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Got Traceability? A Geographical-Price-Informed Choice Experiment Assessing Consumer Preferences for Blockchain-Verified Traceability in Cow's Milk

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Abstract

While blockchain technology holds the potential to provide verifiable food traceability, its adoption in supply chains hinges on its profitability. We test a geographical-price-informed choice experiment design to estimate U.S. consumer willingness to pay for quick-response (QR) codes that lead to blockchain-verified traceability information on cow's milk packaging. We find that consumers are willing to pay a premium of $0.61 per half-gallon carton with QR codes relative to no QR code, but apply a discount of $0.13 when blockchain verification is added. Preferences vary based on consumers' frequency of QR code usage following the COVID-19 pandemic.

Keywords: COVID-19, distributed ledger technology, quick response code, stated preferences, willingness to pay

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Introduction

Food traceability is "the ability to follow the movement of a food product and its ingredients through all steps in the supply chain (FDA, 2024)." Traceability of food products is especially important for responsiveness and accountability in the event of food safety incidents. The United States Centers for Disease Control and Prevention (CDC) estimates that 48 million people get sick and 3,000 people die from foodborne illnesses annually in the United States (CDC, 2024). A robust traceability system can help prevent foodborne illness outbreaks by enabling the rapid identification and containment of contamination sources. Beyond safety, traceability has become increasingly important to consumers, who are demanding greater transparency about food origins, company values, and agricultural production practices, particularly those associated with credence attributes, which cannot be directly verified by consumers and are therefore more susceptible to food fraud. Statistics on internet search and purchasing trends over the past decade show growing consumer interest in sustainability certifications and alternative production practices, with internet searches for sustainable goods increasing 71% from 2016 to 2020, and sales for carbon-labeled products growing from $1.7 billion in 2020 to $3.4 billion in 2021 (Kerle, 2021). Additionally, organic sales in the United States grew by an average of 8% each year over the past decade (USDA-ERS, 2025).

A technology that could modernize food traceability is blockchain, which has been identified as a tool to assist with managing foodborne illness outbreaks, reducing massive inventory losses, and combating inauthentic labeling (Casino et al., 2021; Croft, 2021; Manning and Kowalska, 2021). Blockchain is a distributed digital ledger technology, a shared database accessible to all network participants. All parties involved must agree on the accuracy of information before it can be added to the database as a record, also called a block. When an error is corrected or information is changed, these changes are logged as a new block appended to the existing chain rather than replacing a previous block (Gao, Hatcher, and Yu, 2018). Unlike applications of blockchain in finance, which typically use decentralized systems, food and agriculture companies use more centralized blockchain-based traceability enterprise systems (Collart and Canales, 2022). Blockchain-based traceability applications are being used primarily for food safety purposes in the United States. For example, Walmart collaborated with IBM to implement a blockchain-based system that tracks leafy greens throughout the supply chain and aims to allow faster identification of sources of foodborne illness outbreaks (Walmart, 2021).

One consumer-facing application of blockchain-based traceability is the use of quick response (QR) codes on product packaging. Several companies, including Nestlé, Carrefour, Folgers, and Starbucks, have begun providing blockchain-verified traceability information to consumers via QR codes (Collart and Canales, 2022). Notably, consumers can also access nonverified traceability information via QR codes linked to standard (non-blockchain) traceability systems. However, by combining blockchain's security features and traceability systems with access to information via QR codes, consumers could view relevant product information, such as food origin, supply chain journey, company values, verified organic certification, carbon footprint certificates, or other production practices disclosures. In terms of food safety, blockchain-enabled traceability systems would allow companies to quickly notify consumers of foodborne illness outbreaks or product recalls via QR codes, a feature that some blockchain-based traceability companies, such as IDLocate in New Zealand, already offer. While companies expect consumers to utilize and value QR codes on their products, only a few studies have examined consumer preferences and willingness to pay (WTP) for both QR code traceability and blockchain technology, particularly in the context of beef (Lin et al., 2022; Shew et al., 2022). Understanding whether consumers are willing to pay a price premium for these technologies can help supply chain stakeholders examine the economic viability of their adoption.

The onset of the COVID-19 pandemic heightened concerns about food safety, as supply chain disruptions, labor shortages, and transportation challenges hindered the procurement of safe food products and packaging (Trmčić et al., 2021). The pandemic also reinforced the connection between how food is accessed and technology, with restaurants adopting QR code menus and payment methods. In response to the need for contactless methods of payment and health information dissemination during the pandemic, QR code usage emerged as a touchless way to provide and acquire information, and they have since become more widely used in a variety of settings (Iskender et al., 2022; Tu et al., 2022; Goggin and Wilken, 2024). Overall, the pandemic highlighted the importance of modernizing the food industry, supply chains, and food traceability, and may have impacted the frequency with which consumers use technologies like QR codes (Segovia, Grashuis, and Skevas, 2022).

In this study, we use two discrete choice experiments (DCEs) to investigate consumer preferences and WTP for QR codes that provide blockchain-based traceability information for fluid cow's milk. We study bovine milk—specifically cow's milk—for four main reasons. First, while fluid cow's milk consumption has steadily declined since the 1940s, it remains a staple in American households, with 92% of households purchasing it in 2017 (Stewart et al., 2020) and overall dairy consumption increasing through the consumption of milk solids. We use the term "cow's milk" to denote milk originating from *Bos taurus* cattle, the predominant breed used for milk production in the United States. Second, recent studies are exploring how blockchain technology can enhance dairy supply chains. Studies have suggested potential effectiveness in detecting food fraud, reducing costs, decreasing traceability time, and improving overall product quality (Casino et al., 2021; Leung, Chapman, and Fadhel, 2021). Third, the traceability of cow's milk has gained attention due to the multistate outbreak of Highly Pathogenic Avian Influenza (HPAI) A(H5N1), or "bird flu," among dairy cows and the first mammal-to-human transmission in April 2024 (CDC, 2024). As of May 27, 2025, there have been 1,072 dairy herd outbreaks across 17 states and 70 human cases linked to contact with infected animals (CDC, 2025). While pasteurized milk is considered safe (FDA, 2025) and milk-related foodborne illness is much less common than in high-risk foods like leafy greens, eggs, and raw meat, foodborne illness incidents have occurred—174 cases and 17 deaths were linked to pasteurized milk between 2007 and 2020 (Sebastianski et al., 2022). Traceability improvements could help prevent these incidents and further enhance safety, for example, by tracking raw milk, aged raw milk cheeses, and cold chain integrity. Despite FDA warnings, consumer demand for raw milk is rising (Lando et al., 2022), and ongoing public health concerns remain regarding raw milk and aged raw milk cheeses. While laboratory research methods differ from commercial pasteurization, which the FDA confirms inactivates the virus, recent research indicates that some heat treatments can reduce HPAI A(H5N1) load but may not fully inactivate it (Guan et al., 2024), and that aging of raw milk cheeses, which can legally cross state lines, may not be sufficient to eliminate viable virus (FDA, 2025). Additionally, monitoring temperature control throughout the cold chain is critical for both pasteurized and raw milk. For example, HPAI A(H5N1) has been shown to remain infectious for several weeks in raw milk stored at 4°C (Guan et al., 2024). Fourth, consumer demand for transparency is growing, particularly regarding organic production and carbon footprint claims in high-emission animal-based foods. Enhanced traceability can help verify these credence attributes and build consumer trust.

With growing interest in digital food traceability there is a need for research on consumer and producer preferences to evaluate the economic viability of blockchain technology as a means to modernize the dairy supply chain. To date, few studies have focused on dairy products in this context (Li et al., 2023; Tran et al., 2024). We seek to fill this gap. Our first objective is to estimate consumer preferences and willingness to pay for QR codes that provide access to standard or blockchain-verified traceability information, carbon footprint reduction labels, and organic labels in cow's milk. We hypothesize that consumers will prefer products with QR codes that provide access to traceability information over products without traceability codes. While we are not aware of other studies evaluating consumer WTP for the provision of blockchain-verified information via QR codes on milk products, studies have been conducted for other commodities. Shew et al. (2022) found that consumers placed little additional value on beef products using blockchain for supply chain traceability. In contrast, Lin et al. (2022) found that consumers in China were willing to pay an additional $0.63 per pound for beef that used blockchain traceability over beef that used alternative traceability methods. Although Lin et al. (2023) did not calculate WTP, they found that consumers in China preferred organic milk with blockchain traceability over organic milk with other forms of traceability. More similar to our study, Tran et al. (2024) found that consumers in Greece were willing to pay an additional €0.755 ($0.79) for QR codes on feta cheese and €0.264 ($0.28) for the use of blockchain technology to trace feta products throughout the supply chain.

Our second objective is to evaluate whether and how a novel DCE design with geographically informed price levels that account for geographical differences in prices across U.S. states affects food choice behavior in U.S. consumers. In the geographical-price-informed DCE design, U.S. regions (Northeast, Southeast, Midwest, South Central, Southwest, Northwest, and Alaska) are first classified as either high cost or low cost based on whether the average retail price in the region is higher or lower than the average national retail price. Then, a respondent's state of residence determines the price levels they see in the DCE, *ceteris paribus*. That is, respondents residing in states within high-cost regions are shown higher price levels, whereas those in low-cost regions see lower price levels, aiming to reflect the retail pricing patterns of their respective regions. We hypothesize that this geographically price-informed DCE design will provide a better model fit than a standard DCE design, in which price levels are commonly distributed to encompass the full range of existing prices in the United States. This objective investigates a common challenge when conducting choice experiments: selecting a price range that accurately reflects the market prices for a product (Aravena, Martinsson, and Scarpa, 2014; Contini et al., 2019; Caputo and Scarpa, 2022). Previous studies have found that differing price vectors in DCEs can yield different outcomes (Carlsson and Martinsson, 2008; Aravena, Martinsson, and Scarpa, 2014; Caputo, Lusk, and Nayga, 2018; Contini et al., 2019; Kilders and Caputo, 2023). Furthermore, prices fluctuate over time and across space, impacting consumers' reference prices, which they use to compare the prices presented to them in a DCE, thereby influencing their choices (Caputo, Lusk, and Nayga, 2018). Consumers' reference prices and the prices they might pay in the real world can differ, leading to inaccurate WTP estimates (Lim and Wuyang, 2023). This issue highlights the need for more research into alternative price vector designs, such as our geographical-price-informed design, which better align with consumers' reference prices. We build upon a recent study that evaluated a reference-price-informed DCE design and found that it resulted in more conservative estimates and better model fit than the standard price-vector design (Kilders and Caputo, 2023). In this study, the researchers compared each respondent's self-reported reference price to the average of the price levels used in the experiment (i.e., $20.49 per lb. of ribeye steak) to determine whether respondents in the reference-price-informed design saw higher or lower price levels in the DCE. We propose using a geographical-price-informed design that reflects the different price levels consumers are likely to encounter in their respective regions in the United States, accounting this way for price differences across locations.

Methodology

Survey and Discrete Choice Experiment (DCE) Designs

Following approval from the university Institutional Review Board (Protocol #IRB2023-0841), we developed and administered two online surveys in December 2023 using Qualtrics Research Services, a consumer research panel company. Both surveys included unlabeled DCEs to evaluate consumer preferences for cow's milk. The first survey included a standard DCE design covering a range of prices representative of the whole United States market. The second survey implemented our geographical-price-informed DCE design, where the price range shown to participants was tailored based on their regional location. A total of 557 responses were collected for the survey with the standard DCE design, while 554 responses were collected for the survey with the geographical-price-informed DCE design, for a combined sample size of 1,111 respondents.

Each survey included five sections. The first section consisted of screening and demographic questions. To participate, respondents were required to commit to providing quality answers, be over the age of 18, reside in the United States, be the primary grocery shopper for their household, own a device capable of scanning QR codes (e.g., a smartphone, tablet, or iPod touch), and have purchased cow's milk within the past month. To ensure that our sample was representative of the U.S. population, we established quotas for age, gender, and race. In the second section, respondents were asked about their knowledge of carbon footprint labeling, QR codes, agriculture, and blockchain technology. This section also included information about blockchain technology and QR codes (see Figures A1 and A2 in Appendix), along with the option for respondents to click a link and view an example website illustrating product information to simulate the experience of scanning a QR code on an actual product (see Figure A3 in Appendix). The third section provided information about the choice experiment and descriptions of the different product labels respondents might see during the choice experiment. The fourth section included the DCE. The fifth and final section included questions to gather information on respondents' household consumption of cow's milk, concern for the environment, and frequency of QR code usage before and after the COVID-19 pandemic. This section also inquired about the level of trust in the United States Department of Agriculture (USDA) and third-party verification companies to accurately verify organic and carbon footprint claims. We also gathered sociodemographic information, including income, marital status, political leaning, education level, and employment status.

Before distribution, we pretested each survey instrument. A "speed check" threshold, equal to half the median completion time during pretesting, was implemented in the final version of the survey. We excluded respondents who completed the survey faster than this threshold from the final sample. We also implemented additional measures to ensure response quality. Survey sections that required respondents to read information had a delay before the "submit" button would appear to ensure that respondents could not click through those sections without spending time on each page. Additionally, we included an attention-check question in the DCE section that dropped respondents who failed to read the entire question and answer as instructed to ensure respondents were carefully considering the choice sets and not rushing through them. Lastly, we included a cheap talk script before our DCE to mitigate hypothetical bias (Lusk, 2003; Carlsson, Frykblom, and Lagerkvist, 2005; Fang et al., 2020).

Table 1 outlines the attributes and attribute levels used in our DCEs, which include QR code information, organic status, carbon footprint label, and price. The QR code attribute had three levels: (i) No QR code: the product has no QR code and no access to product traceability information, (ii) Standard QR code: the product has a standard QR code that provides traceability information, and (iii) Blockchain QR code: the product has a blockchain-verified QR code providing traceability information tracked through blockchain technology. In both surveys, respondents were shown examples of the product information accessible via these QR codes, including food tracing information about the product's journey from the farm to the store and, when applicable, copies of the product's organic certificate and carbon footprint claim certificate.

There were two levels for the organic status attribute: (i) USDA organic label and (ii) No USDA organic label. For the carbon footprint label, we used five levels. The first three levels correspond to newly released labels from The Carbon Trust, a nonprofit organization that launched the world's first carbon footprint label in 2007 (Carbon Trust, 2023), whereas the fourth level represents a USDA label. The carbon footprint attribute levels are as follows: (i) Carbon Emissions Reduction Achieved: This label indicates the product's carbon footprint has decreased from one year to the next, with the manufacturer's commitment to future reductions, (ii) Carbon Emissions Reduction Planned: This label indicates that the manufacturer has a carbon management plan to reduce the product's carbon footprint, (iii) Footprint Lower Than Market: This label indicates that the product's carbon footprint is at least 5% lower than the market average for equivalent products, (iv) USDA Process Verified Climate-Friendly: This label indicates that the product's carbon footprint is at least 10% lower than an industry benchmark, and (v) No carbon footprint label.

We used weekly data from the USDA Agricultural Marketing Service's National Retail Reports on Dairy (USDA-AMS, 2023), available at the national and regional levels, to obtain average retail prices for half-gallon containers of cow's milk during October 2023. In the geographical-price-informed DCE design, seven U.S. regions—Northeast, Southeast, Midwest, South Central, Southwest, Northwest, and Alaska—were first classified as either high cost or low cost based on whether their average regional retail price exceeds or falls below the average national retail price. Then, respondents were shown price levels in the DCE based on their stated current state of residence. Specifically, respondents residing in states within high-cost regions where the average retail price exceeded the average national retail price were shown a DCE with price levels ranging from $2.29 to $5.79, in $0.70 increments. Respondents residing in states within low-cost regions where the average price fell below the average national retail price saw a DCE with price levels ranging from $1.79 to $4.29, in $0.50 increments. Figure A4 and Table A3 in the Appendix illustrate the high-cost and low-cost regional classifications and the states included in each. The only difference between the geographical-price-informed and standard DCE designs was the price levels presented to respondents. In the standard DCE design, all respondents, regardless of location, saw uniform price levels ranging from $1.79 to $5.79, in $0.80 increments.

The selection of price ranges across all DCE designs was informed by the distribution of national and regional prices for conventional and organic cow's milk, as well as the behavioral pricing strategy of 9-ending prices (Snir and Levy, 2020). Moreover, following the approach of Kilders and Caputo (2023), the experimental design was structured to better reflect U.S. market conditions, where animal-based food products with lower carbon footprint or organic labels are generally less available and priced higher than conventional options. In our study, if the product had a carbon label (Carbon Trust or USDA Process Verified Climate-Friendly) or a USDA organic label, its price was drawn from the upper end of the price distribution: $3.39 to $5.79 in the standard DCE, $3.69 to $5.79 in high-cost regions, and $2.79 to $4.29 in low-cost regions. Conversely, if the product did not have either label, its price was drawn from the lower end of the price distribution: $1.79 to $4.19 in the standard DCE, $2.29 to $4.39 in high-cost regions, and $1.79 to $3.29 in low-cost regions.

Table 1. Attributes and Levels

Attribute	Level
QR code information	No QR code Standard QR code* Blockchain QR Code
USDA organic label	No USDA organic label* USDA organic label
Carbon footprint label	Carbon footprint reduction achieved label Carbon footprint reduction planned label Carbon footprint lower than market label USDA process verified climate-friendly label No carbon footprint label*

Table 1 (cont.)

Attribute	Level
Price	\$1.79, \$2.59, \$3.39, \$4.19, \$4.99, and \$5.79 if United States \$1.79, \$2.29, \$2.79, \$3.29, \$3.79, \$4.29 if low-cost state \$2.29, \$2.99, \$3.69, \$4.39, \$5.09, \$5.79 if high-cost state

Note: *Represents a reference level in the experimental design.

We generated a fractional factorial efficient experimental design in Ngene 1.3.0 by ChoiceMetrics to identify the optimal combination of attribute levels in our DCEs. The final experimental design consisted of 30 choice sets, each containing three alternatives and a no-purchase option, and assigned into five blocks. Each respondent was randomly sorted into one of the five blocks and answered six choice sets. In addition to the aforementioned attention-check question, which always appeared after the third choice set, we randomized the six choice sets in each block to eliminate ordering effects. Figure 1 shows an example of a choice set.

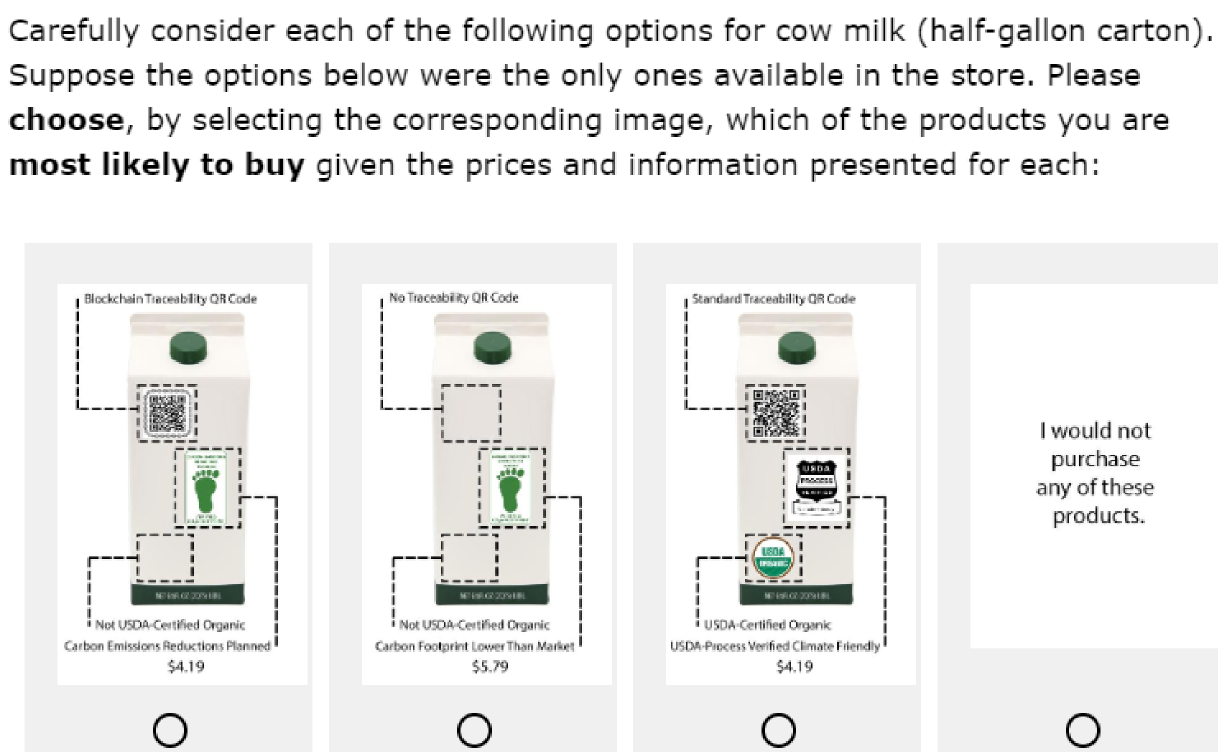

Figure 1. Example DCE Choice Set for the Cow's Milk Survey

Theoretical Framework and Econometric Model

We use two DCEs to elicit consumers' WTP for cow's milk. A DCE is a stated preference method based on the assumption that respondents are rational individuals who make tradeoffs between different product attributes when choosing the product that gives them the greatest utility. DCEs are commonly used to elicit consumer preferences and WTP for products featuring various attributes (Alpiza, Carlsson, and Martinsson, 2001; Louviere, Flynn, and Carson, 2010; Holmes, Adamowicz, and Carlsson, 2017). WTP represents the maximum amount a consumer is willing to pay to purchase a product.

DCEs are based on Random Utility Theory, which posits that a decision maker, or respondent, will choose an alternative from the available choice set only if they expect to derive more utility from that specific alternative than the other alternatives presented (McFadden, 1974). While respondents know the utility they derive from the alternative, we observe which alternative they selected from the choice set. As a result, we have incomplete information about the respondent's utility, and the observed utility is referred to as representative utility. The respondent's utility function (U_{ijt}) can then be modeled as the sum of representative utility (V_{ijt}), which captures preferences for the alternatives and their respective attribute levels, and an error term (e_{ijt}), which captures the unobserved factors influencing the respondent's utility, such that:

$$U_{ijt} = V_{ijt} + e_{ijt} \tag{1}$$

where $U_{ijt}$is the utility derived by each respondent *i* when choosing option *j* out of the three product alternatives or a no-buy option evaluated in each choice set *t*. The observed component of the utility can be expressed as $V_{ijt} = \beta X_{ijt}$, where X_{ijt} is a vector of observed product attributes (i.e., QR code information, organic certification label, carbon footprint label, price), and β represents a vector of unknown utility coefficients to be estimated.

To relax the restrictive assumptions of the conditional logit model and allow for heterogeneity in preferences, we utilize the mixed logit model, which treats parameters as random instead of fixed, such that parameters are distributed randomly across respondents and $\beta_i = \beta_0 + \sigma v_i$, where β_0 is the population mean, $v_i \sim N(0,1)$, and σ is the standard deviation of the distribution of β_i. We report a main effects model along with a model incorporating interactions (equation 2) to investigate whether consumer preferences for QR code traceability vary depending on respondents' frequency of scanning QR codes following the COVID-19 pandemic:

$$\begin{aligned} U_{ijt} = {} & \beta_p Price_{ijt} + \beta_{ACS} NoBuy_{it} + \beta_1 Organic_{ijt} + \beta_2 BlockchainQR_{ijt} + \\ & \beta_3 NoQR_{ijt} + \beta_4 (BlockchainQR_{ijt} \times QRPostCOVID_i) + \beta_5 (NoQR_{ijt} \times QRPostCOVID_i) + \\ & \beta_6 CarbonReduc_{ijt} + \beta_7 CarbonPlan_{ijt}(1) + \beta_8 CarbonLowerThan_{ijt} + \\ & \beta_9 USDAClimate_{ijt} + \varepsilon_{ijt.} \end{aligned} \tag{2}$$

$Organic$ denotes a dummy variable equal to 1 if a product carried the USDA organic label and 0 otherwise. $CarbonReduc$ is a dummy variable equal to 1 if a product carries the Carbon Emissions Reductions Achieved Label from the Carbon Trust and 0 otherwise. Similarly, $CarbonPlan$ and $CarbonLowerThan$ are dummies equal to 1 if a product carried the Carbon Emissions Reduction Planned or Footprint Lower Than Market labels from the Carbon Trust, respectively, and 0 otherwise. $USDAClimate$ is a dummy equal to 1 if the product carried the

USDA process-verified climate-friendly label and 0 otherwise. $BlockchainQR \times QRPostCOVID$ is an interaction term between $BlockchainQR$, which is a dummy equal to 1 if a product has a blockchain QR code and 0 otherwise, and $QRPostCOVID$, which is a respondent-specific dummy equal to 1 if the respondent indicated that they scanned QR codes more frequently following the COVID-19 pandemic and 0 otherwise. Similarly, $NoQR \times QRPostCOVID$ is an interaction term between $QRPostCOVID$ and $NoQR$. The latter is a dummy equal to 1 if a product has no QR code and 0 otherwise. Consumer preferences for $BlockchainQR$ and $NoQR$ are evaluated relative to a standard (non-blockchain) traceability QR code. $Price$ is a continuous variable, and *NoBuy* is an alternative-specific constant that equals 1 if the respondent chose not to buy any of the three product alternatives and 0 otherwise. We assume that the $Price$ variable has a fixed distribution, whereas all other variables, including the interactions, are assumed to have normal random distributions.

Marginal Willingness-to-Pay

To estimate the marginal WTP (MWTP) for attribute k, we calculate the ratio of that attribute's estimated coefficient to the price coefficient, as shown below:

$$Marginal\, WTP = \frac{-\beta_k}{\beta_p} \tag{3}$$

Additionally, for attributes where the mean of the preference parameter varies based on respondents' frequency of QR code use (through the inclusion of an interaction term), the equation for MWTP incorporates both the estimated coefficient of the main effect and the coefficient of the interaction term. For example, the MWTP for blockchain technology in equation (2) would be calculated as -$(\beta_2 + \beta_4)$)/ β_p for respondents who are more likely to scan QR codes after the COVID-19 pandemic (i.e., $QRPostCOVID$ = 1) and -(β_2)/ β_p for those who are not more likely to scan QR codes post-pandemic (i.e., $QRPostCOVID$ = 0).

To estimate our mixed logit model, we used the mixlogit command in StataSE 18 with 2,000 Halton draws. We clustered the standard errors at the respondent level (Abadie et al., 2023), as the same respondents evaluated repeated choice sets. Hence, the unobserved utility for each individual's choice between one set of alternatives is likely correlated with their choices in other sets. We calculate confidence intervals for the MWTP estimates using the Krinsky and Robb procedure (Krinsky and Robb, 1986, 1990).

Results and Discussion

Sample Description

Table 2 provides a summary of the sociodemographic characteristics of our survey samples compared to the general U.S. population, as reported in the American Community Survey (U.S. Census Bureau, 2022). Overall, the samples are representative of the U.S. population in terms of gender, marital status, and employment. Approximately 50% of respondents in both surveys reported being male and 50% being female, equivalent to the gender distribution in the U.S. population. Results from one sample *t*-test indicates that the means for gender, marital status, and part/full-time employment variables in both the standard DCE and geographical-price-informed DCE groups are statistically equal to the U.S. population means. The samples are also representative in terms of the 18–24 age group and the $34,999 or less income group, with no statistical difference between sample and U.S. population means. The average respondent age in the standard DCE survey was approximately 47 years and 48 years in the geographical-price-informed DCE survey, compared to the U.S. population's average age of 38.5 years in 2022. The higher average age of respondents in our samples is likely due to the inclusion criteria requiring respondents to be 18 years or older. We used county-level Rural-Urban Continuum Codes as defined by the USDA Economic Research Service to determine what percentage of our sample of respondents resides in rural (nonmetro) versus urban (metro) areas. Approximately 12% of respondents in the standard DCE survey sample and 14% in the geographical-price-informed DCE survey sample reside in counties classified as rural, compared to 20% of the U.S. population (U.S. Census Bureau, 2022). Lastly, we collected data on respondents' purchase frequency. As required by our screening criteria, all participants in the completed sample reported purchasing cow's milk within the past month. Among them, 73% reported buying conventional (nonorganic) cow's milk at least once per month, whereas 42% indicated purchasing organic cow's milk at the same frequency.

Econometric Models and DCE Designs

The mixed logit estimation results for both the standard DCE and the geographical-price-informed DCE, with main effects and interactions, are reported in Table 3. Across all models, the coefficient for the *Price* variable is negative and statistically significant, as expected. Similarly, the coefficient for the *NoBuy* variable is also negative and significant across all models, suggesting that respondents generally preferred selecting a product over the option not to buy. However, results also indicate significant heterogeneity in respondents' preferences for the no-buy option. Our results confirm the hypothesis that the geographical price-informed DCE improves model fit compared to the standard DCE. The geographical price-informed DCE, which tailored the range of prices shown to respondents to reflect the prices they were more likely to encounter in their state of residence, resulted in a lower AIC and BIC and a higher log likelihood compared to the standard DCE, which used a uniform price range across the entire United States. We find the same increase in model fit across all measures when conducting a preliminary analysis using the Conditional Logit Model (see Table A1 in Appendix). Previous literature shows that reducing price uncertainty improves model fit and enhances the precision of the estimation results (Lim and Wuyang, 2022; Kilders and Caputo, 2023). Consistent with findings by Kilders and Caputo (2023), our results indicate that model fit improves when the DCE design is informed by price vectors that are more closely aligned with respondents' price expectations.

Table 2. Summary Statistics and Variable Definitions

Variable	Definition	Standard DCE	Geographical-Price-Informed DCE	USA[a]
		Mean		
Age	Age 18–24	0.11	0.09	0.09
	Age 25–34	0.19	0.18	0.14
	Age 35–44	0.17	0.15	0.13
	Age 45–54	0.16	0.17	0.12
	Age 55–64	0.17	0.19	0.13
	Age 65 or older	0.21	0.21	0.17
Gender[b]	Female	0.49	0.50	0.50
	Male	0.50	0.50	0.50
Ethnicity	Hispanic or Latino (of any race)	0.09	0.08	0.19
	Not Hispanic or Latino	0.91	0.92	0.81
Race identity	White or Caucasian	0.74	0.74	0.66
	Black or African American	0.13	0.18	0.12
	Another or multiple races	0.13	0.09	0.22
Educational attainment	High school degree or less	0.26	0.26	0.57
	Two-year or associate's degree	0.24	0.23	0.09
	Four-year college or bachelor's degree	0.35	0.35	0.21
	M.S. or doctoral degree	0.15	0.16	0.13
Household size[d]	# of persons per household	2.51	2.48	2.35
Children[d]	# of < 18-year-old persons per household	0.62	0.59	0.52
Yearly household income before taxes	$34,999 or less	0.22	0.23	0.23
	$35,000 to $74,999	0.38	0.36	0.27
	$75,000 to $99,999	0.16	0.18	0.13
	$100,000 to $149,999	0.14	0.13	0.17
	$150,000 or more	0.09	0.10	0.20

Table 2 (cont.)

Variable	**Definition**	**Standard DCE**	**Geographical-Price-Informed DCE**	**USA[a]**
		Mean		
Employment[e]	Part-time or full-time employed	0.61	0.60	0.60
	Unemployed	0.13	0.12	0.03
	Stay at home parent or retired	0.27	0.28	0.37
Marital status	Married	0.45	0.45	0.48
	Not married	0.55	0.55	0.52
Number of respondents		557	554	

Notes:
[a]Source: 2022 American Community Survey (ACS) 5-year estimates
[b]U.S. statistics for grocery shoppers ≥ 18 years old
[c]U.S. statistics for population ≥ 25 years old
[d]U.S. statistics calculated as variable's total population divided by total housing units
[e]U.S. statistics for population ≥ 16 years old. Employment categories in the ASC are: employed civilian or armed forces in labor force, and not in labor force.
Results of one sample *t*-tests indicate that the means for the gender, marital status, part/full-time employment variables in each group (standard DCE or geographical-price-informed DCE) are statistically equal to the means for those variables in the U.S. population. The means for variables indicating "Age 18–24" and "Income $34,999 or Less" in both groups are also statistically equal to the means in the U.S. population.

Table 3. Mixed Logit Estimation Results

	Standard DCE				Geographical-Price-Informed DCE			
	Main Effects		Interactions		Main Effects		Interactions	
	Parameter	Clust. SE	Parameter	Clust. SE	Parameter	Clust. SE	Parameter	Clust. SE
Organic	1.176***	0.123	2.017***	0.726	1.176***	0.137	1.544***	0.216
Blockchain	-0.078	0.080	-0.648	0.405	-0.158**	0.075	-0.570***	0.132
No traceability QR code	-0.740***	0.105	-0.941***	0.289	-0.726***	0.096	-0.708***	0.154
Blockchain × post-COVID			0.521	0.398			0.405*	0.230
No QR code × post-COVID			-2.214*	0.978			-1.104**	0.439
Carbon reduction achieved	0.741***	0.165	1.536***	0.428	0.613***	0.159	0.737***	0.204
Carbon reduction planned	0.791***	0.097	1.307***	0.392	0.636***	0.097	0.830***	0.137
Carbon lower than market	1.141***	0.115	2.074***	0.794	0.851***	0.106	1.114***	0.152
USDA climate-friendly	1.029***	0.099	1.936***	0.718	0.805***	0.098	1.108***	0.148
Price	-1.061***	0.075	-1.850***	0.632	-1.191***	0.115	-1.630***	0.204
No-buy	-4.036***	0.864	-11.781***	4.404	-6.343***	1.328	-9.653***	2.210
SD of random parameters								
Organic	1.326***	0.283	1.614**	0.773	1.352***	0.387	1.510***	0.479
Blockchain	0.011	0.010	1.275	1.115	-0.000	0.015	0.032	0.061
No QR code	0.012	0.034	-0.142	0.231	-0.011	0.027	-0.026	0.134
Blockchain × post-COVID			3.190***	1.125			2.450***	0.657
No QR code × post-COVID			4.973***	1.828			2.705***	0.720
Carbon reduction achieved	1.476***	0.410	2.011	1.324	-1.375**	0.558	-1.973***	0.653
Carbon reduction planned	-0.003	0.038	1.006	1.354	0.001	0.007	0.006	0.036
Carbon lower than market	0.005	0.011	-0.037	0.053	0.005	0.065	0.043	0.082
USDA climate-friendly	-0.000	0.063	0.049	0.092	-0.087	0.243	-0.038	0.147
No-buy	0.759	1.809	7.554**	3.117	2.572**	1.141	4.559***	1.618
No. of respondents (n)	557		557		554		554	
Log-likelihood	-3,687.275		-3,627.099		-3,654.103		-3,614.467	
AIC	7,408.551		7,296.197		7,342.206		7,270.934	
BIC	7,536.061		7,453.71		7,469.625		7,428.334	

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Consumer Preferences for QR Code Traceability

In Table 4, we report MWTP estimates for cow's milk attributes in U.S. dollars per half-gallon carton. Overall, we find that while consumers value access to traceability information via standard (non-blockchain) QR codes, they discount or do not have strong preferences for blockchain traceability QR codes over standard traceability QR codes. In the main effects models, consumers in both DCE designs strongly prefer products with standard QR code traceability over those without any traceability QR codes. However, the parameter for blockchain QR codes was not significant in the standard DCE design, whereas in the geographical-price-informed DCE design, consumers preferred products with standard QR codes over those with blockchain QR codes. Specifically, we find a price premium of $0.70 in the standard DCE design for a half gallon of cow's milk with a standard (non-blockchain) QR code relative to a carton with no QR code. This premium is $0.61 in the geographical-price-informed DCE design. In contrast, we find a price discount of $0.13 in the geographical-price-informed DCE design for a carton with a QR code providing access to blockchain-verified traceability information relative to one with no blockchain verification.

In the models incorporating interaction terms, we included the variable $QRPostCOVID$ to account for the potential effect of changes in the frequency of QR code usage following the COVID-19 pandemic. When asked about their QR code usage, 51% of respondents in the standard DCE design group and 53% of respondents in the geographical-price-informed DCE design reported scanning QR codes more frequently following the pandemic than they did before. We find that consumers preferred products with QR codes with access to standard traceability information over products without QR codes, regardless of whether or not their frequency of scanning QR codes changed following the pandemic. The price premiums associated with a standard traceability QR code among respondents who did not report increased QR code usage after COVID-19 was $0.52 in the standard DCE design and $0.44 in the geographical-price-informed DCE design. In contrast, respondents who indicated more frequent QR code scanning after the pandemic had notably higher premiums, valuing standard QR codes at $1.74 in the standard DCE design and $1.15 in the geographical-price-informed DCE design.

We did not find a statistically significant price premium for blockchain technology across any of the models. The only significant result was that respondents who reported no increase in QR code usage after the pandemic on discounted products with blockchain-verified QR codes by $0.35 relative to those with standard QR codes in the geographical-price-informed DCE design. This result may indicate a general lack of interest in newer technology among this group. Individuals who did not increase their usage of QR code technology during a time of widespread adoption might also be less interested in new applications of that technology, such as blockchain-based QR codes for traceability. While we are unaware of any studies examining consumer preferences or price premiums for access to blockchain traceability through QR codes on cow's milk, our results are contrary to findings from Li et al. (2023), who found preferences for cow's milk products using blockchain for traceability. However, that study did not analyze preferences for accessing traceability information via QR codes.

Overall, our results indicate that consumers value having access to traceability information for cow's milk available on the packaging. However, there were no price premiums associated with QR codes with blockchain technology, with some respondents even discounting products that carried them. These results align with previous research, which found that consumers do not perceive blockchain as being more valuable than other forms of verification methods, such as verification by the USDA (Shew et al., 2022). When respondents were asked about their trust in the U.S. government's ability to efficiently monitor the food system to ensure the authenticity of food labels, 58% of our sample either agreed or strongly agreed, compared to only 44% for for-profit companies. This trend holds across both surveys and among urban and rural respondents. In the standard DCE survey, 53% of rural and 57% of urban respondents stated that they agree or strongly agree in regard to the U.S. government, compared to 43% and 41% in regard to for-profit companies, respectively. In the geographical-price-informed DCE survey, these percentages were 59% of both rural and urban respondents in regard to the U.S. government and 44% and 46% in regard to for-profit companies. This relatively higher level of trust in the U.S. government may help explain why, as we will discuss next, consumers were willing to pay more for USDA-verified organic and carbon footprint reduction labels but not for the blockchain-verified QR codes, which are often implemented by for-profit companies.

Consumer Preferences for Organic and Carbon Footprint Claims

Across all models and DCE designs, respondents consistently showed strong preferences for cow's milk products featuring the USDA organic label over those without it, with all 95% confidence intervals in the positive domain. We find price premiums of $0.94–$0.98 for a half-gallon carton of cow's milk with a USDA organic label relative to a carton with no organic label in the geographical-price-informed design and of $1.08–$1.11 in the standard DCE design. This result aligns with previous literature in which many studies found that consumers prefer organic over non-organic milk and are generally willing to pay a price premium for it (Bernard and Bernard, 2009; Smith, Huang, and Lin, 2009; Akaichi, Nayga, and Gill, 2012; Lombardi, Berni, and Rocchi, 2017; Feucht and Zander, 2018; Yormirzoev, Li, and Teuber, 2021; Badruddoza, Carlson, and McCluskey, 2022). However, the standard deviation of the organic parameter in the mixed logit model estimation is highly statistically significant, indicating heterogeneity in preferences among respondents. While previous literature shows that, in general, consumers are willing to pay a premium for organic cow's milk, the magnitude of this premium varies considerably based on factors such as time, location, and consumer demographics. Additionally, prior studies indicate that consumer perceptions of organic milk's health benefits, environmental impact, and animal welfare impact their valuation of milk products (Akaichi, Nayga, and Gill, 2012; Feucht and Zander, 2018; Yormirzoev, Li, and Teuber, 2021).

Similarly, across all models and DCE designs, respondents strongly preferred products with any of the four carbon footprint labels to products without a carbon footprint reduction label, with all 95% confidence intervals in the positive domain. This result is also in line with previous studies that have shown consumers prefer and are willing to pay a premium for cow's milk products with carbon footprint labels or "climate-friendly" claims (Echeverría et al., 2014; Feucht and Zander, 2018; Canavari and Coderoni, 2020). Among the carbon footprint labels evaluated, the Carbon

Lower Than Market label from the Carbon Trust garnered the highest premiums, with the estimated premiums ranging between \$1.08–\$1.12 in the standard DCE design and \$0.69–\$0.72 in the geographical-price-informed DCE design. Respondents in both samples assigned the second highest premium to the USDA Process-Verified Climate-Friendly label, with premiums of \$0.97–\$1.05 in the standard DCE design and \$0.66–\$0.68 in the geographical-price-informed DCE design. This result may suggest that the specific messaging and the way it is conveyed play an important role in shaping consumers' perceptions and preferences for carbon footprint labels. Notably, labels such as "Carbon Lower Than Market" explicitly indicate that a product's carbon footprint is below a preset benchmark in the market, which may resonate more with consumers than simply signal a reduction or plan to reduce the carbon footprint. While the USDA Climate Friendly label does not certify that a product's carbon footprint is below the market average for comparable products like the Carbon Lower Than Market label, it does indicate that a product has a carbon footprint that is 10% lower than an industry benchmark. Consumers who want to reduce their environmental impact may favor products with labels that clearly indicate a lower carbon footprint compared to other products on the shelf. This preference may arise because such labels reassure consumers that the product's footprint is lower than its competitors, rather than signal a reduction without context or comparison to other products on the shelf. For producers interested in incorporating carbon mitigation practices into their operations, these results suggest that pursuing certifications that demonstrate a product's carbon footprint is lower relative to a defined benchmark, and they may be more effective at capturing consumers than certifications that only highlight broad carbon footprint reductions or plans.

Consumers also preferred products with the Carbon Reduction Achieved and Carbon Reduction Planned labels relative to products with no carbon footprint labels, with all 95% confidence intervals again being in the positive domain. For the Carbon Reduction Achieved label, we find premiums of \$0.69–\$0.83 in the standard DCE design and \$0.48–\$0.54 in the geographical-price-informed DCE design. We find similar price premiums for the Carbon Reduction Planned label, ranging between \$0.72–\$0.75 in the standard DCE design and \$0.51–\$0.53 in the geographical-price-informed DCE design. Interestingly, we observe similar price premiums for labels indicating an achieved reduction (e.g., Carbon Reduction Achieved) and those indicating a planned reduction (e.g., Carbon Reduction Planned). This finding suggests that some consumers are willing to reward companies for their commitment to reducing their carbon footprint, even if the reduction is in the planning stage. Regarding heterogeneity in preferences for carbon footprint labels, the only carbon footprint label exhibiting a significant standard deviation was the Carbon Reduction Achieved Label from the Carbon Trust.

Table 4. Marginal Willingness to Pay (MWTP) Estimates for Cow's Milk Attributes (in US$/half gallon)

Mean	**Standard DCE**	**Geographical-Price-Informed DCE**						
	Main Effects MWTP	**Interactions 95% CI**	**Main Effects MWTP**	**Interactions 95% CI**	**MWTP**	**95% CI**	**MWTP**	**95% CI**
Traceability QR code[a]	0.70	0.53, 0.86			0.61	0.47, 0.76		
Blockchain technology	-0.07	-0.21, 0.08			-0.13	-0.26, -0.01		
Traceability QR code, if more likely to scan post-COVID			1.74	1.03, 2.59			1.15	0.67, 1.58
Traceability QR code, if not more likely to scan post-COVID			0.52	0.33, 0.90			0.44	0.27, 0.62
Blockchain technology, if more likely to scan post-COVID			-0.09	-0.37, 0.33			-0.12	-0.33, 0.12
Blockchain technology, if not more likely to scan post-COVID			-0.34	-0.57, 0.19			-0.35	-0.54, -0.19
Organic	1.11	0.93, 1.28	1.08	0.86, 1.26	0.98	0.83, 1.14	0.94	0.79, 1.11
Carbon reduction achieved	0.69	0.37, 1.03	0.83	0.58, 1.47	0.54	0.26, 0.85	0.48	0.24, 0.74
Carbon reduction planned	0.75	0.58, 0.91	0.72	0.53, 1.11	0.53	0.39, 0.67	0.51	0.38, 0.66
Carbon lower than market	1.08	0.90, 1.26	1.12	0.78, 1.32	0.72	0.56, 0.89	0.69	0.53, 0.87
USDA climate-friendly	0.97	0.80, 1.15	1.05	0.76, 1.25	0.68	0.53, 0.84	0.66	0.52, 0.82

Note: [a]To facilitate interpretation, we report MWTP estimates for the presence of a (Standard) Traceability QR code relative to its absence.

Summary and Future Research

With renewed interest in cow's milk traceability to enhance food safety across the supply chain and meet consumer demand for transparency about food origins, company values, and agricultural production practices, identifying and evaluating ways to modernize food traceability systems has become increasingly relevant. The food industry is exploring blockchain technology as a potential tool to improve traceability throughout dairy supply chains. Blockchain can be used to quickly provide supply chain actors and consumers with information about product recalls and verify product authenticity, thereby reducing occurrences of fraudulent labeling. As with any emerging technology, determining its potential profitability is important for stakeholders along the supply chain. Knowing if consumers are willing to pay price premiums for blockchain-based traceability can help supply chain stakeholders examine its economic feasibility. In this study, we use two unlabeled DCEs to elicit consumer preferences and MWTP for various attributes of cow's milk, including the presence of blockchain and standard (non-blockchain) traceability QR codes, USDA organic certification, and nonprofit and USDA-verified carbon footprint reduction labels. We also propose and evaluate the impact of a geographical-price-informed DCE design, which accounts for geographical price differences that more closely align price levels with those that respondents are likely to encounter in their respective markets, in a DCE on model fit.

Our geographical-price-informed DCE design, which accounts for the variation in price ranges seen by consumers across different states in the United States, resulted in a better model fit as indicated by a lower AIC and BIC and higher log-likelihood. In addition, this approach resulted in more conservative marginal willingness-to-pay estimates. Since we do not conduct a repeated DCE, we cannot account for changes in price over time. However, we account for spatial price differences by presenting respondents with price ranges reflective of those in their state of residence. Future researchers can incorporate similar price vector methodologies into their DCE analyses or build upon our design to estimate more precise and conservative WTP estimates.

We find that consumers prefer cow's milk products with the USDA organic label to products that lack the label, with premiums ranging from \$0.94–\$0.98 in the geographical-price-informed DCE. Similarly, consumers preferred cow's milk products carrying any of the four carbon footprint labels to products with no carbon footprint label. We found the highest carbon footprint label premiums for the Carbon Lower Than Market Label from the Carbon Trust (\$0.69–\$0.72 in the geographical-price-informed DCE) and the USDA Process-Verified Climate-Friendly Label (\$0.66–\$0.68 in the geographical-price-informed DCE). This result suggests that consumers show favor to labels that indicate that a product has a lower carbon footprint than comparative products in the market.

Additionally, our estimates indicate that consumers value access to traceability information for cow's milk. Overall, we find that while consumers strongly prefer access to traceability information through QR codes over no QR codes, they are not willing to pay a premium for blockchain verification. Consumers are willing to pay a premium of \$0.61 for a half-gallon carton of cow's milk with a standard (non-blockchain) QR code providing access to traceability information relative to a carton with no QR code, but apply a price discount of \$0.13 for a carton with a QR code providing access to blockchain-verified traceability information relative to one with no blockchain verification. These preferences vary based on respondent's QR code scanning frequency following the COVID-19 pandemic. The price premiums associated with a standard traceability QR code for those who scanned QR codes more frequently after the pandemic were notably higher ($1.15) compared to those who were not more likely to scan QR codes post-pandemic ($0.44). In addition, those who scanned more frequently after the pandemic were indifferent to blockchain verification, whereas those who did not increase their QR code usage after the pandemic discounted blockchain-enabled QR codes by $0.35 relative to products that carried standard QR codes. This unwillingness to pay for blockchain verification could be explained by the fact that blockchain and its supply chain applications are still relatively novel to many consumers.

Previous studies evaluating consumer preferences for blockchain traceability in various food products have estimated varying price premiums depending on the commodity examined and the location of the study (Lin et al., 2022; Shew et al., 2022; Collart et al., 2025). In our analysis, we do not find a price premium associated with blockchain-traceability QR codes, even after accounting for changes in QR code usage after the COVID-19 pandemic. However, we do find significant premiums for accessing product information for cow's milk through standard QR codes, suggesting that accessing product information, in general, is more important to respondents than the technology used to verify the information. While blockchain technology remains a useful tool for quickly tracking and preventing foodborne illness outbreaks, consumers may not yet perceive the same value in this technology as retailers and producers do. More education about the benefits of blockchain may be necessary before consumers are willing to consistently pay a premium for access to blockchain-verified product information on cow's milk products.

For dairy producers and retailers, it is worth highlighting that implementing standard traceability QR codes may result in consumer price premiums, whereas blockchain-enabled QR codes may not result in a discount relative to a standard QR code. Despite this possibility, implementing blockchain technology along the supply chain could still be profitable due to cost savings associated with preventing and mitigating outbreaks of foodborne illness and other potential gains in production efficiencies. Blockchain could play an important role in ensuring food safety during periods when concerns around food safety and traceability are higher. Beyond food safety concerns, blockchain has been found to increase product quality and minimize costs and could still be a valuable tool within the dairy supply chain (Casino et al., 2021).

Our research specifically investigates consumer preferences for the inclusion of QR codes with access to blockchain-verified product information in cow's milk. However, consumer preferences for blockchain-verified product information could differ greatly depending on the commodity. Most existing research on blockchain traceability and associated price premiums has focused on products such as beef and leafy greens, which are more commonly linked to foodborne illness outbreaks than pasteurized cow's milk (Lin et al., 2022; Shew et al., 2022; Collart et al., 2025). While pasteurized milk carries a lower risk, foodborne illness incidents have been reported, and consumers may have heightened food safety or quality concerns related to cow's milk given the recent publicity surrounding HPAI A(H5N1) outbreaks among dairy cows, which blockchain could help alleviate.

Furthermore, our analysis captured preferences at one point in time. Although we provided respondents with background information about blockchain technology and its applications before the DCEs, this technology is still very novel, and many consumers are unfamiliar with it. As the technology becomes more mainstream and is more widely adopted across various supply chains, consumer valuations of the technology could evolve. Education to increase awareness about the technology and future research is needed to determine if consumers may value the inclusion of blockchain-verified information in years to come. Stakeholders along the dairy supply chain, such as retailers, could identify strategies to increase consumer familiarity with blockchain and its benefits.

Lastly, this research evaluates consumer preferences for access to traceability information via QR codes and the use of blockchain technology to verify traceability information, but it did not assess the underlying reasons why consumers may value verified traceability information (e.g., food safety, origin, or sustainability attributes and product certifications). While blockchain can reduce the time it takes to identify a foodborne illness outbreak and create a verifiable record of a product's journey along the supply chain, consumers may not perceive a direct benefit from the technology in terms of increased food safety. For example, companies could provide information about a recall to consumers using standard or blockchain-verified QR codes. Moreover, consumers may perceive that foodborne illness outbreaks or product recalls are more closely monitored by government agencies, whereas sustainability attributes and product certifications might be more prone to fraud. As such, consumer valuation of the technology may vary depending on the technology's purpose (e.g., preventing foodborne illness outbreaks versus preventing labeling fraud). Because of price premiums associated with sustainability attributes and product certifications, such as organic and carbon footprint claims, there may be economic incentives for labeling fraud. Blockchain could be more valuable in assuring consumer trust in these claims. In fact, blockchain has already been applied to detect labeling fraud in the dairy supply chain (Leung et al., 2021). While we do not investigate preferences for blockchain QR code attributes based on their specific use case (i.e., to verify organic or carbon footprint label information), future research could examine this topic further.

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Appendix

Thank you for answering the questions! Next, please read the following information carefully. After reading, we'll ask you these same questions again to see if this information helps your understanding of the topic.

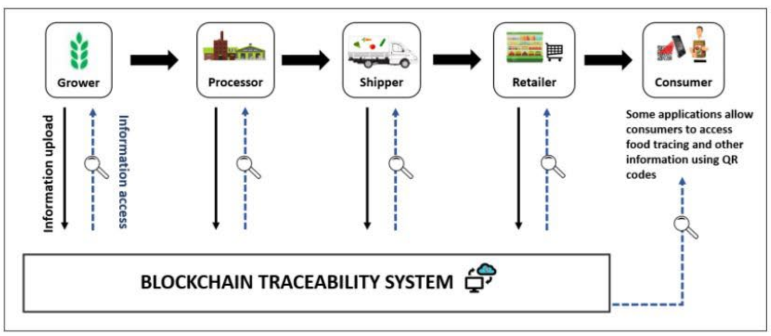
What is Blockchain?
Blockchain is a **digital system used to record transactions** between parties in a shared, transparent, and verifiable way. Parties of a transaction (such as growers and buyers) can upload digital information or documents to a blockchain system and **share** access to it. All parties of a transaction see the same information and **agree** on it before the information is recorded. Also, once added, **records cannot be changed** without all parties knowing. Records can only be changed by adding another entry documenting the change, which creates a history of all changes. This feature helps avoid data manipulation and information disputes. These features have led to blockchain being considered more secure for managing digital information. A popular use of blockchain is in digital currencies (cryptocurrencies) like Bitcoin, but blockchain and Bitcoin are not the same. Blockchain applications are being used in many other industries, including health, logistics, and food and agriculture.

Please take a moment to review the information above. You'll be able to proceed shortly

Figure A1. Information on Blockchain Technology from Online Survey

Blockchain for Tracing Food and its Attributes
The agriculture and food sectors use blockchain applications to **trace food products** more quickly by uploading and **sharing digital information** along the supply chain of a product (see image below). Compared to standard systems, blockchain might be more secure for managing information on food safety, origin, or sustainability attributes, and product certifications. Food companies such as Walmart, Kroger, and Sysco have tested blockchain systems to trace food from farm to consumer.

Regardless of the system used to record the information, companies could share food tracing and other information with consumers using **QR codes.**



Once you're done reviewing, please proceed

Figure A2. Information on Blockchain Technology and QR Codes in Agriculture from Online Survey

Figure A3. Example Cow Milk Product Information Website from Online Survey

Table A1. Conditional Logit Estimation Results

	Standard DCE				Geographical-Price-Informed DCE			
	Main Effects		**Interactions**		**Main Effects**		**Interactions**	
	Parameter	Clust. SE	Parameter	Clust. SE	Parameter	Clust. SE	Parameter	Clust. SE
Organic	1.011***	0.066	1.022***	0.066	0.964***	0.062	0.970***	0.062
Blockchain	-0.055	0.062	-0.390***	0.080	-0.125**	0.059	-0.439***	0.084
No traceability QR code	-0.628***	0.073	-0.626***	0.086	-0.597***	0.071	-0.547***	0.092
Blockchain × Post-COVID			0.628***	0.115			0.554***	0.116
No traceability QR code × Post-COVID			-0.003	0.136			-0.105	0.129
Carbon reduction achieved	0.824***	0.091	0.838***	0.093	0.643***	0.087	0.643***	0.088
Carbon reduction planned	0.663***	0.077	0.662***	0.078	0.496***	0.072	0.501***	0.072
Carbon lower than market	0.976***	0.084	0.995***	0.084	0.715***	0.081	0.724***	0.082
USDA climate-friendly	0.922***	0.079	0.938***	0.080	0.702***	0.076	0.707***	0.076
Price	-0.870***	0.043	-0.876***	0.043	-0.948***	0.053	-0.953***	0.053
No-buy	-3.210***	0.173	-3.217***	0.174	-3.919***	0.216	-3.932***	0.217
No. of observed choices (N)	13,368		13,368		13,296		13,296	
Log-likelihood	-3,697.86		-3,672.24		-3,663.19		-3,639.26	
AIC	7,413.720		7,366.472		7,344.384		7,300.515	
BIC	7,481.226		7,448.979		7,411.841		7,382.963	

Note: ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A2. Marginal Willingness to Pay (MWTP) Estimates from Conditional Logit (in USD)

	Standard DCE				Geographical-Price-Informed DCE			
	Main Effects		Interactions		Main Effects		Interactions	
Mean	MWTP	95% CI	MWTP	95% CI	MWTP	95% CI	MWTP	95% CI
Traceability QR code	0.72	0.56, 0.88			0.63	0.49, 0.77		
Blockchain technology	-0.06	-0.20, 0.08			-0.13	-0.25, -0.01		
Traceability QR code, if more likely to scan post-COVID			0.72	0.47, 0.96			0.68	0.49, 0.89
Traceability QR code, if not more likely to scan post-COVID			0.72	0.52, 0.91			0.57	0.38, 0.77
Blockchain technology, if more likely to scan post-COVID			0.27	0.07, 0.47			0.12	-0.05, 0.29
Blockchain technology, if not more likely to scan post-COVID			-0.44	-0.64, -0.27			-0.46	-0.65, -0.29
Organic	1.16	1.00, 1.33	1.17	1.01, 1.34	1.02	0.87, 1.17	1.02	0.88, 1.18
Carbon reduction achieved	0.95	0.75, 1.13	0.96	0.76, 1.15	0.68	0.51, 0.85	0.67	0.51, 0.85
Carbon reduction planned	0.76	0.59, 0.93	0.76	0.59, 0.93	0.52	0.38, 0.67	0.53	0.38, 0.68
Carbon lower than market	1.12	0.94, 1.30	1.14	0.96, 1.32	0.75	0.59, 0.92	0.76	0.60, 0.93
USDA climate-friendly	1.06	0.89, 1.23	1.07	0.90, 1.24	0.74	0.59, 0.89	0.74	0.60, 0.89

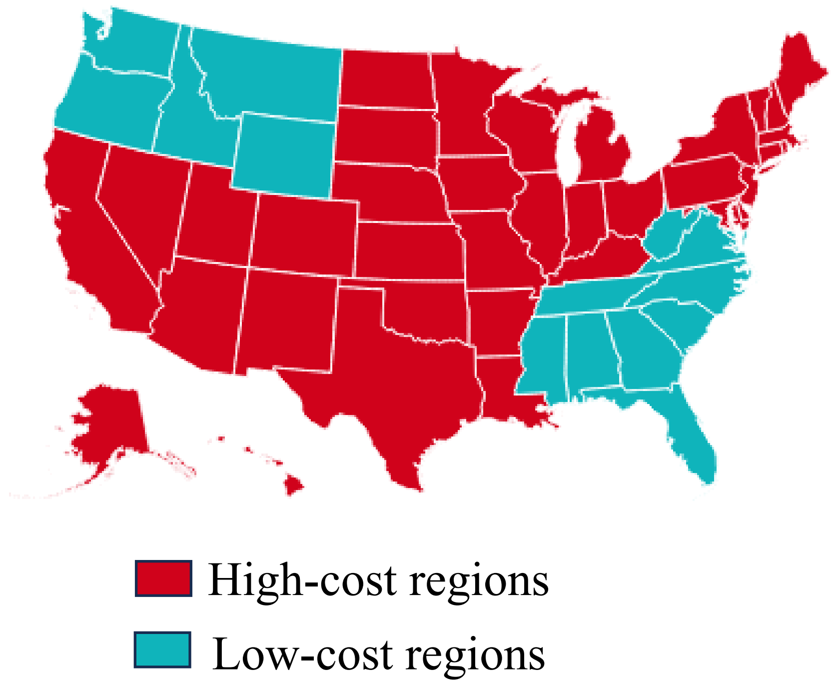


Figure A4. Map of High and Low-Cost States in Geographical-Price-Informed DCE

Table A3. U.S. Average Retail Prices for Half-Gallon Containers of Cow's Milk, October 2023

Locations	States Included	Average Price (USD)
High-cost region		
Northeast	CT, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT	$2.48
Midwest	IA, IL, IN, KY, MI, MN, ND, NE, OH, SD, WI	$2.38
South central	AR, CO, KS, LA, MO, NM, OK, TX	$2.34
Southwest	AZ, CA, NV, UT	$2.36
Alaska	AK	$2.08
Low-cost region		
Southeast	AL, FL, GA, MS, NC, SC, TN, VA, WV	$1.84
Northwest	ID, MT, OR, WA, WY	$1.52
National		
USA	All states (continental USA, excludes HI)	$2.05

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What Makes Consumers More Likely to Take Home and Eat Leftovers after Dining Out?

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Abstract

Restaurant customers can decrease waste by taking their uneaten food home in a to-go box or doggy bag for later consumption. We estimate the probability that a customer will take home and eat their leftovers using logistic regression. Data on 687 customers were collected via an online survey. Results indicate that meal price, type of food, gender, age, and employment status affect a consumer's likelihood of taking home and consuming their restaurant leftovers. This paper is among the few that examine how often customers use or waste their restaurant leftovers once they are taken home.

Keywords: doggy bags, food waste, plate waste, restaurants, restaurant leftovers

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Introduction

With more than 1 billion tons of food wasted annually (United Nations, 2021), food waste has become a global problem (Heng and House, 2022). Food waste is also increasingly acknowledged as a substantial concern in the United States, where more than one-third of the harvested food supply goes unconsumed (Buzby, Wells, and Hyman, 2014; Dsouza et al., 2023). Most of this loss (61%) is happening at the household level (Dsouza et al., 2023; Zhao et al., 2023). Other major contributors to food waste in the United States are the food service and hospitality industries, which contribute 26% and 12% of the total waste, respectively (Dhir et al., 2020; Zhao et al., 2023). Several reasons, including improper storage and/or preparation of food, food being prepared yet never served, and food left uneaten by customers, explain the degree of food loss in these sectors (Engström and Carlsson-Kanyama, 2004). The economic impact of this loss has been estimated at approximately $25 billion per year (Huang, Ma, and Wang, 2021).

The food service and hospitality industries have implemented various strategies to tackle the issue of food waste. For example, many restaurants serve smaller portion sizes, utilize software for inventory management, and ensure proper food supply management so that fresh food is served before spoiling (Blum, 2020). While these actions are helpful, a substantial part of the responsibility for managing food waste also rests with restaurant customers. These customers can reduce waste by requesting a to-go box or doggy bag with the leftovers to take home and consume later. Waste generated when diners do not choose this option is known as "plate waste" and accounts for 20% to 40% of waste at the restaurant level (Bloom, 2011; Blum, 2020). The social acceptability of doggy bags varies from region to region; for instance, the practice of taking leftovers home is uncommon in parts of Europe, such as France (Sirieix, Lála, and Kocmanová, 2017) and Italy (Coldiretti, 2017), but is more accepted in the United Kingdom (Giorgi, 2013).

Several factors that increase the likelihood of an individual asking for a doggy bag have been identified in previous research, including (i) if the consumer felt comfortable around the people with whom they were dining, (ii) if the restaurant server initiated the idea, or (iii) if there was enough food remaining to justify taking it home (Hamerman, Rudell, and Martins, 2017; Mirosa, Liu, and Mirosa, 2018). On the other hand, customers trying to impress those with whom they were dining were less likely to take home leftovers (Hamerman, Rudell, and Martins, 2017). Many people view taking home leftovers as a responsible, positive action, yet they may refrain from doing so because of perceived social shame (Sirieix, Lála, and Kocmanová, 2017) or may take uneaten food home as a result of feeling guilty for not doing so (Talwar et al., 2021).

Additionally, scholars have sought to identify ways in which restaurants can increase consumer uptake of leftovers. For instance, Van Herpen et al. (2021) assessed how changing the structure from "opt-in" to "opt-out" could enable more customers to keep uneaten food and found that customers were more likely to take home leftovers when a doggy bag was given to them by default rather than when they were required to make a special request to take home uneaten food. Although taking home restaurant leftovers is a step in the right direction for reducing plate waste, it does not sufficiently reduce waste; individuals must eat the food they take home rather than throwing it out later for progress to occur. One study from Scotland showed that more than 90% of food taken home is eaten or used (recycled) (Zero Waste Scotland, 2014), though other research suggests that it is less common (Roe, Qi, and Apolzan, 2020).

A common theme in this literature is that women are more prone to not leaving uneaten food at restaurants (Vizzoto et al., 2021; Cerrah and Yigitoglu, 2022). As a result, women are often more likely to ask for a doggy bag (Mirosa, Liu, and Mirosa, 2018). Although some studies illustrate that income and age are not statistically significant factors in the decision to keep leftovers (i.e., Hamerman, Rudell, and Martins, 2017; Vizzoto et al., 2021), divergences do exist (i.e., Cerrah and Yigitoglu, 2022), so further investigation of these factors is warranted. Ambrosius and Gilderbloom (2015) indicate that urban residence can be associated with more environmentally conscious behaviors. Hamerman, Rudell, and Martins (2017) found that those who are more environmentally conscious and live in urban areas are more likely to take home leftovers.

The studies mentioned above took place in New Zealand, Italy, Turkey, France, the Czech Republic, and Scotland, among others (Zero Waste Scotland, 2014; Sirieix, Lála, and Kocmanová, 2017; Mirosa, Liu, and Mirosa 2018; Vizzoto et al., 2021; Cerrah and Yigitoglu, 2022). To the best of our knowledge, limited research exists from the United States regarding the impact of demographic characteristics, lifestyle preferences, or food type on a person's likelihood of taking home leftovers and consuming them at a later time. With the understanding that the uptake of leftovers is highly variable region by region, the present study will examine these impacts for Southeastern U.S. restaurant consumers.

We seek to better understand how common it is for consumers in this region to take home their leftovers and eat them later. Our study has two specific objectives: (i) estimate the relationship among demographic characteristics (i.e., gender, age, education, etc.) and lifestyle characteristic (i.e., living in an urban versus rural area, being vegan/vegetarian, recycling, etc.) and the probability of taking home restaurant leftovers and consuming them later; and (ii) estimate whether consumers are more prone to taking home specific types of restaurant food (i.e., Is steak more desirable than salad as a leftover?). Data regarding plate waste habits and characteristics of American consumers who take home their restaurant leftovers can be very beneficial in identifying ways to further reduce food waste in restaurants.

Methods and Data

Survey Design

The data for this study are obtained from a larger survey focusing on food waste that, in addition to capturing consumers' preferences for taking home and eating leftovers after dining out, also examined household decision makers' evaluation of visually imperfect vegetables.[1] Vegetables

[1] The survey was conducted by (University Anonymized University) per Institutional Board Approved Protocol IRB2021-0459

are the most often wasted food group (Wang et al., 2017; Roe, Qi, and Apolzan, 2020) and thus merit more investigation in the food waste literature.

The survey instrument was distributed by Qualtrics XM. To test the survey, two pilots were distributed to consumers with different demographics (age, income, origin, household location), with 40 respondents per pilot. Online distribution of the final questionnaire was preferred over other alternatives considering that the overwhelming majority (approximately 90%) of households in the study area have access to the internet (U.S. Census Bureau, 2021). Survey respondents were residents of the seven Southeastern U.S. states (Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee).

Several steps were utilized to guarantee the veracity of the responses. For instance, a crosscheck of zip codes and state of residence was completed, and incorrect observations were dropped from the sample. Data validation tools provided by Qualtrics, such as Qualtrics Bot Detection (using Google's reCAPTCHA v3 technology), were enabled to determine the probability that responses were generated by bots. In addition to this method, Qualtrics' RelevantID technology assessed if the same respondent repeatedly took the survey or if a response was fraudulent. Responses with high Bot Detection or RelevantID scores were dropped from the sample. Qualtrics technology was also used to identify "speeders" (respondents whose survey completion time was over 2 standard deviations from the median completion time) taking the survey as they may have been motivated to complete it as quickly as possible to claim the incentive, reducing the quality of responses. In this study, no respondents were flagged as "speeders."

The survey had 808 total responses, but 34 respondents did not answer questions regarding restaurant food that were required for this study and were therefore not included in our sample. Further, one response was removed from the sample because of the respondent's answer regarding year of birth. Additional responses were removed if they did not have an entry for the variables of interest in the final model, bringing the total number of responses used to 687. The average respondent took approximately 16 minutes to complete the survey.

Respondents were only allowed to progress in the survey if they were from one of the seven Southeastern states, were over the age of 18, were the primary grocery shopper in their home, and if they bought vegetables every month. Eligible survey participants then answered a series of questions regarding (i) their dining preferences and habits, (ii) lifestyle characteristics, (iii) whether they took home their restaurant leftovers or left them behind, (iv) what they did with those leftovers, and (v) demographic characteristics.[2] All survey questions were either multiple choice, free response textbox, or sliding scale-style questions.

Demographic Characteristics of Survey Participants

The demographic characteristics of our sample and a comparison with the 2021 American Community Survey (ACS) are presented in Table 1. The age of respondents matches the age

[2] See survey questions in the appendix.

distribution across states from the ACS, and the percentage of respondents identifying as white versus other races follows the ACS. Education levels, income, and employment status percentages are also close approximates of the ACS's values. More than 50% of respondents reported an income lower than $50,000 per year, whereas only 6% reported an income higher than $150,000. In our sample, there are more female respondents (73.4%) than male respondents. This difference is justifiable given that women are more often the primary grocery shoppers in a household (Saphores and Xu, 2021). The higher proportion of female respondents is also beneficial for this study considering that restaurants recognize the importance of better understanding women's behavior regarding restaurant preferences (Jones, 2018). Overall, we can reasonably assume that our survey sample reflects the population of the survey region.

Table 1. Summary of Demographic Variables

Variable	**Survey Data (n = 687)**	**American Community Survey**
Gender		
Male/other	26.6%	48.9%
Female	73.4%	51.1%
Age (years) [c]	39.1	39.6
Race[d]		
White	59.5%	59.6%
Other	40.5%	40.4%
Education[e]		
High school, GED, or less	29.4%	38.6%
Some college (but no degree), associate's, technical school	40.0%	29.0%
Bachelor's, graduate, or professional degree	30.6%	32.4%
Income		
Less than $25,000	22.9%	19.9%
$25,000–$49,999	29.5%	22.4%
$50,000–$74,999	19.4%	18.3%
$75,000–$99,999	13.1%	12.8%
$100,000–$149,999	9.2%	14.2%
$150,000 or more	6.0%	12.4%
Employment[f]		
Employed or student	69.3%	57.0%
Unemployed, retired, disabled	30.7%	43.0%
Married/living with partner	53.7%	N/A[b]
Own home	57.2%	N/A
Household 3+	54.7%	N/A

Table 1 (cont.)

Variable	**Survey Data (n = 687)**	**American Community Survey**
State		N/A
Alabama	9.5%	
Florida	31.3%	
Georgia	18.2%	
Mississippi	4.5%	
North Carolina	16.0%	
South Carolina	8.4%	
Tennessee	12.1%	
Children under 18 in home		N/A
0	59.0%	
1	19.8%	
2	12.2%	
3+	9.0%	

Notes: [a]American Community Survey 1-Year Estimates. Statistics were aggregated for states included in our survey: Alabama, Florida, Georgia, Mississippi, North Carolina, South Carolina, and Tennessee.
[b]The "NA" is included in the table because ACS does not include all demographic variables from the present study.
[c]The value for ACS is the average value of each state's median age.
[d]The American Community Survey allows respondents to record that they are one race, two races, or more. Our survey allowed only one race to be selected. The value for ACS is the number for "Race alone or in combination with one or more other races." Our survey did not allow respondents to select more than one race.
[e]ACS records education level for individuals over the age of 25. The summary statistic for our survey is for those 18 and older.
[f]ACS records employment for those over 16 years of age, whereas our survey only includes results from those 18 and older. "Employed" in our survey included those working part time, full time, or students. "Unemployed" includes those who specified that they are disabled, retired, or unemployed when asked their employment status.

Table 2 outlines summary statistics of food-related survey questions. The majority of respondents indicated that they dine out once or more per month, in line with other results of American dining habits (SWNS News, 2024). Approximately 20% of survey participants left their uneaten food at the restaurant after their most recent restaurant meal. More than 85% of respondents (87.3%) ate home-cooked meals at least three times a week and used rather than discarded the leftovers from their home-cooked meals. Lastly, 13.5% of respondents identify as either vegan or vegetarian.

Table 2. Summary of Restaurant and Food-Related Questions

Variable	**Survey Data (n = 687)**
Dine out once or more/month	86.8%
Took leftovers	81.0%
Last meal cost $30 or less	83.1%
Cook 3+ meals at home per week	87.3%
Eat home-cooked leftovers	84.7%
Recycle	70.7%
Vegan	13.5%

Figure 1 incorporates a visual representation of survey respondents' answers to major questions on our survey.

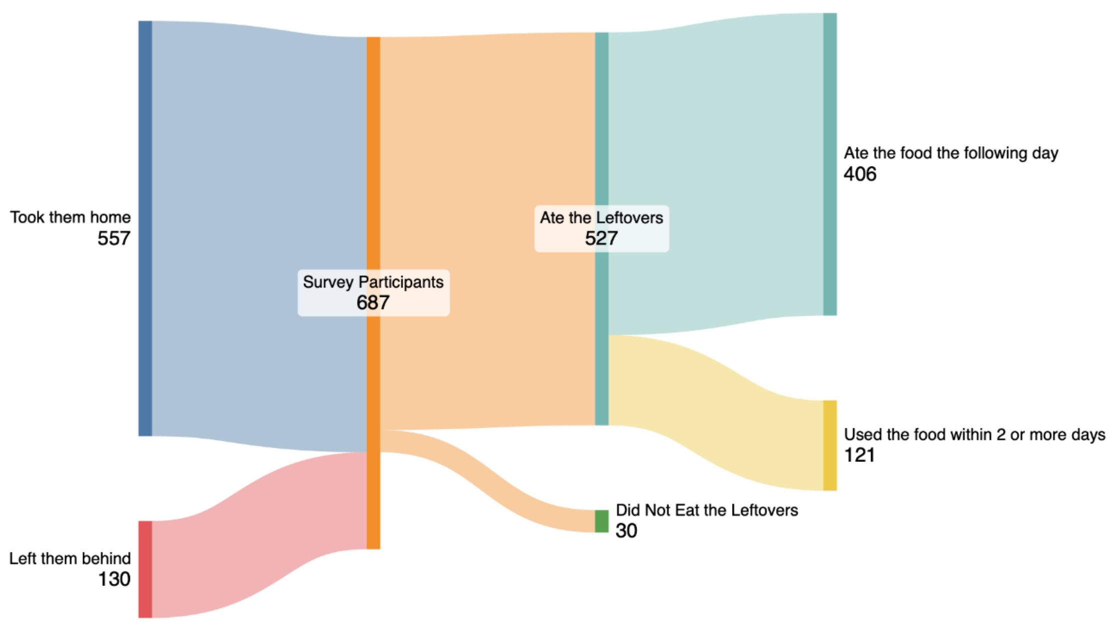

Figure 1. Sankey Chart of Leftover Food Consumption Pattern

The food categories with the highest number of respondents indicating they took leftovers home are pasta (36.5%[3]), followed by pizza (36.1%) and steak (24.9%). On the other hand, the food categories with the lowest number of respondents reporting they consumed leftovers were fast food (14.6%) and "other" food (4.8%). Of the 81% who took their leftovers home, 94.54% ate or used them for other purposes. Respondents to the survey specified whether they used the food

[3] Participants were able to choose more than one food that was part of their leftovers. This allowance implies that percentages do not total 100%.

within one day, within two or more days, or to feed a pet; the overwhelming majority (77%) used the food within one day.

Empirical Strategy

The goal of our study includes gaining insight into a consumer's action between two alternatives. Logistic regression was therefore identified as an appropriate method for modelling our data. Specifically, the dependent variable equals 1 if the consumer took home their leftover food on their previous visit to a restaurant and ate it later, and 0 if the consumer did not take their leftovers home.[4] To test for different specifications, we estimated several logistic regression models, each with a different set of covariates. We discuss these variables in more detail in the Results section.[5]

Set I included as explanatory variables gender (dummy variable equals 1 if female, 0 otherwise), price (dummy variable equals 1 if the meal cost was more than $30, and 0 otherwise), and food type[6] that was uneaten (1 if the food was present as a leftover, 0 if not).

Set II included all variables from Set I in addition to age in years (a continuous variable), ethnicity (dummy variable equals 1 if respondent self-reported to be white, 0 otherwise), education ("12 years or less," "13–15 years," or "16+ years"), income (continuous variable), employment (to capture employment, employment status categories were assigned as "employed" for those employed full time, part time, or selected as a student, and the remaining categories were assigned as "unemployed"), children (0 if no children, 1 otherwise), household size (number of people), marital status, and income. The categorical income variable was transformed into a continuous variable by selecting the center value of each category as the income.

Set III added lifestyle preferences to the variables used in Set I and Set II, including whether the consumer was vegan or vegetarian (a binary variable for categories "vegan or vegetarian" or "not vegan or vegetarian"), if they participated in agritourism, if they cooked at home more than three times a week, and whether they ate leftovers from home-cooked meals.

Set IV includes all previous sets and adds a variable indicating if the respondent lived in an urban area (a dummy variable equal to 1 if the respondent's zip code had a population density[7] greater than 100 people per square mile, and 0 if population density was less than 100 per square mile).

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[4] The logistic regression was run in R. We used the glm function from the "stats" package (R Core Team, 2022). Marginal effects were estimated from the logitmfx function in the "mfx" package (Fernihough, 2019). Code and data are available upon request.

[5] All variables included in each model are show in Table A1 in the Appendix.

[6] Food type options were pizza, steak, pasta, burger, seafood, salad, regional food (Indian, Thai, Chinese, etc.), dessert, fast food (McDonalds, Wendy's, Burger King, etc.), and Other.

[7] Population density was determined using the R package "zipcodeR" (Rozzi, 2021), which sources population data from the 2020 U.S. Census. The population of a zip code was divided by the area in square miles of the zip code to form the population density.

Results

Based on the Akaike Information Criterion (AIC) as well as a likelihood ratio test, the selected model included all sets of variables described above.[8] The model shows that accounting for the additional variables, such as lifestyle characteristics (being vegan/vegetarian, recycling, living in an urban area), is essential when characterizing the consumer's decision regarding taking home and eating leftovers later. In this model, 15 out of 34 variables are statistically significant and are included in Table 3. The discussion in this paper will focus on the marginal effects.[9] Marginal effects from the logistic regression aid in the interpretation of results, but the values of the marginal effects themselves are only meaningful in terms of magnitude.

Table 3. Coefficients and Marginal Effects of Statistically Significant Variables on Whether a Consumer Takes Home and Eats Restaurant Leftovers

Variable	Coeff. (S.E.)	Marginal Effects
Gender: female	0.656***	0.093***
	(0.235)	(0.033)
Ethnicity: white	0.413*	0.059*
	(0.225)	(0.032)
Age	-0.017*	-0.002**
	(0.009)	(0.001)
Employment: non-employed	0.484*	0.069*
	(0.274)	(0.039)
Florida	-0.848*	-0.104**
	(0.444)	(0.049)
North Carolina	-1.086**	-0.141**
	(0.474)	(0.056)
Tennessee	-1.263***	-0.170***
	(0.483)	(0.061)
Had salad as a leftover	-0.835***	-0.119***
	(0.259)	(0.036)
Had regional food as leftover	0.592**	0.084**
	-0.835***	-0.119***
Average price of leftovers: > $30	0.860***	0.122***
	(0.315)	(0.044)
Participated in agritourism	-1.322***	-0.188***
	(0.295)	(0.040)
Eat home-cooked leftovers	1.631***	0.231***
	(0.273)	(0.035)
Cook 3+ meals at home per week	0.575*	0.082**
	(0.295)	(0.042)

[8] All models estimated and AIC and likelihood ratio tests can be obtained upon request.

[9] Marginal effects here refer to the partial effect. It is calculated after determining the average of the observations.

Table 3 (cont.)

Variable	Coeff. (S.E.)	Marginal Effects
Vegan or vegetarian	-0.706**	-0.100**
	(0.297)	(0.042)
Live in urban zip code	0.797***	0.113***
	(0.294)	(0.041)

Notes: Standard errors listed in parenthesis. All state marginal effects are in comparison to the baseline state, Alabama. "Regional food" was described to survey participants as "Indian, Thai, Chinese, etc."
Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We find that among the demographic characteristics examined, gender, ethnicity, age, employment status, urban residency, and state of residence are statistically significant. Among lifestyle characteristics, eating home-cooked leftovers, participating in agritourism, choosing to be vegan or vegetarian, and recycling are statistically significant. Those who eat leftovers at home or participate in agritourism are more likely to take home restaurant leftovers, whereas those who are vegan or vegetarian are less likely to take them home.

Regarding our second objective (estimate whether consumers are more prone to taking home specific types of restaurant food), we find that those who had a more expensive restaurant meal or had leftover regional food are more likely to take them home. "Regional food" was described to survey participants as "Indian, Thai, Chinese, etc." On the other hand, we find that those who had salad are less likely to save it for later consumption.

We did not find a statistically significant effect of income on the likelihood of taking home a doggy bag. This result mirrors the findings of Vizzoto et al. (2021) and Hamerman, Rudell, and Martins (2017). We also find that those who self-reported "white" as their ethnicity are more likely to take home and consume leftover food. Women are 9.3 percentage points more likely than men to take home their restaurant leftovers, holding all else constant. This result is consistent with Mirosa, Liu, and Mirosa (2018) and corroborates the findings of Vizzoto et al. (2021) and Cerrah and Yigitoglu (2022), who reported that women are more prone to eating less. Thus, because they eat less food than men due to larger portion sizes, they tend to take home uneaten food more often.

The result for age indicates that older consumers are less likely to take home leftovers. Specifically, each additional year of age is associated with a 0.2 percentage point decrease in the likelihood of taking home leftovers (holding all else constant). Our results suggest that there was no discernible difference between a person's probability of taking home leftovers if they had different levels of education. Employment status, on the other hand, was significant. We find that unemployed consumers are more likely to take home leftovers.

Respondents from Florida, North Carolina, or Tennessee are less likely compared to those from Alabama (the base state) to take home uneaten food, which indicates regional differences in behavior. A similar phenomenon is seen in the studies mentioned previously that were conducted in different countries (Giorgi, 2013; Coldiretti, 2017; Sirieix, Lála, and Kocmanová, 2017). Thus, local customs and norms affect the likelihood of consuming uneaten food.

Respondents living in an urban zip code are also more likely to take home leftovers. This statistically significant marginal effect might be attributed to those who live in more densely populated zones who are more aware of the massive amount of food waste produced in their area. Therefore, they are more motivated to contribute less to the waste in general.

Among the lifestyle characteristics, a person's status as a vegan/vegetarian, whether they recycle, whether they cook meals at home, whether they eat home-cooked leftovers, and whether they participate in agritourism are included in the model. We find that those who identify as vegan or vegetarian are less likely to take home leftovers. The marginal effects associated with recycling behavior and cooking at home three or more times a week were insignificant. On the other hand, those who eat home-cooked leftovers are more likely to take home restaurant leftovers than those who do not.

Because restaurant type can be defined in many ways, we created two factors capturing differences: the price of the meal and the type of food. Therefore, we asked customers the type of food left uneaten at their most recent restaurant meal and the average price of food per person.

Regarding type of food, salad and food described as "regional food" were two variables that had a statistically significant influence on a consumer's likelihood of taking home a doggy bag. No other food types had statistically significant results. Consumers who had not eaten an entire salad are less likely to take home leftovers, but leftover regional food is more attractive to saving and eating later. Salad tends to be a less attractive food one or two days after being left uneaten. Because of that we hypothesized that consumers refrain from taking home a leftover salad. One with dressing could be even less attractive as a leftover, but serving dressings on the side could solve this issue.

Regarding meal price, consumers with a meal costing greater than \$30 are more likely to take home their leftovers. Holding all else constant, consumers who eat more expensive meals have a predicted probability of taking them home that is 12.2 percentage points higher than those with a less expensive meal. This small price marginal effect on the likelihood of taking home a doggy bag indicates that consumers who eat more expensive food are more likely to take leftovers home, likely because restaurant goers perceive more expensive food as worth saving.

Discussion

Our results reveal interesting patterns. First, we find some connection between a person's residency and the likelihood of taking home leftovers—those from urban areas, as well as those from certain states, are more likely to take home their leftovers. Hypothetically, a person living in Alabama has a predicted probability of 0.85 of taking home and eating leftovers. A person with all the same characteristics[10] as the one from Alabama, with the only difference being that they reside in Florida, has a predicted probability of 0.75 of taking home and eating restaurant leftovers. Further, identical consumers from urban versus rural areas have predicted probabilities of 0.78 and

[10] Characteristics of the hypothetical consumers in this section were chosen based on attributes of the average respondent to the survey.

0.65, respectively, meaning that those in rural areas are less likely to take home and eat their leftovers.

A second pattern that was revealed is that vegans and vegetarians, as well as those who take home salad as a leftover, are less likely to take leftovers home. The predicted probabilities of vegan/vegetarian and non-vegan/non-vegetarian consumers taking home and using their restaurant leftovers are 0.66 and 0.78, respectively. The probabilities for those who did or did not have salad as a leftover are 0.65 and 0.79, respectively.

In our survey sample, 35.5% of vegans/vegetarians had a salad as their last restaurant leftover meal. Only 15.3% of those who are not vegan/vegetarian had salad as a leftover. Therefore, a potential explanation for why vegans and vegetarians are less likely to take home leftovers is that one of the major foods they consume (i.e., salad) is less desirable as a leftover. A day-old salad may be less appealing than a day-old hamburger or pasta, for example, so taking home an uneaten portion may be less expected. Leafy greens from salads have a short shelf life compared with other foods, which may cause consumers to find them less appealing or viable as leftovers.

In addition to the less appealing characteristics of leftover salads, they can be harmful to dogs, as well. The term "doggy bag" derives from feeding leftovers to dogs, which is a common practice for some customers. While typical salad bases, such as lettuce, are technically safe for dogs to consume, others such as kale and spinach can be quite harmful to canines (Lotz, 2022). Additionally, common salad ingredients, such as avocados, almonds, onions, grapes, raisins, dairy products, and macadamia nuts are harmful to dogs (AKC Staff, 2018). Consumers intending to feed leftovers to their dogs will, therefore, be less inclined to take home uneaten salads.

The third pattern that emerges from our analysis relates to food cost. While a respondent's income had no detectable influence on their likelihood of taking home leftovers, we found that a higher priced restaurant meal increases the likelihood of a consumer taking home uneaten food. Furthermore, those who are unemployed are more likely to take home higher priced leftovers These results are in line with the common perception that higher priced meals are more worthy of saving for later. Also, consumers who are unemployed may have less access to food and thus are more likely to save uneaten higher priced meals. Another factor is that higher priced meals may potentially contain more food and therefore produce more leftovers. A person who paid more than $30 for their meal and is unemployed has a predicted probability of 0.85 that they will take home and use their restaurant leftovers. In contrast, a person who spent less than $30 on their meal and is employed has a probability of 0.74.

We also found that the probabilities of taking home restaurant leftovers and consuming them change with the combination of these characteristics. Consider two people who are identical in every way measured on this survey: They are the same age, both are male, and their other characteristics are the same. If person A lives in an urban area, is not vegan, and does not have salad as a leftover, their predicted probability of taking home their restaurant leftovers is 0.82. If person B does not live in an urban area, is vegan, and has salad as a leftover, their predicted probability of taking home their restaurant leftovers is only 0.40. The substantial difference is due only to where they live, what they ordered, and their status as either vegan or non-vegan.

Conclusion

Like most of the nations around the globe, food waste is a substantial problem in the United States. While most food waste happens at the household level, restaurants contribute significantly to the food lost each year. A high percentage of this food loss can be attributed to consumers leaving uneaten food and not taking it home for later consumption. There is a wide margin of research possibilities in this area, and this study expands the literature related to consumer behavior and restaurant leftovers. The objectives of our study were to (i) estimate the relationship between demographic characteristics (i.e., gender, age, education, etc.) and lifestyle characteristics (i.e., living in an urban versus rural area, being vegan/vegetarian, recycling, etc.) and the probability of taking home restaurant leftovers and consuming them later; and (ii) estimate whether consumers are more prone to taking home specific types of restaurant food (i.e., Is steak more desirable than salad as a leftover?).

Our survey results indicate that more than 81% of restaurant goers took home leftovers from the most recent time they had extra food at the end of a restaurant meal, and 94.54% ate or used the uneaten food. This result should prompt retail establishments to assess their portion sizes. There is potential for less revenue loss for restaurants that serve a more balanced variety of food to consumers. Toward this goal, many restaurants have implemented better inventory management, reduced portion sizes, and so on, but the results indicate that more can be done. Actions like these can decrease financial loss in the retail sector as well as contribute to less food waste. In addition to restaurant managers, consumers can play a pivotal role in reducing food waste at restaurants. This study aims to shed light on this issue.

We find that gender, living in an urban area, and, in some cases, state of residence comprise the most vital indicators of a person's probability of taking home their restaurant leftovers. Those who eat leftovers at home or participate in agritourism are more likely to take leftovers home from a restaurant, whereas those who are vegan/vegetarian are less likely to take home leftovers. We find that those who had a more expensive restaurant meal are likely to take home leftovers, and those who had salad are less likely to take it home.

Better understanding restaurant consumers contributes to reduced food waste. For example, this research could be used by restaurants specializing in vegan/vegetarian dishes or restaurants with a typically older clientele to identify that their patrons are more prone to wasting leftovers. Those restaurants could, then, take extra measures to reduce waste and encourage their customers to do so as well.

This research also has some limitations. First and foremost, this is research based solely on a survey. Answers to surveys are self-reported, so there is always a possibility that they will remember their restaurant visits slightly incorrectly or will fail to give a truly accurate estimate of measures such as how often they eat out. Future research regarding restaurant plate waste could include questions regarding time of day or year leftovers are more often taken, as consumers may be more likely to save uneaten food when they are not worried about spoilage in hot weather. Consumers' concerns with food safety may prevent them from taking home leftovers if they are aware that they will be unable to appropriately refrigerate or store the food before it spoils. Additionally, future studies should investigate if restaurant goers are less likely to take their leftovers home if they have to attend an event following their meal. In other words, those with engagements after their meal may find taking leftovers home less viable as they would not have the ability to safely store the leftover food. The style of restaurant food could also affect whether leftovers were taken. The frequency of feeding leftovers to pets could also be more thoroughly investigated. Mode of travel, travel time, and whether the restaurant visit was the sole purpose of the trip could help to further establish reasons for or against taking leftovers home. Finally, future work including an observational study of a physical restaurant could be beneficial in verifying validity of self-reported surveys on taking home or leaving leftovers.

This research focuses on the Southeastern United States. While the responses are likely closely in line with what others from around the United States would report regarding their restaurant habits, it is possible that the results from this study are not representative of other regions of the United States. Although our survey was not distributed across America, it is a great first step toward building a foundation of understanding around this topic in the United States.

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Appendix

Survey Instrument

The restaurant-related questions were addressed in the following way: "*Last time you had left-overs at a restaurant, did you: 1. Took them home in a box; or 2. Leave them behind at the restaurant"*(this response is referred to as "leftover action" for the remainder of the paper), "*At the last time you had left-overs at a restaurant, what was the average price per person you paid for food?*" (This response is referred to as "Average Price"), What did you do with the leftovers? (options for response: *"I did not eat (forgot I had them), I ate it the following day, I ate it in the next 2 or more days, and Other (for example, feed my pet)." "In the last month, how many times did you dine out?"* (referred to as "Dine-Out Frequency hereafter), and finally "*What type of food was the left-over [at your last restaurant meal]"* to which respondents could choose multiple answers from pizza, steak, pasta, burger, seafood, salad, regional food, dessert, fast food, or "other." For our purposes, "regional food" was described to survey participants as "Indian, Thai, Chinese, etc."

Demographic-related questions were addressed as follows:

- What is your gender? 1. Male, 2. Female, 3. Non-binary / third gender 4. Prefer not to say
- At the last time you had left-overs at a restaurant, what was the average price per person you paid for food? 1. Between $10 and $20 dollars 2. Between $20 and $30 dollars 3. Between $30 and $40 dollars 4. Between $40 and $50 dollars 5. More than $50 dollars
- What is your year of birth? (open text box)
- What ethnicity do you most identify with? 1. White 2. Black or African American 3. American Indian or Alaska Native 4. Asian 5. Native Hawaiian or Pacific Islander 6. Hispanic or Latino or Spanish Origin of any race 7. Other
- What is the highest level of education you have completed? 1. *Some high school or less 2. High school diploma or GED 3. Some college, but no degree 4. Associates or technical degree 5. Bachelor's degree 6. Graduate or professional degree (MA, MS, MBA, PhD, JD, MD, DDS etc.) 7. Prefer not to say*
- What was your total household income before taxes during the past 12 months? *1. Less than $25,000 2. $25,000-$49,999 3. $50,000-$74,999 4. $75,000-$99,999 5. $100,000-$149,999 6. $150,000 or more 7. Prefer not to say*
- *Which of the following categories best describes your employment status? 1. Employed full time 2. Employed part time 3. Unemployed 4. Retired 5. Student 6. Disabled 7. How many children under 18 live with you? (open text box)*
- *How many people are currently living in your household? 1. Myself only 2. Myself + 1 3. Myself + 2 4. Myself + 3 5. Myself + 4 6. Myself + more than 4*
- *What is your current marital status? 1. Married 2. Living with a partner 3. Widowed 4. Divorced/Separated 5. Never been married*
- *Which state do you currently reside in? 1. Alabama 2. Florida 3. Georgia 4. Mississippi 5. North Carolina 6. South Carolina 7. Tennesse 8. Other*
- *Do you own your primary residence? 1. Yes 2. No 3. Prefer not to say*

- *What type of food was the left-over? 1. Pizza 2. Steak 3. Pasta 4. Burger 5. Seafood 6. Salad 7. Regional food (Indian, Thai, Chinese, etc.) 8. Dessert 9. Fast-food (McDonald's, Wendy, Burger King, etc.) 10. Other 11. In the last month, how many times did you dine out? 12. None 13. Between 1 and 5 times 14. Between 5 and 10 times 15. More than 10 times*
- *Do you recycle? Yes/No*
- *Are you vegan or vegetarian? Yes/No*
- *Have you done agro-tourism in the last year? Yes/No*
- *Do you cook dinner at home more than 3 times a week? Yes/No*
- *What is your five-digit zip code? (free response text box)*

Table A1. Estimation of the Final Model and Marginal Effects

Variable	Coeff. (S.E.)	Marginal Effects
Gender: female	0.656***	0.093***
	(0.235)	(0.033)
Average price of leftovers: > $30	0.860***	0.122***
	(0.315)	(0.044)
Had pizza as leftover	-0.060	-0.008
	(0.230)	(0.033)
Had steak as leftover	-0.189	-0.027
	(0.246)	(0.035)
Had pasta as leftover	0.273	0.039
	(0.227)	(0.032)
Had burger as leftover	-0.120	-0.017
	(0.258)	(0.037)
Had seafood as leftover	0.235	0.033
	(0.278)	(0.039)
Had salad as leftover	-0.835***	-0.119***
	(0.259)	(0.036)
Had regional food[1] as leftover	0.592**	0.084**
	(0.301)	(0.042)
Had dessert as leftover	-0.152	-0.022
	(0.307)	(0.044)
Had fast food as leftover	-0.192	-0.027
	(0.296)	(0.042)
Had other food as leftover	-0.521	-0.074
	(0.475)	(0.067)
Age	-0.017*	-0.002**
	(0.009)	(0.001)
Ethnicity: white	0.413*	0.059*
	(0.225)	(0.032)
Education: some college/associate's degree/technical school[2]	0.164 (0.263)	0.023 (0.037)

Table A.1 (cont)

Variable	Coeff. (S.E.)	Marginal Effects
Education: bachelor's/graduate degree/professional degree	0.354	0.050
	(0.311)	(0.044)
Income	-0.002	-0.001
	(0.004)	(< 0.001)
Employment: non-employed	0.484*	0.069*
	(0.274)	(0.039)
Children	-0.028	-0.004
	(0.108)	(0.015)
Household size: 3 or more	0.027	0.004
	(0.251)	(0.036)
Marital status: not living with a partner	0.099	0.014
	(0.232)	(0.033)
State: Florida[3]	-0.848*	-0.104**
	(0.444)	(0.049)
State: Georgia	-0.753	-0.090*
	(0.477)	(0.054)
State: Mississippi	0.659	0.055
	(0.716)	(0.057)
State: North Carolina	-1.086**	-0.141**
	(0.474)	(0.056)
State: South Carolina	-0.579	-0.067
	(0.541)	(0.062)
State: Tennessee	-1.263***	-0.170***
	(0.483)	(0.061)
Home owned	0.213	0.030
	(0.237)	(0.034)
Vegan or vegetarian	-0.706**	-0.100**
	(0.297)	(0.042)
Participated in agritourism	-1.322***	-0.188***
	(0.295)	(0.040)
Recycle	0.027	0.004
	(0.250)	(0.035)
Eat home-cooked leftovers	1.631***	0.231***
	(0.273)	(0.035)
Cook 3+ meals at home per week	0.575*	0.082**
	(0.295)	(0.042)
Live in urban[4] zip code	0.797***	0.113***
	(0.294)	(0.041)
Constant	-0.631	
	(0.726)	

Table A1 (cont.)

Variable	Coeff. (S.E.)	Marginal Effects
Observations		687
Log likelihood		-305.734
Akaike Inf. Crit.		681.468

Note: Standard errors are in parentheses.

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What Drives U.S. Consumers to Buy Local and Organic Foods? Beliefs, Perceptions, and Motivations

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Abstract

We conducted an online survey in February 2023 to examine U.S. consumers' food expenditures, definitions of local and organic foods, and perceptions of eight belief statements. We identified key drivers of these beliefs using statistical analysis and regression modeling. Consumers indicated that purchasing local or organic foods enhances perceptions of taste, nutrition, health, safety, and environmental benefits. Notably, 60% of respondents believed local foods benefit the environment, compared to 53% for organic foods. Beliefs about taste, price, and nutrition strongly influence purchase decisions. These findings highlight opportunities for targeted advertising strategies that emphasize the environmental advantages of these foods.

Keywords: local foods, organic foods, perception, survey

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Introduction

Local and organic foods have become cornerstones of sustainable food systems, yet consumer confusion about their attributes persists, complicating efforts to promote these products effectively. Over the past two decades, U.S. sales of local and organic foods are at record highs (Skorbiansky, 2025; Spalding, 2025). Certified organic farmland has tripled, with sales increasing from $609 million in 2002 to nearly $11 billion by 2019, whereas local food sales reached $9 billion in 2020 (USDA, 2022; Carlson et al., 2023). Despite this rapid growth, many consumers conflate the definitions of “local” and “organic,” due in part to some overlap in attributes, creating ambiguity that challenges marketers, policy makers, and producers (Henryks and Pearson, 2010; Ditlevsen et al., 2020).

Governments, community organizations, and researchers have long advocated for local and organic foods, citing benefits like reduced carbon emissions, biodiversity conservation, improved public health, and strengthened local economies (Enthoven and Van den Broeck, 2021). The U.S. Department of Agriculture (USDA) has played a central role in advancing organic farming and local food distribution networks (Peng, 2019). Consumers’ motivations to purchase organic foods often center on health, safety, and environmental benefits, with many willing to pay a premium for these attributes (Roy, Ghosh, and Vashist, 2023). Organic buyers prioritize nutrition, taste, and sustainability over fairness or origin (Magkos, Avaniti, and Zampelas, 2006; Lusk and Briggmen, 2009; Lusk, Schroeder, and Tonsor, 2014; Neuhofer, Lusk, and Villas-Boas, 2023). However, Chang and Lusk (2009) examined the role of fairness in food purchasing decisions for organic foods, suggesting that labels and certification standards for organic foods could be adjusted to reflect these concerns, potentially improving consumer trust and demand. Kim, Lusk, and Brorsen (2018) found the main drivers behind purchasing organic food are health and safety concerns. Consumers who trust organic certification labels are more likely to purchase organic products, but not all consumers prefer organic food, even at comparable prices, to conventional options.

Similarly, local food buyers emphasize freshness, quality, and support for local economies, but definitions of “local” range from proximity-based criteria to broader cultural and economic dimensions (Blake, Mellor, and Crane, 2010; Granvik et al., 2017; Palmer et al., 2017). Ambiguity in these definitions can undermine consumer trust (Jia, 2021). Memery et al. (2015) concurrently used attributes, values, and personal characteristics/situational variables to explain shopping behavior for local food, finding purchases were motivated by local support rather than intrinsic product quality.

A significant overlap exists between consumers of local and organic foods (Ditlevsen et al., 2020). Research reveals that consumers often mix attributes, perceiving local products as organic or assuming farmers’ market goods meet organic standards (Henryks and Pearson, 2010). Over time, preferences have shifted. While organic foods were historically favored for health and environmental attributes, local foods valued for freshness, affordability, and community support have gained prominence since the late 1990s (Adams and Salois, 2010).

Due to increased consumer interest, food manufacturers and retailers highlight the environmental and health benefits of their products on labels, including organic and locally sourced. These labeling practices have become an important marketing tool (Wilson and Lusk, 2020). However, the truth of these label claims can be questionable, making exaggerated or unclear claims about the environmental benefits of their products to attract environmentally conscious consumers. Others make standard environmental practices sound like additional benefits. This misconception misleads consumers, causing confusion and skepticism about claims.

This study investigates U.S. consumers' beliefs and perceptions regarding local and organic foods. Using data from a nationally representative online survey conducted in February 2023, we analyze how demographic and behavioral factors influence consumer perceptions. By identifying how consumers distinguish between local and organic products, these findings provide insights to improve consumer trust, guide marketing strategies, and support sustainable food systems. This research contributes to ongoing efforts in local food and organic food marketing and policy development.

Data and Methodology

Survey Design and Administration

We conducted an online survey in February 2023 using the Qualtrics platform (Silver Lake, 2024) to explore U.S. consumers' food expenditures, shopping behavior, and perceptions of local and organic foods. The survey instrument included questions on demographic characteristics, weekly food expenditures, definitions of local and organic foods, and agreement with eight belief statements. The survey instrument is further detailed in the next few sections and is also available in Appendix A. Respondents were required to be at least 18 years old and were recruited through Kantar's opt-in panel (Kantar, 2024). Oklahoma State University's Institutional Review Board (IRB) deemed the study exempt.[1]

Demographics

To ensure the sample was representative of the U.S. population, we used quotas within Qualtrics for gender, income, education, and geographical region, as defined by the U.S. Census Bureau (U.S. Census Bureau, 2019). A total of 1,000 respondents met the quota criteria and completed the survey, and the test of proportions confirmed the sample's demographic representativeness, with minor deviations in education levels.

Shopping Behavior

Respondents were asked questions about their shopping behavior, including how much they spent each week on food and what kind of information they reviewed when purchasing food. Specific questions regarding whether the respondent purchased local and/or organic foods and their definition of local were also included. Definitions of local were adapted from Bir et al. (2019)

[1] The IRB study number is: IRB-23-24.

following previous definition discussions by Blake, Melor, and Crane (2010) and Granvik et al. (2017). Definitions of local were geographical and included, “from my county of residence,” “100 miles or less from my home,” “from my county and neighboring counties,” “from my state of residence,” “from the United States,” “not sure/don’t know,” and “other.” Respondents were told to indicate the definition that best represented their opinion. Respondents were asked to indicate if they purchased local or organic food. Respondent demographics were compared statistically using the test of proportions.

Belief Statements

Beliefs and motivations for purchasing local and organic foods have been documented throughout the literature but are rarely compared within the same dataset. Consumer preferences are continuously evolving, warranting re-evaluation of similar themes. Early research on U.S. consumers indicated that consumers are motivated to purchase local food in part to support local producers, businesses, and economies (Thilmany, Bond, and Bond, 2008). However, local food does not inherently guarantee ecological sustainability, such as lower emissions, and the nutritional quality of local food can vary (Coelho, Coelho, and Egerer, 2018). Organic is often attributed to health, nutrition, taste, safety characteristics, and environmental benefits (Kim, Lusk, and Brorsen, 2018; Roy, Gosh, and Vashist, 2023). Using the belief statements for local foods outlined in Bir et al. (2019) and other attributes discussed in the literature, the belief statements for organic and local were designed.

Respondents were asked their level of agreement from “1” (agree) to “5” (disagree) for eight statements regarding local food and seven statements regarding organic food. Statements for both local and organic food included, “*Local (organic) food is more expensive than other food,*” “*Local (organic) food tastes better, “Purchasing local (organic) food is better for the environment,*” “*Purchasing local (organic) food is more nutritious,*” “*Local (organic) food is healthier,*” and “*Local (organic) food is safer.*” For local food, additional statements included, “*Local food is organic,*” and “*I like to know who produces the food I eat.*” For organic food, the statement, “*Organic food is local,*” was included.

Analytical Methods

We used statistical and econometric methods to analyze the data. Descriptive statistics summarized respondents’ demographic characteristics, weekly expenditures, and shopping behavior. The test of proportions assessed whether the sample was representative of the U.S. population based on gender, income, education, and region. The test of proportions was also used to evaluate demographic differences among those who purchased organic and local foods.

The beliefs regarding local and organic food were evaluated in two ways. First, to characterize the data, a condensed version of the scale was used. Selections of 1 and 2 were condensed to “agree,” 3 was considered “neutral,” and 4 and 5 were condensed to “disagree.” Next, the test of proportions was used to evaluate differences between “agree,” “neutral,” and “disagree,” as well as across statements.

To evaluate the key drivers of consumer beliefs, we estimated a series of probit models. Each model used agreement with the belief statement as the dependent variable (e.g., "Local food is more expensive than other food."). Agreement was defined as above—selection of "1" or "2" in the 5-part scale, with "neutral" and "disagree" serving as zero. Independent variables included demographic characteristics (e.g., age, income, education, region), shopping behaviors (e.g., purchasing local or organic food), and additional factors, such as looking at price, certification labels, nutritional information, or safety information when shopping. Probit models were tailored to specific belief statements. For example, models for statements about environmental benefits included variables capturing whether respondents reviewed certification or product information, whereas models about nutrition and health included variables related to reviewing nutritional information.

Results

Sample Description

The survey sample closely mirrored the U.S. Census in terms of gender, age, income, and regional representation, as shown in Table 1. Notable deviations included a lower percentage of respondents without a high school diploma (6% compared to 11% in the U.S. Census) and a higher percentage with a college degree (33% versus 29%). The average household included two adults and 0.65 children. These demographic characteristics provide a robust foundation for analyzing consumer beliefs and behaviors.

Table 1. Demographic Information (n = 1,000)

Demographic Variable	Percentage of Respondents	U.S. Census
Gender		
Male	49	49
Female	51	51
Age		
18–24	12	12
25–34	18	18
35–44	17	16
45–54	16	16
55–65	17	17
65+	21	21
Income		
$0–$24,999	18	18
$25,000–$49,999	19	20
$50,000–$74,999	18	17
$75,000–$99,999	13	13
$100,000 and higher	31	31

Table 1 (cont.)

Demographic Variable	**Percentage of Respondents**	**U.S. Census**
Education		
Did not graduate from high school	6Ψ	11
Graduated from high school, did not attend college	27	27
Attended college, no degree earned	21	21
Attended college, associate's or bachelor's degree earned	33Ψ	29
Attended college, graduate or professional degree earned	14	13
Region of residence		
Northeast	18	17
South	39	38
Midwest	21	21
West	23	24
Household number	Mean	
Adults (n = 999)[1]	2	
Children (n = 998)[1]	0.65	

Notes: ΨIndicates the percentage of respondents is statistically different than the U.S. Census at the 0.05 level.
[1]Due to the write in nature of this question, not all respondents participated.

Shopping Behavior

Figure 1 and Table 2 illustrate the distribution of weekly food expenditures across respondents. Respondents reported varied weekly food expenditures, with the largest proportion (23%) spending \$100–\$149 per week, followed by 20% spending \$150–\$199, as detailed in Table 2. Only 5% of respondents reported spending more than \$300 weekly on food.

In terms of purchasing behavior, 74% of respondents indicated they purchase local foods, while 64% purchase organic foods (see Table 2). Definitions of local food varied, with 23% defining it as coming from within 100 miles of their county and neighboring counties, 22% defining it as coming from their state, and only 6% defining it as coming from the United States (see Table 2). These variations underscore the ambiguity surrounding "local" as a concept, which may influence consumer perceptions and purchasing decisions.

Consumers also reported the types of information they reviewed when shopping. Price was the most frequently reviewed attribute (80%), followed by sell-by dates (68%) and nutritional information (57%), whereas certifications were reviewed by only 11% of respondents. These results highlight an opportunity for producers and marketers to emphasize certifications and labeling to build trust and differentiate products.

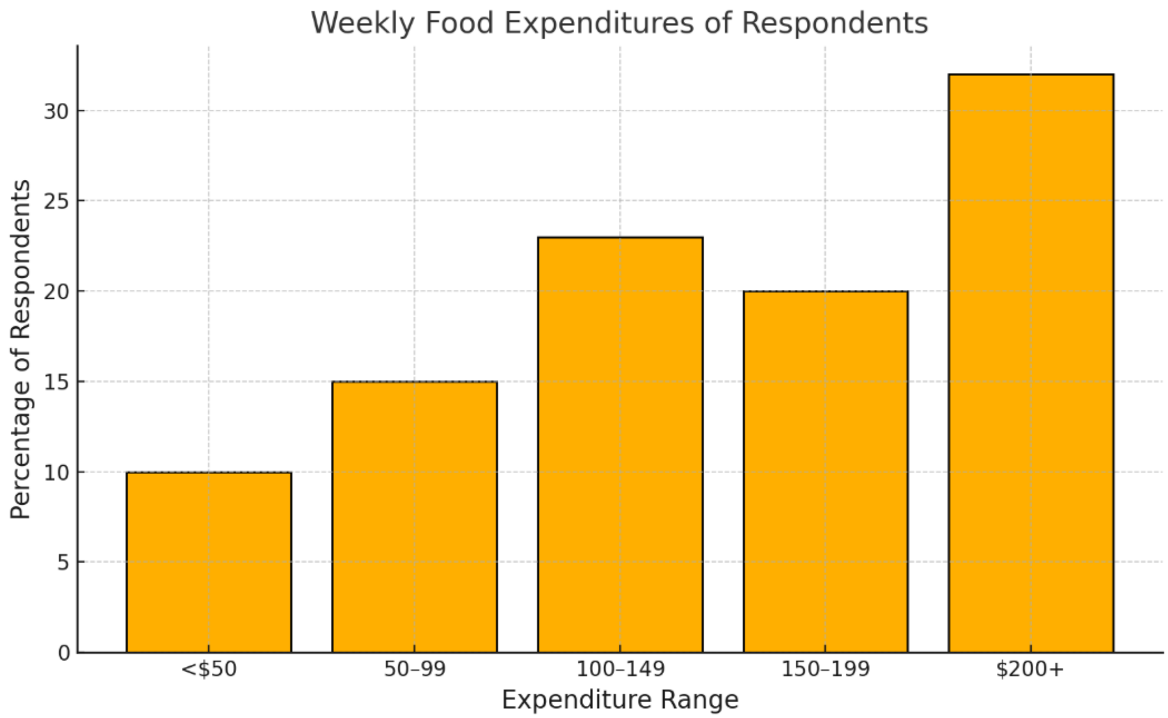

Figure 1. Weekly Food Expenditures of Respondents

Table 2. Shopping Behavior (n = 1,000)

	Percentage of Respondents
Amount household spends each week on total food consumption including at home, groceries, restaurants, take-outs	
Less than $50	8
$50–$99	16
$100–$149	23
$150–$199	20
$200–$249	14
$250–$299	11
$300 or more	5
Don't know	3
Information that respondents assess in reviewing food product packaging (multiple selections allowed)	
Nutritional information	57
Price	80
Food safety information	33
Production information	40
Certifications	11
Product expiration "sell-by" date	68

Table 2 (cont.)

	Percentage of Respondents
None	5
Other	1
Purchases local foods	
Yes	74
No	11
Don't know	15
Respondents' definition of "local food"	
From my county of residence	18
100 miles or less from my home	23
From my county and neighboring counties	23
From my state of residence	22
From the United States	6
Not sure/don't know	8
Other (please describe)	1
Purchases organic foods	
Yes	64
No	30
Don't know	6

Demographic Comparisons on Local and Organic Purchasers

Demographic differences between purchasers of local and organic foods are presented in Table 3. Purchasing patterns were consistent across genders and regions of residence, with no statistically significant differences. However, age showed notable variation. For organic foods, a higher percentage of respondents aged 35–44 (75%) or 25–34 (72%) purchased organic when compared to those aged 55–65 (59%) and those aged over 65 (48%). Similarly, for local foods, a higher percentage of respondents aged 35–44 (82%) purchased organic when compared to those aged 18–24 (71%), aged 55–65 (69%) and those aged over 65 (67%). A lower percentage of respondents aged 65 and older purchased organic food (48%) when compared to all other age groups. A lower percentage of respondents aged 65 and older purchased local food (67%) when compared to those aged 25–34 (77%), 35–44 (82%), and 45–54 (80%). In general, higher percentages of all age groups purchased local food, which may indicate more opportunity for cross-age marketing for local foods.

Income also influences purchasing behavior. Respondents with higher incomes ($100,000 or more) were more likely to purchase local (83%) and organic (75%) foods than those with lower incomes. Similarly, education followed a clear trend: college graduates were significantly more likely to purchase these products than respondents with lower education levels. These findings suggest that higher income and education levels may be associated with greater awareness and ability to pay for local and organic foods. Those with lower income levels may have a preference for local and organic foods but may be unable to afford them. Although there is a lower percentage of those respondents, when compared to respondents with higher incomes (for example, nearly half [45%] of those with an income of $0–$24,999 purchased organic, and more than half [59%] purchased local foods), there is still a high percentage of lower income respondents who would choose local and organic, given potential financial constraints. This result may be related to the incorporation of food stamp programs into farmers' markets, sometimes with discount schemes (USDA, 2024). Many nonprofit organizations have information and programs to help consumers with low incomes access local and organic foods.

Table 3. Demographic Information by Purchasing Behavior—Percentage of Respondents (N = 1,000)

Demographic Variable	***n***	**Purchases Organic Food**	**Purchases Local Food**
Gender			
Male	492	65a[1]	73a
Female	508	64a	75a
Age			
18–24	119	70ab	71ab
25–34	176	72a	77acd
35–44	165	75a	82d
45–54	161	68ab	80ad
55–65	167	59b	69bc
65+	212	48c[1]	67b
Income			
$0–$24,999	181	45d	59c
$25,000–$49,999 (n = 194)	194	59a	71a
$50,000–$74,999 (n = 181)	181	63ab	70a
$75,000–$99,999 (n = 130)	130	73bc	84b
$100,000 and higher	314	75c	83b
Education			
Did not graduate from high school	57	47d	65ab
Graduated from high school, did not attend college	270	57a	66a
Attended college, no degree earned	211	62ab	73ab
Attended college, associate's or bachelor's degree earned	326	72c	82c
Attended college, graduate or professional degree earned	136	71bc	77bc
Region of residence			
Northeast	175	60a	79a
South	392	65a	72a
Midwest	208	64a	75a
West	225	67a	73a

[1]Matching letters indicate the percentage of respondents is not statistically different at the 0.05 level. Mismatched letters indicate the percentages are statistically different. For example, the percentage of males and females who buy organic is not statistically different. Conversely, the percentage of respondents aged 65+ is statistically different from all other organic shopping age categories.

Beliefs about Local and Organic Foods

Respondents' beliefs about local and organic foods are summarized in Figure 2 and Table 4. Regarding specific local statements, "*I like to know who produces the food I eat*" (62% agree) and "*Purchasing local food is better for the environment*" (60% agree), the percentage of respondents who agreed was not statistically different and was higher than all other local statements. Only 31% of respondents agreed with the statement, "*Local food is organic*," which was lower than all other local statements.

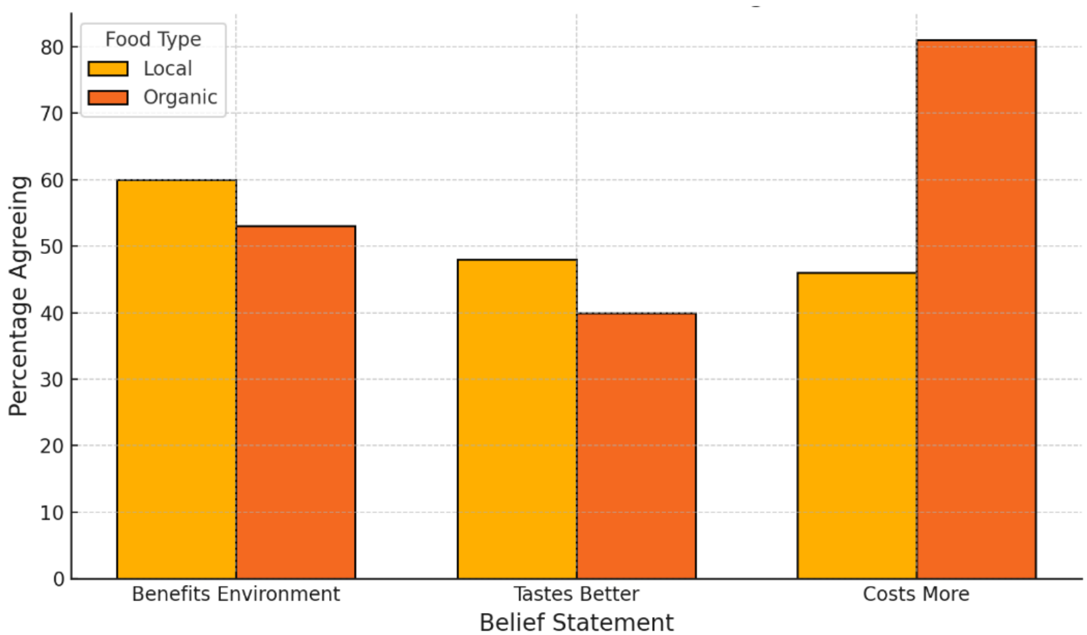

Figure 2. Comparison of Agreements Regarding Beliefs about Local and Organic Foods as Compared to Other Food

Table 4. Beliefs Regarding Local and Organic Food (N = 1,000), Percentage of Respondents

	Agree	Neither Agree or Disagree	Disagree
Statements about local food			
Local food is more expensive than other food.	46ab[1]Ψ	39d Ψ	16a Ψ
Local food is organic.	31e	52a	17a Ψ
Local food tastes better.	48a Ψ	45b	8bc Ψ
I like to know who produces the food I eat.	62c	30e	8bd
Purchasing local food is better for the environment.	60c Ψ	34f	6c Ψ
Purchasing local food is more nutritious.	43bd Ψ	47bc Ψ	11d Ψ
Local food is healthier.	43bd Ψ	48abc Ψ	9bd Ψ
Local food is safer.	41d Ψ	51ac Ψ	9bd Ψ

Table 4 (cont.)

	Agree	Neither Agree or Disagree	Disagree
Statements about organic food			
Organic food is more expensive than other food.	81c Ψ	16c Ψ	3c Ψ
Organic food is local.	26d	52d	22d Ψ
Organic food tastes better.	40e Ψ	42a	18e Ψ
Purchasing organic food is better for the environment.	53a Ψ	37b	11a Ψ
Purchasing organic food is more nutritious.	48b Ψ	38b Ψ	14b Ψ
Organic food is healthier.	56a Ψ	32e Ψ	13ab Ψ
Organic food is safer.	49ab Ψ	39ab Ψ	13ab Ψ

[1]Matching letters indicates the percentage of respondents is not statistically different at the 0.05 level. Mismatched letters indicate the percentages are statistically different. Comparison is made within the column (for example, "Agree") within either the local or organics foods statements.
Ψ Indicates, for corresponding questions, that the percentage of respondents for the local food statement and the matching organic food statement are statistically different.

Within the organic food statements, a higher percentage agreed (81%) with the statement, "*Organic food is more expensive than other food,*" compared to all other statements. A lower percentage (26%) of respondents agreed with the statement, "*Organic food is local,*" when compared to all other statements. Just over half (53%) of respondents agreed that "*Purchasing organic food is better for the environment*."

Results of a comparison of the organic and local statements showed that there were no statistical differences in the percentage of respondents who agreed with the statements, "*Local food is organic*" (31%), and "*Organic food is local*" (26%). A higher percentage of respondents agreed with the statements, "*Organic food is more expensive than other food*" (81%), "*Purchasing organic food is more nutritious*" (48%), "*Organic food is healthier*" (56%), and "*Organic food is safer*" (49%), when compared to the local food statements (46%, 43%, 43%, and 41%, respectively). Conversely, a lower percentage of respondents agreed with the statements, "*Organic food tastes better*" (40%), and that purchasing organic food is better for the environment (53%) when compared to the local statements (48% and 60%, respectively). These findings highlight the need for targeted messaging. For example, marketing campaigns for local foods could emphasize taste and environmental benefits, whereas those for organic foods may benefit from addressing affordability concerns.

Probit Model Results

Probit model results for agreement with beliefs about local foods are presented in Tables 5 and 6, and results for organic foods are shown in Tables 7 and 8. The models examine the effects of demographic characteristics, purchasing behaviors, and information-seeking practices on consumer beliefs. Comparing these tables yields various insights.

Table 5. Probit Models of Beliefs Regarding Local Food, Marginal Effects (standard error) (N = 998)

	Local Food Is More Expensive Than Other Food	Local Food Is Organic	Local Food Tastes Better	I Like to Know Who Produces the Food I Eat
Female	0.010	-0.059**	-0.029	-0.004
	(0.032)	(0.029)	(0.031)	(0.031)
Age				
18–24	0.148**	0.298***	0.080	0.068
	(0.058)	(0.050)	(0.056)	(0.056)
25–34	0.078	0.202***	0.111**	0.075
	(0.054)	(0.048)	(0.052)	(0.052)
35–44	0.100*	0.115**	0.074	0.120**
	(0.058)	(0.052)	(0.056)	(0.055)
45–54	0.076	0.127**	0.061	0.078
	(0.054)	(0.049)	(0.052)	(0.051)
55–65	-0.009	0.016	-0.013	-0.005
	(0.051)	(0.050)	(0.050)	(0.047)
65-plus	Omitted	Omitted	Omitted	Omitted
Income				
$0–$24,999	-0.000	0.002	0.013	-0.022
	(0.052)	(0.046)	(0.050)	(0.049)
$25,000–$49,999	-0.078	0.034	-0.004	-0.016
	(0.047)	(0.042)	(0.046)	(0.045)
$50,000–$74,999	0.070	-0.010	-0.040	-0.006
	(0.046)	(0.042)	(0.045)	(0.044)
$75,000–$99,999	0.023	0.066	0.039	0.020
	(0.051)	(0.044)	(0.049)	(0.050)
$100,000 and higher	Omitted	Omitted	Omitted	Omitted
Education				
Did not graduate from high school	0.003	-0.018	-0.009	0.006
	(0.083)	(0.075)	(0.081)	(0.078)
Graduated from high school, did not attend college	-0.025	0.015	0.055	0.082
	(0.055)	(0.049)	(0.053)	(0.051)
Attended college, no degree earned	-0.010	-0.014	0.060	0.106*
	(0.056)	(0.051)	(0.054)	(0.053)
Attended college, associate's or bachelor's degree earned	0.001	-0.007	-0.007	0.069
	(0.050)	(0.045)	(0.048)	(0.047)
Attended college, graduate or professional degree earned	Omitted	Omitted	Omitted	Omitted

Table 5 (cont.)

	Local Food Is More Expensive Than Other Food	**Local Food Is Organic**	**Local Food Tastes Better**	**I Like to Know Who Produces the Food I Eat**
Region of residence				
Northeast	-0.042	-0.017	-0.023	-0.033
	(0.050)	(0.045)	(0.048)	(0.047)
South	-0.038	-0.010	-0.019	0.005
	(0.042)	(0.037)	(0.041)	(0.040)
Midwest	0.032	-0.025	0.017	0.026
	(0.047)	(0.042)	(0.046)	(0.045)
West	Omitted	Omitted	Omitted	Omitted
Has a kid	0.069*	0.084**	0.087**	0.050
	(0.038)	(0.033)	(0.036)	(0.037)
Purchases local	0.069*	0.146***	0.298***	0.265***
	(0.038)	(0.035)	(0.034)	(0.032)
Definition of Local				
County of residence	0.372***	0.230***	0.238***	0.142**
	(0.071)	(0.065)	(0.068)	(0.063)
100 miles or less	0.275***	0.061	0.151**	0.109*
	(0.071)	(0.066)	(0.068)	(0.062)
From county or neighboring county	0.266***	0.084	0.113*	0.102*
	(0.071)	(0.065)	(0.068)	(0.061)
From state of residence	0.259***	0.050	0.146**	0.081
	(0.072)	(0.066)	(0.068)	(0.062)
From the US	0.361***	0.166**	0.322***	0.175*
	(0.088)	(0.079)	(0.084)	(0.081)
Not sure/don't know	Omitted	Omitted	Omitted	Omitted
Looks at price	-0.007			
	(0.032)			
Looks at certificates		0.051		
		(0.045)		
Looks at product information		0.037		
		(0.029)		
R^2	0.593	0.126	0.109	0.091

Note: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels.

Table 6. Probit Models of Beliefs Regarding Local Food, Marginal Effects (standard error) (N = 998)

	Purchasing Local Food Is Better for the Environment	**Purchasing Local Food Is More Nutritious**	**Local Food Is Healthier**	**Local Food Is Safer**
Female	0.055*	0.005	0.008	-0.011
	(0.030)	(0.031)	(0.031)	(0.030)
Age				
18–24	0.248***	0.186**	0.136**	0.183**
	(0.055)	(0.055)	(0.055)	(0.054)
25–34	0.146**	0.207***	0.218***	0.255***
	(0.051)	(0.051)	(0.051)	(0.050)
35–44	0.185**	0.125**	0.074	0.128**
	(0.054)	(0.055)	(0.054)	(0.054)
45–54	0.107**	0.049	0.028	0.089*
	(0.050)	(0.051)	(0.051)	(0.051)
55–65	0.056	0.013	0.003	0.085*
	(0.047)	(0.050)	(0.050)	(0.049)
65-plus	Omitted	Omitted	Omitted	Omitted
Income				
$0–$24,999	0.023	0.005	-0.002	0.024
	(0.049)	(0.049)	(0.049)	(0.048)
$25,000–$49,999	0.015	-0.053	0.035	0.061
	(0.045)	(0.045)	(0.045)	(0.044)
$50,000–$74,999	0.013	0.027	-0.001	-0.066
	(0.044)	(0.044)	(0.044)	(0.044)
$75,000–$99,999	0.064	0.107**	0.023	0.052
	(0.049)	(0.048)	(0.048)	(0.047)
$100,000 and higher	Omitted	Omitted	Omitted	Omitted
Education				
Did not graduate from high school	-0.126	-0.038	0.094	0.048
	(0.077)	(0.080)	(0.080)	(0.078)
Graduated from high school, did not attend college	-0.064	0.071	0.164**	0.083
	(0.051)	(0.052)	(0.052)	(0.052)
Attended college, no degree earned	-0.025	0.043	0.137**	0.062
	(0.053)	(0.053)	(0.053)	(0.053)
Attended college, associate's or bachelor's degree earned	-0.002	-0.009	0.122**	0.041
	(0.047)	(0.048)	(0.048)	(0.048)

Table 6 (cont.)

	Purchasing Local Food Is Better for the Environment	Purchasing Local Food Is More Nutritious	Local Food Is Healthier	Local Food Is Safer
Attended college, graduate or professional degree earned	Omitted	Omitted	Omitted	Omitted
Region of residence				
Northeast	-0.041	0.023	0.053	-0.005
	(0.047)	(0.047)	(0.047)	(0.047)
South	-0.044	0.039	0.017	0.027
	(0.039)	(0.040)	(0.040)	(0.039)
Midwest	-0.036	0.012	0.006	0.025
	(0.044)	(0.045)	(0.045)	(0.044)
West	Omitted	Omitted	Omitted	Omitted
Has a kid	-0.019	0.046	0.060*	0.097**
	(0.036)	(0.035)	(0.035)	(0.034)
Purchases local	0.229***	0.218***	0.241***	0.209***
	(0.032)	(0.036)	(0.036)	(0.036)
Definition of local				
County of residence	0.309***	0.202*	0.222**	0.204**
	(0.064)	(0.068)	(0.068)	(0.068)
100 miles or less	0.304***	0.049	0.082	0.139**
	(0.063)	(0.068)	(0.068)	(0.068)
From county or neighboring county	0.317***	0.114*	0.103	0.121*
	(0.062)	(0.067)	(0.068)	(0.068)
From state of residence	0.188**	0.068	0.050	0.110
	(0.064)	(0.068)	(0.068)	(0.068)
From the U.S.	0.235**	0.190**	0.212**	0.276**
	(0.080)	(0.083)	(0.083)	(0.082)
Not sure/don't know	Omitted	Omitted	Omitted	Omitted
Looks at price				
Looks at certificates				
Looks at product information		0.043	0.089**	
		(0.031)	(0.030)	
Looks at nutrition information		0.084**	0.050	
		(0.031)	(0.031)	
Looks at safety information				0.097**
				(0.031)
R^2	0.115	0.118	0.123	0.130

Note: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels.

Demographic Insights

Gender was statistically significant in only a few models (see Tables 5–8). Being female decreased the likelihood of agreeing with the statements, "*Local food is organic*," and "*Organic food is more expensive than other food*." Conversely, being female increased the likelihood of agreement that purchasing local food is better for the environment.

Table 7. Probit Models of Beliefs Regarding Organic Food, Marginal Effects (standard error) (N = 998)

	Organic Food Is More Expensive Than Other Food[1]	**Organic Food Is Local**	**Organic Food Tastes Better**	**Purchasing Organic Food Is Better for the Environment**
Female	0.062**	-0.039	-0.020	-0.020
	(0.025)	(0.027)	(0.029)	(0.030)
Age				
18–24	-0.086*	0.225***	0.218***	0.254***
	(0.047)	(0.050)	(0.053)	(0.055)
25–34	-0.096**	0.215***	0.255***	0.231***
	(0.043)	(0.047)	(0.049)	(0.051)
35–44	-0.020	0.160**	0.169**	0.218***
	(0.048)	(0.050)	(0.053)	(0.054)
45–54	-0.051	0.067	0.130**	0.150**
	(0.043)	(0.050)	(0.050)	(0.050)
55–65	-0.048	0.082*	0.107**	0.148**
	(0.040)	(0.048)	(0.049)	(0.047)
65-plus	Omitted	Omitted	Omitted	Omitted
Income				
\$0–\$24,999	-0.052	0.116**	0.140**	0.023
	(0.039)	(0.044)	(0.047)	(0.048)
\$25,000–\$49,999	0.023	0.110**	0.086**	0.019
	(0.038)	(0.041)	(0.043)	(0.045)
\$50,000–\$74,999	0.010	0.098**	0.031	0.014
	(0.038)	(0.040)	(0.042)	(0.043)
\$75,000–\$99,999	0.005	0.142**	0.071	0.080
	(0.041)	(0.041)	(0.046)	(0.048)
\$100,000 and higher	Omitted	Omitted	Omitted	Omitted
Education				
Did not graduate from high school	0.008	0.039	-0.053	-0.071
	(0.065)	(0.068)	(0.076)	(0.079)
Graduated from high school, did not attend college	-0.030	-0.017	-0.001	0.020
	(0.044)	(0.047)	(0.050)	(0.051)

Table 7 (cont.)

	Organic Food Is More Expensive Than Other Food[1]	**Organic Food Is Local**	**Organic Food Tastes Better**	**Purchasing Organic Food Is Better for the Environment**
Attended college, no degree earned	-0.010	-0.061	-0.032	-0.008
	(0.045)	(0.048)	(0.051)	(0.052)
Attended college, associate's or bachelor's degree earned	0.012	-0.032	-0.001	0.042
	(0.040)	(0.043)	(0.045)	(0.047)
Attended college, graduate or professional degree earned	Omitted	Omitted	Omitted	Omitted
Region of residence				
Northeast	0.017	-0.038	-0.028	0.026
	(0.040)	(0.042)	(0.045)	(0.047)
South	-0.032	-0.017	-0.035	-0.048
	(0.033)	(0.035)	(0.038)	(0.039)
Midwest	0.019	-0.072*	-0.037	-0.055
	(0.038)	(0.041)	(0.043)	(0.044)
West	Omitted	Omitted	Omitted	Omitted
Has a kid	-0.007	0.082**	0.094**	0.003
	(0.030)	(0.031)	(0.033)	(0.035)
Purchases organic	0.116***	0.145***	0.348***	0.318***
	(0.025)	(0.030)	(0.027)	(0.026)
Looks at price	0.096***			
	(0.025)			
Looks at certificates		0.121**		
		(0.041)		
Looks at product information		-0.002		
		(0.028)		
R^2	0.075	0.119	0.160	0.135

Note: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels.

Table 8. Probit Models of Beliefs Regarding Local Food, Marginal Effects (standard error) (N = 998)

	Purchasing Organic Food Is More Nutritious	**Organic Food Is Healthier**	**Organic Food Is Safer**
Female	-0.017	0.042	0.028
	(0.029)	(0.029)	(0.029)
Age			
18–24	0.327***	0.152**	0.227***
	(0.052)	(0.053)	(0.053)
25–34	0.279***	0.174***	0.251***
	(0.048)	(0.049)	(0.049)
35–44	0.177**	0.082	0.195***
	(0.052)	(0.052)	(0.052)
45–54	0.142**	0.086*	0.199***
	(0.049)	(0.049)	(0.048)
55–65	0.095**	0.021	0.106**
	(0.047)	(0.046)	(0.047)
65-plus	Omitted	Omitted	Omitted
Income			
\$0–\$24,999	0.120**	0.080*	0.066
	(0.047)	(0.047)	(0.047)
\$25,000–\$49,999	0.097**	0.081*	0.086**
	(0.043)	(0.043)	(0.042)
\$50,000–\$74,999	0.042	0.030	0.090**
	(0.042)	(0.042)	(0.042)
\$75,000–\$99,999	0.121**	0.049	0.119**
	(0.047)	(0.047)	(0.046)
\$100,000 and higher	Omitted	Omitted	Omitted
Education			
Did not graduate from high school	0.151**	0.095	0.050
	(0.076)	(0.077)	(0.075)
Graduated from high school, did not attend college	0.057 (0.050)	0.005 (0.050)	0.007 (0.049)
Attended college, no degree earned	0.034	-0.003	0.022
	(0.051)	(0.051)	(0.050)
Attended college, associate's or bachelor's degree earned	0.016 (0.045)	-0.029 (0.045)	0.055 (0.044)
Attended college, graduate or professional degree earned	Omitted	Omitted	Omitted

Table 8 (cont.)

	Purchasing Organic Food Is More Nutritious	Organic Food Is Healthier	Organic Food Is Safer
Region of residence			
Northeast	0.001	0.020	-0.013
	(0.045)	(0.045)	(0.045)
South	-0.051	0.001	0.029
	(0.037)	(0.038)	(0.037)
Midwest	-0.105**	-0.030	0.021
	(0.043)	(0.043)	(0.042)
West	Omitted	Omitted	Omitted
Has a kid	0.094**	0.049	0.035
	(0.034)	(0.035)	(0.034)
Purchases organic	0.291***	0.338***	0.344***
	(0.028)	(0.025)	(0.025)
Looks at price			
Looks at certificates			
Looks at product information	0.070**	0.114***	
	(0.030)	(0.029)	
Looks at nutrition information	0.082**	0.063**	
	(0.030)	(0.030)	
Looks at safety information			0.111***
			(0.029)
R^2	0.181	0.174	0.193

Note: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels.

Age was a significant predictor of beliefs about both local and organic foods (see Tables 5–8). Younger respondents (aged 18–54) were more likely to agree with the statement, "*Local food is organic,*" and "*Purchasing local food is better for the environment,*" when compared to older respondents (65+). Age groups 18–44 and 55–65 were more likely to agree that organic food was local, when compared to those 65 and older. Those aged 18–44 were more likely to agree that purchasing local food is more nutritious. Those aged 18–34 were more likely to agree that local foods are healthier than other foods and were less likely to agree that organic food is more expensive when compared to the 65+ group. Age groups 18–34 and 45–54 were more likely to agree that organic food was healthier than those 65 and older. All younger age groups were more likely to agree that local and organic food is safer, organic food tastes better, purchasing organic food is better for the environment, and organic is more nutritious compared to those 65 and older.

Income had little statistical significance in the local food models (see Tables 5–8). Having an income of $75,000–$99,999 increased the likelihood of agreement that purchasing local food is more nutritious when compared to an income of $100,000 and higher (see Table 6). Being in any of the lower income groups increased the likelihood of agreement with the statement that organic food is local, compared to incomes of $100,000 and higher. An income between $0–$49,999 increased the likelihood of agreeing with the belief that organic food tastes better, and organic food is healthier. Trends were mixed for the statements, "*Purchasing organic food is more nutritious*," and "*Organic food is safer*."

Attending college with no degree earned increased the likelihood of agreeing with the statement "*I like to know who produces the food I eat,*" when compared to those with a graduate or professional degree. Graduating from high school, attending college without a degree earned, and attending college with a degree earned all increased the likelihood of agreeing with the statement local food is healthier compared to having a graduate or professional degree. Not graduating from high school increased the likelihood of agreeing with the statement purchasing organic food is more nutritious.

Residence in the Midwest decreased the likelihood of agreeing with the statement that organic food is local and that purchasing organic food is more nutritious. Having a child increased the likelihood of agreement with the statements that local food is more expensive and healthier, local food is organic (and the reverse), and local and organic food tastes better and is healthier.

Purchasing Behavior Insights

Purchasing local or organic foods strongly influenced consumer beliefs. Purchasing either organic or local foods increased the likelihood of belief in every one of their respective models, likely reflecting confirmation bias. Klayman (1995, p. 387) gives several sources of confirmation bias including, "Your interpretation of the information you receive might be biased in favor of your hypothesis. For example, you may regard hypothesis confirming data as trustworthy and disconfirming data as dubious." Careful interpretation of belief systems for those who do and do not purchase is important when making projections regarding potential increases in purchases of organic or local foods.

Definition of Local

The impact of the respondent's definition of local is mixed (see Table 6). Having any definition increased the likelihood of agreeing with the statements, "*Local food is more expensive than other food,*" "*Local food tastes better,*" and "*Purchasing local food is better for the environment,*" when compared to not sure/don't know. Having a definition of county of residence and from the U.S. increased the likelihood of agreeing with the statements that "*Local food is healthier,*" and "*Local food is organic.*" Any definition other than from state of residence increased the likelihood of agreeing with the statements, "*Local food is safer,*" and "*I like to know who produces the food I eat.*" A definition of county of residence, from county or neighboring county, and from the U.S. all increased the likelihood of agreeing that purchasing local food is more nutritious when compared to not sure/don't know.

Information-Seeking Behavior

Interestingly, looking at price was not statistically significant for the belief that local food is more expensive, but increased the likelihood of agreeing with the statement that organic food is more expensive. Looking at certificates increased the likelihood of agreeing with the belief that organic food is local, but was insignificant for the belief that local food is organic. This finding may be in part due to a lack of labeling at farmers' markets where many local foods are purchased. Looking at product information increased the likelihood of agreeing with the statements local food is healthier, purchasing organic food is more nutritious, and organic food is healthier. Looking at nutrition information increased the likelihood of agreeing with the beliefs that purchasing local and organic food is more nutritious and organic food is healthier. Looking at safety information increased the likelihood of believing that organic and local food is safer.

Discussion and Implications

This study provides valuable insights into U.S. consumers' beliefs and perceptions about local and organic foods, addressing critical gaps in the literature on sustainable food systems (Enthoven and Van den Broeck, 2021; Adams and Salois, 2010). By analyzing how demographic characteristics, purchasing behaviors, and information-seeking practices influence these perceptions, the findings highlight opportunities for targeted strategies in marketing, policy, and production.

Summary of Findings

Consumers consistently perceived local foods as more environmentally beneficial and better tasting than organic foods. Sixty percent of respondents agreed that local foods benefit the environment, compared to 53% for organic foods. However, organic foods were strongly associated with higher costs, a perception held by 81% of respondents. These findings reinforce the importance of addressing affordability concerns for organic foods and leveraging positive associations for local foods, such as taste and environmental benefits.

Demographic patterns revealed key opportunities for segmentation. Younger consumers were more likely to hold positive beliefs about local and organic foods, particularly regarding health and environmental benefits. Previously, Zepeda and Li (2006) found that gender, age, education, race, and religion had no significant impact on buying local food. Gundala and Singh (2021) found that gender did not impact the purchase of organic food; however, income, age, and education did affect consumers' actual purchases. Higher income and college-educated individuals were also more likely to purchase these products in this study, similar to the findings of Dimitri and Dettman (2012), suggesting that awareness and financial resources play a significant role in adoption. Previous studies showed similar results. They found that lower income households are less likely to purchase local foods, with gender and education having varied effects (Qi, Rabinowitz, and Cambell, 2017; Fernández-Ferrín et al., 2016; Brown, 2003; Jekanowski, Williams, and Schiek, 2000). In contrast, older adults and lower income consumers were less likely to purchase local or organic foods, highlighting the need for tailored interventions, such as subsidies or outreach efforts to address accessibility and cost concerns.

Implications for Marketing and Policy

Purchasing behaviors strongly influenced consumer beliefs, suggesting potential confirmation bias. Respondents who purchased both local and organic foods held stronger positive beliefs about organic food's environmental benefits. Cross-promotional strategies that emphasize the shared benefits of these categories could expand consumer engagement. Although in the past attributes for local and organic foods were often blurred, as standards became clearer, distinct differences in preference have occurred (Adams and Salois, 2010). The growing differentiation between organic and local food is reflected in the survey participants' ability to correctly identify the inaccuracies in the statements, "*Organic food is local*," and "*Local food is organic*."

Additionally, respondents who reviewed certifications, nutritional information, or product labels expressed stronger positive beliefs, particularly for organic foods. Marketers and producers should prioritize transparency and certification labeling to enhance trust and differentiate products in competitive markets (Wilson and Lusk, 2020).

The persistent ambiguity in the definition of "local" continues to challenge consumer understanding (Granvik et al., 2017; Jia, 2021). The majority of respondents selected the option, "*My state of residence or closer*," which was similar to the findings of Bir et al. (2019). Very few people selected "*From the United States*," indicating that for most people, local is more than just domestic (within the United States) production. Standardized definitions or clearer labeling could mitigate this issue and improve consumer confidence. Zepeda and Leviten-Reid (2004) conducted a focus group to evaluate definitions of local foods and found that most respondents use driving time to measure distance. Respondents who reported using this method typically suggested local was less than seven hours. Other respondents indicated similarly to this study choosing within a state, neighboring counties, or within neighboring states (Zepeda and Leviten-Reid, 2004).

Similarly, the low engagement with certification labels (reviewed by only 11% of respondents) represents a missed opportunity for building trust in organic products. Policy makers and producers should explore ways to make certification information more accessible and relevant to consumers.

Limitations and Future Research

This study is not without limitations. The use of an online survey introduces potential sample biases, particularly regarding education levels, which may skew results toward more environmentally conscious attitudes. Additionally, the reliance on self-reported data may limit the generalizability of findings. Future research could explore longitudinal changes in consumer perceptions, investigate regional variations in greater depth, or examine the role of social norms in shaping beliefs about local and organic foods.

Conclusion

By identifying the key drivers of consumer beliefs about local and organic foods, this study offers actionable insights for marketers, policy makers, and producers. Addressing cost perceptions, enhancing labeling transparency, and tailoring strategies to demographic segments can help stakeholders better align with consumer preferences. These efforts have the potential to support the growth of local and organic food markets while fostering sustainable food systems.

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Appendix A. Survey Instrument

I am:

- ○ Male
- ○ Female

I am _____ years old.

- ○ Under 18
- ○ 18 - 24
- ○ 25 - 34
- ○ 35 - 44
- ○ 45 - 54
- ○ 55 - 64
- ○ 65 +

My household (including all other adults and children living in my household) has the following number of members (include yourself), please place a zero if you do not have children in your household:

- ○ Adults (18 years and older) __________
- ○ Children (Under 18 years old) __________

My annual pre-tax, household income is:

- ○ $0-$24,999
- ○ $25,000-$49,999
- ○ $50,000-$74,999
- ○ $75,000-$99,999
- ○ $100,000 and higher

The best description of my educational background is:

- ○ Did not graduate from high school
- ○ Graduated from high school, Did not attend college
- ○ Attended College, No Degree earned
- ○ Attended College, Associate's or Bachelor's Degree earned
- ○ Attended College, Graduate or Professional Degree earned

My region of residence is: ___________. Select one option from the drop down menu.

- ○ Northeast (CT, ME, MA, NH, NJ, NY, PA, RI, VT)
- ○ South (AL, AR, DE, DC, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, WV)
- ○ Midwest (IL, IN, IA, KS, MI, MN, MO, NE, ND, OH, SD, WI) (
- ○ West (AK, AZ, CA, CO, HI, ID, MT, NV, NM, OR, UT, WA, WY)

How much would you **estimate your household spends each week on total food consumption** including at home, in groceries, in restaurants, take-outs, etc.? Please provide your best estimate.

○ Less than $50

○ $50 to $99

○ $100 to $149

○ $150 to $199

○ $200 to $249

○ $250 to $299

○ $300 or more (please specify):
____

○ Don't know.

Please indicate all of the following pieces of information that you assess in **reviewing food product packaging?**

- Nutritional information
- Price
- Food safety information
- Production information
- Certifications
- Product expiration "sell-by" date
- None
- Other ____

Do you ever purchase food in grocery stores that is labeled as **"local"** or **"locally produced"?**

○ Yes

○ No

○ Don't know

Indicate how much you agree or disagree with each statement about local foods.

	Strongly Agree	Agree	Neither Agree or Disagree	Disagree	Strongly Disagree
Local food is more expensive than other food.	○	○	○	○	○
Local food is organic.	○	○	○	○	○
Local food tastes better.	○	○	○	○	○
I like to know who produces the food I eat.	○	○	○	○	○
Purchasing local food is better for the environment.	○	○	○	○	○
Purchasing local food is more nutritious.	○	○	○	○	○
Local food is healthier.	○	○	○	○	○
Local food is safer	○	○	○	○	○

Local food can be defined several ways. Indicate your **definition of “local food”** by checking the response that best represents your opinion, or use the “other” space to describe your thoughts:

○ From my county of residence

○ 100 miles or less from my home

○ From my county and neighboring counties

○ From my state of residence

○ From the United States

◯ Not sure/Don't know

◯ Other (please describe) ____

Do you ever purchase food in grocery stores that is labeled as **"organic"** or **"organically produced"?**

◯ Yes

◯ No

◯ Don't know

Indicate how much you agree or disagree with each statement about organic foods.

	Strongly Agree	Agree	Neither Agree or Disagree	Disagree	Strongly Disagree
Organic food is more expensive than other food.					
Organic food is local.					
Organic food tastes better.					
Purchasing organic food is better for the environment.					
Purchasing organic food is more nutritious.					
Organic food is healthier.					
Organic food is safer					

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Differences in Strawberry Demand Based on Region, Season, and Strawberry Type

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Abstract

This study analyzes consumer demand premiums for organic and local strawberries in different United States regions. Seasonal market power is also examined for each region, illustrating the seasonal and regional viability of new strawberries. The price premium for organic strawberries varies by region. The premium for local strawberries is not statistically significant for any region but may reflect a lack of data. Market power of varying degrees exists outside of peak strawberry season, indicating economic viability for new strawberry varieties with seasonality differences. Combining the premium and market power analyses gives strawberry producers important information about entering new markets.

Keywords: fresh market, market power, price premium, product differentiation, season extension, strawberry

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Introduction

In 2020, strawberry production was valued at more than $2 billion and accounted for 13% of the total U.S. fruit market (Yeh et al., 2023). Between 1980 and 2018, availability of strawberries grew from 2.0 to 8.4 pounds per capita, an increase of 320% (Li et al., 2019). This study estimates the supply and demand for strawberries in different regions in the United States. We test for changes in demand depending on attributes, such as organic, and estimate seasonal market power in regional strawberry markets.

Consumer demand for strawberries is strong for various reasons. Strawberries are associated with multiple health benefits as a nutritional fresh food containing high levels of fiber, vitamins, and other nutraceuticals with antioxidant and anti-inflammatory properties (Samtani et al., 2019). Additionally, since the early 1980s, U.S. strawberry researchers and producers successfully increased strawberry availability through plant breeding efforts, advanced production techniques, season expansion technologies, and sophisticated post-harvest and transportation infrastructure. In 1980, fresh strawberries were available five to six months out of the year and cost about $2.67 per pint when adjusted for inflation (U.S. Bureau of Labor Statistics, 2024). In 2023, domestically grown strawberries were available year round at an average of $2.80 per pint, a minimal increase in price despite substantial growth in production. In real terms (converting to 2023 dollars using the Federal Reserve Bank's Implicit Price Deflator), processing strawberry prices in 2023 have risen 10% relative to their 2010 price, and fresh market strawberries have risen 13% relative to their 2010 price (see Figure 1).

Figure 1. Real Price Growth from 2010 to 2023 in U.S. Strawberries

Source: USDA-NASS (2024)

The United States produces about 2.4 billion pounds of strawberries annually, ranking second in the world behind China, and accounts for 13% of global production (Yeh et al., 2023, UNFAO, 2024). About 91% of US strawberries are produced in California between March and November (Yeh et al., 2023). Another 8% of the crop is produced in Florida between December and March. Other strawberry-producing regions, such as the Pacific Northwest (PNW), Midwest, South Atlantic, and Northeast, together produce less than 1% of the total U.S. strawberry crop and supply local direct and processed wholesale markets (Samtani et al., 2019; Yeh et al., 2023).

Often, challenges to strawberry production are economic in nature, specifically, low access to affordable skilled labor and high production costs. While strawberry prices are up 13% since 2010, agricultural input costs are up almost 25% (see Figure 2) (BEA, 2024). In addition to rising production costs, U.S. producers are also affected by imports of strawberries, primarily from Mexico, which put downward pressure on domestic prices (Suh, Guan, and Khachatryan, 2017). From 2020 to 2023, strawberry imports into the United States rose 35% (see Figure 3). In 2023, 588 million pounds of fresh strawberries, 355 million pounds of frozen strawberries, and 95 million pounds of prepared/preserved strawberries were imported (USDA-ERS, 2024).

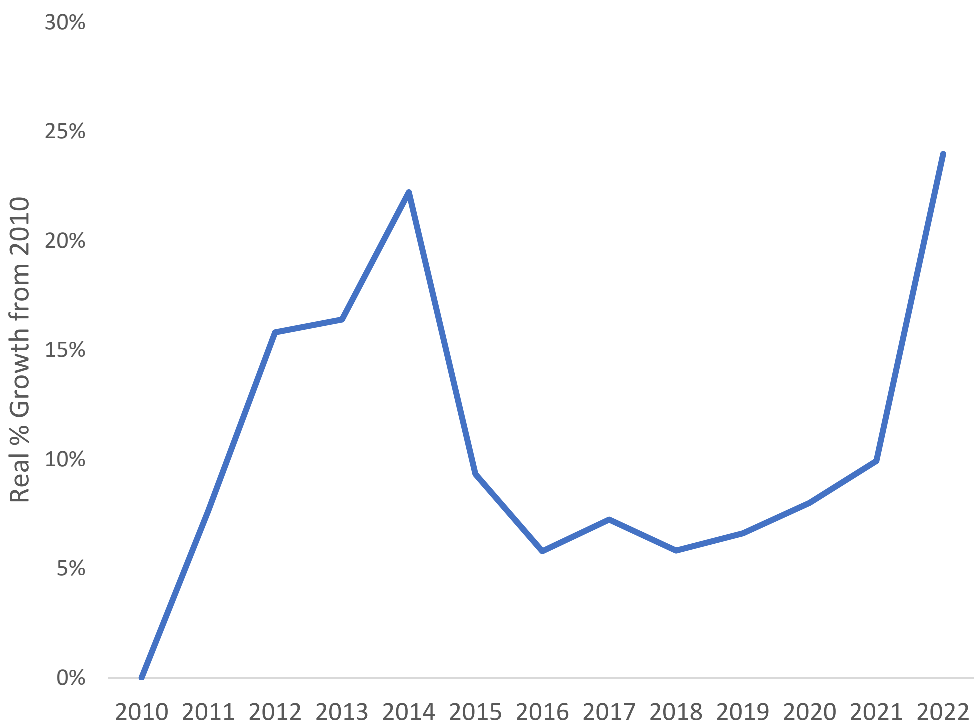

Figure 2. Real Composite Farm Production Expenses Growth from 2010, in the United States

Source: Bureau of Economic Analysis (2024)

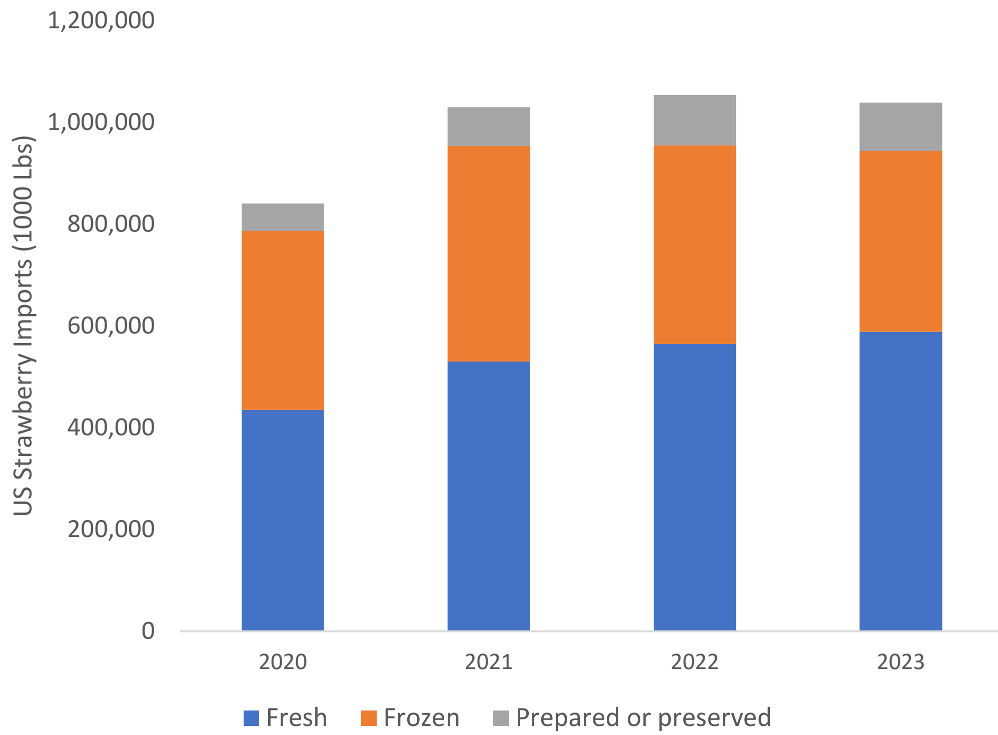

Figure 3. U.S. Imports of Strawberries by 2020-2023

Source: USDA-ERS (2024)

The two marketing channels, direct-to-consumer fresh market sales and wholesale processing sales, have somewhat different cost factors and very different demand factors. Understanding the production costs and earnings of both direct marketed and wholesale processing is crucial to understanding the optimal strategies for producers to pursue given the economic forces, both on the supply/cost side and on the revenue/demand side. Growth in agricultural production costs (see Figure 2) have outpaced the price growth of strawberries (see Figure 1), leading to financial stress among U.S strawberry producers. Better understanding of consumer preferences with regard to strawberries will inform the development of differentiated products and potentially create value in the strawberry market (BEA, 2024, U.S. Bureau of Labor Statistics, 2024).

Product attributes contribute to value differentiation for many U.S. commodities. Labels for organic and locally produced food influences consumer willingness to pay for differentiated strawberry products (Chen et al., 2023). The premium for local strawberries may depend upon whether consumers view local strawberries as being fresher or higher quality (He et al., 2021). Also, new crop varieties and technological innovations have successfully extended the harvest seasons for many fruits.

Consumer preferences vary across regions. This paper analyzes differences in demand for fresh strawberries based on the type of strawberry, the season, and the region where it is sold. Furthermore, we estimate market power, which may serve as a proxy for viability and profitability for producers entering those markets. Economic theory suggests that a lack of market power will lead to a lack of profitability. Therefore, while we do not estimate profitability directly, estimating market power is a strong determinant of profitability. Market power in agricultural supply chains in not uncommon, and it is often seasonal (Steen and Salvanes, 1999; Arnade and Pick, 2000; Richards, Patterson, and Acharya, 2001; Winfree et al., 2004; Acharya, Kinnucan, and Caudill, 2011; Sexton, 2013; Saitone and Sexton, 2017; Azzam and Dhoubhadel, 2022). Also, seasonality is important for commodities like strawberries that are difficult to store (Flaming, Marsh, and Wahl, 2007).

Recognizing the factors that contribute to market power for strawberry growers can be the basis for making production and marketing decisions. This analysis examines regional differences in the United States in the supply and demand of strawberries and looks at potential markets for strawberry producers.

Methodology

Strawberry price fluctuates by region and season (see Figure 4), and organic fresh strawberries consistently have higher prices than conventional fresh strawberries (see Table 1). To determine the proportion of these price differences that are due to differences in supply or demand, a three-stage least squares regression analysis was performed to simultaneously estimate supply and demand for fresh strawberries and test for premiums associated with organic and/or local designations. This analysis allows us to determine whether price differences are largely due to supply (i.e., differences in cost) or to demand (i.e., differences in willingness to pay) and to avoid endogeneity problems that arise when only supply or demand are estimated. Consumer preference differences and market power differences were analyzed across regions using separate regressions for each region.

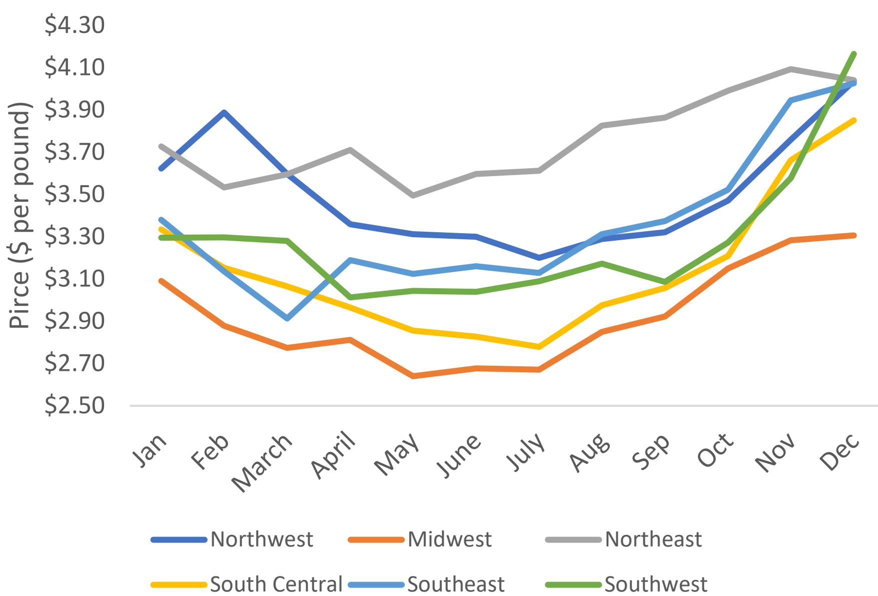

Figure 4. Strawberry Prices by Region and Season, 2010–2022, 2022 Real Dollars

Source: U.S. Bureau of Labor Statistics (2024)

Table 1. Strawberry Prices by Region and by Non-Organic and Organic Designations (2010–2022, in Real 2022 Dollars)

	Northwest	**Midwest**	**Northeast**	**South Central**	**Southeast**	**Southwest**	**Alaska**	**Hawaii**
Non-organic	3.01	2.64	3.24	2.76	3.05	2.84	4.06	4.73
Organic	4.47	3.89	4.98	4.02	4.13	4.14	5.60	6.18

Source: USDA-NASS (2021)

Econometric Model

Weekly price and quantity data from the USDA Agricultural Marketing Service from 2010 to 2022 were used to perform the analysis. Weighted prices across stores were used for price, and number of stores serve as a proxy for quantity.[1] These data also give the date and region of the sale, package size, and whether or not the strawberries were organic or local.

The empirical specification of the inverse supply function was calculated based on consideration of statistical significance, economic interpretability, and data availability using this formula:

$$ln(p_{it}) = \delta_s + \alpha_0\, ln(q_{it}) + \sum_{y=1}^{12} \alpha_y YEAR_t + \sum_{m=13}^{23} \alpha_m MONTH_t + \alpha_{24} FV_{t-1} + \alpha_{25} GAS_{t-1} + \alpha_{26} FERT_{t-1} + \alpha_{27} AGUN_{t-1} + \alpha_{28} PACK_{it} + \alpha_{29} ORG_{it} + \alpha_{30} LOCAL_{it} + \varepsilon_{it}^{S} \quad (1)$$

where p_{it} represents the real price of strawberries for location *i* in time *t*, q_{it} represents the number of stores. $YEAR_t$ represents year fixed effects and $MONTH_t$ is the month of the sale, which included every month but July. July was omitted because it had the lowest month fixed effect and presumably the least amount of monopoly or oligopoly power. FV_{t-1} is the farmland value,[2] GAS_{t-1} is the price of gas,[3] $FERT_{t-1}$ is the price of fertilizer,[4] and $AGUN_{t-1}$ is the unemployment rate in agriculture.[5] Farmland value, gas prices, fertilizer prices, and the unemployment rate in agriculture are used to estimate the costs associated with producing strawberries. Because of the lag between production decisions and sales, these four variables are lagged one year. $PACK_{it}$ is the size of the package in pounds. ORG_{it}, and $LOCAL_{it}$, are dummy variables equaling 1 if they were organic and/or local strawberries; ε_{it}^{S} is a residual term.

These variables were chosen because they may impact production costs. For example, FV_{t-1}, proxies the cost of land and GAS_{t-1}, $FERT_{t-1}$, and $AGUN_{t-1}$ help account for production costs. $PACK_{it}$ is included because there are presumably cost differences associated with different

[1] The data is from USDA-AMS. The number of stores is sometimes used as a measure of output or quantity supplied (Bitler and Haider, 2011; Bonanno, 2012). Further, because the price is weighted by the number of stores selling at the price, the USDA is also (implicitly) using the number of stores as the measure of output.
[2] This is an index of average farm real estate value and can be found at https://www.nass.usda.gov/Publications/Todays_Reports/reports/land0821.pdf.
[3] The index for the price of gas can be found at https://fred.stlouisfed.org/series/CUSR0000SETB01.
[4] The index for the price of fertilizer can be found at https://fred.stlouisfed.org/series/PCU325311325311.
[5] Unemployment in the agricultural industry can be found at https://fred.stlouisfed.org/series/LNU04035109.

package sizes. Organic and Local strawberries may also have different cost structures. Year fixed effects control for costs that are trending.

The empirical specification of the demand function was as follows:

$$ln(q_{it}) = \delta_d + \beta_0\, ln(p_{it}) + \sum_{m=1}^{12} \beta_m YEAR_t + \beta_{13} FAO_t + \beta_{14} BANANAS_t + \beta_{15} ORANGES_t + \beta_{16} GROCERY_t + \beta_{17} WAGES_t + \beta_{18} PACK_{it} + \beta_{19} ORG_{it} + \beta_{20} LOCAL_{it} + \varepsilon_{it}^{d} \quad (2)$$

where FAO_t is the Food and Agricultural Organization food price index. $BANANAS_t$ and $ORANGES_t$ represent the prices of bananas and oranges, respectively.[6] $GROCERY_t$ is grocery store advance retail sales,[7] $WAGES_t$ represents domestic aggregate wages,[8] and ε_{it}^{d} is a residual term.

Variables in the demand equation were chosen because they represent determinants of demand and will impact the willingness to pay for consumers. FAO_t represents the price of other food and can be seen as controlling for the relative price of strawberries compared with other food. Banana and Orange prices are included because those can be close substitutes for strawberries. $GROCERY_t$ shows an overall demand of grocery sales. The $GROCERY_t$ variable may be especially important because the data cover the COVID-19 pandemic, when there was a shift toward grocery stores and away from other retail sources. $WAGES_t$ is included to find the effect of income on consumer demand. Consumer demand may differ for package size, organic, or local strawberries due to tastes and preferences, so those variables are also included in the demand estimation. Year fixed effects were also included to control for other changes in demand.

In both the supply and demand specifications, all variables that represent dollar values were converted to December 2022 dollars (the last month of the dataset), and the natural log was taken for all continuous variables. Therefore, because both price and quantity are logged, the coefficient estimate in the regression represents the own-price elasticity of demand.

Estimates of monopoly and oligopoly power in the strawberry market were calculated according to the methods of Arnade and Pick (2000) and Winfree et al. (2004). Briefly, the market power estimate is equal to $\beta_0(e^{-\alpha_m} - 1)$, and the statistical significance of these values were calculated using the covariance matrix and the derivatives of the parameters used in the market power estimate.

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[6] These prices can be found at https://fred.stlouisfed.org/series/PBANSOPUSDM and https://fred.stlouisfed.org/series/PORANGUSDM.
[7] The data can be found at https://fred.stlouisfed.org/series/RSGCSN.
[8] The data can be found at https://fred.stlouisfed.org/data/A576RC1.txt.

Results and Discussion

Summary statistics of the variables are shown in Table 2. Of note is that the mean for LOCAL is only 0.862, indicating that, on average, less than 1% of the strawberries sold are denoted as local strawberries, which makes a robust statistical analysis of local strawberries difficult. It seems likely that the data are not identifying all of the local strawberries, at least not within the region. We acknowledge that due to specific labeling decisions, we may be underreporting local production to some degree.

Table 2. Summary Statistics

Variable	Mean	St Dev	Min	Max
ln price	1.230	0.301	0.086	2.314
ln q	5.725	1.874	0.000	9.961
Constant	1.000	0.00	1.000	1.000
January	0.058	0.234	0.000	1.000
February	0.076	0.265	0.000	1.000
March	0.102	0.303	0.000	1.000
April	0.109	0.312	0.000	1.000
May	0.115	0.318	0.000	1.000
June	0.115	0.319	0.000	1.000
August	0.099	0.299	0.000	1.000
September	0.079	0.269	0.000	1.000
October	0.061	0.239	0.000	1.000
November	0.038	0.190	0.000	1.000
December	0.029	0.167	0.000	1.000
Farm value	8.160	0.087	7.961	8.252
Gas	5.683	0.208	5.223	6.057
Fertilizer	6.027	0.190	5.740	6.486
Ag unemployment	9.111	3.641	3.600	21.300
Pack	1.264	0.441	1.000	2.000
Organic	0.335	0.472	0.000	1.000
Local	0.862	6.571	0.000	100
FAO	4.873	0.157	4.658	5.218
Bananas	7.169	0.082	6.977	7.430
Oranges	0.515	0.205	0.110	0.982
Grocery	4.184	0.077	4.005	4.429
Wages	9.213	0.089	9.048	9.358

Note: Year fixed effect variables are removed for brevity.

The three-stage least-squares estimates of the supply and demand system are presented in Table 3. Most of the statistically significant variables have signs consistent with economic theory, and many of the estimated parameters were statistically significant at the 1% level or better of type I error, based on asymptotically valid Z-statistics and a standard normal asymptotic distribution.

Many of the off-season months are positive and statistically significant in the supply estimation, indicating that supply is smaller in those months. Early- and late-season months are significant for all regions except the Midwest, and early-season months are not significant for the Northeast. The unemployment rate for the agricultural industry is statistically significant for the South Central and Southeast regions. ORGANIC is positive and significant in the supply estimation for every region, implying that part of the price increase for organic strawberries is due to the cost of production. LOCAL was only significant at the 95% level for the Southwest region, possibly due to limited availability of data on strawberries labeled as local.

On the demand side, the estimated own-price elasticities ranged from -2.40 to -8.60, implying that an increase of price by 1% reduces quantity demanded by 0.12% (-8.60 elasticity) to 0.42% (-2.40 elasticity), depending upon the region. FAO food prices, which serve as a proxy for substitute goods, are positively correlated with strawberry demand in all regions at the 95% level, indicating that as prices for substitutes increase, demand for strawberries rises as well. This finding is consistent with standard economic theory, suggesting strawberries are seen as a desirable alternative when other food becomes more expensive. Wages, a proxy for consumer purchasing power, have a negative impact on demand in five regions, suggesting that higher wages lead consumers to substitute strawberries with other, potentially more expensive, food products. The packaging size (PACK) variable was found to be negative and statistically significant across all regions, indicating a preference for smaller packages when priced equivalently per pound.

The coefficient on ORGANIC is positive and statistically significant at the 5% level for the Midwest, Northeast, and Southwest regions. This result implies consumers are willing to spend more for organic strawberries in these regions. In the Northeast, the estimate for ORGANIC is 2.33, implying that consumers are willing to pay 233% more for organic strawberries, which is a much larger estimate than other regions. LOCAL is not statistically significant for any regions, possibly due to a lack of data showing local strawberries.

Estimates of seasonal market power are derived from the monthly parameter estimates and the demand elasticity. A value of 1 represents complete monopoly power, implying the price is set the same as a monopolist would price strawberries. While some of the market power estimations are greater than 1 (as illustrated in Figure 5), a value of 1 is within the statistical confidence interval, with the exception of November and December in the Southeast. Therefore, estimates are not statistically higher than monopoly power with two exceptions. The results show more market power in the U.S. strawberry market in months where supply is low. This finding implies that profitability may increase if strawberry producers could produce strawberries during those months. While there are some regional differences in market power, Figure 5 shows that most differentiation in market power is seasonal.

Table 3. SLS Estimation Results for Equation System

Region	Northwest		Midwest		Northeast		South Central		Southeast		Southwest	
	Estimate	**St. dev.**	**Estimate**	**St. dev.**	**Estimate**	**St. dev.**	**Estimate**	**St. dev.**	**Estimate**	**St. dev.**	**Estimate**	**St. dev.**
Supply												
Quantity	0.04	(0.09)	-0.03	(0.06)	< 0.01	(0.04)	0.01	(0.05)	0.07	(0.06)	-0.06	(0.03)
Constant	29.18	(20.88)	-13.16	(17.86)	-6.60	(12.63)	15.05	(11.98)	50.91	(31.05)	11.44	(14.30)
January	0.43**	(0.13)	0.15	(0.13)	0.12	(0.07)	0.34**	(0.08)	0.35**	(0.12)	0.22**	(0.08)
February	0.39**	(0.09)	0.15	(0.12)	0.08	(0.05)	0.28**	(0.05)	0.28**	(0.10)	0.20**	(0.06)
March	0.26**	(0.06)	0.10	(0.09)	0.03	(0.03)	0.16**	(0.04)	0.16*	(0.07)	0.11**	(0.04)
April	0.16**	(0.04)	0.06	(0.05)	0.03	(0.02)	0.12**	(0.02)	0.16**	(0.06)	0.05	(0.02)
May	0.10**	(0.02)	0.01	(0.02)	-0.02	(0.01)	0.03**	(0.01)	0.03	(0.02)	0.02	(0.02)
June	0.04*	(0.02)	0.01	(0.02)	-0.01	(0.01)	0.01	(0.01)	-0.01	(0.02)	0.01	(0.01)
August	0.08	(0.04)	0.08	(0.04)	0.05*	(0.02)	0.10**	(0.03)	0.12**	(0.04)	0.03	(0.02)
September	0.14	(0.08)	0.11	(0.07)	0.09**	(0.04)	0.17**	(0.05)	0.22**	(0.06)	0.06	(0.03)
October	0.22**	(0.09)	0.17	(0.11)	0.14**	(0.05)	0.28**	(0.08)	0.34**	(0.10)	0.12**	(0.04)
November	0.38**	(0.12)	0.27	(0.18)	0.23**	(0.09)	0.47**	(0.13)	0.61**	(0.20)	0.19*	(0.08)
December	0.51**	(0.18)	0.26	(0.21)	0.25*	(0.11)	0.51**	(0.14)	0.51**	(0.14)	0.30**	(0.11)
Farm Value	-3.47	(2.48)	1.67	(2.12)	0.96	(1.53)	-1.69	(1.43)	-5.99	(3.76)	-1.19	(1.70)
Gas	-0.07	(0.15)	0.08	(0.17)	0.01	(0.09)	-0.11	(0.10)	-0.40	(0.23)	-0.05	(0.12)
Fertilizer	-0.04	(0.16)	0.13	(0.10)	0.06	(0.06)	0.02	(0.07)	-0.05	(0.09)	< 0.01	(0.07)
Ag Unemp.	< 0.01	(< 0.01)	< 0.01	(< 0.01)	< 0.01	(< 0.01)	< 0.01*	(< 0.01)	-0.01**	(< 0.01)	< 0.01	(< 0.01)
Pack	-0.13	(0.12)	-0.20	(0.15)	-0.19*	(0.09)	-0.11	(0.08)	0.06	(0.19)	-0.20**	(0.06)
Organic	0.45**	(0.09)	0.34**	(0.12)	0.40**	(0.05)	0.40**	(0.07)	0.51**	(0.13)	0.32**	(0.05)
Local	< 0.01	(< 0.01)	0.03	(0.02)	< 0.01	(0.01)	< 0.01	(< 0.01)	< 0.01	(0.01)	< 0.01*	(< 0.01)
Demand												
Price	-2.40**	(0.34)	-7.51**	(0.47)	-8.60**	(0.58)	-4.21**	(0.30)	-6.57**	(0.56)	-5.42**	(0.37)
Constant	170.57**	(29.60)	118.60**	(32.26)	69.58*	(28.23)	140.38**	(20.94)	100.34**	(33.84)	58.88*	(28.91)
FAO	2.16*	(0.89)	2.22*	(0.87)	1.97*	(0.79)	2.88**	(0.68)	1.98**	(0.77)	3.22**	(0.83)
Bananas	0.96	(0.76)	-0.60	(0.86)	-0.48	(0.69)	0.82	(0.51)	-2.56**	(0.82)	0.68	(0.64)

Table 3 (cont.)

Region	Northwest		Midwest		Northeast		South Central		Southeast		Southwest	
	Estimate	St. dev.	Estimate	St. dev.	Estimate	St. dev.	Estimate	St. dev.	Estimate	St. dev.	Estimate	St. dev.
Demand												
Oranges	-0.64*	(0.32)	-0.69*	(0.34)	-0.06	(0.29)	-0.32	(0.21)	0.29	(0.32)	-0.35	(0.27)
Grocery	-0.92	(0.93)	-2.00	(1.06)	-0.83	(0.88)	-1.51*	(0.71)	-1.53	(0.95)	-0.71	(0.88)
Wages	-19.23**	(3.08)	-10.88**	(3.44)	-5.62	(3.02)	-15.51**	(2.31)	-7.41*	(3.69)	-6.86*	(3.04)
Pack	-1.71**	(0.11)	-3.42**	(0.13)	-3.65**	(0.15)	-2.07**	(0.08)	-3.95**	(0.15)	-2.20**	(0.10)
Organic	-0.04	(0.14)	0.97**	(0.19)	2.33**	(0.23)	0.19	(0.12)	0.35	(0.20)	0.68**	(0.16)
Local	-0.01	(0.01)	0.23	(0.15)	0.03	(0.09)	< 0.01	(0.01)	0.02	(0.04)	< 0.01	(< 0.01)
R^2 - Supply	0.642		0.585		0.764		0.705		0.652		0.628	
R^2 - Demand	0.224		0.395		0.278		0.394		0.425		0.315	
Observations	1,407		1,438		1,515		1,494		1,408		1,575	

Notes: *denotes statistical significance at the 95% level. **denotes statistical significance at the 99% level.

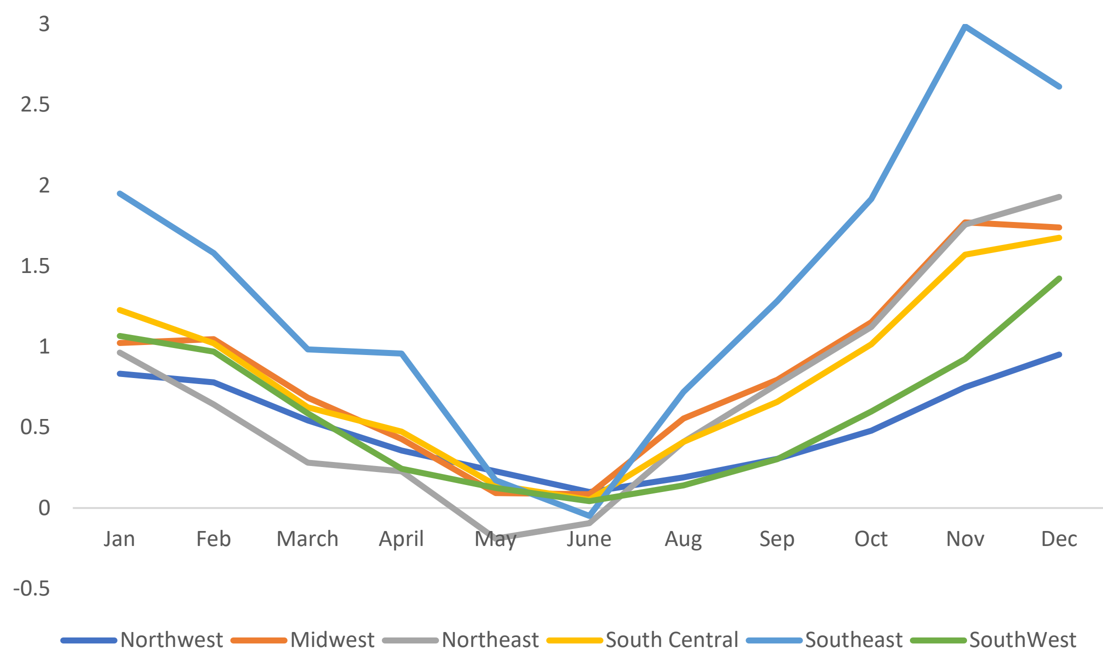

Figure 5. Market Power Estimates for U.S. Strawberries by Region and Month, 2010–2022

Policy Implications

The results of this study offer several significant policy implications for agricultural policy, market regulation, and support for strawberry producers. Policy makers can leverage these four policy recommendations to support strawberry producers, enhance market competitiveness, and promote consumer welfare.

Support for Organic Strawberry Production

The price premiums for organic strawberries for some regions indicate a strong consumer willingness to pay for organic products. Policy makers could consider expanding subsidies or offering tax incentives for organic certification for growers wishing to implement organic practices and cater to strong demand for organic strawberries. Programs that help lower the cost of organic farming methods—such as grants for organic pest control, soil management, and plant nutrition—could lower the entry barriers for smaller farms. Additionally, outreach programs educating farmers on the long-term profitability of organic strawberries, especially in regions like the Northeast, could further encourage organic supply.

Promoting Market Access for Off-Season Strawberries

The study highlights the potential for producers to exercise market power and increase profitability during off-season months when strawberry supply is low. Policy makers could incentivize the development and adoption of new strawberry varieties and methods for use in off-season conditions, extending the domestic strawberry supply and smoothing out seasonal price fluctuations. Additionally, investment in greenhouse or controlled-environment agriculture (CEA) infrastructure could enable year-round production, mitigating the effects of seasonal market power and stabilizing consumer prices.

Addressing Local Strawberry Production Challenges

The lack of significant evidence showing consumer demand for local strawberries and limited data on local strawberry sales suggest a need for policy intervention to bolster local agricultural markets. Policy makers can enhance consumer awareness of locally grown produce through labeling initiatives like "local" or "regional" certifications that emphasize the benefits of supporting local farms, such as fresher produce and reduced carbon footprints. Additionally, providing financial support to local farmers via grants or low-interest loans for infrastructure improvements, such as cold storage or transportation logistics, could increase the supply and visibility of local strawberries in retail markets.

Expanding farm-to-school or farm-to-institution programs could also serve as a reliable market for local strawberries, including processed fruit. These programs encourage public institutions, such as schools, hospitals, and universities, to procure locally grown fruits and vegetables, creating a stable demand for local strawberries.

Addressing Data Gaps in Local Food Markets

The lack of significant results for local strawberries likely stems from limited data on their market presence. Investments in more robust data collection systems that track the sales, prices, and quantities of local produce across regions would allow for more targeted agricultural policy interventions and provide valuable insights for farmers and retailers. Establishing a standardized reporting system for local food markets could help policy makers and researchers better understand the dynamics of local agriculture and craft more effective policies to promote local farming.

Discussion

The results of this study offer several important implications for both producers and policy makers in the U.S. strawberry market. First, the price premium for organic strawberries suggests a robust consumer demand for organic products across some regions, which aligns with broader trends toward health-conscious food choices. This finding underscores the opportunity of organic strawberry farming, particularly when sold in Northeast markets, where consumers demonstrate a high demand and therefore a willingness to pay substantially more for organic products. However, the lack of significance for local strawberries in most regions may indicate that consumers either do not prioritize locally grown strawberries or there is insufficient data on local strawberry production. More granular data on local strawberry production and sales could provide better insights into whether local strawberries command a premium in specific regions. However, while the data on local strawberries may be insufficient, it could also be a weak signal that consumers would not discount strawberries from other regions.

The inelastic demand for strawberries across regions, coupled with the substantial price premiums for organic varieties, indicates that producers may be able to charge higher prices without significantly reducing sales. These factors are especially relevant in off-peak seasons, where supply limitations result in greater market power and higher profitability. Producers may benefit from extending the growing season or investing in new strawberry varieties that can be cultivated during these off-peak months. This practice could increase profitability by capitalizing on market power during periods of low supply, as indicated by the significant market power estimates in certain regions, suggesting that if it is agronomically feasible, it may be profitable for growers to develop off-season varieties.

Conversely, the competitive nature of the peak-season strawberry market suggests limited room for price increases during these months. Producers face stiff competition, and the data indicate that retail markets are highly competitive, certain times of the year. The low levels of market power during peak months may suggest that efforts to differentiate products, either through organic certification or other means, may be necessary to maintain profitability.

The study's findings on packaging preferences also provide valuable insights for retailers. The negative coefficient for package size indicates that consumers prefer smaller packaging, which could reflect concerns over waste or a desire for fresher products. Retailers may want to consider offering smaller packaging options, especially in regions where this preference is more pronounced.

Conclusions

The data show consistently higher prices across all regions for organic strawberries over conventionally produced strawberries. When estimating supply and demand, the results show that increases in price for organic strawberries are due to a combination of supply and demand issues, and depend on the region. An increase in consumer demand for local strawberries is not statistically significant for any region. However, this finding may be due to a lack of data on local fresh strawberries. These results have direct implications for growers.

The results also show that there is market power of varying degrees in the off season for strawberries in every region except the Midwest. Because market power can be a proxy for economic profits, there are opportunities for generating market power for strawberries produced outside of typical harvest seasons. Conversely, the data seem to imply that the retail market is quite competitive during the peak season, which may have implications for the future production of strawberries and the viability of new strawberry varieties that produce strawberries during the off season.

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