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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<br>Standard QR code*<br>Blockchain QR Code |
| USDA organic label | No USDA organic label*<br>USDA organic label |
| Carbon footprint label | Carbon footprint reduction achieved label<br>Carbon footprint reduction planned label<br>Carbon footprint lower than market label<br>USDA process verified climate-friendly label<br>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<br>$1.79, $2.29, $2.79, $3.29, $3.79, $4.29 if low-cost state<br>$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.

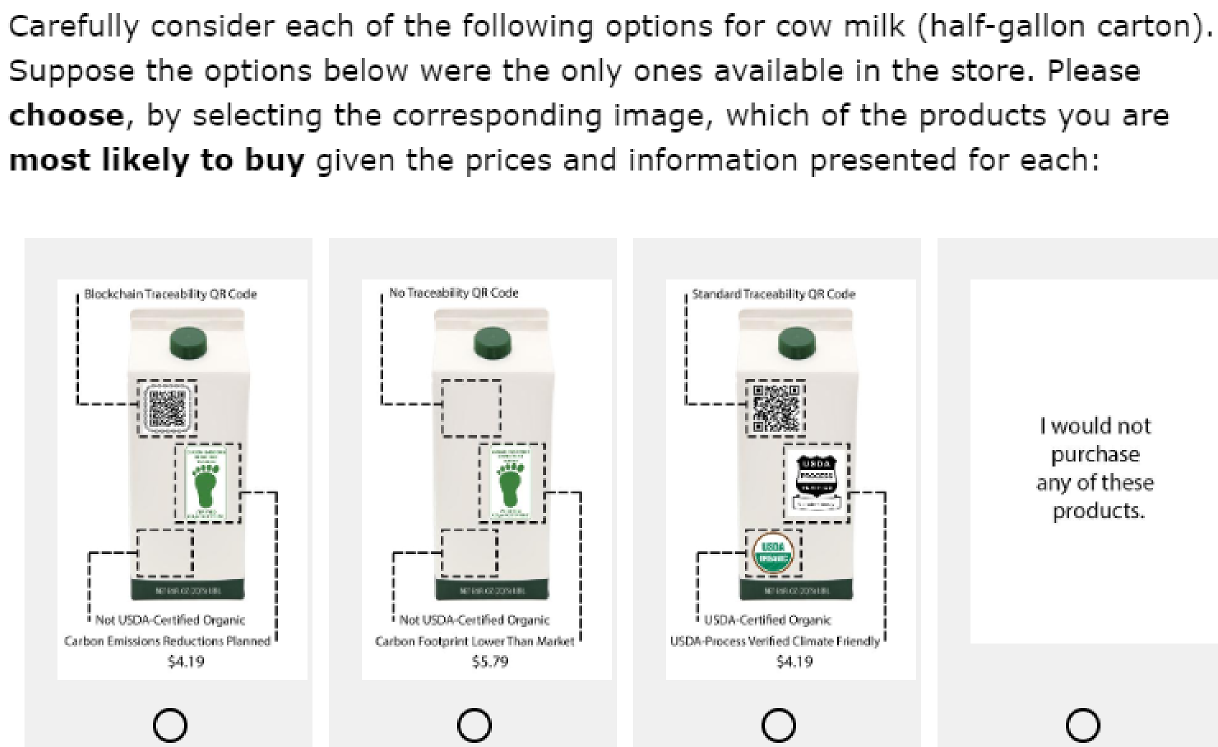



**Figure 1.** Example DCE Choice Set for the Cow's Milk Survey

*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 $\beta_0$ is the population mean, $v_i \sim N(0,1)$, and $\sigma$ is the standard deviation of the distribution of $\beta_i$. 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 -$(\beta_2 + \beta_4)$)/ $\beta_p$ for respondents who are more likely to scan QR codes after the COVID-19 pandemic (i.e., $QRPostCOVID$ = 1) and -($\beta_2$)/ $\beta_p$ 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.

## References

Abadie A., S. Athey, G.W. Imbens, and J.M. Wooldridge. 2017. "When Should You Adjust Standard Errors for Clustering?" *The Quarterly Journal of Economics* 138(1):1–35.

Akaichi, F., R.M. Nayga, Jr., and J.M. Gil. 2012. "Assessing Consumers' Willingness to Pay for Different Units of Organic Milk: Evidence from Multiunit Auctions." *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie* 60:469–494.

Alpizar, F., F. Carlsson, and P. Martinsson. 2001. "Using Choice Experiments for Non-market Valuation." Göteborg, Sweden: Göteborg University, Department of Economics Working Paper 52.

Aravena, C., P. Martinsson, and R. Scarpa. 2014. "Does Money Talk?—The Effect of a Monetary Attribute on the Marginal Values in a Choice Experiment." *Energy Economics* 44:483–491.

Badruddoza, S., A.C. Carlson, and J.J. McCluskey. 2022. "Long-term Dynamics of US Organic Milk, Eggs, and Yogurt Premiums." *Agribusiness* 38:45–72.

Bernard, J.C., and D.J. Bernard. 2009. "What Is It about Organic Milk? An Experimental Analysis." *American Journal of Agricultural Economics* 91:826–836.

Canavari, M., and S. Coderoni. 2020. "Consumer Stated Preferences for Dairy Products with Carbon Footprint Labels in Italy." *Agricultural and Food Economics* 8(1):4.

Caputo, V., and R. Scarpa. 2022. "Methodological Advances in Food Choice Experiments and Modeling: Current Practices, Challenges, and Future Research Directions." *Annual Review of Resource Economics* 14(1):63–90.

Caputo, V., J.L. Lusk, and R.M. Nayga. 2018. "Choice Experiments Are Not Conducted in a Vacuum: The Effects of External Price Information on Choice Behavior." *Journal of Economic Behavior & Organization* 145:335–351.

Carbon Trust. 2023. *Our History*. Available online: https://www.carbontrust.com/who-we-are/our-history.

Carlsson, F., and P. Martinsson. 2008. "How Much Is Too Much?" *Environmental Resource Economics* 40:165–176.

Carlsson, F., P. Frykblom, and C.J. Lagerkvist. 2005. "Using Cheap Talk As a Test of Validity in Choice Experiments." *Economics Letters* 89:147–152.

Casino, F., V. Kanakaris, T.K. Dasaklis, S. Moschuris, S. Stachtiaris, M. Pagoni, and N.P. Rachaniotis. 2021. "Blockchain-based Food Supply Chain Traceability: A Case Study in the Dairy Sector." *International Journal of Production Research* 59(19):5758–5770.

Centers for Disease Control and Prevention. 2024. *About Food Safety*. Atlanta, GA: CDC. Available online: https://www.cdc.gov/food-safety/about/index.html#:~:text=Overview,are%20hospitalized%2C%20and%203%2C000%20die.

Centers for Disease Control and Prevention. 2025. *Current Situation: Bird Flu in Dairy Cows.* Atlanta, GA: CDC. Available online: https://www.cdc.gov/bird-flu-situation-summary/mammals.html [Accessed May 27, 2025].

Collart, A.J., and E. Canales. 2022. "How Might Broad Adoption of Blockchain-Based Traceability Impact the U.S. Fresh Produce Supply Chain?" *Applied Economic Perspectives and Policy* 44(1):219–236.

Collart, A.J. M.G. Interis, A. Giri, and E. Canales. 2025. "Consumer Willingness-to-Pay for Blockchain-Based QR Code Traceability of Leafy Greens." Clemson, SC: Clemson University Working paper.

Contini, C., F. Boncinelli, C. Romano, G. Scozzafava, and L. Casini. 2019. "Price Vector Issue in a Choice Experiment: A Methodological Proposal." *Food Quality and Preference* 75:23–27.

Croft, G.K. 2021. *Blockchain Technology and Agriculture.* Washington, DC: Congressional Research Service, Report No. IF11829. Available online: https://crsreports.congress.gov/product/pdf/IF/IF11829#:~:text=Participants%20in%20agricultural%20supply%20chains,the%20terms%20of%20certification%20programs.

DeJong, M.D.T., K.M. Harkink, and S. Barth. 2018. "Making Green Stuff? Effects of Corporate Greenwashing on Consumers." *Journal of Business and Technical Communication* 32(1):77–112.

Echeverria, R., V.H. Moreira, C. Sepúlveda, and C. Wittwer. 2014. "Willingness to Pay for Carbon Footprint on Foods." *British Food Journal* 116(2):186–196.

Fang, D., R.M. Nayga, G.H. West, C. Bazzani, W. Yang, B.C. Lok, C.E. Levy, and H.A. Snell. 2020. "On the Use of Virtual Reality in Mitigating Hypothetical Bias in Choice Experiments." *American Journal of Agricultural Economics* 103:142–161.

Feucht, Y., and K. Zander. 2018. "Consumers' Preferences for Carbon Labels and the Underlying Reasoning. A Mixed Methods Approach in 6 European Countries." *Journal of Cleaner Production* 178:740–748.

Gao, W., W.G. Hatcher, and W. Yu. 2018. "Survey of Blockchain: Techniques, Applications, and Challenges." *Proceedings of the 2018 27th International Conference on Computer Communication and Networks (ICCCN),* Hangzhou, China, July 30-August 2, pp. 1–11.

Goggin, G., and R. Wilken. 2024. "QR Codes and Automated Decision-making in the COVID-19 Pandemic." *New Media & Society* 26(3):1268–1289.

Guan, L., A.J. Eisfeld, D. Pattinson, C. Gu, A. Biswas, T. Maemura, S. Trifkovic, L. Babujee, R. Presler Jr., R. Dahn, P.J. Halfmann, T. Barnhardt, G. Neumann, A. Thompson, A.K. Swinford, K.M. Dimitrov, K. Poulsen, and Y. Kawaoka. 2024. "Cow's Milk Containing Avian Influenza A(H5N1) Virus—Heat Inactivation and Infectivity in Mice." *New England Journal of Medicine* 391(1):87–90.

Holmes, T.P., W.L. Adamowicz, and F. Carlsson. 2017. "Choice Experiments." In P. Champ, K. Boyle, and T. Brown, eds. *A Primer on Nonmarket Valuation*. Berlin, Germany: Springer Link, pp. 133–186.

Iskender, A., E. Sirakaya-Turk, D. Cardenas, and N. Hikmet. 2022. "Restaurant Patrons' Intentions toward QR Code Menus in the U.S. during COVID-19: Acceptance of Technology Adoption Model (ATAM)." *Journal of Foodservice Business Research* 27(5):497–522.

Johnson, G. 2014. *Lawsuits: Costco, Others, Sold Organic Milk That Wasn't Organic*. Viroqua, WI: Cornucopia Institute. Available online: https://www.cornucopia.org/2007/12/lawsuits-costco-others-sold-organic-milk-that-wasnt-organic/.

Kerle, A. 2021. "An Eco-wakening. Measuring Global Awareness, Engagement, and Action for Nature." *Economist Impact*. Available online: https://impact.economist.com/sustainability/ecosystems-resources/an-eco-wakening-measuring-global-awareness-engagement-and-action-for-nature.

Kilders, V., and V. Caputo. 2023. "A Reference-Price-Informed Experiment to Assess Consumer Demand for Beef with a Reduced Carbon Footprint." *American Journal of Agricultural Economics* 106(1):3–20.

Krinsky, I., and A.L. Robb. 1986. "On Approximating the Statistical Properties of Elasticities." *Review of Economics and Statistics* 68(4):715–719.

Krinsky, I., and A.L. Robb. 1990. "On Approximating the Statistical Properties of Elasticities: A Correction." *Review of Economics and Statistics* 72 (1):189–190.

Lando, A., M. Bazaco, C.C. Parker, and M. Ferguson. 2022. "Characteristics of U.S. Consumers Reporting Past Year Intake of Raw (Unpasteurized) Milk: Results from the 2016 Food Safety Survey and 2019 Food Safety and Nutrition Survey." *Journal of Food Protection* 85(7):1036–1043.

Leung, H., A. Chapman, and N. Fadhel. 2021. "Identifying Food Fraud Using Blockchain:" In M. Lazaar, E.M. En-Naimi, A. Zouhair, M. Al Achhad, and O. Mahboub, eds. *Proceedings of the 6th International Conference on Internet of Things, Big Data and Security*. Berlin, Germany: Springer Link, pp. 185–192.

Li, Y., A. Liao, L. Li, M. Zhang, X. Zhao, and F. Ye. 2023. "Reinforcing or Weakening? The Role of Blockchain Technology in the Link between Consumer Trust and Organic Food Adoption." *Journal of Business Research* 164:113999.

Lim, K.H., and H. Wuyang. 2023. "Contextual Reference Price in Choice Experiments." *American Journal of Agricultural Economics* 105(4):1288–1306.

Lin, W., D.L. Ortega, D. Ufer, V. Caputo, and T. Awokuse. 2022. "Blockchain-based Traceability and Demand for U.S. Beef in China." *Applied Economic Perspectives and Policy* 44(1):253–272.

Lombardi, G.V., R. Berni, and B. Rocchi. 2017. "Environmental Friendly Food. Choice Experiment to Assess Consumer's Attitude toward 'Climate Neutral' Milk: The Role of Communication." *Journal of Cleaner Production* 142:257–262.

Louviere, J.J., T.N. Flynn, and R.T. Carson. 2010. "Discrete Choice Experiments Are Not Conjoint Analysis." *Journal of Choice Modelling* 3(3):57–72.

Lusk, J.L 2003. "Effects of Cheap Talk on Consumer Willingness-to-Pay for Golden Rice." *American Journal of Agricultural Economics* 85(4):840–56.

Manning, L., and A. Kowalska. 2021. "Considering Fraud Vulnerability Associated with Credence-Based Products Such as Organic Food." *Foods* 10(8):1879.

McFadden, D. 1974. *Conditional Logit Analysis of Qualitative Choice Behavior*. Berkeley, CA: University of California, Berkeley, Institute of Urban and Regional Development.

Sebastianski, M., N.A. Bridger, R.M. Featherstone, and J.L. Robinson. 2022. "Disease Outbreaks Linked to Pasteurized and Unpasteurized Dairy Products in Canada and the United States: A Systematic Review." *Canadian Journal of Public Health* 113(4):569–578.

Segovia, M., J. Grashuis, and T. Skevas. 2022. "Consumer Preferences for Grocery Purchasing during the COVID-19 Pandemic: A Quantile Regression Approach." *British Food Journal* 124(11):3595–3623.

Shew, A.M., H.A. Snell, R.M. Nayga Jr., and M.C. Lacity. 2022. "Consumer Valuation of Blockchain Traceability for Beef in the United States." *Applied Economic Perspectives and Policy* 44(1):299–323.

Smith, T., C. Huang, and B.-H. Lin. 2009. "Estimating Organic Premiums in the US Fluid Milk Market." *Renewable Agriculture and Food Systems* 24.

Snir, A., and D. Levy. 2021. "If You Think 9-Ending Prices Are Low, Think Again." *Journal of the Association for Consumer Research* 6(1):33–47.

Spink, J., and D.C. Moyer. 2011. "Defining the Public Health Threat of Food Fraud." *Journal of Food Science* 76:R157–R163.

Stewart, H., F. Kuchler, J. Cessna, and W. Hahn. 2020. "Are Plant-Based Analogues Replacing Cow's Milk in the American Diet?" *Journal of Agricultural and Applied Economics* 52(4):562–579.

Tran, D., H. De Steur, X. Gellynck, A. Papadakis, and J.J. Schouteten, 2024. "Consumers' Valuation of Blockchain-Based Food Traceability: Role of Consumer Ethnocentrism and Communication via QR Codes." *British Food Journal* 126(13):72–93.

Trmčić, A., E. Demmings, K. Kniel, M. Wiedmann, and S. Alcaine. 2021. "Food Safety and Employee Health Implications Of COVID-19: A Review." *Journal of Food Production* 84(11):1973–1989.

Tu, M., W. Lei, W. Hua, D. Zhoujin, G. Zizheng, and C. Jiayi. 2022. "The Adoption of QR Code Mobile Payment Technology During COVID-19: A Social Learning Perspective." *Frontiers in Psychology* 12.

U.S. Department of Commerce. 2022. *Selected Social Characteristics in the United States. American Community Survey, ACS 5-Year Estimates Data Profiles, Table DP02, 2022*. Washington, DC: U.S. Department of Commerce, Bureau of the Census. Available online: https://data.census.gov/table/ACSDP5Y2022.DP02?q=DP02 [Accessed December 20, 2024].

U.S. Department of Agriculture. 2023. *National Retail Report—Dairy (DYBRETAIL*). Washington, DC: USDA, Agricultural Marketing Service. Available online: https://mymarketnews.ams.usda.gov/viewReport/2995.

U.S. Department of Agriculture. 2025. "Overview." *Organic Agriculture.* Washington, DC: USDA, Economic Research Service. Available online: https://www.ers.usda.gov/topics/natural-resources-environment/organic-agriculture/#:~:text=Sales%20Increase%20in%20All%20Organic%20Food%20Categories&text=Retail%20sales%20of%20organic%20fresh,decades%20(NBJ%2C%202022) [Accessed April 9, 2024].

U.S. Department of Agriculture. 2024. *NRCS Climate Smart Mitigation Activities.* Washington, DC: USDA, Natural Resources Conservation Service. Available online: https://www.nrcs.usda.gov/conservation-basics/natural-resource-concerns/climate/climate-smart-mitigation-activities.

U.S. Food and Drug Administration. 2024. *Tracking and Tracing of Food.* Silver Spring. MD: US-FDA. Available online: https://www.fda.gov/food/new-era-smarter-food-safety/tracking-and-tracing-food.

U.S. Food and Drug Administration. 2025. *Investigation of Avian Influenza A (H5N1) Virus in Dairy Cattle*. Silver Spring. MD: US-FDA. Available online: https://www.fda.gov/food/alerts-advisories-safety-information/investigation-avian-influenza-h5n1-virus-dairy-cattle.

Yormirzoev, M., T. Li, and R. Teuber. 2021. "Consumers' Willingness to Pay for Organic versus All-Natural Milk—Does Certification Make a Difference?" *International Journal of Consumer Studies* 45(5):1020–1029.

# 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.

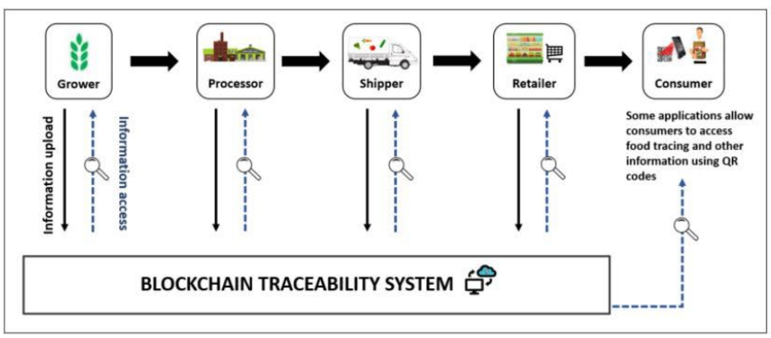
*Please take a moment to review the information above. You'll be able to proceed shortly*

**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

Product Information: Cow Milk

The following is an example of additional product information a manufacturer could supply using a QR Code. The information is managed with blockchain systems if the package has a Blockchain Traceability QR Code and with standard (non-blockchain) systems if the package has a Standard Traceability QR Code.

Please return to the previous webpage to continue the survey.

Grower

- Here, you might see the location of where the dairy cow was raised, as well as any growing practices the producer used (e.g., rotational grazing, feedlots, etc.).
- If applicable, you could view a copy of this product's organic certificate here.
- If applicable, you could view a copy of this product's carbon footprint verification here.

Processor

- Here, you might see the date that the milk was processed, as well as the location of the processing plant.
- You would also be able to view the various measures taken in quality control.

Shipper

- Here, you could potentially see how many miles the milk traveled from processor to retailer, as well as the location and number of stops the product made.
- Here, you would be able to see shipping company information as well as truck temperature throughout the product's journey.

Retailer

- Here you might see what date the product arrived at its final destination.
- You might also see the milk's best-by date.

**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 |

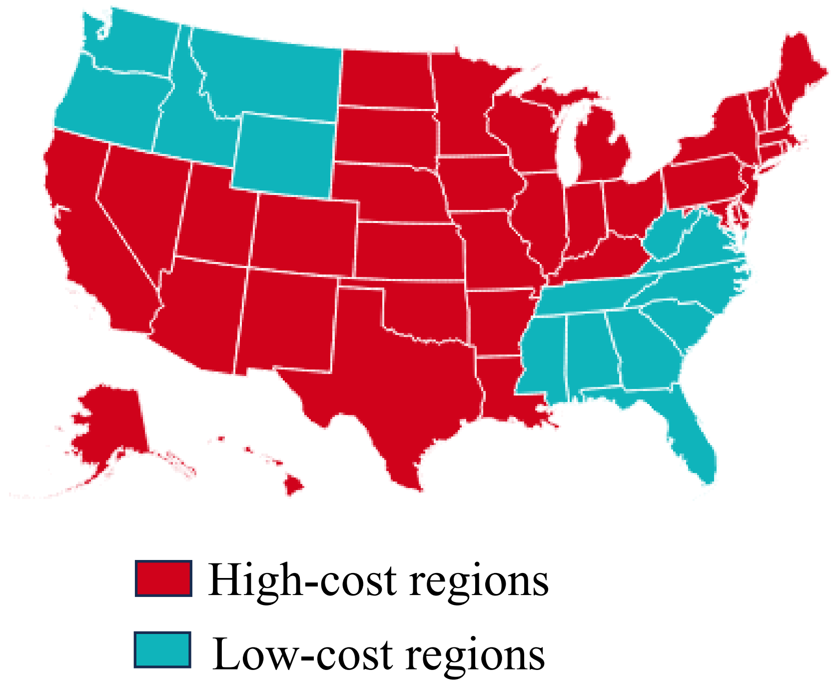



**Figure A4.** Map of High and Low-Cost States in Geographical-Price-Informed DCE

**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 |