Willingness to Pay for Produce: A Meta-Regression Analysis Comparing the Stated Preferences of Producers and Consumers

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Abstract

Willingness-to-pay (WTP) estimates help agribusinesses estimate whether a new product is likely to be profitable. For produce, new products, such as new fruit varieties, need to be adopted by producers before they can be sold to consumers. The study of *ex ante* produce producer preferences is relatively new. This study uses meta-regression analysis to compare the estimated WTP premium between U.S. producers and consumers to determine whether they systematically differ. After controlling for differences in study methods, product attributes, and potential publication bias, we find that producer WTP is between 14.16 and 27.73 percentage points higher. Subject to several caveats and limitations, this suggests that consumer WTP can be a sufficient metric for the profitability of new produce products.

Keywords: Produce, Economics, Willingness-to-Pay, Product Adoption, Meta-Regression Analysis.

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Introduction

The market for produce is increasingly differentiated, with consumers able to choose between a host of sensory attributes, such as color, size, flavor, and credence attributes, such as organic, GM, or locally grown. Each of these options may factor into a consumer's decision to purchase and affect the amount of money they are willing to spend on the product. When an agribusiness considers bringing a new product to market, it is essentially proposing to introduce consumers to a new bundle of sensory and credence attributes (Louviere et al., 2000; Moser et al., 2011).

Developing new varieties or introducing novel crops to market is a slow and expensive process. For example, the 'Covington' sweetpotato was first identified in 1997 and was released to the public eight years later (Yencho et al., 2008). In addition, the 'WA 38' apple was first crossed in 1997, released to growers in 2014, and presented to the public as 'Cosmic Crisp' in 2019 alongside a marketing campaign in excess of 10 million dollars (Evans et al., 2012; Luby and Bedford, 2015; Katz, 2019).

Before embarking on a new venture, the developer (and its financial backers) would like to know whether there is a market for the new product, or, if there are multiple potential products, which would be most successful. In other words, are they likely to see a positive net return from the time and effort involved in development? Their net return will depend on the costs of development and the revenues from sales. Thus, a reliable forecast of net returns requires a reliable forecast of consumer demand for the new product.

Economists have developed tools for estimating demand for hypothetical and novel products before they come to market. These tools, including experimental auctions, contingent valuation, and conjoint analysis, are able to estimate subjects' willingness-to-pay (WTP) for a hypothetical or novel product, and, in some cases, even estimate WTP for particular attributes of the product (Lusk and Hudson, 2004). These WTP estimates can be used to construct demand curves for use in estimating the net returns from the new production.

We have found that the majority of studies looking at demand for novel or hypothetical produce are looking at the final consumers' demand, e.g., the shoppers in the supermarket. However, for new produce to make it to the consumer, it first must be adopted and grown by producers, whose adoption criteria may differ from those of consumers. Producers' WTP can be affected by factors such as marketable yield levels, production costs, and ease of harvest, factors which may or may not correlate with traits consumers find desirable (Yue et al., 2017). Yue and co-authors provide the example of tart cherries, where growers may place a high value on firmness, which would prevent damage during harvest, while consumers would be indifferent to firmness since tart cherries are usually sold processed, dried or as juice.

The main goal of this paper is to explore any divergence between producer and consumer WTP. If, in general, producer WTP is similar to consumer WTP, or higher, then an agribusiness considering introducing a new product on the basis of a sufficiently high consumer WTP can be confident that producers are likely to adopt it, too. On the other hand, if producers have lower WTP then innovation developers run the risk that their product will fail in the market due to insufficient adoption by producers, even if the consumer market appears to be there.

We find after controlling for publication bias, year fixed effects, differences in methods, and differences in attributes studied, that the producer WTP premium (WTPP) is on average 21.17 percentage points higher than consumer WTPP for produce, with a 95% confidence interval of 14.61% to 27.73%, providing initial evidence that consumer WTP studies may be sufficient for estimating potential producer adoption.

In addition, this paper surveys the existing literature on measuring WTP for produce, providing an unfamiliar reader background on the main concepts in WTP estimation and a map for finding existing WTP estimates for particular produce crop or attributes of interest

Willingness to Pay

Willingness to pay (WTP) is the maximum income a consumer would be willing to give up in exchange for a change in the price or quality of the good, while keeping their utility constant[1]. In the case of a quality improvement, the increase in quality would increase their utility, so their income must be reduced by an amount to exactly offset the quality-induced increase in utility. This amount is the consumer's WTP.

[1] Utility is a measure of the total satisfaction a consumer gets from the goods and services they consume.

The WTP concept can be extended to producers in a straightforward manner. Instead of utility, producers' WTP is calculated by keeping their profit constant. Increasing the quality of an input could increase their profit by increasing revenues or decreasing costs. The producer's WTP for the change in the input is the difference in profit before and after the change (Lusk and Hudson, 2004).

This definition assumes a discrete change in the quality or price of the good. Alternatively, marginal WTP (MWTP) may be calculated and reported, which is the change in WTP with respect to a marginal change in the price or quality. It represents, depending on the context, the first derivative of the value, expenditure, indirect utility, or profit function (Rosen, 1974).

In an agribusiness setting, WTP measures can be used to estimate demand for novel or hypothetical products, guiding firms' pricing and marketing decisions before the product is launched (Lusk and Hudson, 2004). With a measure of the distribution of WTP in a potential market in hand, the firm can construct an estimate of the demand curve for the product, and hence identify its profit maximizing pricing strategy or offering of product attributes and qualities.

In our sample, researchers present estimated WTP in four main ways:

- as a dollar value, e.g., Yue et al. (2017) found that U.S. apple growers would be willing to pay $0.16/lb to improve apple size from less than to larger than 2.9 inches;
- as a percentage premium, e.g, Onozaka et al. (2006) found that consumers in Northern California were willing to pay a 15 percent price premium for bananas labeled "pesticide free" compared to bananas without the label;
- as a probability of adoption for a given price, e.g, Blend and van Ravenswaay (1999) found that 72.6 percent of U.S. consumers were willing to purchase eco-labeled apples with zero price premium (compared to unlabeled apples), while 52.4 percent would purchase at a $0.20 price premium, falling to 42.3 percent with a $0.40 price premium; or,

- as an own- or cross-price elasticity, e.g., Bernard and Bernard (2010) found that consumers in four Atlantic coast states would decrease their purchases of conventional potatoes by 3.15 percent in response to a 1 percent increase in the price of conventional potatoes, while purchases of organic potatoes would rise by 1.20 percent in response to this price increase.

From these estimates, demand curves can be derived (e.g. Choi et al., 2017), which Lusk and Hudson (2004) argue is the object of interest for agribusinesses, since it can be used to determine the potential revenues from the new product.

Methods used to measure WTP

To measure WTP, researchers typically turn to choice modeling methods, which provide opportunities to observe how consumers choose which products to purchase and how they make trade offs between similar goods. Choice modeling methods come in two varieties: revealed preference methods and stated preference methods. Revealed preference methods use observed choices, while stated preference methods rely on asking how the respondent would choose, if they were faced with the choice (Johnston et al., 2017).

Experimental auctions (EA) are a common revealed preference technique where subjects bid real money on a good, and the underlying assumption is that participants will not bid more than their the valuation of the good (Lusk, 2003). While EAs are exposed to less risk of hypothetical bias, since any transactions are binding, they can be time intensive and costly compared to survey instruments (Lusk and Hudson, 2004). Additionally, since they require real transactions, the good on which consumers are bidding must already exist, which does not allow for preferences for hypothetical goods to be captured while products are in development. Many market researchers, therefore, turn to choice experiments.

Choice experiments are part of a subset of choice modeling approaches in which subjects are asked to evaluate a set of at least two options and indicate their preferences by selecting a subset of these options or ordering these options according to a predetermined criterion (Street and Burgess, 2007). Following McFadden (1974), one approach to choice experiment design is contingent valuation method (CVM). The most basic form of this is a dichotomous choice experiment, wherein consumers are asked to evaluate a product profile and indicate if they would or would not purchase the product at a given price by choosing "yes" or "no" (Lloyd-Smith et al., 2018; Street and Burgess, 2007; Johnston et al., 2017). A double-bounded dichotomous choice asks respondents if they would be willing to purchase at a benchmark price; if yes, they are presented with a second, higher price and asked if they are willing to purchase for the higher price. If they indicated they would not be willing to purchase at the benchmark price, they are presented with a lower price and asked again if they would be willing to purchase (Lusk and Hudson, 2004). Alternatively, consumers may be asked the maximum they would be willing to pay for the product, a technique known as open-ended valuation (Johnston et al., 2017). Finally, with the payment-card approach, consumers may be shown ranges of premiums or prices and asked into which range their maximum WTP falls (Johnston et al., 2017).

Alternatively, respondents may be asked to compare multiple product profiles in a technique known as conjoint analysis (CA), largely based on the hedonic prices framework developed in 1974 by Rosen (Lloyd-Smith et al., 2018). Chief among these, and the most popular choice experiment procedure in our sample, is known as choice-based conjoint analysis (CBC), discrete choice experiment (DCE), or sometimes simply a choice experiment. In CBC surveys, respondents are presented with profiles for different but comparable products and asked to indicate which, if any, they would be most likely to purchase or select (Lloyd-Smith et al., 2018; Lusk and Hudson, 2004). In lieu of CBC, some studies have participants rank options from best to worst or give each option a rating (Orme, 2006).

In CA surveys, product profiles consist of a few key attributes, such as price, size, and organic versus conventional in the case of fruits and vegetables, and each of these attributes has two or three levels (Johnson et al., 2007). By having consumers complete several choice tasks with different product profiles, researchers are able to estimate the trade-offs between particular attributes. Estimating the trade-offs between prices and other attributes allows researchers to estimate WTP (Alberini et al., 2007).

In our analysis, we exclude WTP estimates from experimental auctions and other revealed preference approaches. Experimental auction estimates are generally lower than estimates from stated preference methods (Johnston et al., 2017; Dolgopolova and Teuber, 2018), although this was not the case in the recent meta-analysis by De Steur et al. (2016). None of the producer studies in our sample used an experimental auction to collect data. Additionally, many of the producer studies sought to capture preferences for hypothetical products, such as Yue et al. (2017); Zhao et al. (2017) and Gallardo and Wang (2013), for which experimental auctions are an inappropriate approach.

Existing Reviews of WTP Related to Produce

No existing reviews of preferences for produce focus on the differences between producers and consumers. Some existing reviews have focused on consumer preferences for food traits, such as sustainability (Boccaletti and Nardella, 2000; Cecchini et al., 2018), health benefits (Dolgopolova and Teuber, 2018; De Steur et al., 2016), or local production (Printezis et al., 2019), while others consider the characteristics of producers, such as their willingness to adopt new technologies (Olum et al., 2020) or preferences over contract types (Mamine et al., 2020). In these cases, no special emphasis is placed on produce, and the included papers that do study produce are captured as part of a wider search. In contrast, reviews that do focus on produce look only at consumers' preferences (Moser et al., 2011; Vecchio and Borrello, 2019).

Both Cecchini et al. (2018) and Boccaletti and Nardella (2000) sought to summarize the determinants of consumer preferences for sustainably-produced food products. Of the forty-one studies investigated by Cecchini et al. (2018), the majority (86%) used experimental auctions to elicit consumers' valuation for products. Further, 63% of the studies included for analysis were conducted in European Union countries. The authors determined that consumers are generally willing to pay a premium for organic and other eco-labeled food products, and relevant information on sustainably-produced foods can influence over consumers' WTP for these products.

This latter finding is echoed in Boccaletti and Nardella (2000), who considered both *ex ante* and *ex post* evaluation of consumer WTP for sustainable products through a review of studies which leveraged purchase data and revealed preference studies alongside CBC and CVM stated preference surveys. The analysis highlights the centrality of risk attitudes to WTPP for sustainable products and the consequent potential for information signals to affect WTP. The authors underscore conclusions about the sociodemographic predictors of higher WTP for sustainably produced products, such as age (under 50), gender (female), income (high), and the presence of children in the home.

Dolgopolova and Teuber (2018) examined 36 studies that focused on consumer willingness to pay for food products with health benefits. From these, they extracted or imputed 186 MWTP estimates, ranging from -50% to 400% marginal percent premiums, and concluded that products with advertised health benefits were associated both with increased MWTP as well as decreased heterogeneity between bids. They found further evidence that hypothetical elicitation methods were associated with higher MWTP than non-hypothetical methods, supporting the existing literature on the effects of hypothetical bias. Of the 36 studies, eight were conducted in the United States and five focused on produce.

De Steur et al. (2016) explored the influence of methodological choices on reported consumer preferences for bio-fortified foods. Meta-regression results uncovered detectable differences in WTPP for hypothetical vs. non-hypothetical choice contexts, information treatments, and study types (rank-based conjoint, CVM, CBC, experimental auction, and random-utility methods). However, only three of the twenty-three studies considered were conducted in the United States, of which one focused on produce (broccoli), and seven papers in the sample focused produce.

Printezis et al. (2019) used 35 studies to conduct a meta-regression analysis of consumers' WTP for locally produced food. Like Dolgopolova and Teuber (2018), they extracted 86 WTP measures from these studies converting the estimates to a common measure of $/lb. They found robust evidence of a positive WTP for locally produced food as well as evidence of publication bias in this literature. Only 27 percent of their WTP estimates were for produce, and 61 percent were from the United States.

Olum et al. (2020) conducted a review of choice experiments with agricultural producers which measured WTP or willingness to adopt (WTA) for novel agricultural practices and technologies. They found that WTP premiums depend on the specific innovation under consideration. The valuation of water management and agrienvironmental variables were generally high for agricultural producers, suggesting that producers are willing to experiment with new practices and technologies. Of the eighty studies considered, only eleven focused on WTP for crop attributes, and only two of these eleven focused on specialty crops. Four studies in the sample were based in the U.S., of which one studied WTP for cotton varieties.

Mamine et al. (2020) also analyzed results from seventy-nine choice experiments with producers to investigate broader trends in preferences for contracts for the adoption of agro-environmental practices. Their sample only included studies that employed a choice-based conjoint survey instrument, and discovered that while the number of choice scenarios had a negative impact on WTA, sample size was positively associated with the acceptance of contract clauses. However, once again only 12% of studies in the sample were conducted in the United States. Further, WTA, rather than WTP, was the outcome of interest, so studies that focused exclusively on WTP were not included in the sample.

Moser et al. (2011) investigated compare consumer preferences for credence attributes of fruits and vegetables across 40 papers. Their sample is not confined to studies conducted in the United States, and for all attributes but one, the proportion of studies that employ an econometric model to analyze their data is quite small. Only five studies in the sample used price as a key attribute and included an econometric model. They find that experience attributes, health benefits, and quality were consistently more important to consumers than what they term "publicly-oriented" attributes, such as products that advertise their link to job creation. Further, the importance of these publicly-oriented attributes varied widely across regions around the globe, unlike the "privately-oriented" attributes.

Lastly, Vecchio and Borrello (2019) provide a "narrative review" of experimental auction studies for food products, once more focused exclusively on consumers. In lieu of extrapolating broader trends from the results of these studies, they note how various studies have adapted experimental auction methods to reduce bias and improve validity, both external and internal. Subsequently, the authors conducted a survey of scholars who had recently published papers on preferences for food products that included an experimental auction as part of their data collection. They found that about 30% of respondents were concerned with selection bias. Further, most ranked collaboration with psychologists, increasing the number of experiments conducted *in situ*, and reporting results in a manner which allows for replication as "medium", "high", or "very high" priorities for researchers. Lastly, a majority of respondents were strongly against the use of deceptive practices in experimental auctions, with the exception of providing participants with incomplete information if necessary for the study design.

Methods

Database searches

In our literature search, we aimed to systematically identify papers looking at producer willingness-to-pay for produce. By contrast, we only sought to identify a representative sample of papers looking at consumer willingness-to-pay for produce, since the population is large.

To gather the papers for inclusion in our review, we used a combination of database and citation searching. For each search, titles were read and the relevance was assessed. At this stage, papers were deemed relevant if their titles indicated that the study measured willingness-to-pay for fruits and/or vegetables. If there was any likelihood that the paper was relevant, the metadata (including abstract) was saved and, where possible, the paper was downloaded.

We used two sources for the database search: Google Scholar, and ECONLIT. We used four boolean search strings for Google Scholar: “Willingness to pay AND producer AND fruit”, “Willingness to pay AND producer AND vegetable, “Choice modeling AND producer AND fruit”, and “Choice modeling AND producer AND vegetable”. We used three boolean search strings for the ECONLIT database: “(Willingness to pay OR WTP) AND producer AND fruit”, “(Willingness to pay OR WTP) AND producer AND vegetable, and “(Willingness to pay OR WTP) AND producer AND agriculture”. For Google Scholar searches, the first 10 pages of results were reviewed. All returned results from the ECONLIT database were reviewed. The database searches were performed on Dec 7, 2020.

We also identified papers using citation searching, that is, reviewing the papers cited by several key papers, as well as the papers that cite these key papers. We used four key papers for the citation search (Lusk and Hudson, 2004; Yue et al., 2017; Zhao et al., 2017; Li et al., 2020a). The Lusk and Hudson paper introduced the idea of using stated preference willingness-to-pay results in agribusiness decision making and it is widely cited by both consumer and producer WTP studies. The other three papers emerged from the RosBREED project, a USDA funded interdisciplinary project to develop improved cultivars of rosaceous fruits and to estimate *ex ante* valuations of these improvements. At the time of our literature search, RosBREED was the first project we were aware of that sought to measure growers’ willingness-to-pay for fruits and vegetables.

Initially, we identified 175 papers with titles that suggested they may be candidates for inclusion. Only papers in English were considered for inclusion. The papers’ abstracts were screened for several characteristics: the use of a choice experiment, the measurement of willingness-to-pay for an agricultural product, or a focus on producers of specialty crops. If the abstracts were ambiguous, we skimmed the content of the paper for clarification.

We screened this initial sample to consider only studies which included data from the United States. We also discarded theoretical papers, conference posters, opinion pieces, and supply chain analyses. Additionally, we excluded any papers that focused on non-crop agricultural products, such as meat, eggs, or dairy, and substituted published versions for dissertation chapters and theses where possible. If no published version was found, we kept the original. This screening resulted in a set of 70 papers.

We excluded seven additional papers. First, we excluded Yue et al. (2012), which looks at breeders’ priorities, since our focus is not on crop production technology providers. If we

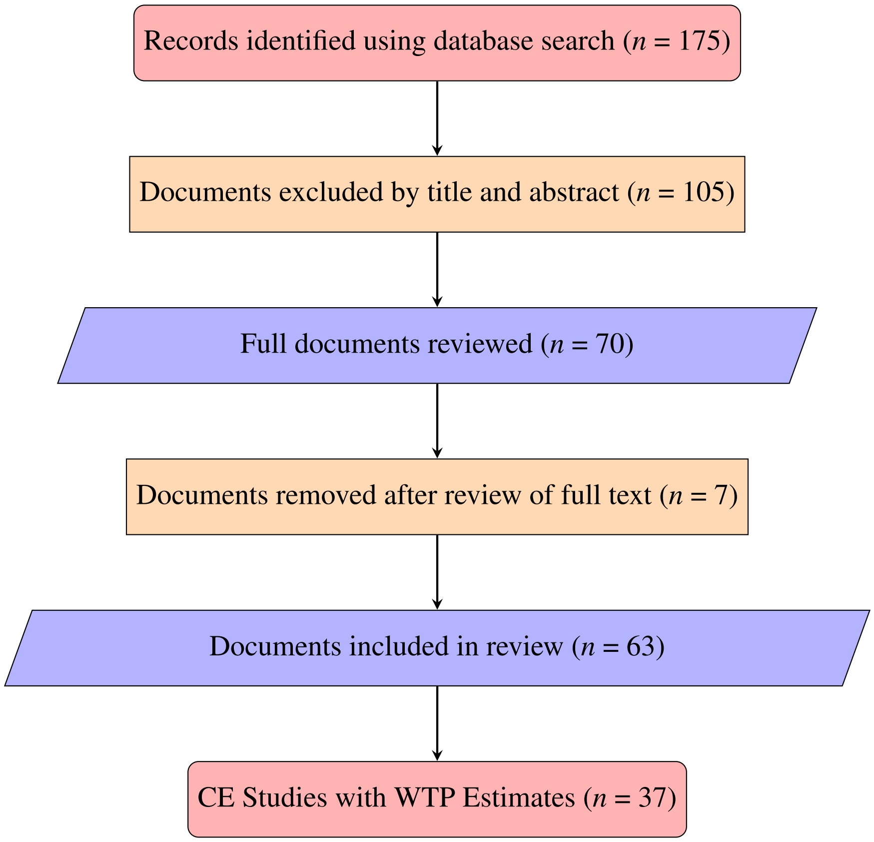

Figure 1: Process for identifying papers to include in review and analysis.

were to include this paper, we may also have to include other technology providers: irrigation, greenhouses, fertilizers etc. In addition, this paper is not looking at breeders' trait priorities, rather, their sources of information they use to set their trait priorities. This differentiates it from the other producer papers. Second, we excluded Fernandez-Cornejo et al. (1992) because it used revealed preference data, rather than stated preference. Third, we excluded budget analysis paper, (Barrett et al., 2012), which did not estimate WTP from consumers or producers directly. Fourth, we excluded three papers (Gallardo et al., 2018b,a; Dentoni et al., 2013) because they elicited respondent priorities, rather than an WTP estimate. Finally, we removed Guthman and Zurawski (2020) because it elicited producer preferences through qualitative interviews. Table 9 lists all included studies.

The presence of outliers and their removal

In total, there were 700 WTP estimates extracted from the data (see appendix B for details on this extraction). We defined outliers as 1.5 times the interquartile range. Through this we identified 79 outliers. Additionally, no calculable sample size was available for 6 observations, leaving 615 observations for use in our analysis. The two largest outliers came from Gallardo and Wang (2013). In this study, apple and pear growers were asked both what they were willing to pay per acre for chemical controls with reduced environmental impacts. Then, respondents were asked what they believed *other* growers were WTP for the same products. The base price was given by industry experts to be around \$35.00 per acre. While the direct valuation estimates were close to this base price, respondents estimated that other producers would be willing to pay between \$100 and \$350 per acre for the same products. Other papers that contained outlier estimates included: Hu et al. (2011, 2009); Carroll et al. (2013); Xie et al. (2016); Sackett et al. (2012); Yue et al. (2005); Choi et al. (2017, 2018); Li et al. (2020a); Vassalos et al. (2016); Meas et al. (2014); Hu et al. (2021); Yue et al. (2017); Zhao et al. (2017); Li et al. (2020b) and Chen et al. (2020).

Meta-Regression Analysis

Meta-regression analysis (MRA) is a form of meta-analysis that seeks to quantify how some outcome variable is affected by methods used in each paper included in the analysis, such as study design, data, and target population (Stanley, 2001). This technique has successfully been used to analyze WTP of food attributes, such as biofortification (De Steur et al., 2016), health benefits (Dolgopolova and Teuber, 2018), and local foods (Printezis et al., 2019).

We use the percentage (WTPP) as the summary statistic for the meta-regression analysis. This controls for differences in baseline prices among different crops and between locations. The studies included in our sample sought to calculate the marginal WTP for a variety of different product attributes, including observable changes and credence attributes. The common thread is that the respondent is asked about the WTP for a novel or hypothetical product. By combining these percent WTP estimates in the meta-regression analysis, we can interpret the

Table 1: Independent variables for meta-regression analysis

Variable	
$\sqrt{n}$	= The square root of the underlying study's sample size
Year	= Year the study was published
Producer	= 1 if the sample group was producers
Collect	= 1 if a survey was used to collect data (baseline is interview)
WTP in Dollars	= 1 if results were reported as WTP in dollars
Benchmark Price	= Price used for the products(s) evaluated
Credence	= 1 if WTP for a credence attribute
Local	= 1 if product was locally grown
Organic	= 1 if study product was organic
Processed	= 1 if product was processed

average percent WTP as the average WTP for a novel or hypothetical produce product. The percent premium was calculated using an equation adapted from Dolgopolova and Teuber (2018):

$$WTPP = \left(\frac{tWTP - P_{bench}}{P_{bench}}\right) * 100 \tag{1}$$

where $tWTP$ is the total WTP (in dollars) for a given product and P_{bench} is the benchmark or baseline price for the study. Our meta-regression analysis estimating equation is given by

$$WTPP = \beta_0 + \beta_1 \sqrt{n} + \beta_{\mathbf{X}} \mathbf{X} + \varepsilon \tag{2}$$

where WTPP is the percent premium WTP, β_0 is the average WTP for a novel or hypothetical produce product, $\sqrt{n}$ is the square root of the underlying study's sample size, $\mathbf{X}$ is a vector of independent explanatory variables listed in table 1, and ε is a classical *i.i.d* error term.

In addition to the ability of meta-regression analysis to identify the effect of methodological choices on outcome variables, it can also uncover publication bias in a literature (Stanley, 2005). Publication bias occurs when researchers and editors are more likely to publish certain types of results over others, such as statistically significant results or results that are consistent with existing views (Card and Krueger, 1995). Stanley (2005) explains that the presence of publication bias creates a disadvantage for studies with small samples. These studies will have less statistical power and therefore less ability to find a significant effect, compared to a larger study. Hence, they will need to search through more model specifications to find an effect large enough for publication. The presence of publication bias can be investigated by looking for evidence of an inverse relationship between sample size and effect size.

To test and control for potential publication bias, we include the square root of the study's sample in the MRA estimating equation. For MRAs on outcome variables which are combinations of the estimated regression coefficients—which is the case for percentage WTP estimates—Printezis et al. (2019) note that the square root of the underlying study's sample size is the most appropriate variable to control for publication bias. The reason is twofold. First, the inverse standard error of the WTP estimate ($1/SE$ — the most commonly used variable to control for publication bias) is impossible to calculate given the reported data in many cases. In addition, ($1/SE$) is an estimated value and subject to sampling error, while $\sqrt{n}$ is not, but is highly correlated with ($1/SE$).

We do not include a funnel plot, a common, informal tool for identifying the presence of publication bias Stanley (2005). A funnel plot indicates the absence of publication bias if the data points are symmetrically distributed around the most precise estimates, and the its presence if the data are skewed. However, this assumes that there is a *single* true effect. Since we are combining studies examining the percentage WTP for a variety of effects, we have no *a priori* grounds for expecting a single, central estimate of percentage WTP. Instead, we only include the results of the Funnel Asymmetry Test (FAT), which indicates the presence of publication bias if $H_0 : \hat{\beta}_1 = 0$ in equation (2) can be rejected (Stanley, 2005). Since this estimating equation controls for methodological differences between studies, including different effects of interest, the FAT is a more robust indicator of publication bias.

An important caveat is that rejection of the FAT's null hypothesis is consistent with the presence of publication bias, but there are other reasons why the hypothesis might be rejected, including true heterogeneity, and data irregularity (Egger et al., 1997). A significantly negative value of $\hat{\beta}_1$, meaning less precise estimates are likely to be larger, is more indicative of a bias towards publishing statistically significant results. On the other hand, a positive value of $\hat{\beta}_1$

is unlikely to indicate a bias towards publishing statistically significant results, and that an alternative reason is likely the cause of the asymmetry (Sterne et al., 2011).

Alternative regression specifications

We consider two alternative specifications of the model specified by equation 2. In the first specification, we included only $\sqrt{n}$, a dummy variable indicating whether the study subjects were producers, and year fixed effects. The base specification with only $\sqrt{n}$ and the dummy had a time trend in the residuals, which we controlled for by including the year fixed effects period. The full specification includes method variables and product attribute variables listed in table 1. These additional variables count for methodological differences between the studies as well as differences in the types of good being studied.

In addition, we estimate the full model on two subsets of the data: a subset with only consumers and another with only producers. In the full model on the complete dataset, the specification allows consumer and producers to have different mean levels of WTPP, but it assumes that their marginal responses are identical, i.e. a one dollar increase in the baseline price would have the same effect on a consumer and a producer's WTPP. Estimating the model on the two subsets allows the marginal responses to differ.

Each observed willingness to pay estimate is not drawn from an i.i.d distribution because multiple estimates are drawn from the same study. The estimates are clustered at the study level and consequently may have intra-study correlations. In addition, there may be intra-year correlations, even after the year fixed effects have been added to the model. These correlations may bias the estimated standard errors, making point estimates appear more precise than warranted. To control for both of these possibilities we cluster the standard errors at both the paper and year level (Cheah, 2009). Following Printezis et al. (2019) we also estimate wild bootstrapped standard errors. Angrist and Pischke (2009) suggest that the minimum number of clusters for robust inference is 42. This threshold is met for clustering at the paper level but not at the year level. Facing a similar problem, Printezis et al. use wild bootstrapped standard errors as a robustness check, noting that it is well suited to meta- regression analysis. The two-level

Table 2: Paper-Level Characteristics

Key Variables	Full Sample (N= 37)	Consumer Studies (N= 27)	Producer Studies (N=10)
Focus Attributes (Means):			
Locally Grown	0.30	0.41	0.00
Multiple Crops	0.16	0.11	0.30
Processed Product	0.22	0.30	0.00
Credence	0.30	0.37	0.10
Organic	0.32	0.44	0.00
Data Collection Method			
In-Person Survey (Interview)	25 (67.57%)	18 (66.67%)	7 (70.00%)
Remote Survey	12 (32.43%)	9 (33.33%)	3 (30.00%)
Study Type			
CA	28 (75.68%)	19 (70.37%)	9 (90.00%)
CVM	11 (29.73%)	10 (37.04%)	1 (10.00%)
Results Measures			
Dollar	29 (78.38%)	19 (70.37%)	10 (100.00%)
Percent Premium	9 (24.32%)	8 (29.63%)	1 (10.00%)
Elasticity	1 (2.70%)	1 (3.70%)	0 (0.00%)
Probability of Purchase	6 (16.22%)	6 (22.22%)	0 (0.00%)
Year Published			
Min:	1999	1999	2013
Mean	2012.22	2010.34	2017.3
Median	2013	2009	2017
Max:	2021	2021	2020

clustered standard errors were calculated using the `multiwayvcov` package in R (Graham et al., 2016).

Results and Discussion

Paper attributes

The umbrella "produce" encompasses a diverse range of crops whose cultivation and consumption vary widely. Table 2 lists the crops featured in the sample studies. Further, several studies consider processed food products, such as applesauce, while still others *only* considered processed versions of a given crop. Many studies sought to quantify preferences for particular credence attributes related to the origin or cultivation of particular goods. Table 3 presents tallies for the most common attributes studied in the sample.

There are far fewer papers looking at produce producer adoption decisions. In our search of the literature, we found 47 papers that estimated the WTP of U.S. produce consumers for some crop or attribute, but only 16 papers studying U.S. producers.

Three attributes, locally grown, organic, and processed product, were only applicable to consumers. However, both consumers and producers were asked about their WTP for crops with a variety of credence attributes, such as non-GM or GM crops, the use of novel pest control technologies, preferences for sustainable cultivation practices, health benefits, and country of origin labelling. Consumers were asked about these attributes more frequently than producers (30% of consumer studies compared to 10% of producer studies).In our sample, a minority of studies investigated preferences for multiple crops, constituting 16% of the overall sample, 11% of consumer studies, and 30% of producer studies.

Only one approach (whether survey instrument, experiment, or other) was employed to collect data in a majority of both consumer and producer studies in our sample, and in both samples, CBC was the most popular approach, used in 83% of producers studies and 62% of consumer studies. Only one producer study (Coffey et al., 2020) used a CVM survey instrument.

For 71% of consumer studies and 55% of producer studies, only one measure was used to report preferences. Further, only one study (Liaukonyte et al., 2012) in the combined sample used more than two measures to frame results. In both groups, the dollar measure is used to report WTP in most studies, and it can be easily inferred that many studies use *only* this dollar measure to report outcomes.

It is important to consider that time may contribute to any differences between consumer and producer studies: the popularity of certain methods or interest in certain topics normally ebb and flow as researchers' understanding of these tools and phenomena evolve. In our sample, producer studies were notably newer than the consumer studies, as figure 2 demonstrates. On average, the producer studies were published in 2017, with a standard deviation of 2.5 years. By

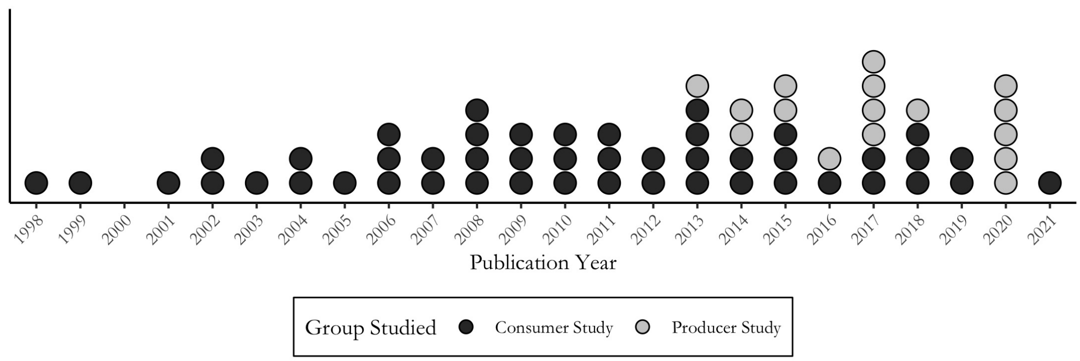

Figure 2: Count of Studies in Each Year by Subject Group (1 dot = 1 study)

contrast, the mean publication year for consumer studies was 2010 with a standard deviation of 5.6 years.

Meta-Regression Analysis Results

Table 3 summarizes the variables used in the meta-regression analysis. Several explanatory variables—WTP in Dollars, Local, Organic, Processes—have no variation for the producer studies so they are dropped from the producer studies.

Table 4 presents the results of the two regression specifications estimated on the complete dataset and the full specification estimated on only consumer or producer estimates. In the baseline model the FAT null hypothesis cannot be rejected. However, the hypothesis of is rejected at a 95 percent confidence level for the full, conusmer only, and producer only models. In the full and consumer models there is evidence of a positive relationship between sample size and WTPP. This is unlikely to indicate the presence of publication bias (Sterne et al., 2011). These positive relationships in the base and consumer models are robust to the specification

Table 3: WTPP Summary Statistics

Variable	Full (N = 621)	Consumers (N = 516)	Producers (N = 105)
WTP Premium (%)			
Min.	-41.85	-41.85	-41.00
Max.	68.89	68.40	68.89
Mean (SD)	14.76	12.12	27.69
Sample Size (n)			
Min.	13	56	13
Max.	8,036	8,036	321
Mean	683.87	809.87	71.85
Baseline Price			
Min.	0.10	0.24	0.10
Max.	150.00	5.38	150.00
Mean	4.37	3.09	10.67
Year			
Min.	1999	1999	2013
Max.	2021	2021	2020
Mean	2012.04	2011.22	2016.07
Methods Indicators (Means)			
Collect	0.24	0.18	0.52
WTP in Dollars	0.88	0.86	1.00
Attributes Indicators (Means)			
Credence	0.32	0.36	0.15
Local	0.25	0.30	0.00
Organic	0.18	0.22	0.00
Processed	0.43	0.51	0.00

of the standard errors. Furthermore, When wild bootstrapped standard errors are used, the coefficients for $\sqrt{n}$ in the base models becomes significant at a 5 percent level (table 5). In the producer only model, the FAT null hypothesis is strongly rejected, with a negative correlation between sample size and WTPP. This is consistent with the presence of publication bias in this literature. The significance of this estimate for the producer only model is robust to the standard error specification, suggesting that statistically significant estimates are more likely to be selected for publication. In addition to identifying potential publication bias, including $\sqrt{n}$ in the regression specification also controls for any publication bias that varies systematically with the WTPP estimate's precision, removing this bias from the estimates of the other variables.

The estimate of the *producers* dummy variable in the base specification indicates that WTPP estimates are 18.67 percent higher when producers are studied, compared to consumers. This result is robust to controlling for differences in methods and product attributes, increasing only slightly to 21.17 percent in the full specification.

The majority of method and attribute variables are not significantly different from zero. In the full and producer only models, the data collection method did not impact the estimated WTPP. However, in the consumer only model, estimates collected by surveys had a 12.51 percent lower WTPP than estimates from in-person interviews. However, this estimate is only significant with bootstrapped standard errors.

In each specification an increase in the baseline price decreased the WTPP. In the full dataset, a \$1 increase in the baseline price would reduce the percentage willingness to pay by 0.12 percent. This result was similar for the producer only model with a 0.19 percent decrease in WTPP per dollar increase. It was larger for consumers, where a \$1 increase in the baseline price would decrease the WTPP by 4.49 percentage points, but this was not robust to standard error specification. Part of this sensitivity can be explained by the different ranges in baseline prices between producers and consumers. Consumer prices range from \$0.24 to \$5.38, while producer prices range from \$0.10 to \$150.

Table 4: Meta-Regression Results: Comparing alternative models

	Base	Full	Consumers	Producers
$\sqrt{n}$	0.16	0.28*	0.26*	−1.73*
	[−0.01; 0.33]	[0.11; 0.44]	[0.05; 0.48]	[−2.73; −0.74]
Producers	18.67*	21.17*		
	[7.17; 30.18]	[14.61; 27.73]		
Collect		−5.36	−12.51	0.57
		[−15.57; 4.86]	[−25.21; 0.19]	[−0.33; 1.47]
WTP in Dollars		5.44	5.58	
		[−8.52; 19.40]	[−12.38; 23.53]	
Benchmark		−0.12*	−4.49	−0.19*
		[−0.16; −0.09]	[−9.09; 0.11]	[−0.19; −0.19]
Credence		7.16	9.84	−21.76*
		[−2.99; 17.31]	[−3.74; 23.43]	[−21.95; −21.58]
Local		24.79*	28.39*	
		[11.35; 38.23]	[10.73; 46.06]	
Organic		7.15	10.06	
		[−4.00; 18.29]	[−4.58; 24.70]	
Processed		5.96	12.17	
		[−7.83; 19.76]	[−3.65; 27.99]	
FE	Year	Year	Year	Year
Clustered SE	Year, Paper	Year, Paper	Year, Paper	Year, Paper
Bootstrap SE	No	No	No	No
Adj. R^2	0.46	0.55	0.49	0.73
Num. obs.	615	615	510	105
F statistic	26.29	27.75	19.84	29.62

95% Confidence intervals. * Null hypothesis value outside the confidence interval.

In the full and consumer only models, the presence of a credence attribute had no significant impact on WTPP. On the other hand, the presence of this variable presence decreased WTPP for producers by 21.76 percentage points.

Finally, the presence of a local attribute increased WTP by 24.79 percentage points in the full model. When excluding producers, this effect increased to 28.39 percentage points. There was insufficient variation of this variable in the producer only sample so it was excluded from the producer only regression.

Discussion and Conclusion

For a new crop to be successfully adopted by consumers, it must first be adopted by its producers. This study aimed to identify whether producers' WTP for novel or hypothetical fruits and vegetables is different than for consumers. The results of our meta-regression analysis find that producers are, on average, willing to pay about 20 percent more for novel or hypothetical products. This result suggests that a product developer who estimates a consumer WTP high enough to justify developing the product, would, all else being equal, find producers also willing to adopt it. This makes intuitive sense since the producers may also capture a share of the potential returns to the new product. This finding is consistent with the meta-analysis by Olum et al. (2020), who found that agricultural producers generally have a high WTP for novel practices and technologies. However these results do not imply the converse; that is, if producers are likely to adopt the new product, it does not necessarily imply that consumers also will.

However, there are limitations to this result. The study of produce producer WTP is relatively new, and there are far fewer studies in this field. This led to a relative lack of variation or availability in many of the methodological and attribute variables that were available for consumer estimates, preventing these variables from being used as controls. Therefore, these results are not a direct apples to apples comparison, and could be improved as additional producer studies are published.

Moreover, the meta regression analysis found significant evidence consistent with publication bias in the producer studies, suggesting that studies with a significant result are more likely to be published and that the true producer willingness to pay may be lower than reported. The meta-regression analysis controls for the bias that is directly proportional to the square root of sample size, but the result would be more robust with an unbiased set of WTPP estimates.

The meta regression analysis also found systematic effects of method and product attributes that affected WTPP. Consumer estimates were approximately 14 percentage points higher when respondents answered a survey compared to an in person interview. On the other hand, the elicitation method had no measurable impact on producer answers. Consumers were willing to pay, on average, 30 percentage points more for locally grown produce. This is broadly consistent with the findings of Printezis et al. (2019), whose meta-regression analysis found an average 41 to 52 percentage point premium for local produce, animal, and processed foods. Furthermore, they found that WTP for produce is lower than for animal or processed foods.

An issue that may potentially confound the estimation of producers willingness to pay is the difference in decision making contexts between producers and consumers. *Ex post* studies of technological adoption have long been a mainstay of agricultural economics research, but our literature search shows that measuring produce producer valuation *ex ante* using stated preference methods is relatively new. These studies use established methods of measuring consumer preferences for novel food products. The approaches developed for *ex ante* evaluation of consumer purchase behavior, particularly for fruits and vegetables, center around small, routine purchases for final consumption—for example, the choice between alternative types of apples considered for a few moments at the grocery store. On the other hand, when producers consider adopting a new crop or process, they must choose from many more input combinations (such as cultivars, production systems, marketing channels) over a much longer horizon (at least a season). These decisions must be made in a context subject to substantial risk. A survey asking a producer to make this hypothetical decision in a short time-frame may not accurately reflect the decision they would make if they engaged in their normal decision making process. Without further study it is unclear if this would systematically bias producer WTPP estimates upwards or downwards, but it is likely that it would increase the variance of estimated WTPP, relative to consumers.

These results provide initial evidence that producers are systematically willing to pay a higher premium for novel or hypothetical produce compared to consumers. Despite the control variables used in the meta regression analysis, there still may be unobserved variable bias due to differences in the methods used for collecting data, the types of attributes studied, and the decision making context, preventing a apples to apples comparison between the two groups. A useful avenue for future research would be to survey producers and consumers directly about the same product.

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Author Contributions

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Conflict of Interest

The authors declare no conflicts of interest.

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A Regression Results

The results of the meta-regression analysis using wild bootstrap clustered standard errors is reported in table 5.

A.1 Diagnostics

A.1.1 Tests for Auto-Correlation

A Durbin-Watson test was conducted to determine if there was detectable auto-correlation in each of the models. For all but one specification, the test strongly rejected the null hypothesis of no auto-correlation (for each, the test statistic was $DW = 1$, with a p-value of $< 2e-16$). Thus, there is strong evidence for autocorrelation in our data. Only the specification for the producers subsample failed to reject the null hypothesis of no auto-correlation, with a test statistic of $DW = 2$ and a p-value of 0.8.

A.1.2 Tests for Heteroskedasticity

An F-Test was conducted to test for heteroskedasticity in the models White (1980).

These tests rejected the null hypothesis of homoskedasticity only for the base model and the model which included only the methods controls ($\alpha = 0.05$).

These tests rejected the null hypothesis of homoskedasticity for the base model, the model which included only the methods controls, and the full model which excluded organic and EA observations ($\alpha = 0.05$).

Table 5: Meta-Regression Results: Comparing alternative models with wild bootstrap standard errors

	Base	Full	Consumers	Producers
$\sqrt{n}$	0.16^{*}	0.28^{*}	0.26^{*}	-1.73^{*}
	$[0.01; 0.31]$	$[0.13; 0.43]$	$[0.11; 0.41]$	$[-2.37; -1.09]$
Producers	18.67^{*}	21.17^{*}		
	$[7.26; 30.09]$	$[9.66; 32.68]$		
Collect		-5.36	-12.51^{*}	0.57
		$[-11.59; 0.87]$	$[-22.08; -2.93]$	$[-0.10; 1.24]$
WTP in Dollars		5.44^{*}	5.58	
		$[0.12; 10.76]$	$[-2.55; 13.71]$	
Benchmark		-0.12	-4.49^{*}	-0.19^{*}
		$[-0.30; 0.06]$	$[-7.82; -1.16]$	$[-0.19; -0.19]$
Credence		7.16	9.84	-21.76^{*}
		$[-1.25; 15.56]$	$[-3.31; 23.00]$	$[-21.97; -21.56]$
Local		24.79^{*}	28.39^{*}	
		$[17.36; 32.23]$	$[12.51; 44.28]$	
Organic		7.15^{*}	10.06	
		$[1.83; 12.46]$	$[-5.32; 25.44]$	
Processed		5.96	12.17^{*}	
		$[-3.70; 15.63]$	$[4.06; 20.28]$	
FE	Year	Year	Year	Year
Clustered SE	Year, Paper	Year, Paper	Year, Paper	Year, Paper
Bootstrap SE	Wild	Wild	Wild	Wild
Adj. R^2	0.46	0.55	0.49	0.73
Num. obs.	615	615	510	105
F statistic	26.29	27.75	19.84	29.62

95% Confidence intervals. * Null hypothesis value outside the confidence interval.

Table 6: White Tests for Heteroskedasticity

Model	**Stastistic**	**p-Value**
Base	0.038	0.85
Full	2.83	0.09
Consumers	6.73	0.01
Producers	2.56	0.11

B Constructing the WTPP Estimate Dataset

B.1 Sample size

The sample sizes used to calculate the variable $\sqrt{n}$ represent the number of participants whose responses were used to calculate each WTP estimate. For example, Gallardo et al. (2015) calculate nine groups of market intermediaries' WTP for traits in the crops they handled: fresh apples, processed apples, fresh peaches in California, fresh peaches not in California, processed peaches, fresh sweet cherries, processed tart cherries, fresh strawberries, and processed strawberries. On the other hand, Silva et al. (2007) used different hypothetical and non-hypothetical experimental methods to capture WTP for grapefruits, resulting in four distinct subsamples.

In certain cases, sample size had to be imputed from the information given by the authors. Carroll et al. (2013) and Onken et al. (2011) reported purchasing 1,000 addresses for five states in the mid-Atlantic region (5,000 in total) as well as the number of these which were determined to be undeliverable (N = 339). Then, the response rate for each of the five states was reported, but each states' share of the undeliverables was not. Therefore, we assumed that the number of undeliverable addresses was equally distributed across the five states to calculate sample size.

Further, there were some observations for which sample size could not be determined. Hu et al. (2011) reported WTP for novel blueberry products for a subsample with two characteristics: aware of the health benenefits of blueberries and given an information treatment; however, while the number of respondents who belonged to each of these groups was reported, the number of individuals who belonged to *both* was not. Bond et al. (2008) conducted a factor and cluster analysis for crop attributes and reports WTP for four consumer clusters they identify; however, two of the estimates reported do not specify to which cluster they belong, and the remaining results are reported in bar graphs that could not be read with sufficient precision to extract WTP estimates. Thus, these estimates were excluded from the data set.

B.2 Merging

Because several papers were authored by the same scholars, WTP estimates were merged by title with the Zotero data by title. Non-WTP papers and papers with no WTP estimates that could be transformed into a percent premium were excluded from the new data set: Evans et al. (2017); Gifford and Bernard (2008); Govindasamy et al. (2018); Govindasamy and Italia (1998); Hamilton et al. (2003); Lagoudakis et al. (2020); Loureiro et al. (2001); Nelson et al. (2015); Yu et al. (2018); Yue et al. (2014b) and Yue et al. (2014a).

B.3 Calculating percentage WTP premium

B.3.1 Extracting Estimates

The WTP estimates in the new data set were taken from tables, figures, and text in the papers written. Every WTP estimate included in a paper (excluding duplicates) was added to an Excel database and tagged for product attributes, participant sub-sample, and experimental treatments/methods. Results were initially recorded exactly as reported in the paper (whether percent premium, total WTP, or marginal WTP). Then, benchmark prices were added as reported, and total WTP was calculated by combining the reported results with the benchmark price, and this calculation was sensitive to the type of result (i.e., a total WTP estimate was not added to the benchmark price the way a marginal WTP estimate would be).

B.3.2 Types of Benchmark Prices

The benchmark prices used in our database were primarily drawn from the papers themselves; however, there was no uniform procedure for reporting a baseline price against which other results were compared. As a result, our database has six types of benchmark prices.

Table 7: Benchmark Price Types

Constructed Market	No base price is given in the paper. External data was used to reconstruct the national market price during the year the study was conducted.
Given	In a choice scenario, the base price is set by the researchers, but this base price is varied across respondents or choice scenarios.
Market	A contemporary market price for the good is given in the paper. This can be how much consumers report spending on the good typically, prices given by market experts, or price data collected by a government agency such as the USDA.
Range Average	A discrete number of price levels are chosen for the price attribute, and the benchmark price is the average of these price levels.
Reference	The base price is set by researchers and is constant across all subjects and choice scenarios. Usually for experimental auctions, where the minimum bid is $0. The benchmark price is the average bid or responses given by participants.
Response Average	Usually for experimental auctions, where the minimum bid is $0. Then, the reference price is the average bid, or the average of responses given by participants.

B.3.3 Missing Benchmark Prices

Some studies reported results in dollars without reporting a benchmark price (Gallardo et al., 2015; Yue et al., 2017; Onozaka et al., 2006). In these instances, data from the USDA were used to to represent the national market price at the time data were collected (Service, 2022b,a, 2021).

B.3.4 Multiple Benchmark Prices

In two papers (Sackett et al., 2012; Schmit et al., 2013), conflicting candidate benchmark prices were offered in the paper. In both cases, both a market price and a response average were presented, but the response average was much lower than the market price. In Schmit et al. (2013), consumers reported typically spending an average pf $12.50 per bottle of wine, but the average bid was only $6.32. The authors attributed this mismatch to the experimental auction setting. Similarly, the prevailing market price for apples was $1.49 in 2010, when the data for Sackett et al. (2012) was collected; however, the average bid was only $0.28 due to the number of respondents who indicated the "No choice" option on the CBC survey instrument. In both cases, the average bid price was used to more accurately reflect changes in WTP within the context of each experiment.

C Tables

Table 8: Crops Studied in Included Papers

Apples*	Bananas	Blackberries*
Blueberries*	Broccoli	Cherries
Citrus	Cranberries	Fruits$^{*\circ}$
Grapefruits	Leaf Vegetables	Melons
Olives$^+$	Onions	Papayas
Peaches	Pears	Potatoes
Strawberries*	Sweet Corn	Tomatoes*
Vegetables$^{*\circ}$		

* Both fresh and processed versions of this crop were studied.

$^+$Only a processed version of this crop (olive oil) was examined.

$^\circ$ These terms were utilized by the studies' authors, though their meaning is inconsistent across studies. We utilize this term only where the authors have not provided a more specific description of the crops on which their study is focused.

Table 9: Papers Included in Sample

Paper	Year	Type	Crops	Group	Growing Method	Crop Type	Attributes	Study Type	Collect	Number of Measures	Measures
Blend and van Ravenswaay	1999	JA	Apples	C	O	P	Credence	CVM	C	2	D; PR
Bond et al.	2008	JA	Potatoes; melons	C	O	A	Local; credence; multiple crops	CVM	S	1	PP
Campbell et al.	2004	JA	Citrus	C	O	P	-	CA	I	0	-
Carpio and Isengildina-Massa	2010	JA	Fruits; vegetables	C	-	-	Local	CVM	S	2	E;PP
Carroll et al.	2013	JA	Tomatoes	C	O	A	Local; credence	CA	S	1	D
Chen et al.	2020	JA	Fruits; vegetables	P	-	-	-	CA	I	1	D
Chen et al.	2019	JA	Strawberries	C	-	A	Credence	CVM	S	1	D
Choi et al.	2018	JA	Apples	P	-	P	-	CA	S	1	D
Choi et al.	2017	JA	Strawberries	P	-	A	-	CA	S	1	D
Coffey et al.	2020	JA	Strawberries	P	-	A	Credence	CVM	I	1	D
Darby et al.	2008	JA	Strawberries	C	-	A	Local; credence	CA	I	1	D

Table 9: Papers Included in Sample

Paper	Year	Type	Crops	Group	Growing Method	Crop Type	Attributes	Study Type	Collect	Number of Measures	Measures
Ernst et al.	2006	JA	Strawberries	C	O	A	Local; credence	CA; CVM	I	1	D
Gallardo et al.	2015	JA	Apples; cherries; peaches; strawberries	P	-	A and P	Multiple Crops	CA	I	1	D
Gallardo and Wang	2013	JA	Apples; pears	P	C	P	Credence	CA	I	1	D
Gifford and Bernard	2008	JA	Potatoes; sweet corn	C	O and C	A	Credence	CVM; EA	I	1	PP
Govindasamy et al.	2018	JA	Fruits; grapes; vegetables	C	O	P	Multiple crops; Processed	CVM	S	1	PR
Govindasamy and Italia	1998	JA	Vegetables	C	O and C	-	Credence	CVM	I	1	PR
Hu et al.	2009	JA	Blueberries	C	-	P	Credence; processed	CA	I	1	D
Hu et al.	2011	JA	Blueberries	C	-	P	Processed	CVM	I	1	D

Table 9: Papers Included in Sample

Paper	Year	Type	Crops	Group	Growing Method	Crop Type	Attributes	Study Type	Collect	Number of Measures	Measures
Hu et al.	2021	JA	Citrus	C	C	P	Processed; credence	CA	S	2	D; PR
James et al.	2009	JA	Apples	C	O	P	Credence; local; processed	CA	S	1	D
Jones and Brown	2019	CP	Blueberries; citrus	C	C	P	Credence; processed	CA	S	1	PP
Li et al.	2020	JA	Peaches	P	-	P	Credence	CA	S	1	D
Li et al.	2020	JA	Strawberries	P	-	A	-	CA	S	1	D
Loureiro and Hine	2002	JA	Potatoes	C	O	A	Credence; local	CVM	I	1	D
Loureiro et al.	2001	JA	Apples	C	O	P	Credence	CA	I	1	PR
Loureiro et al.	2002	JA	Apples	C	-	P	Credence	CA; CVM	I	2	D; PR
Markosyan et al.	2009	JA	Apples	C	-	P	-	CVM	I	2	PP; PR
Meas et al.	2014	JA	Blackberries	C	O	P	Credence; local; processed	CA	S	1	D

Table 9: Papers Included in Sample

Paper	Year	Type	Crops	Group	Growing Method	Crop Type	Attributes	Study Type	Collect	Number of Measures	Measures
Oh et al.	2015	JA	Apples; grapes	C	-	P	Credence; multiple crops	CA	S	2	D; PP
Onken et al.	2011	JA	Strawberries	C	O	A	Local; processed	CA	S	2	D; PP
Onozaka et al.	2006	JA	Apples; bananas; leaf vegetables; broccoli	C	O and C	A and P	Credence; multiple crops	CA	S	2	D; PP
Sackett et al.	2012	CP	Apples	C	O	P	Credence; local	CA	S	1	D
Silva et al.	2007	JA	Grapefruits	C	-	P	-	CA ; EA	I	1	D
Silva et al.	2011	JA	Grapefruits	C	-	P	-	CVM ; EA	I	1	D
Teratanavat and Hooker	2006	JA	Tomatoes	C	-	A	Credence; processed	CA	-	S	1
D											
Thilmany et al.	2008	JA	Melons	C	-	A	Credence; local	CVM	S	1	PP
Vassalos et al.	2016	JA	Tomatoes	P	-	A	-	CA	S	2	D; PP

Table 9: Papers Included in Sample

Paper	Year	Type	Crops	Group	Growing Method	Crop Type	Attributes	Study Type	Collect	Number of Measures	Measures
Wang et al.	2017	JA	Strawberries	C	-	A	-	CA	S	1	PR
Xie et al.	2016	JA	Broccoli	C	O and C	A	Credence	CA	S	1	D
Yu et al.	2018	JA	Leaf vegetables	C	C	A	-	CVM	S	1	PR
Yue et al.	2007	JA	Apples	C	O	P	-	CA	I	1	D
Yue et al.	2017	JA	Apples; cherries; peaches; strawberries	P	-	A and P	Multiple Crops	CA	S	1	D
Zhao et al.	2017	JA	Peaches	P	-	P	-	CA	S	1	D

Abbreviations:

Column 3 (Type): JA = Journal Article, CP = Conference Paper, T = Thesis.

Column 5 (Group): C = Consumers, P = Producers.

Column 6 (Growing Method): - = Not Specified, O = Organic, C = Conventional.

Column 7 (Crop Type): A = Annual, P = Perennial.

Column 9 (Study Type): EA = Experimental Auction, CA = Conjoint Analysis, CVM = Contingent Valuation Method.

Column 10 (Data Collection): - = S = Survey, I = Interview.

Column 12 (Measures): D = Dollars, E = Elasticity, PP = Percent Premium, PR = Probability.