Consumer valuation of blockchain traceability for beef in the United States

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Abstract
Blockchain (BC) technology, defined as a shared information system to validate, secure, and permanently store transactions among multiple parties on a distributed ledger, presents many applications in agricultural and food industries. This study examines the application of BC in food traceability for beef in the United States using a choice experiment. Findings indicate that consumers value USDA certifications over BC traceability to guide their meat preferences. Our study suggests a number of industry implications, the most important of which suggests focusing business and consumer education on the value of product data, rather than on the value of the technologies that manage data.

KEYWORDS
blockchain, food safety, supply chain management, traceability, US beef demand

JEL CLASSIFICATION
D12; O33; Q18

The US food industry is a $6 trillion sector, and consumers directly purchase $641 billion of food from retail stores annually (Statista, 2018). US consumers want better assurances that the foods they purchase are fresh, safe, and authentic (Charlebois et al., 2016; Yu et al., 2018).
While much of the food consumed in the United States is safe, there is significant justification for concern. The US Center for Disease Control and Prevention (CDC) estimates that 48 million Americans get sick from food, 128,000 are hospitalized, and 3000 die of foodborne diseases each year (Hoffmann & Scallan, 2017; Scallan et al., 2011). To further illustrate, the US Department of Agriculture (USDA) Food Safety Inspection Service (FSIS) reported 61 active food recalls in January 2020 (USDA FSIS, 2020), primarily for beef, pork, poultry, seafood, and salads. On average for 2016–2019, USDA FSIS reported an average of 27 beef recalls per year with approximately 15.4 million pounds of beef product recalled. Examples of such recalls include Ohio-based Advance Pierre Foods recalling approximately 16,000 pounds of ready-to-eat (RTE) beef patty products that may have been contaminated with extraneous materials like soft plastics (USDA Recall No. 123-2019), and the Pride of Florida recalling nearly 70,000 pounds of raw beef products that may have been contaminated with E. coli (USDA Recall No. 101-2019). Thus, the impetus exists for a traceability system that has the capacity to track food, specifically meat products, from the producer through the supply chain to retail stores and consumers with greater automation and transparency.

Given that implementation of such a system will cost money, it is important to understand the potential benefits for companies and consumers that may arise from the adoption of blockchains (BCs) as a viable option for improving food distribution systems. BCs may provide internal, business-to-business (B2B), and business-to-consumer (B2C) efficiencies that save both time and money. BC could benefit a number of agricultural and food applications, including farm data tracking and digital agriculture (Griffin et al., 2021), international trade and policy (Guerra & Boys, 2021; Lakkakula et al., 2021), fresh produce supply chains (Collart & Canales, 2021), and demand for international traceability with country-of-origin information (Lin et al., 2021). Additionally, companies may extract price premiums in cases where consumers value product information and certification. Hence, in this study, we specifically explore US consumer preferences and willingness to pay (WTP) premiums for BC as a food distribution solution with particular emphasis on information tracking and certification of beef.

Regulatory issues in interstate and international traceability play a major and complex role in how food moves through the supply chain, specifically information about how meat is produced, slaughtered, and transported to consumers. Today, USDA is the primary governing agency responsible for certifying the safety and quality of meat by checking physical samples at various points along the supply chain. USDA has recognized the need for a more comprehensive and digital traceability system, primarily out of concern for animal disease, human health issues, and potential import–export challenges for US livestock producers. It is also responsible for maintaining safety guidelines for traceability and conducts spot inspections of farms, slaughter facilities, and food processors via the FSIS and validates consumer-facing information via the Agricultural Marketing Service (AMS). Although the United States does not currently have a mandated by-the-animal traceability system after slaughter, some have argued that imports and exports have not been greatly affected (Ishmael, 2018). Should US beef importing countries change their regulations, however, this could place US beef producers at a competitive disadvantage, which again highlights the need for an improved traceability system (Schroeder & Tonsor, 2012).

Beyond health and regulatory concerns with traceability, US consumers have shown increasing interest in where their meat comes from and the manner in which it was produced. In some cases, producers can capture premiums for their meat by providing additional information about their products or including certification labels (Li et al., 2016; Lin et al., 2021; Loureiro & Umberger, 2007; Lusk et al., 2003; Syrengelas et al., 2018; Verbeke & Ward, 2006).
For producers to take advantage of this, food production, safety, and label authenticity require much better tracking of information as food passes through the entire supply chain (Feng et al., 2020). Today, every party of the food supply chain manages its own systems of records (software and data) within the boundaries of the firm or relies on a trusted third party to manage their traceability systems. Because of this, the system is rather opaque to the consumer even though it is spot-checked by USDA. Moreover, each party can see only data coming in and out of their own systems, which is why it can take weeks to trace a food recall from a retail store back to the source.

BC technologies, a type of distributed ledger, present a promising means to trace beef and other foods from farm to fork, addressing the health, regulatory, and consumer demand issues highlighted above and in previous studies (Crandall et al., 2013). Already, BC pilots have been created in the meat industry to improve traceability and transparency; for example, BeefChain™ (Mapperson, 2020; Pirus 2019). Companies adopting BCs may absorb upfront costs for developing new information system architecture, but in the long run most companies expect to see cost savings due to semiautomation in traceability. Moreover, these BC systems have the potential to provide more detailed information about each step of the food supply chain with improved timing for trace-back to origin and greater transparency to the consumer (Kamilaris et al., 2019).

Consumers may be willing to pay premiums for the additional information, near real-time tracking, and the extra layer of transparency provided and validated by a BC. However, BCs are relatively new, decentralized, and often closely associated with cryptocurrencies such as Bitcoin, which may obfuscate consumer understanding and trust of the new technology with respect to food traceability. Thus, in this study, we are interested in learning how consumers might value the improved traceability and certification of products as a result of easier access and more detailed information about the beef supply chain made available through BCs. Our findings provide important information for companies and policymakers considering BC implementations for beef traceability and product certification.

BACKGROUND
What is blockchain technology?

Satoshi Nakamoto (2008), the inventor of Bitcoin, approached the problem of traceability in a remarkable way. Nakamoto solved the problem by moving from individual, party-level record-keeping to a process of shared (or distributed) record-keeping for transactions. The Bitcoin network maintains a digital ledger (DL), called a blockchain, to serve as the universal bookkeeping record for the cryptocurrency. Since the invention of Bitcoin, a number of individuals, organizations, and working groups have applied BC technologies, which encompass more than cryptocurrencies, to securely share information with ecosystem partners, and potentially with the end consumer. When ecosystem partners share software and data, many benefits arise. First, parties of an information exchange, including internal, B2B, and B2C, can instantly determine the status of an asset (such as a food product) by reading the ledger. Furthermore, transactions involving the assets on the distributed ledger are immutable (though appendable), so every party can be confident that they are always dealing with the same historical data, guaranteeing consistent data provenance and verifiable information (Lacity, 2018).
In the food industry, a number of BC-based shared applications have been developed, ranging from large global platforms like the IBM Food Trust to smaller applications like the Grass Roots Farmer Cooperative based in Little Rock, Arkansas. Other notable examples include OpenSC, cofounded by the World Wildlife Fund and Boston Consulting Group, to help Austral Fisheries trace fish from “bait to plate” (OpenSC, 2020), and Minnesota-based Cargill, which traced 200,000 turkeys from 70 farms to retail stores (Whalen, 2019). Some food giants have developed their own solutions, like France-based Carrefour (partnered with IBM) did to trace milk, and US-based Bumble Bee Foods for fish with SAP (O’Neal, 2019). In 2019, Walmart launched the Walmart China Blockchain Traceability Platform, with the help of PwC and VeChain, a BC solution provider based in Singapore (Palmer, 2019). Business benefits have been reported; for example, Walmart found that the IBM Food Trust pilot reduced traceability time for mangos from retail stores to the farm from 7 days to under 3 s (Kamath, 2018). So far, food traceability solutions enabled by these BC applications focus on high-value, high-volume perishable goods to justify the investment costs. BC applications in the food and meat industries are likely to expand as the benefits become more widely known and the cost of transitioning information systems decrease.

Gaining a critical mass of ecosystem participants remains a major challenge to supply-chain-wide adoption of BC, particularly for small-sized farmers and producers who sell to large distribution systems. Every party in the supply chain will need to participate in order to achieve end-to-end traceability, but parties will join only if they are convinced that they will earn a positive return on investment. Currently, food can be tracked using radio frequency identification (RFID), but there remain limitations to sharing across more complex supply chains with multiple stakeholders, and efficiencies are primarily geared toward producers/sellers (Ohkubo et al., 2005). For instance, RFID allows sellers to passively track products through the supply chain but often omits consumer-facing information such as product quality or food safety attributes. RFID and other electronic information could be joined systematically to a BC to provide transparency and product information not only to producers and sellers but also to consumers. Still, BC may come with privacy concerns due to the transparency of sharing data beyond individual entities (Kumar & Mallick, 2018; Ohkubo et al., 2005). Additionally, there may be environmental costs to BC implementation which are often unaccounted for in supporting arguments of the technology (Imbault et al., 2017). An important unanswered question with respect to these various BC issues is, “Are consumers willing to pay premiums for food traced on a blockchain?” If not, many parties in the food supply chain may delay adoption, join a BC platform only for internal or B2B benefits, or wait for new legislation or powerful supply chain partners to mandate adoption. This could delay, prevent, or limit the full vision for “farm-to-fork” traceability.

Blockchain governance—permissioned and permissionless systems

Public BC applications like Bitcoin are open to the public—anyone may transact in the system, anyone with a web browser may view a copy of the ledger, and anyone may operate a node in the network by downloading the software from a public repository such as Github. Public BCs like Bitcoin value anonymity, and the identities of people transacting in public networks remain anonymous. Bitcoin and other public networks (like Ethereum, Monero, Zcash) are governed by an open-source community of volunteers who debate proposed improvements to the
software and ultimately vote on changes by either downloading or failing to download software upgrades.

In business contexts like food traceability in supply chains, industry participants must comply with regulations that require vetting trading partners. Industry partners value confidentiality, where parties are known but data is shared only with authorized participants. As a result, many of the BC applications being explored for food traceability are private and require permission to transact in the network, to view ledger entries, and to operate a node in the network. Permissioned BCs may be governed by a benevolent dictator, which might be a private company or a government agency, or by a consortium of participants. The IBM Food Trust, for example, is governed by IBM and an advisory council, comprising nine members: Walmart, Dole, Nestlé, Kroger, Carrefour, Danone, Driscoll’s, Golden State Foods (GFS), and GS1 (IBM, 2020). Similarly, the FDA is administering a BC pilot test for prescription drug traceability, and the Wyoming-based BeefChain™ is using a permissioned BC for certified beef and sheep in a public–private partnership focused on recapturing value in the supply chain.

Do consumers trust certification by a government agency like the USDA more than certification by a private company like IBM managing a BC ecosystem, and therefore would they be willing to pay more for one governance body over another? Consumers may have preferences for specific types of governance with respect to food safety and traceability information just as they do for different labels. All of these factors could play a role in how quickly companies adopt BC technologies and how consumers perceive and value the newfound capabilities of food tracking provided by distributed DLs.

**Consumer preferences and WTP for traceability**

Beef is an excellent vehicle to investigate food traceability and safety for several reasons. First, beef steak requires monitoring through the supply chain to ensure proper food safety. Beef, along with many meat and poultry products, is susceptible to spoilage in relatively short time-frames compared to other products, and consumer perceptions of food safety affect beef purchasing and consumption habits (Schroeder et al., 2007). Second, beef is produced and consumed domestically but is also imported and exported, which creates additional complexity and concerns for safety inspections and traceability (Loureiro & Umberger, 2007; Pendell et al., 2013). Third, beef quality, origin, and production methods are important attributes for many consumers in how they value products (Verbeke & Ward, 2006), but how these attributes are traced and verified at the retail level remains opaque (Brashears & Chaves, 2017).

Currently, all parties in the beef supply chain (including farmers, feed lots, meat processors, wholesalers, and retail stores) conduct their own quality control checks and maintain their own records for USDA to check. Typically, however, there is no end-to-end visibility of how beef travels from farm to fork in the United States, which can lead to slower traceability in the event of a food safety issue. Tracking beef is no small task given the United States consumed approximately 19 billion pounds of it in 2018 alone (Knight, 2019). If an event occurs, like mad cow disease (Bovine spongiform encephalopathy), E. coli, or Salmonella, government institutions and supply chain partners struggle to trace the product back to the point of origin, making it difficult to rapidly identify and respond to food safety risks. Moreover, traceability in beef supply chains is expensive for producers (H. Shear et al., 2019; H. E. Shear & Pendell, 2020), which is partially the reason for the United States lagging behind other countries in developing more
robust traceability systems. However, it could provide a means to add value based on product information and label validation (Lin et al., 2021; Schroeder & Tonsor, 2012).

New BC technologies have shown promise to address these issues by tracing food from farm to fork using one shared or distributed system viewable by the public. In a permanent, secure, and public (or shared) manner, BC technologies could verify and record transactions involving beef with cryptography and advanced computer algorithms. BCs are a type of DL that allows consumers to know exactly where their beef came from, how the beef was raised and treated, and what the environmental impacts were. Still, implementing BC technologies cost money, which may result in higher priced beef—in other words, consumers may need to pay a premium for the additional tracking offered by BC—at least in the short run. Economic costs will primarily be incurred during the short run while companies transition to BC platforms and hire BC-trained staff. Costs may include hiring software engineers and developers who have specific (and more expensive) expertise in BC. Moreover, transactional costs could increase in the short run because of the required changes in hardware and other infrastructure needs. However, in the long run, firms are likely to experience greater efficiencies in product traceability and could potentially extract premiums from the company’s customers in B2B transactions and end consumers based on newfound abilities to validate product information.

Although there are potential increases in short-run costs, many companies are betting on an economy of scale wherein supply chain transparency, improved contract validation, and more detailed product information will generate market opportunities from BCs. Anecdotally, early industry adopters of BC technology have improved food supply chain traceability from farms to retail stores for meat and produce, but so far the economic costs of developing and governing a shared BC application have not been systematically studied. For example, Carrefour reported increased sales for some of its products that are tracked on a BC and accessible to consumers via QR codes (Wieck, 2019).

In this study, we use a choice experiment (CE) to investigate the consumer side of BC traceability in the US beef supply chain. We are also interested in examining the effect of different types of BC information on consumers’ valuation for traceability. Specifically, we investigate whether the use of the term “blockchain” will elicit different responses from the use of the more general term “digital ledger”. We further examine whether consumers would prefer permissioned government administration of the BC system over third-party governance of the BC system or a no-governance, permissionless BC. Hence, in our CE, we randomly assigned respondents to four treatment groups: (1) blockchain-no information (BCN), representing no governance (permissionless) type for the BC, (2) blockchain-third-party governance (BCT), indicating an anonymous third party that governs the BC, (3) blockchain-government governance (BCG), stating a government entity that manages BC, and (4) digital ledger-no information (DL) without information for governance. Results generally suggest that consumers do not differentiate much between the terms “blockchain” and “digital ledger”, but that they prefer government over third-party governance of the BC system when presented with particular attributes.

METHODS AND DATA

Choice experiment

Substantial attention in recent literature and in popular media has focused on meat product attributes and traceability (Pendell et al., 2013; Schroeder et al., 2007; Ates &
Lusk, 2020; Ortega et al., 2020; H. E. Shear & Pendell, 2020; Lin et al., 2021), specifically beef, which is why beef steak makes an ideal medium to test the effects of BC traceability on consumer preferences, which in this case have implications not just for business implementations of BC technology but also for policies relating to how the technology is managed and governed. To investigate the potential value of BC traceability to consumers and consider governance factors, a discrete CE was designed similar to previously implemented methods (Liu et al., 2019; Fiebig et al., 2010; Balcombe, Fraser, and Falco 2010; Ublava & Foster, 2009).

The online CE was designed in Qualtrics and administered through Dynata to recruit a representative sample of respondents across the United States based on gender, age, income, and education. Dynata charges a fixed rate per respondent for a prespecified minimum number of responses, in this case 1000. A total of 3560 cases were surveyed via Dynata, and 1096 responses were kept for analysis while the others were dropped. The

| Attribute label | Attribute description |
|-----------------|-----------------------|
| **Blockchain Certified** | The presence of this label indicates that independent parties (food producers, feed lots, food processors and retailers) are sharing blockchain technology to verify the source, quality and other attributes of the beef. |
| **USDA Certified** | This label indicates that the United States Department of Agriculture verified the source, quality, and other attributes of the beef. |
| **QR code** | This image is known as a QR code. It can be easily scanned by compatible mobile devices to view a particular website on the internet. While this particular QR code leads to the University of Arkansas website, on a beef product the QR code indicates you can immediately view information regarding the beef product on a smartphone or other device (provided there is a connection to the Internet). |
| **Grassfed** | The grassfed label indicates that the beef was fed only grass (as opposed to grains) following weaning from its mother's milk. |

Note: “Blockchain Certified” is replaced with “Digital Ledger Certified” in one of the four treatments. The label had the same size and font as the one above.
CE was conducted from July 18 to 24, 2019, using the following attributes in the CE: price, BC/DL-certified, USDA-certified, QR code for product information, grassfed, and reduced carbon. These attributes were highlighted using labels placed on an image from a common grocery store in the United States (Table 1). As mentioned above, we also tested the effect of different types of BC governance information by randomly assigning respondents to different treatment groups.

In the experiment, respondents first read an introduction to the topic of interest, namely food traceability for beef steak. The description was the same for all respondents except that the words “blockchain” or “digital ledger” were used according to the information treatment. Information treatments for BC governance were placed in the attribute label description for BC technology. We required respondents to be at least 18 years old, spend 8 s when reading the treatment descriptions, 7 s on the attribute table, and 4 s on the cheap talk script (based on length) to help ensure that they were attentive. Minimum completion time was 3.3 min with a maximum of 17 h (due to the browser remaining open after completion). Median completion time for the entire survey was approximately 10 min, with 2465 (30.8%) responses screened out because of inadequate time on screening pages. Additionally, respondents were screened out if they had not purchased beef in the last 6 months. Time constraints on treatment-reading accounted for 54% of screened-out responses. A total of 1096 quality responses were retained for analysis. See Figure 1 for the introduction (red text added to indicate where information treatment names were different).

The attributes were then presented on labels with descriptions following the introduction to prepare respondents for a series of 10 choice tasks. Between the table of attribute labels and descriptions (Table 1) and the first choice task, respondents read a “cheap talk script” to alleviate potential hypothetical bias prior to beginning the series of choice tasks (Carlsson et al., 2005; Fang et al., 2020; Lusk, 2003; Silva et al., 2011). The attribute labels were presented in different combinations with random placements on a beef steak image. For each choice task, we asked respondents to assume they were shopping for a 10-ounce beef steak and subsequently asked them to make a series of hypothetical purchasing decisions between two beef options and a “neither of these” (no-buy) option. Including a no-buy option makes the choice task more realistic because consumers may not purchase items that are unacceptable (Bazzani et al., 2017; Fang et al., 2020; Gao et al., 2016). The two beef options were presented in the same image and stated to be of the same size, quality, taste, and other characteristics. The only differences presented to respondents were price and the method in which the steak was produced and/or certified as indicated by the presence or absence of attribute labels. Respondents were told they would see many different combinations of labels and prices. Choice tasks with labels were randomly sorted to avoid order effects (Loureiro & Umberger, 2007; Savage & Waldman, 2008).

We follow previous methods based on Scarpa and Rose (2008) and Bazzani et al. (2017) to implement an efficient sequential Bayesian experimental design for the CE. After a pre-survey of 41 respondents to gather priors on attributes for the optimal design of the choice set, the Bayesian simulation yielded a final design of 40 choice sets broken into 4 blocks of 10 each with an efficiency D-error of 0.384 (Kuhfeld et al., 1994). Respondents in the full CE averaged 15.1 min (median of 9.8 min) to complete the survey with a total of 1096 complete responses retained for analysis. Price levels varied between $15.00/lb and $5.00/lb in $2.50/lb increments to cover the main range of product prices available in a US grocery setting. Figure 2 illustrates one of the choice tasks provided to respondents.
Previous studies have shown that socioeconomic, demographic, and qualitative characteristics may influence consumer perceptions and WTP for products with varying attributes (Folkes, 1988; Lusk et al., 2018; Schaninger & Sciglimpaglia, 1981). Hence, we included several qualitative questions in our survey to understand some of these drivers behind the respondents’ product choices and preferences (Powe et al., 2005). Specifically, we expect age to be inversely related to WTP for BC, and education to increase WTP for BC. Additionally, willingness to take risks, particularly toward health, could potentially affect preference for food traceability and product information, so a self-assessed risk survey was included (Dohmen et al., 2011). Respondents’ familiarity with labels and logos could also influence their choices, as well as their knowledge of cryptocurrencies or BC technology. As such, respondents ranked their familiarity with BC (or more general DL) technology and their familiarity with other attribute labels on a Likert scale between 1 and 5. Moreover, respondents having experienced food poisoning (and its severity) or their awareness of major foodborne illnesses reported by media might influence their choices, so questions were included to capture these potential effects. Respondents were specifically asked if they experienced food poisoning, and if they responded yes, they were asked how recently with response options: within 6 months, 1 year, or 5 years. Additionally, they were asked about severity with options: minor, moderate at home, moderate at doctor, moderately severe, or severe. Finally, respondents were asked if they were aware of major foodborne illnesses in the United States within the last 6 months.

**Econometric models**

To elicit consumer preferences, we implement a discrete choice model using the attribute-based choice method following the Lancaster Consumer Theory (LCT; Lancaster, 1966) and Random Utility Theory (RUT; Manski, 1977; McFadden, 1973; McFadden & Train, 2000). In this theoretical framework, consumers are rational actors maximizing utility based on

**FIGURE 1** Choice experiment introduction with treatment names [Color figure can be viewed at wileyonlinelibrary.com]

Read all information carefully. Failure to do so may result in you being kicked out of the survey!

**Food Traceability:**
Beef steak is a commonly consumed food product in the USA that requires monitoring through the supply chain to ensure proper food handling and safety. Currently, all parties in the food supply chain (including farmers, feed lots, meat processors, wholesalers, and retail stores) conduct their own quality control checks and maintain their own records.

Government agencies like the USDA (United States Department of Agriculture) are responsible for certifying the safety and quality of beef through the supply chain by employing officials to check physical samples of beef at various points along the supply chain. They also sample the records kept by the parties in the supply chain.

Usually, there is no end-to-end visibility of how beef travels from farm to fork. If an event occurs, like mad cow disease, government institutions and supply chain partners may struggle to recreate the chain of events, making it difficult to rapidly identify and respond to food safety risks. New digital ledger technologies, however, promise to address these issues by tracing food from farm to fork using one shared system viewable by the public.

In a permanent, secure, and public fashion, digital ledger technologies verify and record transactions with cryptography and advanced computer algorithms. This digital ledger allows consumers to easily know exactly where their beef came from, how the beef was raised and treated, and what the environmental impacts were. However, these new digital ledger technologies cost money that may result in higher-priced beef. We are interested in learning how consumers like you would value the reduction in food safety risks and ability to easily access detailed information about the supply chain through digital ledger technology.
their preferred combination of product attributes. When presented a product, beef steak in this case, along with attributes or combinations of attributes as described above, consumers are assumed to select the option that generates the highest utility. RUT posits that we can observe certain aspects of consumer utility while others remain random and unobservable. Thus, the probability of consumer preferences for alternative product attributes in a given choice set provides insight into consumers’ derived utility from stated product attributes. Utility can be illustrated as

$$U_{nit} = V_{nit} + \varepsilon_{nit}$$

where utility ($U$) of individual $n$ chooses product alternative $i$ from a finite set of options in choice scenario $t$, and where $V_{nit} = \beta' X_{nit}$ is observable and non-random with $X_{nit}$ as a vector of attributes for the $i$th product alternative scenario and $\beta'$ as a vector of preference parameters for the exogenous variables. The random component is represented by $\varepsilon_{nit}$. The specific forms of error terms and $\beta$ can lead to different model types with varying interpretative advantages. For more detailed discussion of the theoretical framework and some model types, see McFadden and Train (2000) and Train (2001).

### Analysis—likelihood ratio tests

In the first phase of the analysis, we conduct likelihood ratio tests (LRT) to examine differences in treatments pairwise. That is, a base model is estimated on a subset including only two treatments, and the same model plus treatment parameters (treatment interacted with attributes) is estimated on the same subset. LRT determines whether there is a significant improvement in model fit when treatment effects are included. Utility for the base model is given as

$$U_{nit} = ASC_n + \beta_p Price_{nit} + \beta_{1,n} BC_{nit} + \beta_{2,n} Grassfed_{nit} + \beta_{3,n} USDA_{nit} + \beta_{4,n} Carbon_{nit} + \beta_{5,n} QR_{nit} + BC_{nit}*(\delta_{1,Grassfed_{nit}} + \delta_{2,QR_{nit}}) + USDA_{nit}*(\delta_{3,Grassfed_{nit}} + \delta_{4,QR_{nit}}) + Grassfed_{nit}*(\delta_{5,Carbon_{nit}} + \delta_{6,QR_{nit}}) + \gamma_{1,BC_{nit}}*Grassfed_{nit}*QR_{nit} + \gamma_{2,USDA_{nit}}*Grassfed_{nit}*QR_{nit} + \eta_n,$$

FIGURE 2  Choice task for a digital ledger treatment. This choice task includes attributes for grassfed, low carbon footprint, QR code, and digital ledger certified [Color figure can be viewed at wileyonlinelibrary.com]
where \( n \) is the survey respondent and \( i \) is the alternative in \( t \) choice scenario. An example for alternative \( i \) in a specific choice scenario can be examined in Figure 2. ASC is the alternative-specific constant for the two beef alternatives, followed by attribute coefficients \((\beta_n)\) with attributes Price for price levels, blockchain (BC)-certified, Grassfed, USDA-certified (USDA), low carbon footprint (Carbon), and QR code with producer information (QR), along with interaction effects for BC certification with grassfed and QR code and USDA certification with grassfed and QR codes with \( \delta_{1-6} \) as coefficients. Additional three-way interactions were included for BC certification, grassfed, and QR code and USDA, grassfed, and QR code where \( \gamma_{1-2} \) are the coefficients. Utility for the treatment model follows, with all variables as defined in Equation (2), but a Treatment binary variable is added to capture the effects of each of the alternative treatments: BCN, BCT, BCG, and DL. Note that we do not include all third-order interactions, as they were insignificant and did not improve the model fit.

Additionally, we estimated a pooled model including all treatments using a similar specification to Equation (2), although here we interacted the treatment binary variables for DL, BCT, and BCG with the BC certification to determine specific treatment effects on the WTP for BC-certified beef. In all these models, we used a mixed multinomial logit (MMNL), where all attributes except price are distributed normally. Price is non-random to avoid possible infinite mean WTP values, and \( L \) is the lower triangular matrix in the Cholesky decomposition capturing correlation among attributes (Train, 2009).

**Analysis—latent class model**

Following the LRT and MMNL, we estimate latent class (LC) models to provide insights into naturally occurring groups or profiles of consumer preferences by allowing individual consumer choices to help estimate probabilities of falling into each class (Thiene et al., 2018). Furthermore, each class has its own set of utility parameters as in the models described above. The likelihood equations for the LC are similar to those of the MMNL, although estimates instead represent the probability of falling into a discrete number of classes.

The LC model type is preferred here as opposed to an MMNL because of the complexity of interpreting and estimating the numerous interaction terms between attributes and treatments. Additionally, it is rare that public opinion should follow only one set of guiding preferences. Heterogeneity of preferences is modeled for different numbers of classes, for example, 2, 3, 4, and 5 in this case, and the coefficients provide insights into how consumers value the information treatments as well as the attributes. Akaike information criterion (AIC) and Bayesian information criterion (BIC) are used to determine the optimal number of classes to explain how consumer characteristics relate to preferences with respect to the information treatments (Allenby, 1990; Gupta & Chintagunta, 1994; Kamakura & Russell, 1989). Based on the LC model, we discuss consumer preferences for the information treatments and labels and discuss the implications for food and technology policy.

**RESULTS**

There were a total of 1096 respondents to the survey. Table A2 (Supporting Information) shows respondents’ demographics. Most participants had no children, were employed full time, had a high school diploma or bachelor’s degree, lived in suburban environments, eat beef a few times
per week, and had an average age of 48 years. Gender and income levels were similar. Importantly, more than 85% consume beef on a weekly basis and 99% consume monthly. Ten respondents (0.91%) did not consume beef, and nine of these selected the no-buy option in every choice set. This suggests respondents are regular purchasers of beef products and likely have developed purchasing habits toward beef. Balance across demographic characteristics and follow-up questions were analyzed, and no significant differences across treatments were found ($p > 0.05$). See Tables A1, A2 (Supporting Information) for respondents’ demographics and balance across treatments.

Beef consumption preferences, previous knowledge, rankings of product characteristics, and additional follow-up questions for respondents are documented in Table 2. Respondents were fairly certain about their responses to survey questions following their choices in the treatment tasks with an average of 8.39 (SD of 1.55; median of 9 out of 10 where 10 was “very certain” and 1 was “very uncertain”). In the self-assessment of willingness to take risks in different domains based on Dohmen et al. (2011), respondents showed risk-averse behavior, especially toward driving (3.12/10) and health (3.20/10). In other categories, participants were more risk-neutral. When asked to rank beef product characteristics in terms of importance on a Likert scale of 1–5, taste, appearance, price, and USDA grade were most important to participants at means of 4.59, 4.15, 3.99, and 3.92, respectively. Conversely, novelty and environmental impact were relatively unimportant in respondents’ purchase decisions, with means of 1.89 and 2.97, respectively. Notably, participants’ rankings varied less for taste and appearance than for all other characteristics, with standard deviations of only 0.64 and 0.83, respectively. Beef products tend be more expensive relative to chicken and pork, which may be a reason behind consumers’ focus on taste and appearance over price, environmental impacts, and so on. Familiarity on a scale of 1–5 with low carbon footprint labels, DL, and BC technologies was low for respondents, averaging 1.80, 1.57, and 1.49, respectively.

Respondents demonstrated varying preferences for BC and DL technologies in food traceability for US beef steak. The treatment comparisons for BC, DL technology, BC with government governance, and BC with third-party governance are presented in Table 3. The results of the likelihood ratio tests (LRTs) are sensitive to model specification; specifically, we see very different results when varying the number of interaction terms with the treatment indicator. For example, when Equation (3) is used, we see significant chi-squared $p$-values for all pairings of treatments except for the BCN–BCT pairing. However, the parameter estimates for treatment interactions with BC are not always significant (see the left column of Table 3). Of note, the BC certification interacting with the DL treatment was significantly different in the BCN–DL and BCT–DL comparison.

To examine whether the additional terms were deterring from the treatment–BC interaction, we repeated the LRT using a treatment model with only the treatment–BC interaction wherein $\alpha_2$, $\alpha_3$, and $\alpha_4$ are set to zero in Equation (3). In this case, only one of the LRTs was significant, and all treatment–BC interactions were not significant. This led us to believe that it is not the treatments that cause a higher or lower value of the BC certification, but simply that the inclusion of additional parameters changes the likelihood enough to cause a significant test in terms of the $p$-value. Additional specifications for the treatment model were also estimated with varying results. Ultimately, these findings suggest that the governance information provided was unimportant to respondents, or at least inconsistently so.

Since the LRT results were inconclusive, we looked at a pooled MMNL model and interacted the treatments with the BC certification label (Table 4). The treatment parameters were insignificant, which suggests that there are no real measurable treatment effects on the BC
Table 2: Responses to qualitative follow-up questions about choice certainty, beef product attributes, and willingness to take risks

| Question category | Variable                                      | Measurement                                                                 | Mean  | SD   |
|-------------------|-----------------------------------------------|-----------------------------------------------------------------------------|-------|------|
| Choice certainty  | Certainty about choices tasks                 | Likert: 1–10 with (1) very uncertain and (10) very certain                 | 8.39  | 1.55 |
| Willingness to take risks | in general                                    | Likert: 1–10 with (1) not at all willing and (10) very willing to take risk | 5.22  | 2.29 |
|                   | while driving                                  |                                                                             | 3.12  | 2.23 |
|                   | in financial matters                           |                                                                             | 4.13  | 2.34 |
|                   | in sports and leisure activities               |                                                                             | 5.17  | 2.56 |
|                   | with your health                               |                                                                             | 3.20  | 2.19 |
|                   | in your career                                 |                                                                             | 4.64  | 2.55 |
| Importance of beef product characteristics | Nutritional Value                              | Not important at all (1) to extremely important (5)                         | 3.57  | 1.02 |
|                   | Novelty (new or original)                      |                                                                             | 1.89  | 1.07 |
|                   | Appearance (texture, color)                    |                                                                             | 4.15  | 0.83 |
|                   | Taste                                          |                                                                             | 4.59  | 0.64 |
|                   | Packaging                                      |                                                                             | 3.07  | 1.09 |
|                   | Brand Name                                     |                                                                             | 2.53  | 1.13 |
|                   | Price                                          |                                                                             | 3.99  | 1.13 |
|                   | Environmental impact                           |                                                                             | 2.97  | 1.17 |
|                   | Country of beef origin                         |                                                                             | 3.43  | 1.22 |
|                   | Grassfed label                                 |                                                                             | 3.14  | 1.25 |
|                   | Fat marbling                                   |                                                                             | 3.43  | 1.10 |
|                   | USDA grade                                     |                                                                             | 3.92  | 1.00 |
| Familiarity and food attributes sought | Carbon footprint familiarity                   | Not at all familiar (1) to extremely familiar (5)                          | 1.80  | 1.02 |
|                   | Digital ledger familiarity                     |                                                                             | 1.57  | 0.95 |
|                   | Blockchain familiarity                         |                                                                             | 1.49  | 0.92 |
| Label-seeking preferences | Seek grassfed labels                           | Ranked never (0) to always (4)                                             | 1.44  | 1.20 |
|                   | Seek organic labels                            |                                                                             | 1.47  | 1.18 |
|                   | Seek local labels                              |                                                                             | 1.73  | 1.09 |
| Food poisoning and recall awareness | Experienced food poisoning                     | No                                                                          | 539   | 49.18|
|                   |                                               | Yes                                                                         | 404   | 36.86|
|                   |                                               | Maybe                                                                       | 153   | 13.96|
|                   | Severity of food poisoning                     | Minor                                                                       | 136   | 12.41|
|                   |                                               | Moderate-home                                                              | 181   | 16.51|
|                   |                                               | Moderate-doctor                                                            | 44    | 4.01 |
|                   |                                               | Moderately severe                                                          | 25    | 2.28 |
|                   |                                               | Very severe                                                                 | 18    | 1.64 |
|                   | Recency of food poisoning                      | 6 months                                                                    | 188   | 17.15|
|                   |                                               | 1 year                                                                      | 108   | 9.85 |
|                   |                                               | 5 years                                                                     | 67    | 6.11 |

(Continues)
attribute. The baseline treatment was the no-buy options, so the alternative specific constant to buy beef (Buy-ASC) was $3.89, which can be interpreted as the mean respondent utility derived from purchasing beef without regard to specific product attributes. Respondents' marginal willingness to pay (mWTP)² for a 10-oz. beef steak in the study was $9.03, and all individual attributes were associated with higher mWTP than the WTP for beef with no information, including $5.36 for grassfed, $0.54 for low carbon, $3.06 for QR code, $5.61 for BC certification, and $7.87 for USDA certification. WTP for these attributes seems to align with observed premiums in beef markets at the time the survey was administered. Additionally, the BC (and DL) certification components for traceability are significant when interacted with many of the other attributes. For example, we find a –$3.05 mWTP for the grassfed and a –$1.54 mWTP for the QR interactions with BC certification, respectively. This suggests a total mWTP for grassfed beef with the BC certification of $7.92 or a premium of $2.56 for the addition of the BC certification to grassfed beef. Compared to the value of grassfed beef with the USDA certification, we see $8.29 mWTP or a premium of $2.93 for the addition of USDA certification for grassfed beef. We conclude that treatments were not valued differently and that while BC certification for traceability is significantly valued, it does not surpass the value contributed by the more familiar USDA certification of traceability.

Both the LRT above and the pooled model below reinforce the lack of treatment influence on respondent choices. Overall, based on the treatment groups and the pooled model, we find weak evidence for BC governance or naming influencing choices. However, the LC models may provide further insights into heterogeneity or natural groupings of preferences, which would not otherwise be apparent from the other models.

We investigated heterogeneity of responses using latent class models with 2–5 classes. The five-class model did not have improved BIC over the four-class model. Of the models including two to four classes, the four-class model achieved the minimum AIC and BIC (Allenby, 1990; Gupta & Chintagunta, 1994; Kamakura & Russell, 1989), which suggests four classes is the optimal segmentation of respondents into latent preferences and taste profiles (Liu et al., 2020; Thiene et al., 2018). Heterogeneity of preference structures are presented for the four classes in Table 5. The latent classes are discussed with respect to differences between classes and how demographics, follow-up questions, and treatments relate to membership in a given class. Class 1 is the reference class, and the membership equations in Table 5 reflect the characteristics of individuals who belong to each class relative to class 1 in terms of the utility they derive from the treatments and attributes. We refer to the four classes as follows: class 1 is price and certification oriented, class 2 has weak beef preferences, class 3 is grassfed sensitive, and class 4 is the everything matters class.

Class 1 with a class weight of 23.6% is the most price conscious group, followed closely by class 4. Class 1 profiles those willing to pay a premium for beef steak with any certification

| Question category | Variable | Measurement | Mean | SD |
|-------------------|----------|-------------|------|----|
|                   | Aware of foodborne illnesses in the United States within 6 months | No | 463 | 42.24 |
|                   | | Yes | 631 | 57.57 |

Note: N = 1096. Numbers in parentheses in the measurement column indicate how the responses were coded for analysis.
### TABLE 3  Likelihood ratio tests with treatment and blockchain interactions

| Parameter       | Estimate | Std. Err. | p-Value |
|-----------------|----------|-----------|---------|
| Buy*DL          | -0.9355  | 0.3227    | 0.0037  |
| BC*DL           | 0.6817   | 0.2691    | 0.0113  |
| GF*DL           | 0.5647   | 0.2041    | 0.0057  |
| GF*BC*DL        | -0.7212  | 0.2742    | 0.0085  |

(Continues)
However, the negative interactions between the certifications indicated that there is a limit to how much respondents in this class are willing to pay for specialized products. Class 1 might be deemed price and certification oriented, as nothing else was important in this category. Of the four classes, class 2 (19.6% class weight) represents individuals who likely do not purchase beef steak often and probably not at all unless it is USDA-certified or has a low carbon footprint; hence this class might be suggested to have the common thread of weak beef preferences. This is the only class with an insignificant price coefficient. The significant interaction between the QR code with grassfed and QR with BC may indicate that the QR code is valued only if it serves to verify these certifications. The probability of falling into this class is increased by being younger, having a college degree (possibly more tech savvy), having low income, and being relatively unfamiliar with DL technology and low carbon labels. Class 2 also shows a preference for grassfed beef steak but is less characterized by environmental impacts and nutrition. BC and DL treatments slightly increase the likelihood an individual falls in the weak beef preference class, but this class did not value the BC label one way or the other.

Class 3 (18.2%) represents respondents who prefer grassfed, BC, USDA, and QR code attributes. Class 3 is similar to class 1 except that respondents in this class have a slightly higher preference for grassfed and lower preference for BC. Class 3 prefers to know the beef's history via the QR code (possibly to verify the grassfed claim), so they might be called grassfed sensitive.

TABLE 3 (Continued)

| Treatment interacted with all BC terms | Treatment interacted with BC only |
|---------------------------------------|----------------------------------|
| Likelihood Ratio Test: BCT-DL         | Likelihood Ratio Test: BCT-DL     |
| Model DF | LogLik | Chisq | Pr(>Chisq) | Model DF | LogLik | Chisq | Pr(>Chisq) |
| 36 | −3644.5727 | 36 | −3643.67 | 1.7997 | 0.1798 |
| 40 | −3640.3134 | 8.5187 | 0.0743 | 37 | −3640.3134 | 8.5187 | 0.0743 |
| Parameter | Estimate | Std. Err. | p-Value | Parameter | Estimate | Std. Err. | p-Value |
| Buy*DL | −1.2357 | 0.353 | 0.0005 | BC*DL | 0.303 | 0.2258 | 0.1797 |
| BC*DL | 0.7017 | 0.2804 | 0.0123 | GF*DL | 0.0156 | 0.2029 | 0.9388 |
| GF*BC*DL | −0.5158 | 0.2786 | 0.0641 | |

| Likelihood Ratio Test: BCG-DL         | Likelihood Ratio Test: BCG-DL     |
|---------------------------------------|----------------------------------|
| Model DF | LogLik | Chisq | Pr(>Chisq) | Model DF | LogLik | Chisq | Pr(>Chisq) |
| 36 | −3648.1608 | 36 | −3648.06 | 0.207 | 0.6491 |
| 40 | −3640.0887 | 16.1442 | 0.0028 | 37 | −3640.0887 | 16.1442 | 0.0028 |
| Parameter | Estimate | Std. Err. | p-Value | Parameter | Estimate | Std. Err. | p-Value |
| Buy*DL | −0.5852 | 0.319 | 0.0666 | BC*DL | 0.0977 | 0.2146 | 0.6489 |
| BC*DL | 0.5508 | 0.2675 | 0.0395 | GF*DL | −0.0277 | 0.2094 | 0.8948 |
| GF*BC*DL | −0.5346 | 0.2824 | 0.0584 | |

Note: BC, blockchain; BCG, blockchain government governance; BCN, blockchain no governance information; BCT, blockchain third-party governance; DL, digital ledger; GF, grassfed.
College degree and willingness to take risk had a negative association with membership in the grassfed sensitive class. Finally, with the highest probability of 38.6%, class 4 represents respondents to whom everything matters, or at least different combinations of attributes matter. Of all attributes by themselves, the BC and USDA attributes mattered the most, with mWTP of $6.29 and $5.82, respectively. The mWTP premiums after USDA and BC descend to grassfed ($4.27), QR code ($2.84), and low carbon ($1.04). This group had the highest significant buying preference for beef steak at $10.78. Classes 3 and 4 having more than double mWTP for buying beef may signal that those who value beef steak more highly also value more information and additional product attributes (whatever they may be). Individuals in the BC government and DL treatments were more likely to fall in the everything matters class. High importance of grassfed characteristics and highly seeking grassfed labels also increased the likelihood of belonging to this class.

### Table 4

Pooled attribute interactions MMNL model with blockchain treatments

| Parameter      | Estimate | Std. error | p-Value | mWTP estimate | Std. error | Pr(>|t|) |
|----------------|----------|------------|---------|---------------|------------|---------|
| Price          | -0.4308  | 0.0148     | 0.000***|               |            |         |
| Buy-ASC        | 3.891    | 0.2745     | 0.000***| 9.0324        | 0.5115     | 0.000***|
| Grassfed       | 2.3084   | 0.198      | 0.000***| 5.3585        | 0.4751     | 0.000***|
| Carbon         | 0.2336   | 0.0817     | 0.004***| 0.5422        | 0.1907     | 0.005** |
| QR             | 1.3182   | 0.1833     | 0.000***| 3.6061        | 0.4326     | 0.000***|
| BC             | 2.4182   | 0.2467     | 0.000***| 5.6135        | 0.6255     | 0.000***|
| USDA           | 3.3897   | 0.2018     | 0.000***| 7.8686        | 0.502      | 0.000***|
| BC.DL          | 0.2098   | 0.2214     | 0.343   | 0.4869        | 0.5137     | 0.343   |
| BC.BCG         | 0.0748   | 0.229      | 0.744   | 0.1737        | 0.5315     | 0.744   |
| BC.BCT         | -0.0615  | 0.2193     | 0.779   | -0.1428       | 0.5092     | 0.779   |
| Grassfed:Carbon| 0.1834   | 0.101      | 0.070*  | 0.4257        | 0.2354     | 0.071   |
| Grassfed:QR    | -0.9178  | 0.2228     | 0.000***| -2.1305       | 0.5251     | 0.000***|
| Grassfed:BC    | -1.3153  | 0.2523     | 0.000***| -3.0532       | 0.6006     | 0.000***|
| QR:BC          | -0.6654  | 0.2273     | 0.003***| -1.5445       | 0.5287     | 0.004** |
| Grassfed:USDA  | -2.1254  | 0.2478     | 0.000***| -4.9337       | 0.5653     | 0.000***|
| QR:USDA        | -1.0166  | 0.2235     | 0.000***| -2.3598       | 0.5265     | 0.000***|
| Grassfed:QR:BC | 0.5154   | 0.3172     | 0.104   | 1.1965        | 0.7392     | 0.106   |
| Grassfed:QR:USDA| 0.9669  | 0.306      | 0.002***| 2.2445        | 0.7243     | 0.002** |
| SD.Buy-ASC     | 3.3225   | 0.1762     | 0.000***|               |            |         |
| SD.Grassfed    | 1.5258   | 0.0709     | 0.000***|               |            |         |
| SD.Carbon      | 1.0542   | 0.086      | 0.000***|               |            |         |
| SD.QR          | 0.9392   | 0.0853     | 0.000***|               |            |         |
| SD.BC          | 1.7457   | 0.1101     | 0.000***|               |            |         |
| SD.USDA        | 1.7333   | 0.111      | 0.000***|               |            |         |

Note: Significance levels are represented as ‘-’ for $p < 0.10$, * for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$. Models were estimated in R 3.3.2 using the ‘gmnl’ package (Sarrias & Daziano, 2017).
| Parameter               | Class 1     | CL1 mWTP | Class 2     | CL2 mWTP | Class 3     | CL3 mWTP | Class 4     | CL4 mWTP |
|------------------------|-------------|----------|-------------|----------|-------------|----------|-------------|----------|
| Buy ASC                | 2.25 (0.38)***** | $4.02    | 0.07 (0.31) | $3.50    | 1.86 (0.68)** | $11.63   | 4.85 (0.58)***** | $10.78   |
| Grassfed (GF)          | 1.50 (0.38)***** | $4.02    | $0.07 (0.31) | $11.63   | 2.90 (0.47)***** | $18.13   | 1.92 (0.27)***** | $4.27    |
| Low carbon (LC)        | 0.03 (0.14)  | $0.07    | 0.32 (0.13)* | $11.63   | 0.27 (0.19)  | $1.69    | 0.47 (0.12)***** | $1.04    |
| QR code                | 0.60 (0.36). | $1.07    | $0.15 (0.24) | $7.13    | 1.14 (0.47)*  | $7.13    | 1.28 (0.27)***** | $2.84    |
| Blockchain (BC)        | 2.00 (0.33)***** | $3.57    | $0.08 (0.27) | $4.00    | 1.24 (0.53)*  | $3.57    | 1.92 (0.27)***** | $1.92    |
| USDA                   | 2.04 (0.37)***** | $3.64    | 2.27 (0.27)***** | $113.50  | 2.00 (0.51)***** | $12.50   | 2.62 (0.28)***** | $5.82    |
| Price                  | $0.56 (0.03)***** | $1.00    | $0.26 (0.02) | $13.00   | $0.39 (0.24)  | $2.44    | $0.31 (0.15)*   | $0.69    |
| GF:LC                  | $0.01 (0.18) | $0.02    | $0.26 (0.18) | $13.00   | $0.39 (0.24)  | $2.44    | $0.31 (0.15)*   | $0.69    |
| GF:QR                  | $0.11 (0.50) | $0.20    | 0.77 (0.34)* | $38.50   | $0.86 (0.55)  | $5.38    | $1.05 (0.31)***** | $2.33    |
| GF:BC                  | $1.34 (0.43)** | $2.39    | 1.04 (0.42)* | $52.00   | $1.05 (0.63). | $6.56    | $1.70 (0.38)***** | $3.78    |
| QR:BC                  | $0.67 (0.40). | $1.20    | 0.98 (0.38)** | $49.00   | $1.09 (0.58). | $6.81    | $0.02 (0.37) | $0.04    |
| GF:USDA                | $1.27 (0.45)** | $2.27    | $0.01 (0.37) | $0.50    | $1.72 (0.60)** | $10.75  | $2.15 (0.41)***** | $4.78    |
| QR:USDA                | $0.08 (0.48) | $0.14    | 0.10 (0.32)  | $5.00    | $0.35 (0.57)  | $2.19    | $1.16 (0.32)***** | $2.58    |
| GF:QR:BC               | $0.20 (0.57) | $0.36    | $1.54 (0.57)** | $77.00  | 1.75 (0.79)*  | $10.94   | $0.43 (0.50) | $0.96    |
| GF:QR:USDA             | $0.27 (0.62) | $0.48    | $0.26 (0.46) | $13.00   | 1.01 (0.84)  | $6.31    | 1.82 (0.60)***** | $4.04    |

**Membership Equations**

| Parameter               | Class 2     | Class 3     | Class 4     |
|------------------------|-------------|-------------|-------------|
| Intercept              | 1.29 (0.31)***** | $1.07 (0.42)*  | 0.36 (0.30) |
| Age                    | $0.01 (0.00)***** | $0.00 (0.00)  | $0.01 (0.00)***** |
| College degree         | $0.27 (0.07)***** | $0.43 (0.08)*** | 0.06 (0.06) |
| Household size         | $0.05 (0.03).   | $0.02 (0.03)  | $0.12 (0.02)***** |
| High income            | $0.05 (0.08)   | 0.38 (0.09)***** | $0.06 (0.07) |
| Low income             | $0.21 (0.09)*  | 0.26 (0.09)*** | 0.14 (0.07)* |
| Average risk           | $0.02 (0.02)   | $0.05 (0.02)*** | $0.01 (0.02) |
| BC-Government treatment| 0.14 (0.10)   | 0.12 (0.09)  | 0.33 (0.08)***** |
| Parameter                        | Class 1          | CL1 mWTP | Class 2 | CL2 mWTP | Class 3 | CL3 mWTP | Class 4 | CL4 mWTP |
|---------------------------------|------------------|----------|---------|----------|---------|----------|---------|----------|
| BC-Third-party treatment        |                  | 0.18 (0.09)* |         | -0.13 (0.09) |         | 0.12 (0.08) |         |          |
| Digital ledger (DL) treatment   |                  | 0.19 (0.10)* |         | 0.22 (0.09)* |         |          | 0.26 (0.08)*** |          |
| High familiarity-LC             |                  | -0.44 (0.10)*** |         | 0.21 (0.08)* |         | -0.10 (0.07) |         |          |
| High familiarity-DL             |                  | -0.61 (0.12)*** |         | -0.10 (0.11) |         | -0.17 (0.09) |         |          |
| High importance-Appearance      |                  | -0.22 (0.17) |         | 0.56 (0.21)** |         | 0.33 (0.16)* |         |          |
| High importance-Environment impacts |              | -0.28 (0.08)*** |         | 0.17 (0.08)* |         | -0.00 (0.06) |         |          |
| High importance-GF              |                  | 0.38 (0.08)*** |         | 0.31 (0.08)*** |         | 0.30 (0.07)*** |         |          |
| High importance-Nutrition       |                  | -0.77 (0.29)*** |         | 0.11 (0.41) |         | -0.14 (0.29) |         |          |
| Highly seek GF                  |                  | -0.10 (0.10) |         | -0.30 (0.11)** |         | 0.32 (0.08)*** |         |          |
| Highly seek local               |                  | 0.02 (0.08) |         | -0.32 (0.09)*** |         | -0.31 (0.07)*** |         |          |
| Severity of food poisoning      |                  | 0.07 (0.03)* |         | 0.09 (0.03)*** |         | 0.02 (0.02) |         |          |

Note: Significance levels are represented as “.” for $p < 0.10$, * for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$. Parameters with no significance for any class were removed from the table, including Male, High familiarity-BC, Highly seek organic.
Overall, the CE results confirm what has been found in the past, that is, consumers prefer more information when it is available to them. However, consumer knowledge of BC technology and its potential for improving food traceability from farm to fork remains limited. Companies considering BC in their product traceability systems may consider investing in both B2B and consumer education about how their products are validated to ensure returns on investment (at least partially) derived from consumer premiums for the information desired. Consumers ultimately seem to care most about the attributes labeled on their products, but in a quickly changing world of products moving through a complex distribution system, the validation of product labels may be all the more important. BC may represent a key validating component of food traceability, but without more consumer understanding it may be challenging for companies to incur the transitional costs, even with the promise of greater efficiencies in the long run. Additionally, if government agencies such as USDA AMS or FSIS require certain technologies to be used for traceability in the future, there may need to be considerations for generic public education about the technologies being implemented.

CONCLUSION

BC has the potential to enhance supply chain management and traceability in food distribution. Prominent companies and government agencies, including Walmart, IBM, and the USDA, have set pilot BC ecosystems in motion to become the new paradigm for food distribution. In this study, we examined how consumers might respond to BC systems based on information about governance. We provided a treatment for generic, government-permissioned BCs, but we included this treatment effect only for the BC and DLC attribute labels. Based on this treatment, we tested whether consumers value third party, private governance, or government governance compared to a generic, permissionless BC system and compared BC to a USDA certification label. While the treatment effects lead us to believe that consumers may not differentiate between BC governance systems, our respondents did show preferences and higher WTP for certain attributes presented on labels. Specifically, consumers valued USDA certification and BC certification labels at premiums, with USDA being valued at approximately $2.00 more than BC.

Overall, our results suggest that consumers trust the USDA label and are willing to pay a premium for it. Respondents were not presented USDA and BC certification labels simultaneously, but it is possible that the combination of the two would warrant a higher premium than either did individually. Future research could explore the implications of defining a treatment of BC governance for USDA certification specifically and examine the potential implications for beef traceability. The results from this study imply that BC integration with USDA certification could improve BC's viability for traceability and might increase consumer value and trust in beef traceability. This reinforces the recent momentum by the USDA to begin supporting BC technology in the current system of food safety, inspection, and traceability.

Implications and future research

Early industry adopters of BC-enabled food traceability solutions have invested time and resources in developing distributed applications to trace food through supply chains. Food safety is a major driver of industry adoption, and BC technology will likely lead to improved
efficiencies in the overall cost of beef traceability. However, it has remained an unanswered question as to whether the software development and enhanced production information provided about beef products could lead to premiums paid by end consumers. Our choice experiment aimed to provide insight into that question.

We found that consumers place little to no additional value in technology-specific labels which certify that the food’s journey was verified and traced by BC technologies as compared to being certified by the USDA without any technological claims. One likely reason is the low familiarity with these technologies among our research participants. BC technologies are still an emerging set of innovations with which the public are largely unaware; if they are aware of them, they may associate BCs only with cryptocurrencies like Bitcoin and not with permissioned BCs used in food supply chain solutions. One policy implication calls for more education on the benefits and limitations of BC, in the same way the public eventually became educated about the benefits and limits of the Internet. Companies may benefit from providing this education both internally and across B2B partners, as it may act as a source of validating the efficiencies generated and lead to B2C premium-levying labels. Government entities such as the USDA may also encourage education of BCs in the food supply traceability system if it becomes notably important for food safety improvements.

Another possible reason for our findings is that consumers may not care about the technologies but may care about what BC technologies enable. In our experiment, we showed consumers the BC and DL labels, but not the data behind the labels. In future research, we suggest a treatment group that shows consumers the data. For example, participants could be asked to hover their phones over a QR code to reveal the food’s entire journey, something that can be enabled only with industry-shared solutions, which are uniquely suited for BC technologies.

Consumers in our study valued a recognized government institution (USDA) more than they valued obfuscated governance over a particular BC solution for beef certification. As a final recommendation, future treatments could consider governance by an open-source community or a recognized industry brand/institution (IBM, Walmart, Tyson) in addition to a recognized government institution like the USDA, and this information could be displayed more prominently within the experiment.

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ENDNOTES
1 https://www.dynata.com/services/online-qualitative/
2 mWTP = −βattribute/βprice

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**SUPPORTING INFORMATION**

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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