face a pair of regular carrots identical except for baby-cut attribute. The other group of respondents faces a pair of organic carrots identical except for the baby-cut attribute. The remaining two groups of respondents allow us to adopt another approach to inferring the relationship between the organic attribute and the convenience attribute. That is, if respondents facing organic carrots are less likely to choose baby-cut carrots, compared to respondents facing regular carrots, organic attribute negatively relates to the convenience attribute in carrot demand. Formally, we specify the following linear probability model: For all i ,

$$(2) y_i = \beta_0 + \beta_1 Bid_i + \beta_2 Organic_i + \beta_3 X_i + \omega_i.$$

The notations and variables are consistent with those in Equation 1. The main difference is the term, $Organic_i$. The term, $Organic_i$, is a dummy variable whose value is one if respondent i faces a pair of organic carrots identical except for baby-cut attribute. Our interest is the sign of the coefficient of the term, $Organic_i$.

Regression results

Table 6 reports the regression results of Equation 1 (Model 1 in Table 6) and Equation 2 (Model 2 in Table 6). Before inference on the relationship between organic attribute and convenience attribute, several points are noticeable. First, overall, both models are significant, based on the F-test statistics. Second, in both models, the bid (that is, the price difference) coefficient is precisely estimated to be negative, which is consistent with the law of demand.

Of our interest is the interaction between the organic attribute and the convenience attribute. In Model 1 (Equation 1), the coefficient of the baby-cut variable is precisely estimated to be positive under 5% significance level. As discussed earlier, we can also use Model 2 for the inference. In Model 2 (Equation 2), we also reject the zero-coefficient hypothesis and the coefficient of the organic variable is precisely estimated to be positive. The results of the two models support the positive interdependence between the organic attribute and the convenience attribute in carrot demand.

It is noticeable that the magnitude of the coefficient estimate is small: The choice probability of the organic product than the regular product increases by about 2%, on average, if those two carrot products are baby-cut ones rather than full-sized ones. Hence, the interdependence of the two attributes would not be substantial, although we fail to reject the zero-coefficient hypothesis.

Discussion on the inference result

Regarding the relationship between the organic attribute and the convenience attribute, we propose two hypotheses. First, the convenience attribute may raise organic food demand because the following three conditions hold: (1) The convenience attribute can be obtained through further process (for example, cutting, peeling, and washing). (2) Consumers concern about food

safety more on processed products than fresh products. (3) Consumers use the organic attribute as a signal for safe products (Hypothesis 1). Second, the convenience attribute may interfere with the perception of full-sizedness, healthfulness, authenticity, or environmental sustainability that underlies some of the demand for organic food (Hypothesis 2).

Two points are noticeable. First, two hypotheses are opposite in terms of the relationship between the two attributes. That is, the first hypothesis implies a positive relationship, while the second hypothesis implies a negative relationship. Second, the two hypotheses can hold at the same time. If the two hypotheses hold simultaneously, we can observe only a gross effect of the two hypotheses in the regression results.

Although we reject the zero-coefficient hypothesis, the coefficient estimate of the baby-cut variable in Equation 1 (and the organic variable in Equation 2) is small, which supports the case when the two hypotheses hold at the same time. Moreover, given the assumption that the two hypotheses hold at the same time, the positive coefficient estimate implies that the effects of Hypothesis 1 may dominate the effects of Hypothesis 2, on average, among carrot consumers.

IV. Robustness of Inference of the Relationship between Organic Attribute and Convenience Attribute: Potential Effects of COVID-19

In the previous section, we find evidence on the positive relationship between the organic attribute and the convenience attribute in carrot demand. As one way to see the robustness of that inference, in this section, we consider the potential effects of COVID-19.

Potential COVID-19 effects

For inference on food demand or preference, food consumption surveys are often conducted in one time period because of a limited survey budget and time, and, as a result, the inference is often based solely on the cross-sectional variations. Under such limited variations of data over time, researchers often assume that preference or consumer demand is robust across time. However, it is not apparent that food demand or consumer preference is robust over time. One potential concern would be that consumers often face a transient exogenous shock on income (or food budget) through temporary unemployment, inflation, and recession. Such transient exogenous shocks are not often random among respondents because those shocks usually occur nationwide or regionwide. Such nationwide or regionwide shocks may cause a bias in the estimation, which prevents researchers from valid inference. However, transient exogenous shocks may not result in a substantial change in food demand or consumer preference on food products within a narrow category. We can analyze the potential effects of a transient income change by empirical analysis, but the problem is that it is challenging to solve such bias using cross-sectional survey data.

In this section, we exploit COVID-19 to explore the robustness of inference in response to a transient exogenous shock on income (or food budget). In the United States, the first case of COVID-19 was detected in late January 2020, and COVID-19 became widely perceived from March 2020. Because of COVID-19, many people suffered from transient income loss because of unemployment. We conducted our survey before and after COVID-19 became widely perceived among people. Specifically, we conducted our surveys in four separate periods (December 2019, January 2020, March 2020, and June 2020). Using the variations in responses before and after the pandemic, we attempt to explore the potential effects of a transient exogenous income shock on food demand.

Econometric specification

We specify the following two models:

$$(3) y_i = \gamma_0 + \gamma_1 Bid_i + \gamma_2 Baby_i + \gamma_3 March_i + \gamma_4 June_i + \gamma_5 X_i + \epsilon_i.$$

$$(4) y_i = \delta_0 + \delta_1 Bid_i + \delta_2 Organic_i + \delta_3 March_i + \delta_4 June_i + \delta_5 X_i + \phi_i.$$

Equation 3 corresponds to Equation 1, and Equation 4 corresponds to Equation 2. The notations and variables of Equations 3 and 4 are consistent with those in Equations 1 and 2. The difference between the paired equations is the existence of survey time dummies ($March_i$ for March 2020 and $June_i$ for June 2020). The base period is the period of December 2019 and January 2020, which represents the period before COVID-19 was widely perceived.

We consider the two periods (December 2019 and January 2020) as one period to make a balanced panel data. For that purpose, we test whether response results differ between December 2019 and January 2020, using the balanced panel part of the sample between the two periods. As Table 7 reports, we fail to find evidence on the difference in the response results between December 2019 and January 2020.

In this section, our goal is to see whether including those survey time dummies affects the inference on the relationship between the organic attribute and the convenience attribute. For that goal, we mainly focus on the two coefficients: the coefficient of the baby-cut variable in Equation 3 (γ_2) and the coefficient of the organic variable in Equation 4 (δ_2). If those two coefficients are precisely estimated to be positive, the inference on the relationship between the two attributes is robust in response to a transient exogenous shock on income (or food budget).

Regression results

Table 8 reports the regression results of Equation 3 (Model 1 in Table 8) and Equation 4 (Model 2 in Table 8). Overall, both models (Equations 3 and 4) are significant, based on the F-test statistics. Also, in both models, the bid (that is, the price difference) coefficient is precisely estimated to be negative, which is consistent with the law of demand.

Of our interest is the interaction between the organic attribute and the convenience attribute (here the baby-cut attribute). In both models, again, we find evidence on the positive interdependence between organic attribute and convenience attribute under a 5% significance level. That is, the inference on the positive relationship between the two attributes is robust in response to a transient exogenous shock on income (or food budget). For both Equations 3 and 4, the estimate of the coefficient changes little after controlling COVID-19.

Discussion on the regression results

Our finding on the positive relationship between the organic attribute and the convenience attribute is robust even after controlling a transient exogenous shock of COVID-19.

Although we interpret COVID-19 as a transient exogenous shock on income, earlier in this section, it is not apparent whether COVID-19 has different types of effects on carrot demand. Based on the regression results, we propose the following two potential effects of COVID-19 on carrot demand. First, COVID-19 may make consumers concern more about safety in food consumption. In Model 1 of Table 8 (corresponding to Equation 3), the coefficients of COVID-19 periods (March 2020 and June 2020) are precisely estimated to be positive. That is, the probability of choosing organic products than regular products increased in the COVID-19 period. Considering a transient income loss by COVID-19, the income effect cannot explain the positive coefficient estimates. After COVID-19 was widely perceived, people may concern more

about health and may attempt to use food consumption to keep or improve their health conditions. Under this assumption, consumers may use the organic attribute as a signal for safe food products, which may result in those positive coefficients of the COVID-19 period dummies.

Second, COVID-19 may give consumers more time for cooking at home. In Model 2 of Table 8 (corresponding to Equation 4), the coefficients of COVID-19 periods (March 2020 and June 2020) are precisely estimated to be negative. That is, the probability of choosing baby carrots than full-sized carrots decreased in the COVID-19 period. Considering a transient income loss by COVID-19, the income effect may explain the negative coefficient estimates. However, if the income effect occurred by COVID-19, the income effect must have affected the organic carrot consumption as well, but, as discussed in the previous paragraph, the estimation results of the organic attribute (Model 1 in Table 8) are not consistent with the income effect hypothesis. Hence, we expect that the income effect of COVID-19 would not be substantial at least in carrot demand. To explain the negative coefficient estimates of the baby-cut attribute demand (Model 2 in Table 8), we propose another hypothesis: COVID-19 may make people visit restaurants (or use food service) less frequently, which may result in more time for cooking at home. The main difference between baby carrots and full-sized carrots is the ease in cooking and consuming carrots. If people got more time for cooking at home by COVID-19, people would value less the convenience attribute of baby carrots. However, under the current identification strategy, we cannot distinguish the potential effects of more time for cooking from the potential income effects.

Although COVID-19 may affect carrot consumption behaviors in many different aspects, the inference on the positive relationship between the organic attribute and the convenience attribute is robust.

V. Conclusions

This paper explores the relationship between the organic attribute and the convenience attribute in food demand. Here convenience means ease in cooking and consuming food products. We used carrots as a case because baby carrots are an appropriate example for exploring the relationship between the two attributes. For data, we conducted a national online survey. In the survey, respondents faced a pair of carrot products and stated the preferred one between the two products. The paired products were identical except for one attribute (either the organic attribute or the baby-cut attribute). We provided different pairs across respondents, which allows the identification of the relationship between the two attributes. Based on regressions, we find evidence on the positive relationship between the organic attribute and the convenience attribute. The finding was robust to a transient exogenous shock on income, which was measured by COVID-19.

References

- Bazzani, C., G. W. Gustavsen, R. M. Nayga, Jr., and K. Rickertsen. 2018. “A Comparative Study of Food Values between the United States and Norway.” *European Review of Agricultural Economics* 45(2): 239-272.
- Bernard, J. C., and D. J. Bernard. 2009. “What Is It About Organic Milk? An Experimental Analysis.” *American Journal of Agricultural Economics* 91(3): 826-836.
- Brynjolfsson, E., A. Collis, and F. Eggers. 2019. “Using Massive Online Choice Experiments to Measure Changes in Well-Being.” *Proceedings of the National Academy of Sciences* 116(15): 7250-7255.

- Frederick, S., L. Lee, and E. Baskin. 2014. "The Limits of Attraction." *Journal of Marketing Research* 51(4): 487-507.
- Gao, Z., and T. Schroeder. 2009. "Effects of Label Information on Consumer Willingness-to-Pay for Food Attributes." *American Journal of Agricultural Economics* 91(3): 795-809.
- Hulland, J., and J. Miller. 2018. "'Keep on Turkin'?" *Journal of the Academy of Marketing Science* 46: 789-794.
- Lusk, J. L., and B. C. Briggeman. 2009. "Food Values." *American Journal of Agricultural Economics* 91(1): 184-196.
- McDonald, P., M. Mohebbi, and B. Slatkin. 2013. "Comparing Google Consumer Surveys to Existing Probability and Non-Probability Based Internet Surveys." White Paper. Available at: https://www.google.fi/insights/consumersurveys/static/consumer_surveys_whitepaper_v2.pdf. Accessed January 10, 2020.
- Meas, T., W. Hu, M. T. Batte, T. A. Woods, and S. Ernst. 2015. "Substitutes or Complements? Consumer Preference for Local and Organic Food Attributes." *American Journal of Agricultural Economics* 97(4): 1044-1071.
- Sostek, K., and B. Slatkin. 2017. "How Google Surveys Works." White paper. Google Inc. Available at: <https://marketingplatform.google.com/about/resources/how-google-surveys-works/>.
- Stephens-Davidowitz, S., and H. Varian. 2015. *A Hands-On Guide to Google Data*. Working Paper. Google. Available at: <http://people.ischool.berkeley.edu/~hal/Papers/2015/primer.pdf>. Accessed January 14, 2020.

Waterfield, G., S. Kaplan, and D. Zilberman. 2020. "Willingness to Pay versus Willingness to Vote: Consumer and Voter Avoidance of Genetically Modified Foods." *American Journal of Agricultural Economics*. Advanced Access. Available at: <https://onlinelibrary.wiley.com/doi/full/10.1002/ajae.12001>.

Figure 1. An Illustration of a Survey Question Distributed by Google Surveys

The Daily Globe


Top StoriesWorldUSBusinessEnter

Fair Use Digital Circulation Strategy Information Overload

The Work of Art in the Age of Mechanical Reproduction

Matthew Dodd from the January 16, 2013 issue


Jurgen Habermas R&D Android cops beat The Weekender mathewi Tim Carmody attracting young readers tweets, collaboration tags the medium is the message blog plagiarism horse-race coverage advertising the other longer Book Review....



Privacy put the paper to bed Fuego news.me photo source: proimos/flickr

Please complete the following survey to access this premium content.

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?



⌵ Select an answer

SUBMIT

OR

↺ Show me a different question

↶ Skip survey

Google

INFO PRIVACY

Table 1. Demographics of survey sample			
Demographics	All respondents (aged 18 or more only)		U.S. Census data (2010)
	With unknowns	Without unknowns	
Gender			
Male	38.1%	47.7%	49.1%
Female	42.0%	52.3%	50.1%
Unknown	19.9%	-	-
Age			
18 – 24	8.3%	10.7%	12.8%
25 – 34	14.0%	18.1%	17.9%
35 – 44	14.1%	18.2%	17.6%
45 – 54	13.8%	17.8%	19.4%
55 – 64	14.2%	18.4%	15.4%
65 +	13.0%	16.8%	16.8%
Unknown	22.6%	-	-
Region			
North East	13.6%	13.3%	17.9%
Midwest	29.0%	29.0%	21.7%
South	34.4%	34.9%	37.1%
West	22.8%	22.8%	23.3%
Unknown	0.2%	-	-
Number of observations	132,291	102,280	-
Note. The share of “unknown” differs by demographics. The column considers only respondents who report all the demographics.			

Table 2. Response shares by options: Organic full-sized versus regular full-sized					
Price of organic full-sized	\$1.50	\$2.00	\$2.00	\$1.00	\$1.50
Price of regular full-sized	\$1.00	\$1.50	\$1.00	\$1.00	\$1.50
Price difference	\$0.50	\$0.50	\$1.00	\$0.00	\$0.00
Options					
(a) I don't buy carrots	14.6%	14.2%	14.8%	14.6%	16.0%
(b) Organic full-sized	22.5%	23.1%	17.6%	47.8%	47.8%
(c) Regular full-sized	56.1%	54.5%	60.2%	28.5%	26.0%
(d) Neither of these packages	6.8%	8.1%	7.3%	9.1%	10.3%
Difference of (b) from (c)	-33.6%	-31.4%	-42.6%	19.3%	21.8%
Survey periods					
December 2019	Yes	Yes	Yes	No	No
January 2020	Yes	Yes	Yes	Yes	Yes
March/April 2020	Yes	Yes	Yes	Yes	Yes
June 2020	Yes	Yes	Yes	Yes	Yes
Number of observations	8,030	8,022	8,045	6,011	6,012

Table 3. Response shares by options: Organic baby-cut versus regular baby-cut					
Price of organic baby-cut	\$1.50	\$2.00	\$2.00	\$1.00	\$1.50
Price of regular baby-cut	\$1.00	\$1.50	\$1.00	\$1.00	\$1.50
Price difference	\$0.50	\$0.50	\$1.00	\$0.00	\$0.00
Options					
(a) I don't buy carrots	14.0%	14.2%	15.2%	15.3%	15.0%
(b) Organic baby-cut	23.4%	22.7%	18.1%	48.4%	48.8%
(c) Regular baby-cut	55.0%	54.6%	58.4%	27.7%	27.2%
(d) Neither of these packages	7.7%	8.5%	8.2%	8.7%	9.0%
Difference of (b) from (c)	-31.6%	-31.9%	-40.3%	20.7%	21.6%
Survey periods					
December 2019	Yes	Yes	Yes	No	No
January 2020	No	No	No	Yes	Yes
March/April 2020	Yes	Yes	Yes	Yes	Yes
June 2020	Yes	Yes	Yes	Yes	Yes
Number of observations	6,013	6,009	6,013	6,018	6,016

Table 4. Response shares by options: Regular baby-cut versus regular full-sized					
Price of regular baby-cut	\$1.50	\$2.00	\$2.00	\$1.00	\$1.50
Price of regular full-sized	\$1.00	\$1.50	\$1.00	\$1.00	\$1.50
Price difference	\$0.50	\$0.50	\$1.00	\$0.00	\$0.00
Options					
(a) I don't buy carrots	15.2%	14.8%	15.6%	14.1%	13.5%
(b) Regular baby-cut	39.7%	39.6%	32.9%	53.0%	54.1%
(c) Regular full-sized	37.4%	37.4%	43.5%	25.9%	24.6%
(d) Neither of these packages	7.7%	8.2%	8.1%	7.1%	7.8%
Difference of (b) from (c)	2.3%	2.2%	-10.6%	27.1%	29.5%
Survey periods					
December 2019	Yes	Yes	Yes	No	No
January 2020	Yes	Yes	Yes	Yes	Yes
March/April 2020	Yes	Yes	Yes	Yes	Yes
June 2020	Yes	Yes	Yes	Yes	Yes
Number of observations	8,014	8,011	8,011	6,013	6,009

Table 5. Response shares by options: Organic baby-cut versus organic full-sized					
Price of regular baby-cut	\$1.50	\$2.00	\$2.00	\$1.00	\$1.50
Price of regular full-sized	\$1.00	\$1.50	\$1.00	\$1.00	\$1.50
Price difference	\$0.50	\$0.50	\$1.00	\$0.00	\$0.00
Options					
(a) I don't buy carrots	14.9%	14.6%	16.1%	13.6%	14.3%
(b) Organic baby-cut	39.3%	37.6%	31.1%	54.2%	52.9%
(c) Organic full-sized	36.0%	35.6%	40.8%	22.7%	21.9%
(d) Neither of these packages	9.8%	12.2%	12.0%	9.5%	10.9%
Difference of (b) from (c)	3.3%	2.0%	-9.7%	31.5%	31.0%
Survey periods					
December 2019	Yes	Yes	Yes	No	No
January 2020	No	No	No	Yes	Yes
March/April 2020	Yes	Yes	Yes	Yes	Yes
June 2020	Yes	Yes	Yes	Yes	Yes
Number of observations	6,005	6,006	6,008	6,009	6,016

Table 6. Probability change of buying organic carrots or baby-cut carrots, based on a linear probability model		
	Model 1	Model 2
Dependent variable	1 if organic product is chosen, and 0 if regular product is chosen	1 if baby-cut product is chosen, and 0 if full-sized product is chosen
Bid (price difference)	-0.43 (0.00697)	-0.26 (0.00739)
Common attribute between two products		
Baby-cut	0.018 (0.00493)	N/A
Organic	N/A	0.015 (0.00522)
Reference price	-0.064 (0.0110)	-0.028 (0.0115)
Location of reference picture		
Left	Base	Base
Right	0.021 (0.00498)	0.013 (0.00535)
Gender		
Male	Base	Base
Female	0.025 (0.00500)	0.0062 (0.00537)
Age		
18 – 24	Base	Base
25 – 34	0.023 (0.0100)	-0.016 (0.0107)
35 – 44	0.039 (0.00994)	-0.018 (0.0106)
45 – 54	0.015 (0.00983)	-0.030 (0.0106)
55 – 64	0.0082 (0.00980)	-0.055 (0.0105)
65 +	-0.011 (0.00986)	-0.096 (0.0107)
Region		
North East	Base	Base
Midwest	-0.069 (0.00809)	0.048 (0.00872)
South	-0.041 (0.00789)	0.074 (0.00849)
West	0.0092 (0.00851)	-0.023 (0.00906)
Response time of day		
Midnight to 6 AM	0.0068 (0.00772)	-0.00061 (0.00858)
6 AM to noon	0.013 (0.00722)	-0.0088 (0.00800)
Noon to 6 PM	Base	Base
6 PM to midnight	0.017 (0.00639)	0.0027 (0.00702)
Constant	0.62 (0.0198)	0.66 (0.0270)
Number of observations	39,874	39,117
R squared	0.1067	0.0483
Note. Robust standard errors in parentheses. Each observation is weighted by the inverse of the probability that the observation is included to represent the U.S. population in terms of demographics. The responses of two options, “I don’t buy carrots” and “Neither of these packages,” are not included in the two regressions.		

Table 7. Probability change of buying organic carrots or baby-cut carrots, based on a linear probability model		
	Model 1	Model 2
Dependent variable	1 if organic full-sized product is chosen, and 0 if regular full-sized product is chosen	1 if regular baby-cut product is chosen, and 0 if regular full-sized product is chosen
January 2020	-0.0066 (0.0106)	0.012 (0.0119)
Constant	0.31 (0.0471)	0.54 (0.0538)
Number of observations	7,369	7,051
R squared	0.0104	0.0139
<p>Note. Robust standard errors in parentheses. Each observation is weighted by the inverse of the probability that the observation is included to represent the U.S. population in terms of demographics. The responses of two options, “I don’t buy carrots” and “Neither of these packages,” are not included in the two regressions. Although we do not report the estimation results, the price variables, the demographics (gender, age, and region), and survey characteristics are controlled in the regressions.</p>		

Table 8. Probability change of buying organic carrots or baby-cut carrots by survey months, based on a linear probability model		
	Model 1	Model 2
Dependent variable	1 if organic product is chosen, and 0 if regular product is chosen	1 if baby-cut product is chosen, and 0 if full-sized product is chosen
Bid (price difference)	-0.43 (0.00676)	-0.27 (0.00711)
Common attribute between two products		
Baby-cut	0.013 (0.00472)	N/A
Organic	N/A	0.018 (0.00499)
Survey periods		
December 2019 / January 2020	Base	Base
March 2020	0.010 (0.00566)	-0.018 (0.00607)
June 2020	0.019 (0.00575)	-0.011 (0.00609)
Reference price	-0.059 (0.0106)	-0.027 (0.0112)
Location of reference picture		
Left	Base	Base
Right	0.022 (0.00482)	0.014 (0.00519)
Gender		
Male	Base	Base
Female	0.023 (0.00484)	0.0041 (0.00523)
Age		
18 – 24	Base	Base
25 – 34	0.026 (0.00973)	-0.015 (0.0103)
35 – 44	0.041 (0.00965)	-0.017 (0.0103)
45 – 54	0.018 (0.00960)	-0.031 (0.0103)
55 – 64	0.012 (0.00952)	-0.058 (0.0102)
65 +	-0.0095 (0.00961)	-0.096 (0.0104)
Region		
North East	Base	Base
Midwest	-0.076 (0.00805)	0.048 (0.00872)
South	-0.043 (0.00789)	0.074 (0.00853)
West	0.0062 (0.00849)	-0.021 (0.00909)
Response time of day		
Midnight to 6 AM	0.0040 (0.00756)	-0.0012 (0.00842)
6 AM to noon	0.013 (0.00701)	-0.0067 (0.00778)
Noon to 6 PM	Base	Base
6 PM to midnight	0.017 (0.00622)	0.0024 (0.00682)
Constant	0.62 (0.0193)	0.65 (0.0261)
Number of observations	39,874	39,117
R squared	0.1069	0.0492
Note. Robust standard errors in parentheses. Each observation is weighted by the inverse of the probability that the observation is included to represent the U.S. population in terms of demographics. The responses of two options, “I don’t buy carrots” and “Neither of these packages,” are not included in the two regressions.		

