USING NOVEL EXPERIMENTAL PROCEDURES TO ELICIT CONSUMER FOOD PREFERENCES AND DEMAND UNDER DIFFERENT CHOICE ENVIRONMENTS

By

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ABSTRACT

USING NOVEL EXPERIMENTAL PROCEDURES TO ELICIT CONSUMER FOOD PREFERENCES AND DEMAND UNDER DIFFERENT CHOICE ENVIRONMENTS

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The food system is in a constant state of change driven by the social and bio-physical environment. Acknowledging the role that innovations and preference adaptations on the consumer side play in this process, in this dissertation I use cutting-edge experimental procedures to assess consumer demand in three areas: food-away-from-home (FAFH), sustainable food products, and new food technologies.

In the first chapter I determine the impact dining settings have on consumer demand for FAFH, while also evaluating how a tax levied on red meat dishes would impact low- and high-income consumers. Capturing both substitution and complementarity patterns, I employ a food menu basket-based choice experiment approach, which permits respondents to freely pick and combine a range of food items at different price levels. I find that respondent's orders in the delivery setting are typically higher in calories and most items act as complements for one another, while menu items are substitutes in the dine-in setting. The red meat tax that I simulate is regressive towards low-income individuals in the delivery setting but not in the dine-in setting.

Thematically corresponding with the red meat tax, in the second chapter I study the market potential of "low carbon" ribeye steaks. In conjunction with this empirical component, I also propose the use of a reference price informed design that mirrors respondent's price expectations for actual food shopping situations. I find the market potential of meat with a lower carbon footprint is relatively small, with conventional meat taking up most of the market share. Our results

also show that a reference price informed design best describes choices and leads to more conservative market share estimates than traditional designs.

One way to achieve a lower carbon footprint could be the use of gene-editing. In my third chapter, I therefore assess consumer preferences and willingness to pay (WTP) for milk from cows gene-edited to produce less methane. In doing so, I also analyze whether and how preferences for new food technologies are affected by information on the climate impact of dairy production. I supplement this analysis with an exploration of what medium of information (video vs. text) has the strongest impact on consumer acceptance and how responses change depending on whether respondents get to opt-in to seeing information or are forced to see the respective information. I find that gene-edited milk is discounted relative to other available alternatives. Results also show that choice outcomes differ between respondents seeking additional information and those remaining willfully ignorant. Giving respondents autonomy over their knowledge gathering is a significant factor in determining choice behavior.

In sum, findings from these three chapters can be used to inform producers, policymakers, and the food industry, as well as improve the way food experiments are designed within the realm of food choices and beyond.

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1. Introduction

In 2021 almost 53% of all household food expenditures in the U.S. were attributable to food-away-from-home (FAFH) despite a significant drop in FAFH spending during the COVID-19 pandemic (USDA ERS 2022). This rapid recovery is partially attributable to the increased use of food delivery services during the pandemic: A 2020 survey showed that 41% of respondents used online services to order food from restaurants in 2020 compared to only 24% in 2019 (Edmondson et al. 2021). This change in the food landscape begs the question: How might FAFH choices change in a delivery vs. dine-in setting?

Studies have shown that overall eating behavior, satisfaction and satiety change based on the eating location (see e.g., Meiselman et al. 1996; Edwards et al. 2003; King 2004; García-Segovia 2015; Mouta et al. 2016; Lorenz and Langen 2017; Hendricks et al. 2021; Gough et al. 2021). Recent research also indicates that consumers ordering food for delivery focus on aspects such as convenience as well as how well food travels and particularly enjoy ordering calorie-dense comfort-food (Yeo et al. 2017; Upserve 2020, Tandon et al. 2021). If that is the case, then these food preferences suggest that there might be differences in order behavior for FAFH across dining settings (e.g., ordering food for delivery vs. dine-in a restaurant). Recognizing whether these differences in ordering behavior exist and what they are is central to the economic and food policy debate especially given the observed changes in consumption values and dietary patterns.

To date, there are a few studies that have explored how FAFH affects diet quality (see among others Kim and Ahn 2020; Gugliucci et al. 2021) or how diet quality of FAFH meals can be improved for example through calorie labeling (see e.g., Ellison et al. 2013, 2014a,b). However, research on differences in consumers' order behavior across delivery and in-restaurant dining settings (regarding for example the calorie density of orders or the meal composition) is lacking. One of the main obstacles limiting research on FAFH consumption is the lack of in-depth and timely data sources. Apart from the FoodAPS data, which provides rich food consumption and expenditure data for food consumed away from home, other public data sources providing in-depth information of FAFH are scant. Yet, the last FoodAPS survey was conducted in April 2012 - January 2013, thus it fails to provide timely information on emerging FAFH consumption patterns, especially for food delivery. Scanner data for FAFH is also limited in its availability and data sets like the out-of-home panel from Kantar as used by Law et al. (2022) also provide no information on the alternatives available to consumers at the purchase place.

Likewise, no previous study utilizing primary data has investigated differences in choice behavior for FAFH across dining settings. A few studies focus on how consumers make trade-offs between available items, but often only look at one specific product (e.g., Hoefkens et al. 2012; Paci et al. 2018) or a very small subset of products (e.g., Drichoutis et al. 2009). Even those offering a larger number of items to choose from, are limited in the geographic reach of their data collection as they look at only a few restaurants (see e.g., Ellison et al. 2013, 2014a,b) or tend to limit respondents in their selection to just one item (see e.g., Zaffou and Campbell 2015; Sturm et al. 2018; Gugliucci et al. 2021). Limiting respondents to the selection of only one item not only contradicts recent developments in the food choice literature on food at home (FAH) consumption (Caputo and Lusk 2022) but is also counterintuitive when considering choice behavior for FAFH; typically, when ordering FAFH consumers are permitted to choose multiple items from different categories. For example, in an observation of real dining orders in a restaurant, Ellison et al. (2013)

observed that customers derived on average about 20% of the total meal calories from additional items they ordered.

In this article we address this gap in the literature concerning the understanding of FAFH order behavior by utilizing a food menu basket-based choice experiment (FM-BBCE). We determine consumer preferences and demand for FAFH in two dining settings: in-restaurant dining and food delivery. We expand upon the work by Caputo and Lusk (2022) and integrated our FM-BBCE into an online survey on FAFH consumption of more than 2000 U.S. consumers. Instead of being limited to a single-select format, the FM-BBCE approach allows respondents to freely compose their meal from a food menu consisting of appetizers, entrées, and side dishes. This design permits us to not only create a more realistic choice environment reflecting what people would experience in a real situation but also lets us capture relevant substitution and complementarity patterns, which occur during actual food orders. Using a between-subject approach, respondents were either allocated into a hypothetical delivery or in-restaurant setting. This allocation allowed us to observe whether order behavior for FAFH significantly differs across choice contexts.

By deriving the item-specific own- and cross-price utilities and elasticities using a Multivariate Logistics (MVL) model (Song and Chintagunta 2006; Kwak et al. 2015; Richards et al. 2018; Caputo and Lusk 2022), we then compare the interdependencies between the included items across the two settings and also evaluate the demand and income-specific welfare effects of a red meat tax across the different dining settings. Indeed, we find that such a tax has a setting dependent impact on demand, which extends beyond the affected meat products. In addition, we observe that the tax would lead to a reduction in consumer welfare and is regressive in nature in a delivery setting, but not a dine-in one. These results stem from differences in own- and cross-price elasticities as well as disparities in substitution and complementarity patterns across the two settings. The average meal in the two settings also differs in terms of the nutritional composition, which sees a higher calorie, protein, fat, carbohydrate, and cholesterol content in the *Delivery* setting. General preferences also vary across socio-demographics. For example, women derive lower utility from meat options and rural and suburban consumers have a significantly lower preference for plant-based alternatives like plant-based burgers.

This study provides several significant contributions to our understanding of FAFH consumption that benefit a diverse array of stakeholders. First, by examining how consumer preferences and demand differ for FAFH in a restaurant and delivery setting, we report timely insights into consumer expenditures and item-specific order behavior for FAFH across dining settings. We show that FAFH is not a homogenous category. Instead, consumer preferences are affected by socio-demographics, demand varies across dishes and courses, and order behavior is affected by the setting in which the food is ordered. This knowledge can for example be utilized by marketers, food delivery companies, and restaurants to target their consumers more effectively. The findings also concern producers of different commodities such as beef, where a majority (about 60%) is consumed away from home (California Beef Council 2021). A shift in demand towards for example different cuts of meat can substantially affect production decisions of farmers and correspondingly the subsequent processing. Secondly, serving the academic community and enriching the data available on FAFH, we show that the food basket approach can be extended to evaluate consumer demand and preferences for FAFH. Given the limited data sources available for FAFH consumption, new survey tools are needed to realistically capture what people experience in actual consumption situations, while also allowing for the estimation of richer substitution and complementarity patterns. In doing so, academics and policy makers can rely on more accurate and comprehensive data to facilitate the research and policy decision making process. Relatedly, in a third contribution we show how a red meat tax would impact consumers in terms of item-specific demand and welfare effects. These insights are crucial to understanding how such a monetary intervention might lead to unintended outcomes in terms of consumption changes and regressive effects across different socio-demographic groups. Our results can therefore be used by policy makers to make more informed decisions on related monetary issues and policies.

2. Background

2.1 FAFH: Its importance and the increase in popularity of food delivery

The economic importance of FAFH has increased over the last several decades. According to a 2018 USDA report by Saksena et al. the average adult in the U.S. consumes food-away-from-home (FAFH) between around 3.5 to 5.5 times a week depending on their age. This data relied on the 2013 National Household Food Acquisition and Purchase Survey (FoodAPS) survey. At the time of the FoodAPS survey, total expenditures for FAFH already exceeded those of FAH by more than 2.5% or $36.6 billion (USDA ERS 2021c)[1]. Right before the COVID-19 pandemic the gap expanded to more than 9.5% or $170.2 billion (Ibid.) and despite the pandemic induced drop, a rapid recovery in demand resulted in almost 53% of all household food expenditures in the U.S. being attributable to FAFH in 2021 (USDA ERS 2022)

While the overall FAFH industry experienced losses during COVID-19, the pandemic also fueled the growth of food delivery services, specifically online platforms (Oblander and McCarthy 2021; Mesaric et al. 2021; Edmondson 2021). For example, DoorDash, Uber Technologies Inc., GrubHub Inc., and Postmates generated $5.5 billion in revenue between April and September of

[1] Based on nominal food expenditures including taxes and tips for all purchasers

2020 compared to $2.5 billion in the same period in 2019 (Sumagaysay 2020). A recent study by Oblander and McCarthy (2021) found that the observed growth for food delivery companies during COVID-19 was mainly attributable to a higher purchase frequency of existing customers and a higher average order value, with both aspects stemming from the substitution away from restaurant dining. While Oblander and McCarthy (2021) caution that this increase could be just a temporary development, other projections estimate that the global market for online food delivery has grown from $115.07 billion in 2020 to $126.91 billion in 2021 and foresee it to reach $192.16 billion in 2025 (The Business Research Company 2021).

As the data demonstrates, food delivery has become a fundamental part of FAFH. However, research specifically accounting for food choices in this setting is limited. The main foci of existing studies incorporating food delivery center around motivating factors behind using delivery applications (see e.g., Ray et al. 2019; Gunden et al. 2020; Kaur et al. 2021), food availability (Brar and Minaker 2019), or aggregated nutritional quality (Gugliucci et al. 2021). There is no real comparison of how order behavior might differ depending on whether food was ordered for delivery or eaten at a restaurant. A few studies exist which contrast how respondent's sensory perception, feeling of satiety, and quantitative food intake varies given differences in the dining setting or location (see e.g., see e.g., Meiselman et al. 1996; Edwards et al. 2003; King 2004; García-Segovia 2015; Mouta et al. 2016; Lorenz and Langen 2017; Hendricks et al. 2021; Gough et al. 2021). All these studies find substantial differences for the chosen indicators across the settings/locations they considered. For example, King et al. (2004) found that the acceptability of pizza was higher when study participants were in an actual restaurant compared to a mock-restaurant setting in a laboratory. In addition, recent studies emphasized the importance of convenience for ordering food for delivery (see e.g., Yeo et al. 2017; Tandon et al. 2021) and the

2020 State of the Restaurant report by Upserve stressed that consumers look at how well food travels and prefer comfort food when ordering meals for delivery.

Thus, the motivations and intentions behind ordering FAFH for delivery compared to ordering food for in-restaurant dining are likely to be different from one another and could possibly affect the items ordered. Considering these earlier studies, we hypothesize to see differences in item-specific preferences (e.g., pizza, an item that tends to travel well, being more popular in the delivery setting than the in-restaurant dining setting). The earlier studies' findings also lead us to hypothesize that the elasticity of items and their substitution and complementarity relationship with one another differ across settings. For example, some items might act as complements in one setting and substitutes in another as they are perceived differently in terms of sensory characteristics and role within the meal by respondents.

Understanding these aspects allows us to then observe whether differences in order behavior will also affect the nutritional composition of the meal and how a (tax induced) price change might affect consumers differently across settings.

2.2 Limitations of available FAFH Data

The above hypotheses are built upon relatively straight forward questions, but they have so far not been explored in-depth within the academic literature. This is surprising given that FAFH accounts for around a third of the mean daily energy intake (Lin and Guthrie 2012; Saksena et al. 2018) and frequent FAFH consumption is associated with several dietary-related diseases including obesity (Todd et al. 2010; Seguin et al. 2016; Kim and Ahn 2020). Thus, policy makers looking at food and nutrition and aiming to curb dietary related diseases cannot ignore the relevance of FAFH consumption in their policy design.

One possible explanation for this relates to issues pertaining to the availability of data. As mentioned above, existing secondary data sources have several limitations (see Caputo and Just 2022 for a review). For example, Taylor and Villas-Boas (2016) analysis of food acquisition patterns of poor households of FAH and FAFH relies on data from the 2012-2013 FoodAPS survey. The study generates valuable insight on how poor households make food decisions and the data set even provides insights on what items were chosen. However, we lack several key variables like what alternatives were available to consumers when they made their choice; meaning we cannot determine the substitution and complementarity patterns between the items. Moreover, there has not been an updated version of the survey since the initial data collection in 2012-2013. Thus, any changes in consumption patterns over the last decade and especially during the COVID-19 pandemic are not captured. Studies like Powell and Nguyen (2013) and Nguyen and Powell (2014) used NHANES data to look at the consumption of FAFH from fast-food and full-service restaurants and how it affects energy and nutrient intakes. While more recent NHANES data is available, there is a high level of aggregation stemming from the general nature of the questions included in the questionnaires (National Research Council 2005; Va et al. 2019) and we again miss key variables like the alternatives available or even the price of the selected items (National Center for Health Statistics 2021).

Alternative secondary data sets such as scanner data, which is widely available for retail locations or from household panels, is also limited for restaurants. Typically, it is limited to just the name and location of the restaurant (National Academies of Sciences, Engineering, and Medicine 2020). Some recent panels have become available, like the out-of-home sample by Kantar. Used by Law et al. (2022), the data provides information on the out-of-home purchases of food and non-alcoholic beverages at item-level that were collected by individuals through the use of a mobile application. Yet even though the data provides interesting insights, it also does not provide information on available alternatives at the time of purchase. Lastly, private companies like online food delivery websites commonly do not make purchase data available outside of their company given the proprietary nature of their data.

Another standard approach used to evaluate FAFH consumption patterns is the collection of primary data. Typically, the data collection centers around specific population subgroups and some influencing factors. Some of these studies mirror set-ups akin to large household panel data sets but integrate more specific questions and have a more targeted data collection (e.g., Anzman-Frasca et al. 2014; Barnes et al. 2015; Partridge et al. 2020; Dana et al. 2021; Brar and Minaker 2021; Moyeda-Carabaza et al. 2021). However, while this line of studies provides informative findings (for example on the [lower] dietary quality of FAFH compared to FAH) they do not provide any insights on specific food choices for FAFH. This knowledge gap has been targeted by studies using hypothetical and non-hypothetical experiments (e.g., Drichoutis et al. 2009; Hoefkens et al. 2012; Ellison et al. 2013, 2014a,b; Zaffou and Campbell 2015; Malone and Lusk 2017; Sturm et al. 2018; Gugliucci et al. 2021). The non-hypothetical experiments conducted by Drichoutis et al. (2009) and Ellison et al. (2013, 2014a,b) provide important insights into the efficacy of nutritional labeling and calorie labeling relative to the imposition of a fat tax but is very limited in the geographic reach of their data collection- which can affect the representativeness of the findings. Moreover, similar to Hoefkens et al. (2012) who also looked at nutritional labeling programs, Drichoutis et al. (2009) focused on only one specific product each (sandwiches and pasta) and does not provide any information on substitution and/or complementarity effects between multiple dishes people typically order when eating FAFH. Zaffou and Campbell (2015), Gugliucci et al. (2021), and Sturm et al. (2018) created fictitious menus to observe consumers choice behavior for different dishes included in the menu. In contrast to normal choice experiments, where one sets up an experimental design that allows for the variation of at least one attribute and thus requires respondents to answer multiple questions, the authors presented the individual menus only once and thus did not have any variation in price or other attributes for the individual respondents. Neither of these three studies conducted any economic analysis of substitution or complementarity patterns.

Caputo and Lusk (2022) recently introduced a basket-based choice experiment in a grocery store setting. The experimental design allowed respondents to freely compose their shopping basket from more than 20 items and varied prices across the choice questions. Their results indicate that some products act as complements instead of substitutes to one another, something not previously captured by single-select choice experiments. The authors also find that respondents tend to select multiple items when given the chance. This design aligns with what one would expect in a FAFH setting, where consumers are usually able to order and combine multiple items. In fact, statistics show that almost two-thirds of consumers tend to order appetizers at least some of the time when dining out, with 20% doing so often and 11% always ordering them (Statista Research Service 2016a).

As can be noted from this literature review, so far none of these studies have employed multi-select experimental instruments or used secondary data sources to determine the substitution and complementarity patterns underlying consumer preferences and demand for FAFH across different dining settings. To close this gap in the literature, we implement a food menu basket-based choice experiment (FM-BBCE) approach to reflect two commonly used dining settings: in-restaurant dining and food delivery.

3. Material and Methods

3.1 The FM-BBCE Experiment

In our FM-BBCE, we asked respondents to choose the dish or combination thereof that they would most likely order given the 21 available menu items and corresponding prices. Following what can be found in standard DCEs, respondents also had the option to indicate that they would not order any of the offered dishes (see Figure 1.1).

We grouped the selected dishes into six appetizers (mozzarella sticks, spinach artichoke dip, crab cakes, onion rings, chicken wings, avocado toast), nine main entrées (beef burger, salmon, medium pizza, plant-based burger, Caesar salad, steak, full rack of ribs, vegetarian fettucine alfredo, chicken sandwich) and six side dishes (fries, mac and cheese, broccoli, bread, side salad, baked potato). Each individual dish was offered at three dish-specific price levels across the choice questions, i.e., across the choice questions the dish was accompanied by one of three price levels. We selected the items using a three-step process. First, we consulted existing literature on popular U.S. restaurant dishes based on notoriety, order volume, and survey results. In a second step, we then narrowed the selection of items derived in step one down to offer a reasonable balance of high- and low-calorie items as well as plant- and meat-based alternatives. Lastly, we confirmed our selection by consulting several menus from each of the four U.S. census regions in both rural and urban settings. We also used this last step to determine the three price levels employed in the experiment. The lowest and highest prices found across the regions were used to form the approximate upper and lower limit of the price levels. To reduce the mental load for respondents, we kept the distance between prices for dishes categorized as appetizers, entrees, and sides equidistant, meaning for all appetizers the difference between price levels was \$4, for entrees it was \$5, and for side dishes \$2[2].

This combination of prices and food items results in a full factorial design of 3^{21} possible price combinations or possible menus. We used an orthogonal fractional factorial design to reduce the full factorial design to 72 food basket-choice questions grouped into eight blocks, and respondents were randomly assigned to one block. Hence, during the experiment respondents were presented with 9 choice questions, each asking them to freely compose their FAFH meal.

[2] The item-specific price levels can be found in Table A1.1 in the Appendix.

Figure 1.1 Example of a Choice Question in the *Restaurant* Setting

3.2 Dining Settings

In the first FM-BBCE setting (which we will call *Restaurant*), we asked respondents to make their order as if they were dining in a restaurant. In the second FM-BBCE setting (which we will call *Delivery*) we framed the choice scenario as respondent's ordering food for delivery. Assignment to *Restaurant* vs. *Delivery* was conditional on respondent's having ordered food in the respective setting. This means, we assigned respondents who indicated to have only ordered food for delivery automatically to the *Delivery* setting, while we grouped respondents that only ordered food in a restaurant into the *Restaurant* setting. If respondents stated to have ordered food in both settings, then the assignment was random. Each respondent was assigned to only one experiment.

In an effort to increase the realism of the choice questions and to create tangible differences between the settings, we made slight adjustments to the wording of the general choice experiment and individual choice question instructions across the experiments. These changes only affected the general scenario description (see Figures A1.1 and A1.2 in the Appendix). In addition, we adjusted the menu header accompanying each choice question to read "Restaurant Menu" in the *Restaurant* setting, while the header in the *Delivery* setting read "Delivery Menu".

3.3 Survey Design and Sampling Procedure

We collected our data through an online survey of 2032 respondents. The survey was implemented in Qualtrics (https://www.qualtrics.com) and the sample was obtained from Dynata (https://www.dynata.com/) a leading provider of survey samples[3]. To qualify for participation in the study, respondents had to have ordered food for delivery and/or eaten at a restaurant in the last three months. We also restricted participation to respondents that were at least 18 years old. To ensure that the sample approximately matched the U.S. population in terms of age, gender, and

[3] The pre-registration protocol of the survey can be found here: https://aspredicted.org/ZSB_PHY.

income we integrated sample quotas into the data collection based on screening questions at the beginning of the survey.

After answering the screening questions, respondents provided some information about their consumption and expenditure habits for FAFH before they were assigned to one of the above-mentioned settings. Immediately after the assignment, we integrated a scene setting section into the survey. The purpose of this section was to ensure that respondents were mentally engaged in the setting presented to them in the FM-BBCE they were assigned to. Specifically, we presented respondents with word association questions, a heat map, and an image selection question focusing on themes related to the setting they were assigned to. For example, we asked respondents in the *Restaurant* setting to indicate what they think when hearing “Restaurant Dining”, while we requested respondents in the *Delivery* setting to state what they think upon hearing “Food Delivery”.

This section was then followed by the choice exercise. At the beginning of the choice exercise, we gave respondents instructions on how to answer the following questions and reminded them of how much they usually spend on FAFH in the presented setting and how much they spent last time[4]. We did not impose a budget on respondents based on those values as this would be unrealistic compared to what a consumer might experience/do in a non-hypothetical scenario. A short version of the instructions was provided before each choice question. A detailed breakdown of the choice experiment and individual choice question instructions can be found in the Appendix, Figures A1.1 and A1.2[5]. We summarized some key demographics and basic average expenditure information of our sample in Table 1.1

[4] These values had been derived in consumption and expenditure habits section of the survey.
[5] A full transcript of the survey questionnaire is available upon request.

Table 1.1 Sample Demographics

	Description[a]	Setting		
		Combined	Restaurant	Delivery
Female	1 if female; 0 if male	0.52	0.52	0.53
Age	Age in years (Mean)	51	53	50
College	1 if obtained college degree; 0 otherwise	0.47	0.48	0.47
Income				
Low Income	1 if household income below $75,000; 0 otherwise	0.63	0.62	0.64
High Income	1 if household income above $75,000; 0 otherwise	0.37	0.38	0.36
Area of Residence				
Rural	1 if respondent lives in rural area; 0 otherwise	0.24	0.24	0.24
Suburban	1 if respondent lives in suburban area; 0 otherwise	0.51	0.50	0.52
Urban	1 if respondent lives in urban area; 0 otherwise	0.25	0.26	0.24
Average weekly expenditure on FAFH[b]				
In-Restaurant Dining	In US$	$40.20	$40.31	$40.07
Food Delivery	In US$	$29.92	$30.87	$29.16
Cost of last FAFH meal[b]				
In-Restaurant Dining	In US$	$29.41	$28.62	$30.43
Food Delivery	In US$	$24.90	$23.84	$25.76
Respondents per Experiment		2032	1052	980

[a] Values presented are the mean or respective median.
[b] The displayed amounts were derived from all respondents who had indicated to have consumed FAFH in the respective setting

Our sample mostly aligns with the U.S. population. The higher average age compared to the U.S. median age of 38.5 years is likely a result of the imposed age restriction in our sample (respondents had to be at least 18 years of age to participate) and corresponds to other studies using choice experiments (e.g., Loureiro and Umberger 2007; Kilders and Caputo 2021). The same can be said for the comparably higher educational attainment of our sample (47% college educated respondents vs. a national average of 37%).

Looking at the weekly expenditures on FAFH we see that respondents spend on average $10.28 more per week on in-restaurant dining relative to ordering food for delivery from a restaurant. When looking at the last meal consumers ordered, the difference between what they paid and the basket they formed is $4.50. There are no significant differences in spending between the two settings[6]. Not displayed in Table 1.1 but mostly in line with the 2020 U.S. Bureau of Labor Statistic data on FAFH consumption (Paulin 2020), we find that our respondents preferred restaurants over alternative locations (e.g., fast food places and cafes) for dining out (89.33%) and ordering food for delivery (80.87%). This can be seen as validation for framing the choice questions as respondents ordering food from a restaurant.

4. Data Analysis

The FM-BBCE data from each setting were analyzed using a MVL model. In our approach, we follow earlier work by Song and Chintagunta (2006) and Kwak et al. (2015) as well as the applications by Richards et al. (2018) and Caputo and Lusk (2022). We selected the model due to its ability to handle the substantially increased computational burden of the free choice format and the integration of conjoint effects, which cannot be handled by using conventional random utility models such as the Multinomial Logit (MNL) or Random Parameter Logit (RPL) model.

[6] Please note that the expenditures were only derived for respondents that indicated to have consumed FAFH in the respective setting in the last three months earlier in the survey. Only 8.71% and 12.80% of respondents indicated to not have ordered food for dining-in or for delivery in the last three months, respectively.

The MVL model is based in random utility theory (McFadden 1973, Hanemann 1984) and Lancaster theory of consumer demand (Lancaster 1966), meaning utility can be separated into a systematic and random part: $U_{nb} = V_{nb} + \varepsilon_{nb}$. We model the systematic part of respondent n's utility from order b, V_{nb}, as a discrete, second-order Taylor series approximation, where:

$$V_{nb} = \sum_{j=1}^{J} \vartheta_{nj} x_j + 0.5 \sum_{j=1}^{J} \sum_{k \neq j}^{J} \gamma_{jk} x_j x_k \qquad (1)$$

The baseline utility of item j for respondent n is signified by ϑ_{nj}. The accompanying dummy variable x_j equals 1 if the specific menu item j was added to the order and 0 if the item is absent. The utility-affecting interaction between the different items selected for the food order is described by the parameter γ_{jk}, i.e., the parameter captures the interdependence (complementarity and substitution) in demand between the items. We can interpret $\gamma_{jk} > 0$ as an increase in item j's utility, when the respondent also orders item k, while $\gamma_{jk} < 0$ means that the goods are acting as substitutes for one another. A value of 0 indicates that j's utility is invariant to k's presence or absence. Taking a closer look at ϑ_{nj} in equation (1), we can disassemble the parameter into a function of additional variables such as the item's price p_j and individual-specific factors, which are captured in the vector $\boldsymbol{X_n}$ below:

$$\vartheta_{nj} = \alpha_{0,j} + \beta p_j + \boldsymbol{X_n} \boldsymbol{\delta_j} \qquad (2)$$

where, $\alpha_{0,j}$, β, and $\boldsymbol{\delta_j}$ are the corresponding parameters.

Given these elements of equations (1) and (2), and assuming it holds that ε_{nb} is i.i.d. extreme value type 1, the probability of order b being composed can then be derived using the standard MNL specification (Train 2009; Richards and Bonnet 2018):

$$Prob[n\ chooses\ basket\ b] = \frac{e^{V_{nb}}}{\sum_{b=1}^{B} e^{V_{nb}}} \quad (3)$$

However, since we not only estimate the selection of a single item out of several alternatives but instead evaluate the probability of ordering a combination of up to 21 items to compose a meal, we need to integrate the restriction that $\gamma_{jj} = 0$ and $\gamma_{jk} = \gamma_{kj}$ to accommodate the more than $B = 2^{21} = 2{,}097{,}152$ possible orders and ensure the identification of the model. This restriction follows earlier results by Besag (1974), Russell and Petersen (2000), and the recent applications by Richards et al. (2018). With this restriction, we can rewrite the model in terms of conditional probabilities and estimate a series of J logit models with cross-equation restrictions (Richards et al. 2018). Accordingly, the model can be expressed as follows:

$$Prob[n\ orders\ option\ j\ as\ part\ of\ the\ meal] = \frac{e^{z_{nj}}}{1+e^{z_{nj}}} \quad (4)$$

where $z_{nj} = \vartheta_{nj} + \sum_{k \neq j}^{J} \gamma_{jk} y_{nk}$, with $y_{nk} = 1$ if item k is added to the basket and zero otherwise. This set-up allows us to derive the total probability of ordering item j by summing across all the meals that contain j. These probabilities were then utilized to derive arc-elasticities of the individual items. To derive the elasticities, we followed the standard procedure for standard discrete choice experiments as outlined in Hensher et al. (2015).

5. Descriptive Results of the FM-BBCE

To begin with, we took a closer look at differences in the specific items ordered by consumers. Specifically, we looked at how many items respondents added to their order in the choice exercise in total and by course. Overall, we find that respondents ordered 2.70 and 2.92 items on average in the *Restaurant* and *Delivery* setting, respectively. Possibly, the selection of more items on average in the *Delivery* setting could be motivated by consumers typically being able to order more food in a restaurant if they feel like they are not sated, while this is not as easily possible if food is ordered for delivery. The fact that more than one item was ordered per course can also be seen as an indication for the validity of our approach particularly as it hints at underlying cross-course consumption patterns. The difference in the total number of items ordered predominantly stems from a lower order frequency of appetizers in the *Restaurant* setting, where 0.60 appetizers were ordered on average per choice question compared to 0.72 appetizers in the *Delivery* setting. A basic statistical test of equality of means reveals that the difference for total number of dishes ordered and number of appetizers ordered are indeed significant at the 1% level. The difference in entrees ordered is significant at the 5% level, with more entrees being ordered on average when the setting asked respondents to order food for delivery. There is no significant difference between the number of sides ordered in either dish. For each course, the standard deviation ranges from 0.74 to 0.99, which highlights a substantial spread of the number of items added to the order. We see this variation as a further indication that the FM-BBCE approach holds substantial value in its application to this context.

Following the analysis of total order volume, we looked at the probability of each item being ordered as part of the meal in each setting (see Figure 2). We find that mozzarella sticks, and avocado toast are the most and least popular appetizers, respectively, in both the *Restaurant* (added to around 17% vs. 5% of orders) and *Delivery* (added to around 20% vs. 5% of orders) settings. This selection aligns with a recent New York Times article that proclaimed the resurgence of mozzarella sticks as a popular food (Krishna 2021) and DoorDash's 2021 report on popular game day eats, which was headed by mozzarella sticks (DoorDash 2021). The second most popular game day food according to the delivery platform are boneless chicken wings, which also corresponds to our results, where chicken wings were selected in almost 16% of all orders in the *Delivery* setting. For the *Restaurant* setting onion rings are the second most popular order (12.5%).

Differences across the dishes are significant for all appetizers except the spinach artichoke dip and the avocado toast.

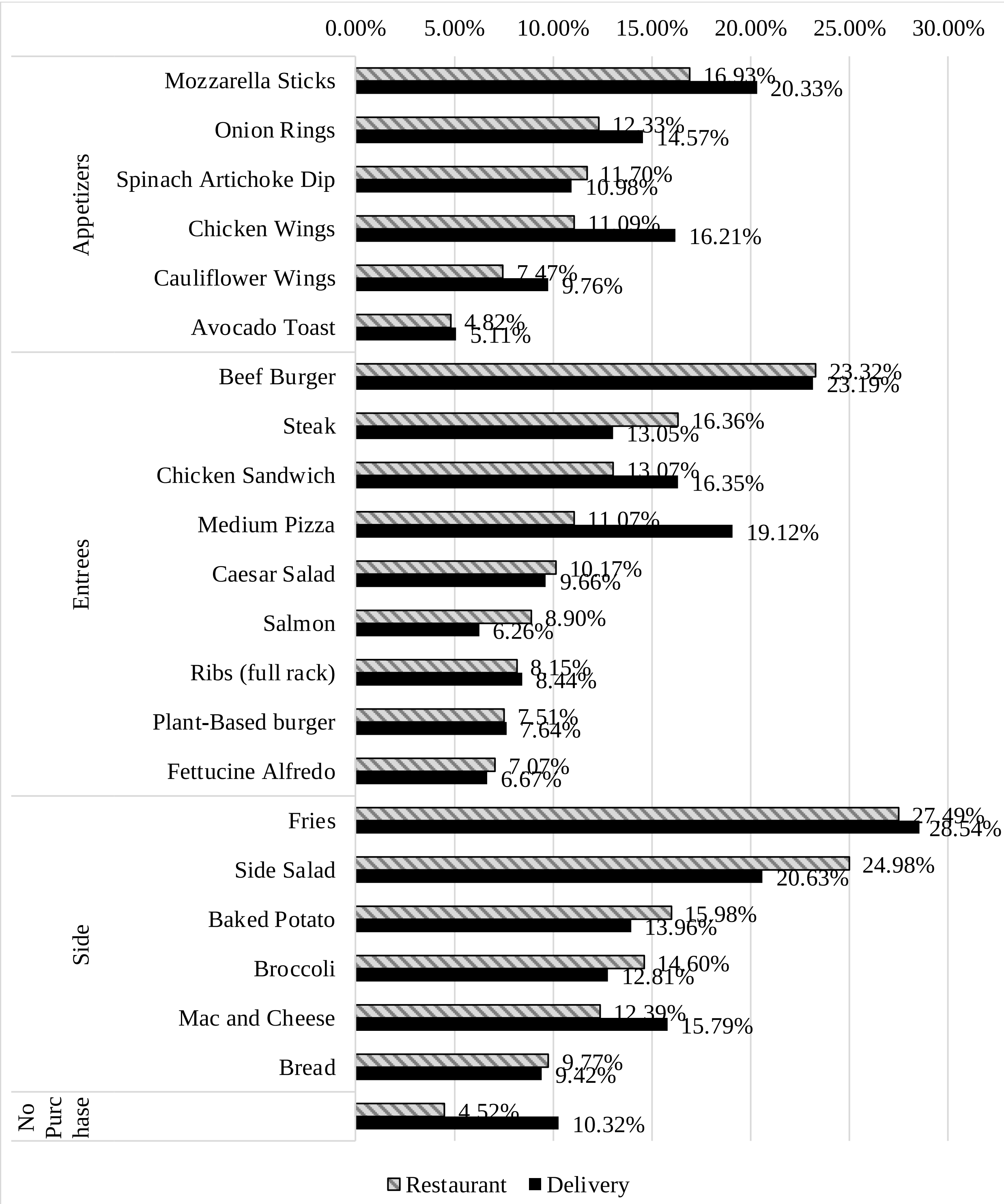

Figure 1.2 Probability of item being selected

For entrees, we only find significant differences between the settings for four of the nine entrees (steak, chicken sandwich, medium pizza, salmon). Both the chicken sandwich and the pizza are more frequently ordered in the *Delivery* setting (13% vs. 16% and 11% vs. 19%, respectively). According to DoorDash (2020), fried chicken sandwiches were the second most popular dish in 2020, while GrubHub reported in 2014 that pizza is among the most beloved foods on their platform (GrubHub 2014a). Meanwhile, steak is the second most popular dish in the *Restaurant* setting with around 16% of respondents choosing to order steak. The only dish more popular is the beef burger which holds the top spot in both settings with around 23%. According to the website Beef2Live (2021a), beef in restaurants is most commonly served as a burger (72%) followed by steak (9%).

As for the side dishes, fries were added to around 28% of orders in both settings, making them the most popular side item in our list. A side salad is the second most popular item, albeit it is ordered substantially more in the *Restaurant* setting (25%) compared to the *Delivery* (21%) one. Both results again correspond to Grubhub's 2014 report (GrubHub 2014a). All other sides, except mac and cheese are also more commonly ordered by respondents presented with the in-restaurant dining setting. We also found that the no-purchase option was selected significantly less in the *Restaurant* setting (4%) compared to the *Delivery* one (10%). Possibly, this stems from respondent's ability to easily choose another restaurant to order for delivery from, while dining in a restaurant involves a certain level of commitment. Taken together, the descriptive results reveal several significant differences between the two settings, which aligns with our overarching hypothesis that the dining setting significantly impacts food choices.

6. Results of MVL Model

Following the evaluation of the choice data in a purely descriptive manner, we now describe the results derived through the MVL model[7]. The model was specified to incorporate baseline, cross-utility effects and a vector of demographic variables as specified in equation (2)[8]. We first conducted a likelihood ratio (LR) test testing the null hypothesis of preference equality across choice settings (restaurant dine-in and delivery). To this end, we estimated two segmented models, one for each choice setting (restaurant dine-in and delivery), as well as a pooled model merging the choice data from the *Restaurant* and *Delivery* experiments. We then computed the LR test statistic[9] (see Table 1.2), which suggests that the hypothesis of equality of choice responses across the restaurant and delivery experiments is strongly rejected (${\chi^2}_{342}$ = 386.1252; $p < 0.01$). This evidence indicates differences in choice behavior across choice settings. In the following sub-section, the results of the Restaurant and Delivery experiments are discussed separately.

Table 1.2 Likelihood Ratio Test

Model	**Pooled**	**Segmented** Restaurant	Delivery
# of Parameters	343	343	343
# of Choices	18,279	9,459	8,820
Log-Likelihood	-127,839	-62,712	-63,075
LR statistic		4,104	
Degree of Freedom		342	
P-Value		<0.01	

[7]We estimated additional models, e.g., with only the baseline utility or just the baseline and cross-utility effects as well as models assuming individual price parameters or course specific price parameter. Given the model fit criteria, we selected the model incorporating a single price parameter, the baseline and cross-utility effects, as well as demographic effects.

[8]We limited our inclusion of demographic variables to some of the key indicators of differences in consumption patterns given that each newly included variable adds 21 additional parameters. We chose to incorporate five different dummy variables: gender, education, income, and area of residence (rural & suburban relative to urban), as described in Table 1.3.

[9]The LR statistic is $-2[LL_P - LL_S]$ which is distributed χ^2 with $K(E-1)$degrees of freedom, where LL_P is the log likelihood value for the pooled model, LL_s is the sum of the log likelihood values of the two segmented MVL models from each choice setting, K is the number of restrictions, 343, and T is the number of experiments, 2.

6.1 Restaurant Setting

The baseline utility estimates of Model 3 are reported in Table 1.3. As expected, the price coefficient is negative and significant, which means that higher prices are associated with a lower order probability. Looking then at the baseline utility levels of the different items, signified by $\alpha_{0,j}$, we find a large consistency with what we showed in Figure 1.2. For example, the plant-based burger who was the second least chosen alternative, has the lowest utility (-1.557). This also aligns with the findings by Van Loo et al. (2020) and Caputo et al. (2022), who found that on average consumers prefer traditional beef options over the plant-based alternatives. Thus, it appears that while some respondents might have integrated plant-based meat alternatives in their diets, the average respondent still prefers traditional protein options when dining at a restaurant. This matches our finding that among the entrees all plant-based options are less preferred than the available meat options except for Caesar Salad, which is the third most popular dish with a baseline utility of -0.113. The baseline utility of the fries (-1.058) and side salad (-0.826) is especially high among the side dishes, even exceeding that of some of the entrees. This emphasizes the importance some side dishes hold in the composition of a meal and also shows that considerations of FAFH should not only be limited to the main protein component of the meal. Further in line with the choice probabilities shown in Figure 1.2, we estimate the highest baseline utility among appetizers for chicken wings (-1.703) and mozzarella sticks (-1.812). Interestingly, the preference ranking among the items places all appetizers below the entrees, which could be seen as an indication of the importance of entrees in consumers' minds.

Table 1.3 Baseline Utility Estimates from the MVL Model – *Restaurant* Setting

	Constant	Female	College	Low Income	Rural	Sub-urban	Price
Appetizers							
Mozzarella Sticks	-1.812*	0.232*	-0.059	-0.037	-0.069	-0.239*	-0.099*
	(0.100)	(0.062)	(0.066)	(0.067)	(0.083)	(0.072)	(0.002)
Spinach Artichoke Dip	-2.120*	0.683*	0.251*	-0.292*	-0.120	-0.426*	-0.099*
	(0.116)	(0.074)	(0.077)	(0.076)	(0.096)	(0.082)	(0.002)
Cauliflower Wings	-1.983*	0.093	0.232*	-0.267*	-0.363*	-0.692*	-0.099*
	(0.137)	(0.089)	(0.096)	(0.095)	(0.117)	(0.098)	(0.002)
Onion Rings	-2.038*	-0.123	0.080	0.062	-0.033	-0.290*	-0.099*
	(0.110)	(0.069)	(0.073)	(0.074)	(0.092)	(0.080)	(0.002)
Chicken Wings	-1.703*	-0.116	-0.149	-0.098	-0.430*	-0.404*	-0.099*
	(0.114)	(0.073)	(0.078)	(0.079)	(0.100)	(0.082)	(0.002)
Avocado Toast	-2.568*	0.565*	0.147	-0.175	-0.766*	-0.720*	-0.099*
	(0.163)	(0.108)	(0.114)	(0.114)	(0.149)	(0.114)	(0.002)
Entrees							
Beef Burger	0.079	-0.334*	-0.145	-0.097	0.044	-0.026	-0.099*
	(0.104)	(0.065)	(0.069)	(0.071)	(0.089)	(0.077)	(0.002)
Plant-Based burger	-1.557*	0.141	0.288	0.009	-0.713*	-0.999*	-0.099*
	(0.146)	(0.095)	(0.104)	(0.105)	(0.123)	(0.105)	(0.002)
Chicken Sandwich	-0.283*	-0.137	-0.178*	-0.224*	-0.040	0.047	-0.099*
	(0.114)	(0.071)	(0.076)	(0.078)	(0.099)	(0.083)	(0.002)
Caesar Salad	-0.113	0.123	-0.161*	-0.324*	-0.159	0.044	-0.099*
	(0.119)	(0.076)	(0.080)	(0.081)	(0.107)	(0.087)	(0.002)
Salmon	-0.417*	-0.238*	0.296*	-0.145	-0.215	0.089	-0.099*
	(0.136)	(0.083)	(0.087)	(0.088)	(0.121)	(0.096)	(0.002)
Steak	0.066	-0.429*	0.013	-0.271*	0.003	-0.003	-0.099*
	(0.115)	(0.069)	(0.073)	(0.074)	(0.096)	(0.080)	(0.002)
Ribs (full rack)	-0.391*	-1.032*	-0.004	-0.058	0.057	0.070	-0.099*
	(0.138)	(0.089)	(0.091)	(0.093)	(0.119)	(0.099)	(0.002)
Fettucine Alfredo	-0.972*	0.470*	0.078	0.042	-0.171	-0.117	-0.099*
	(0.145)	(0.094)	(0.095)	(0.099)	(0.123)	(0.104)	(0.002)
Medium Pizza	-0.511*	-0.099	-0.104	-0.145	-0.019	0.043	-0.099*
	(0.116)	(0.072)	(0.077)	(0.078)	(0.100)	(0.084)	(0.002)
Sides							
Fries	-1.058*	-0.096	-0.096*	-0.035	0.048	0.116*	-0.099*
	(0.088)	(0.056)	(0.06)	(0.061)	(0.078)	(0.066)	(0.002)
Mac and Cheese	-2.057*	-0.138*	-0.147	0.218*	0.080	-0.009	-0.099*
	(0.112)	(0.071)	(0.077)	(0.079)	(0.096)	(0.083)	(0.002)
Broccoli	-2.117*	0.249*	0.268*	0.225	-0.130	-0.040	-0.099*
	(0.103)	(0.065)	(0.068)	(0.07)	(0.091)	(0.075)	(0.002)
Bread	-2.757*	0.053	0.068	-0.003	0.076	0.085	-0.099*
	(0.122)	(0.077)	(0.081)	(0.082)	(0.107)	(0.089)	(0.002)
Side Salad	-0.826*	0.032	0.221*	-0.099	0.193*	0.189*	-0.099*
	(0.083)	(0.052)	(0.054)	(0.056)	(0.073)	(0.062)	(0.002)
Baked Potato	-1.556*	0.080	-0.234*	0.001	0.039	0.217*	-0.099*
	(0.101)	(0.064)	(0.067)	(0.069)	(0.091)	(0.076)	(0.002)
Opt-Out							
No-Order	-3.022*	-0.240	-0.188	0.52*	0.041	-0.474	-0.099*
	(0.150)	(0.103)	(0.111)	(0.123)	(0.129)	(0.122)	(0.002)

Note: Numbers in parentheses are standard errors; * denotes significance at the 5% level or higher.

The baseline utility should be considered in context to the demographic variables included in the model. In this regard, the constants can be understood as the utility of an item if all demographics and price effects are equal to zero. As can be seen in Table 1.3, we find that females tend to order significantly more of several plant-based items such as mozzarella sticks (0.232), spinach artichoke dip (0.683), avocado toast (0.565), and vegetarian Fettucine Alfredo (0.470). Similarly, females order less of most meat-based entrees (beef burger, salmon, steak, and ribs). This difference aligns with the findings by Grubhub (2014). Respondents that were at least college educated had a higher preference for the side salad (0.221), broccoli (0.268), cauliflower wings (0.232), and salmon (0.296) which could indicate a higher preference for items that are often considered to be healthy. Looking at income, which is often closely related to education, we find that respondents with a household income below $75,000 were more likely to not order anything when eating in a restaurant (0.520), which could be indicative of their financial constraints. It can also be seen as a confirmation of prior studies' results that FAFH is considered a normal good (see e.g., Okrent and Alston 2012), i.e., people with higher income spend a higher share of their income on FAFH than FAH compared to lower income households. Meanwhile, respondents living in rural and especially suburban areas among other things had a lower preference for cauliflower wings (rural: -0.363, suburban: -0.692) or plant-based burgers (rural: -0.713, suburban: -0.999) relative to urban respondents. This result suggests that urban consumers are more open towards or accustomed to plant-based alternatives than their counterpart. In addition, suburban consumers generally displayed a lower utility for all appetizers included in the menu relative to urban consumers. Possibly, this can be interpreted as suburban consumers putting more emphasis on other sections of the menu than the appetizers.

With a better understanding of the general preferences for the different items, we then wanted to take a closer look at the substitution and complementarity patterns between the items. We did so by first evaluating the cross-utility effects of the different items[10]. We find that within courses most cross-utility effects are negative, which suggests that the items of one course constitute substitutes of one another. For example, we observe significant negative cross-utility effects between all entrees especially the beef burger and the chicken sandwich (-2.769) and the plant-based burger (-2.337), which display the largest negative cross-utility effect. This suggests that most sandwich/burger type dishes are direct substitutes of one another within a utility space. As expected, the cross-utilities between the entrees and most appetizers and side dishes are positive, with the most prominent pairing being the fries and the beef burger (2.094). Similar patterns can be observed for both the appetizers and the sides, as cross-utilities within a course are mostly negative, but positive across courses.

While providing useful insights, the cross-utility effects are insufficient to fully decide whether an item constitutes a demand complement or substitute (Richards et al. 2018). Thus, we derived the own- and cross-price elasticities of the different menu items from the cross-utilities, which allow us to see which items are demand substitutes and complements. The results are reported in Table 1.4.

As can be seen, the own and cross-price elasticities reveal a rich set of complementarity and substitution patterns across items and courses. Looking first at the own-price elasticities, we observe that all entrees aside from the beef burger are elastic in demand, especially the salmon (-1.817). Outside of the entrees, only the avocado toast (-1.024) has an own-price elasticity >|1|. The elastic demand might be due to the product being considered a relative luxury good. Even at the

[10] Table A1.2 in the Appendix report the cross-utility estimates for the *Restaurant* setting.

retail level, Ambrozek et al. (2019) found that the own-price elasticity of avocados ranged from -0.71 up to -1.64 depending on the U.S. region. The somewhat processed avocado toast in our hypothetical restaurant menu falls in between this range. Comparing the own-price elasticity of the appetizers with that of the sides, it is easily noticeable that all side options are less elastic than the appetizers with fries (-0.246) showing the lowest change in demand relative to price changes. This result suggests that consumers regard each course and its role in the order composition differently.

Turning to the cross-price elasticities, as expected, the no-buy option represents a substitute to all menu items, meaning that as the items' prices increase, the probability of the no-order option being selected also increases. This pattern is particularly pronounced for the steak (0.409) and the beef burger (0.355), which corresponds with their popularity. It could indicate that respondents who have a high preference for either of those two entrees will forego ordering anything if their price is unacceptable. Furthermore, in line with the previously observed cross-utility effects, we find that most entrees are demand substitutes of one another, with the substitution effects being most pronounced for the beef burger. In fact, the only complements of the beef burger are mozzarella sticks (-0.135), onion rings (-0.198) and fries (-0.234). This corresponds to the preferred side dishes for beef patties reported by Beef2Live (2021b), which were headed by French fries. Other entrees show more extensive complementarity patterns with other dishes. This is particularly true for the steak and ribs, which are complemented by most appetizers and side dishes, although to a lesser degree than the beef burger. The side dishes themselves vary significantly in the extent to which they are either complements or substitutes of other dishes. Broccoli, and bread are slight complements of most dishes, while fries are substitutes for all side dishes and most other items.

Table 1.4 Own- and Cross-Price Elasticities at Mean Demographics and Prices – *Restaurant* Setting

		Change in Price of…																				
	Change in Quantity of:	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	Mozzarella Sticks	-0.726* (0.018)	0.035* (0.005)	0.030* (0.004)	0.010* (0.005)	-0.017* (0.007)	0.016* (0.003)	-0.141* (0.012)	-0.052* (0.008)	-0.031* (0.01)	0.018* (0.007)	-0.003 (0.01)	-0.008 (0.014)	-0.008 (0.009)	0.002 (0.006)	-0.146* (0.011)	-0.066* (0.004)	-0.028* (0.003)	0.014* (0.003)	-0.017* (0.003)	0.023* (0.004)	0.015* (0.003)
2	Spinach Artichoke Dip	0.051* (0.007)	-0.876* (0.022)	0.022* (0.005)	0.035* (0.005)	-0.019* (0.008)	0.002 (0.004)	0.069* (0.013)	-0.156* (0.014)	-0.026* (0.013)	-0.021* (0.01)	-0.042* (0.014)	-0.15* (0.021)	-0.06* (0.013)	-0.035* (0.01)	-0.018 (0.011)	0.011* (0.005)	-0.062* (0.005)	-0.024* (0.004)	-0.02* (0.003)	-0.007 (0.005)	-0.012* (0.004)
3	Cauliflower Wings	0.067* (0.009)	0.033* (0.007)	-1.012* (0.025)	0.058* (0.006)	-0.015 (0.01)	-0.047* (0.008)	0.183* (0.014)	-0.191* (0.018)	-0.163* (0.019)	-0.088* (0.014)	-0.009 (0.017)	-0.055* (0.023)	-0.085* (0.019)	-0.002 (0.011)	0.004 (0.014)	0.03* (0.006)	-0.032* (0.006)	-0.09* (0.007)	-0.006 (0.004)	-0.014* (0.006)	-0.01 (0.006)
4	Onion Rings	0.016* (0.007)	0.038* (0.006)	0.042* (0.004)	-0.688* (0.017)	0.015* (0.006)	0.014* (0.004)	-0.2* (0.014)	0.003 (0.007)	-0.036* (0.012)	0.029* (0.008)	-0.007 (0.012)	-0.027 (0.017)	-0.035* (0.011)	0.023* (0.007)	-0.055* (0.011)	-0.028* (0.004)	-0.011* (0.004)	0.006 (0.003)	-0.019* (0.003)	0.004 (0.004)	0.007 (0.004)
5	Chicken Wings	-0.023* (0.009)	-0.017* (0.008)	-0.009 (0.006)	0.013* (0.005)	-0.964* (0.024)	0.007 (0.004)	0.027* (0.013)	-0.08* (0.011)	-0.075* (0.014)	-0.02* (0.01)	-0.026 (0.014)	-0.139* (0.02)	-0.062* (0.014)	0.003 (0.009)	-0.131* (0.014)	-0.025* (0.005)	-0.064* (0.005)	-0.003 (0.004)	-0.023* (0.003)	-0.003 (0.005)	-0.017* (0.005)
6	Avocado Toast	0.057* (0.011)	0.006 (0.01)	-0.076* (0.012)	0.031* (0.008)	0.019 (0.011)	-1.04* (0.026)	0.209* (0.015)	-0.135* (0.019)	-0.043* (0.02)	-0.109* (0.019)	-0.066* (0.022)	-0.104* (0.032)	-0.091* (0.023)	-0.043* (0.015)	-0.029 (0.018)	0.038* (0.006)	-0.010 (0.006)	-0.046* (0.007)	-0.02* (0.005)	-0.039* (0.009)	-0.055* (0.008)
7	Beef Burger	-0.073* (0.006)	0.024* (0.005)	0.043* (0.004)	-0.065* (0.005)	0.01* (0.005)	0.03* (0.003)	-0.867* (0.023)	0.064* (0.005)	0.143* (0.007)	0.098* (0.005)	0.117* (0.008)	0.222* (0.011)	0.094* (0.006)	0.079* (0.005)	0.042* (0.007)	-0.105* (0.004)	0.000* (0.003)	0.03* (0.002)	0.009* (0.002)	0.035* (0.003)	0.038* (0.003)
8	Plant-Based burger	-0.089* (0.013)	-0.181* (0.014)	-0.148* (0.013)	0.004 (0.008)	-0.101* (0.014)	-0.065* (0.009)	0.21* (0.013)	-1.382* (0.034)	0.047* (0.014)	0.061* (0.009)	0.041* (0.015)	0.023 (0.023)	-0.024 (0.016)	0.044* (0.008)	-0.066* (0.017)	-0.021* (0.006)	-0.096* (0.008)	-0.015* (0.006)	0.002 (0.004)	-0.017* (0.007)	0.011* (0.005)
9	Chicken Sandwich	-0.025* (0.008)	-0.015* (0.007)	-0.06* (0.007)	-0.019* (0.006)	-0.045* (0.008)	-0.01* (0.005)	0.227* (0.011)	0.022* (0.007)	-1.278* (0.033)	0.061* (0.007)	0.113* (0.009)	0.152* (0.014)	0.015 (0.01)	0.049* (0.006)	0.031* (0.01)	-0.03* (0.004)	-0.029* (0.004)	-0.011* (0.004)	0.02* (0.002)	0.017* (0.004)	0.006 (0.004)
10	Caesar Salad	0.021* (0.008)	-0.016* (0.008)	-0.045* (0.008)	0.021* (0.006)	-0.017* (0.009)	-0.035* (0.006)	0.217* (0.011)	0.041* (0.006)	0.086* (0.01)	-1.238* (0.031)	0.059* (0.011)	0.082* (0.016)	0.054* (0.01)	0.015* (0.008)	0.074* (0.01)	0.048* (0.004)	0.009* (0.004)	-0.018* (0.004)	-0.038* (0.004)	0.066* (0.004)	0.001 (0.004)
11	Salmon	-0.002 (0.01)	-0.026* (0.009)	-0.004 (0.007)	-0.004 (0.007)	-0.018 (0.009)	-0.017* (0.006)	0.212* (0.012)	0.022* (0.008)	0.129* (0.01)	0.048* (0.009)	-1.792* (0.045)	0.166* (0.015)	0.087* (0.009)	0.062* (0.007)	0.032* (0.012)	0.057* (0.005)	0.009* (0.004)	-0.08* (0.006)	-0.017* (0.004)	-0.058* (0.006)	-0.019* (0.005)
12	Steak	-0.004 (0.007)	-0.05* (0.007)	-0.012* (0.005)	-0.008 (0.005)	-0.051* (0.007)	-0.014* (0.005)	0.212* (0.011)	0.007 (0.007)	0.092* (0.009)	0.035* (0.007)	0.088* (0.008)	-1.637* (0.042)	0.054* (0.008)	0.064* (0.006)	0.031* (0.008)	0.019* (0.004)	-0.009* (0.003)	-0.027* (0.004)	-0.011* (0.003)	-0.04* (0.005)	-0.113* (0.005)
13	Ribs (full rack)	-0.009 (0.01)	-0.045* (0.01)	-0.042* (0.01)	-0.024* (0.008)	-0.05* (0.011)	-0.028* (0.007)	0.199* (0.012)	-0.015 (0.01)	0.021 (0.013)	0.052* (0.009)	0.102* (0.011)	0.12* (0.017)	-1.818* (0.045)	0.048* (0.008)	0.025* (0.012)	-0.01 (0.005)	-0.03* (0.005)	-0.026* (0.005)	0.001 (0.003)	-0.012* (0.006)	-0.039* (0.006)
14	Fettucine Alfredo	0.003 (0.01)	-0.037* (0.01)	-0.001 (0.008)	0.023* (0.007)	0.003 (0.01)	-0.019* (0.007)	0.24* (0.013)	0.04* (0.007)	0.094* (0.011)	0.021* (0.01)	0.105* (0.011)	0.203* (0.016)	0.069* (0.011)	-1.374* (0.034)	0.073* (0.011)	0.074* (0.005)	0.015* (0.004)	-0.017* (0.005)	-0.05* (0.005)	-0.027* (0.007)	0.015* (0.005)
15	Medium Pizza	-0.133* (0.01)	-0.011 (0.007)	0.002 (0.006)	-0.031* (0.007)	-0.089* (0.01)	-0.007 (0.005)	0.074* (0.012)	-0.035* (0.009)	0.034* (0.011)	0.059* (0.008)	0.031* (0.011)	0.057* (0.016)	0.02* (0.01)	0.042* (0.007)	-1.398* (0.035)	-0.006 (0.005)	-0.025* (0.004)	0.024* (0.003)	-0.021* (0.003)	-0.008 (0.005)	0.029* (0.004)
16	Fries	-0.085* (0.005)	0.009* (0.004)	0.018* (0.003)	-0.023* (0.004)	-0.024* (0.005)	0.014* (0.002)	-0.264* (0.011)	-0.016* (0.005)	-0.048* (0.007)	0.054* (0.005)	0.079* (0.007)	0.049* (0.011)	-0.012 (0.006)	0.061* (0.005)	-0.009 (0.006)	-0.269* (0.007)	0.018* (0.002)	0.039* (0.002)	0.013* (0.001)	0.067* (0.003)	0.055* (0.002)
17	Mac and Cheese	-0.075* (0.009)	-0.111* (0.009)	-0.039* (0.007)	-0.019* (0.006)	-0.126* (0.01)	-0.008 (0.005)	0.000 (0.013)	-0.149* (0.013)	-0.095* (0.013)	0.021* (0.009)	0.025* (0.012)	-0.05* (0.018)	-0.073* (0.013)	0.025* (0.007)	-0.072* (0.012)	0.036* (0.004)	-0.433* (0.011)	0.019* (0.003)	-0.001 (0.003)	0.05* (0.004)	0.029* (0.004)
18	Broccoli	0.034* (0.006)	-0.039* (0.007)	-0.1* (0.008)	0.01 (0.005)	-0.005 (0.007)	-0.032* (0.005)	0.143* (0.011)	-0.022* (0.008)	-0.032* (0.011)	-0.037* (0.009)	-0.21* (0.017)	-0.134* (0.018)	-0.058* (0.012)	-0.027* (0.008)	0.064* (0.008)	0.074* (0.004)	0.018* (0.003)	-0.428* (0.011)	0.005* (0.002)	0.016* (0.004)	-0.018* (0.004)
19	Bread	-0.069* (0.011)	-0.056* (0.009)	-0.011 (0.007)	-0.049* (0.008)	-0.07* (0.01)	-0.023* (0.006)	0.074* (0.014)	0.004 (0.008)	0.103* (0.009)	-0.138* (0.014)	-0.074* (0.016)	-0.095* (0.022)	0.002 (0.012)	-0.13* (0.013)	-0.096* (0.014)	0.041* (0.005)	-0.002 (0.004)	0.008* (0.004)	-0.356* (0.009)	-0.005* (0.005)	-0.028* (0.005)
20	Side Salad	0.029* (0.005)	-0.006 (0.004)	-0.008* (0.004)	0.004 (0.004)	-0.003 (0.005)	-0.014* (0.003)	0.086* (0.008)	-0.013* (0.005)	0.026* (0.007)	0.074* (0.005)	-0.079* (0.009)	-0.102* (0.012)	-0.014* (0.007)	-0.021* (0.005)	-0.011 (0.007)	0.066* (0.003)	0.024* (0.002)	0.008* (0.002)	-0.002 (0.002)	-0.366* (0.009)	-0.005 (0.003)
21	Baked Potato	0.03* (0.006)	-0.016* (0.006)	-0.009 (0.005)	0.009 (0.005)	-0.026* (0.007)	-0.031* (0.005)	0.148* (0.01)	0.014* (0.006)	0.015 (0.009)	0.003 (0.008)	-0.041* (0.011)	-0.462* (0.022)	-0.071* (0.011)	0.019* (0.006)	0.064* (0.008)	0.086* (0.004)	0.022* (0.003)	-0.015* (0.003)	-0.014* (0.003)	-0.008 (0.004)	-0.414* (0.011)
22	No-buy	0.165* (0.006)	0.112* (0.004)	0.075* (0.004)	0.104* (0.004)	0.123* (0.005)	0.046* (0.003)	0.321* (0.012)	0.097* (0.005)	0.202* (0.008)	0.144* (0.006)	0.177* (0.008)	0.335* (0.013)	0.151* (0.007)	0.105* (0.005)	0.181* (0.007)	0.128* (0.004)	0.062* (0.002)	0.068* (0.002)	0.04* (0.002)	0.13* (0.004)	0.082* (0.003)

Note: Numbers in parentheses are standard errors. *Indicate significance at the 5%-level or above.

6.2 Delivery Setting

Table 1.5 reports the baseline utility estimates derived from an estimation of the data using the specifications of Model 3. The price coefficient is again negative and significant. In contrast to the *Restaurant* setting, we have a less clear preference ordering between plant-based and meat options. For example, the plant-based burger has a higher utility than both the ribs (-1.551) and the salmon (-2.277). We also find that the chicken sandwich (-0.835) and pizza (-0.259) are among the items with the highest baseline utility. This corresponds to recent statistics according to fried chicken sandwiches were the second most ordered dish on DoorDash and most ordered one on Grubhub in 2020 (DoorDash 2021; Grubhub 2020). Likewise, consumer spending on pizza delivery reached a new record high for 2020 with $14 billion dollar (Lock 2022). Also, in line with the report by Grubhub, we find that fries are the side dish with the highest baseline utility (-1.479) placing them among the five most popular dishes for delivery overall.

Looking at demographic differences, we observe that females again order less of all meat-based entrées which aligns with the findings by Grubhub (2014b). Interestingly, we also find that females order less of the plant-based burger (-0.446) compared to their counterparts. Possibly this indicates that males still want to order a burger via delivery but are open to substitute it with a plant-based alternative. Preferences for plant-based alternatives are again different between urban consumers and those living in suburbs or rural areas, with the former showing a higher preference for both the cauliflower wings and the plant-based burger. Respondents from rural and suburban areas were also significantly more likely to refrain from ordering anything, which could indicate that urban consumers are less selective about their delivery food than others.

Table 1.5 Baseline Utility Estimates from the MVL Model – *Delivery* Setting

	Constant	Female	College	Low Income	Rural	Suburban	Price
Appetizer							
Mozzarella Sticks	-1.810 *	0.245*	-0.145*	0.002	0.012	-0.179*	-0.076 *
	(0.104)	(0.060)	(0.067)	(0.070)	(0.083)	(0.072)	(0.002)
Spinach Artichoke Dip	-2.167 *	0.386*	0.069	-0.235*	-0.034	-0.234*	-0.076 *
	(0.128)	(0.079)	(0.086)	(0.087)	(0.106)	(0.089)	(0.002)
Cauliflower Wings	-1.869 *	-0.198	0.239	-0.077	-0.357*	-0.696*	-0.076 *
	(0.131)	(0.083)	(0.092)	(0.093)	(0.112)	(0.092)	(0.002)
Onion Rings	-2.304 *	0.058	-0.115	0.276*	0.003	-0.011	-0.076 *
	(0.117)	(0.067)	(0.074)	(0.079)	(0.095)	(0.082)	(0.002)
Chicken Wings	-1.758 *	-0.136	0.176*	0.342*	-0.525*	-0.487*	-0.076 *
	(0.11)	(0.065)	(0.072)	(0.076)	(0.090)	(0.074)	(0.002)
Avocado Toast	-2.493 *	-0.027	0.207	-0.108	-0.618*	-0.720*	-0.076 *
	(0.17)	(0.111)	(0.123)	(0.124)	(0.152)	(0.119)	(0.002)
Entree							
Beef Burger	-0.854 *	-0.372*	-0.105	-0.066	-0.062	0.035	-0.076 *
	(0.108)	(0.062)	(0.069)	(0.072)	(0.089)	(0.076)	(0.002)
Plant-Based burger	-1.531 *	-0.446*	0.038	-0.292*	-0.568*	-0.697*	-0.076 *
	(0.153)	(0.095)	(0.110)	(0.110)	(0.126)	(0.104)	(0.002)
Chicken Sandwich	-0.835 *	-0.256*	-0.164	-0.171*	-0.397*	-0.186	-0.076 *
	(0.112)	(0.067)	(0.075)	(0.077)	(0.094)	(0.077)	(0.002)
Caesar Salad	-1.717 *	0.354*	0.080	0.025	-0.075	-0.069	-0.076 *
	(0.134)	(0.080)	(0.086)	(0.090)	(0.109)	(0.092)	(0.002)
Salmon	-2.118 *	-0.148*	0.596*	-0.053	-0.607*	-0.156	-0.076 *
	(0.168)	(0.099)	(0.110)	(0.109)	(0.149)	(0.109)	(0.002)
Steak	-1.224 *	-0.360*	0.002	-0.041	-0.148	-0.188	-0.076 *
	(0.129)	(0.074)	(0.083)	(0.085)	(0.102)	(0.085)	(0.002)
Ribs (full rack)	-1.551 *	-0.615*	-0.009	-0.035	-0.092	0.316*	-0.076 *
	(0.148)	(0.086)	(0.095)	(0.097)	(0.127)	(0.101)	(0.002)
Fettucine Alfredo	-2.277 *	0.369*	0.147	-0.013	-0.495*	-0.160	-0.076 *
	(0.161)	(0.097)	(0.104)	(0.107)	(0.137)	(0.107)	(0.002)
Medium Pizza	-0.259 *	-0.035	-0.081	-0.273*	0.061	0.017	-0.076 *
	(0.104)	(0.059)	(0.065)	(0.067)	(0.084)	(0.072)	(0.002)
Sides							
Fries	-1.479 *	0.185*	-0.092	0.247*	-0.080	-0.21*	-0.076 *
	(0.095)	(0.057)	(0.063)	(0.066)	(0.079)	(0.068)	(0.002)
Mac and Cheese	-1.833 *	0.265*	-0.260*	-0.064	-0.060	-0.306*	-0.076 *
	(0.108)	(0.066)	(0.075)	(0.077)	(0.089)	(0.077)	(0.002)
Broccoli	-2.421 *	0.151	0.037	0.170	-0.152	-0.107	-0.076 *
	(0.12)	(0.073)	(0.08)	(0.084)	(0.103)	(0.084)	(0.002)
Bread	-2.871 *	0.209*	-0.096	-0.359*	-0.136	0.009	-0.076 *
	(0.138)	(0.083)	(0.093)	(0.093)	(0.118)	(0.096)	(0.002)
Side Salad	-2.007*	0.493	0.188	0.055	0.275*	0.204*	-0.076*
	(0.1)	(0.058)	(0.063)	(0.065)	(0.083)	(0.071)	(0.002)
Baked Potato	-1.807*	0.200	-0.398*	-0.103	-0.105	-0.120	-0.076*
	(0.113)	(0.069)	(0.077)	(0.079)	(0.097)	(0.082)	(0.002)
Opt-Out							
No-Order	-2.175*	-0.526*	0.010	-0.166	0.669*	0.350*	-0.076*
	(0.114)	(0.073)	(0.080)	(0.081)	(0.107)	(0.095)	(0.002)

Note: Numbers in parentheses are standard errors; * denotes significance at the 5% level or higher.

To gain a deeper understanding of potential substitution and complementarity patterns, we again considered the cross-utilities derived via the MVL model[11]. We find that similar to the *Restaurant* setting, the beef burger and plant-based burger have the largest negative cross-utility (-1.685), followed by the beef burger and chicken sandwich which have a negative cross-utility of (-1.656). Also resembling the other setting: almost all entrees share a negative and mostly significant cross-utility. One exception are Fettucine Alfredo and the Caesar Salad with a significantly positive utility of 0.286 meaning respondents on average derived a greater utility from ordering both dishes. Looking at the other cross-utilities, a mostly similar picture emerges as for the *Restaurant* setting, where cross-utilities are negative within courses and positive across courses.

Nevertheless, to truly evaluate whether dishes were complements and substitutes we again proceeded with deriving the own- and cross-price elasticities for the different dishes using the cross-utilities. The results are shown in Table 1.6. In line with what we hypothesized above, comparing the two settings' elasticities reveals additional differences. For example, in terms of the own-price elasticities of the items we notice that all items are substantially less elastic than in the *Restaurant* setting, meaning that respondents are less sensitive to price changes when ordering food for delivery. Nevertheless, as before, we can see that items in the entrée category are the most elastic, followed by the appetizers, and finally the side dishes. We also find that salmon has the highest own price-elasticity among all options (-1.407) and fries (-0.199) the lowest. Interestingly, several striking differences between dining settings can be noted when looking at the cross-price elasticities. To begin with, a large share of items recorded as demand substitutes in the *Restaurant* setting act as complements in the *Delivery* setting. For example, Caesar salad, which was a

[11] Table A1.3 in the Appendix report the cross-utility estimates for the *Delivery* setting.

substitute of all other entrees in the *Restaurant* setting, represents a complement to all entrees but the pizza in the delivery setting. Outside of the entrees, broccoli and side salads which complemented several dishes in the *Restaurant* setting, now complement the dishes even more extensively as they only serve as substitutes for four and two dishes, respectively. For appetizers, onion rings complement 16 items compared to only 9 in the *Restaurant* setting. These differences in substitution and complementarity pattern could partially explain the higher number of items ordered and the corresponding higher average order price in the *Delivery* setting. These differences also again emphasize how the setting can influence consumption choices meaning FAFH cannot be viewed as just one homogenous category.

Table 1.6 Own- and Cross-Price Elasticities at Mean Demographics and Prices – *Delivery* Setting

		Change in Price of…																				
	Change in Quantity of:	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	Mozzarella Sticks	-0.529* (0.017)	0.022* (0.004)	0.024* (0.004)	-0.016* (0.004)	-0.016* (0.006)	0.007* (0.003)	-0.125* (0.009)	-0.048* (0.006)	-0.061* (0.008)	0.014* (0.005)	-0.033* (0.007)	-0.057* (0.01)	-0.005 (0.007)	-0.016* (0.005)	-0.069* (0.009)	-0.046* (0.003)	-0.025* (0.003)	0.000 (0.002)	-0.019* (0.002)	0.000 (0.003)	0.015* (0.003)
2	Spinach Artichoke Dip	0.04* (0.006)	-0.675* (0.022)	-0.01 (0.007)	0.026* (0.005)	-0.019* (0.008)	-0.011* (0.005)	0.047* (0.01)	-0.163* (0.013)	-0.065* (0.012)	-0.051* (0.009)	-0.055* (0.011)	-0.164* (0.018)	-0.042* (0.012)	-0.044* (0.009)	0.039* (0.011)	0.021* (0.004)	-0.065* (0.005)	-0.041* (0.004)	-0.009* (0.003)	-0.01* (0.004)	-0.012* (0.004)
3	Cauliflower Wings	0.047* (0.007)	-0.01 (0.007)	-0.757* (0.024)	0.025* (0.005)	-0.008 (0.009)	-0.051* (0.007)	0.072* (0.011)	-0.087* (0.011)	-0.197* (0.015)	-0.08* (0.011)	-0.093* (0.015)	-0.107* (0.017)	-0.12* (0.017)	-0.047* (0.01)	0.032* (0.012)	0.018* (0.004)	-0.016* (0.004)	-0.075* (0.006)	-0.012* (0.003)	-0.01* (0.004)	-0.01* (0.006)
4	Onion Rings	-0.026* (0.006)	0.023* (0.004)	0.02* (0.004)	-0.511* (0.016)	-0.001 (0.006)	0.012* (0.003)	-0.18* (0.011)	0.001 (0.006)	-0.053* (0.01)	0.004 (0.006)	-0.003 (0.007)	-0.09* (0.013)	-0.034* (0.009)	-0.018* (0.006)	-0.011 (0.01)	-0.041* (0.003)	-0.007* (0.003)	0.004* (0.003)	-0.015* (0.002)	-0.013* (0.003)	0.007 (0.004)
5	Chicken Wings	-0.017* (0.006)	-0.011* (0.005)	-0.005 (0.005)	0.000 (0.004)	-0.69* (0.022)	0.003 (0.003)	-0.009 (0.008)	-0.052* (0.007)	-0.054* (0.009)	-0.019* (0.007)	-0.023* (0.008)	-0.15* (0.013)	-0.076* (0.01)	-0.025* (0.006)	-0.141* (0.011)	-0.025* (0.003)	-0.036* (0.003)	-0.006 (0.003)	-0.013* (0.002)	-0.02* (0.003)	-0.017* (0.005)
6	Avocado Toast	0.029* (0.01)	-0.024* (0.01)	-0.102* (0.014)	0.029* (0.007)	0.013 (0.011)	-0.796* (0.025)	0.123* (0.013)	-0.114* (0.016)	-0.172* (0.02)	-0.138* (0.017)	-0.077* (0.018)	-0.077* (0.024)	-0.152* (0.023)	-0.051* (0.014)	0.02 (0.016)	0.037* (0.005)	-0.007 (0.005)	-0.061* (0.007)	-0.02* (0.004)	-0.03* (0.007)	-0.055* (0.008)
7	Beef Burger	-0.079* (0.006)	0.016* (0.004)	0.024* (0.004)	-0.072* (0.004)	-0.005 (0.005)	0.02* (0.002)	-0.668* (0.022)	0.044* (0.004)	0.084* (0.007)	0.047* (0.004)	0.032* (0.005)	0.056* (0.008)	0.055* (0.006)	0.024* (0.004)	0.05* (0.007)	-0.091* (0.004)	0.002 (0.002)	0.017* (0.002)	-0.002 (0.002)	0.014* (0.002)	0.038* (0.003)
8	Plant-Based burger	-0.09* (0.011)	-0.168* (0.012)	-0.083* (0.01)	0.001 (0.007)	-0.092* (0.012)	-0.055* (0.008)	0.131* (0.011)	-1.056* (0.033)	0.016 (0.013)	0.036* (0.008)	-0.022 (0.012)	-0.045* (0.019)	-0.032* (0.014)	0.007 (0.008)	0.041* (0.014)	-0.002 (0.004)	-0.07* (0.006)	-0.029* (0.005)	-0.006 (0.003)	-0.013* (0.005)	0.011 (0.005)
9	Chicken Sandwich	-0.048* (0.006)	-0.028* (0.005)	-0.079* (0.007)	-0.026* (0.005)	-0.039* (0.007)	-0.035* (0.005)	0.103* (0.008)	0.007 (0.005)	-0.941* (0.031)	0.015* (0.006)	0.018* (0.006)	0.016 (0.01)	-0.002 (0.008)	0.019* (0.005)	0.048* (0.009)	-0.031* (0.003)	-0.028* (0.003)	-0.029* (0.003)	-0.002 (0.002)	-0.003 (0.003)	0.006* (0.004)
10	Caesar Salad	0.02* (0.007)	-0.041* (0.007)	-0.06* (0.008)	0.004 (0.006)	-0.026* (0.009)	-0.052* (0.007)	0.109* (0.009)	0.028* (0.006)	0.029* (0.011)	-0.957* (0.03)	-0.046* (0.012)	-0.016 (0.014)	-0.038* (0.013)	-0.057* (0.009)	0.048* (0.011)	0.026* (0.004)	0.001 (0.004)	-0.031* (0.004)	-0.024* (0.003)	0.005 (0.004)	0.001* (0.004)
11	Salmon	-0.056* (0.011)	-0.052* (0.011)	-0.081* (0.012)	-0.004 (0.008)	-0.036* (0.012)	-0.033* (0.008)	0.087* (0.013)	-0.02 (0.011)	0.039* (0.014)	-0.053* (0.013)	-1.424* (0.045)	-0.102* (0.022)	-0.083* (0.02)	-0.023* (0.011)	0.046* (0.015)	0.027* (0.005)	-0.014* (0.005)	-0.091* (0.007)	-0.027* (0.004)	-0.043* (0.006)	-0.019* (0.005)
12	Steak	-0.042* (0.007)	-0.067* (0.007)	-0.041* (0.007)	-0.042* (0.006)	-0.106* (0.009)	-0.015* (0.005)	0.066* (0.01)	-0.018* (0.007)	0.015 (0.01)	-0.008 (0.007)	-0.045* (0.01)	-1.31* (0.042)	-0.071* (0.012)	0.002 (0.007)	0.039* (0.01)	0.001 (0.004)	-0.04* (0.004)	-0.037* (0.004)	-0.021* (0.003)	-0.048* (0.004)	-0.113* (0.005)
13	Ribs (full rack)	-0.006 (0.009)	-0.028* (0.008)	-0.074* (0.01)	-0.026* (0.007)	-0.086* (0.011)	-0.047* (0.008)	0.103* (0.01)	-0.021* (0.009)	-0.003 (0.012)	-0.031* (0.01)	-0.059* (0.014)	-0.113* (0.019)	-1.387* (0.044)	-0.044* (0.01)	0.064* (0.012)	0.018* (0.004)	-0.046* (0.005)	-0.038* (0.005)	-0.016* (0.003)	-0.045* (0.005)	-0.039* (0.006)
14	Fettucine Alfredo	-0.034* (0.01)	-0.049* (0.01)	-0.05* (0.01)	-0.023* (0.008)	-0.048* (0.012)	-0.027* (0.007)	0.076* (0.013)	0.007 (0.009)	0.051* (0.012)	-0.079* (0.013)	-0.028* (0.013)	0.006 (0.018)	-0.074* (0.017)	-1.063* (0.034)	0.014 (0.015)	0.04* (0.004)	-0.009* (0.005)	-0.05* (0.006)	-0.058* (0.005)	-0.046* (0.006)	0.015* (0.005)
15	Medium Pizza	-0.042* (0.005)	0.013* (0.004)	0.01* (0.004)	-0.004 (0.004)	-0.081* (0.007)	0.003 (0.003)	0.048* (0.007)	0.013* (0.004)	0.037* (0.007)	0.02* (0.005)	0.017* (0.005)	0.031* (0.008)	0.032* (0.006)	0.004 (0.004)	-0.961* (0.031)	0.012* (0.003)	0.005 (0.002)	0.018* (0.002)	-0.013* (0.002)	-0.028* (0.003)	0.029* (0.004)
16	Fries	-0.07* (0.005)	0.017* (0.003)	0.014* (0.003)	-0.039* (0.003)	-0.035* (0.005)	0.014* (0.002)	-0.217* (0.009)	-0.001 (0.004)	-0.059* (0.006)	0.028* (0.004)	0.024* (0.005)	0.001 (0.007)	0.023* (0.005)	0.03* (0.003)	0.031* (0.007)	-0.202* (0.007)	0.01* (0.002)	0.022* (0.002)	0.001 (0.001)	0.023* (0.002)	0.055* (0.002)
17	Mac and Cheese	-0.062* (0.006)	-0.088* (0.007)	-0.02* (0.005)	-0.011* (0.005)	-0.083* (0.008)	-0.005 (0.004)	0.007 (0.009)	-0.091* (0.009)	-0.088* (0.01)	0.001 (0.006)	-0.02* (0.008)	-0.13* (0.014)	-0.093* (0.011)	-0.011 (0.006)	0.021* (0.009)	0.017* (0.003)	-0.317* (0.01)	-0.003 (0.003)	-0.011* (0.002)	0.009* (0.003)	0.029* (0.004)
18	Broccoli	0.00 (0.007)	-0.073* (0.008)	-0.125* (0.01)	0.009 (0.005)	-0.017* (0.008)	-0.051* (0.006)	0.089* (0.009)	-0.051* (0.009)	-0.118* (0.012)	-0.07* (0.01)	-0.173* (0.015)	-0.158* (0.017)	-0.102* (0.014)	-0.08* (0.01)	0.095* (0.01)	0.046* (0.003)	-0.003 (0.003)	-0.333* (0.011)	-0.01* (0.003)	0.004 (0.004)	-0.018* (0.004)
19	Bread	-0.095 (0.01)	-0.025* (0.007)	-0.031* (0.008)	-0.047* (0.007)	-0.061* (0.01)	-0.026* (0.006)	-0.018 (0.013)	-0.017 (0.009)	-0.012 (0.012)	-0.083* (0.011)	-0.082* (0.013)	-0.145* (0.019)	-0.07* (0.015)	-0.146* (0.013)	-0.108* (0.015)	0.003 (0.004)	-0.024* (0.004)	-0.016* (0.004)	-0.274* (0.009)	-0.018* (0.004)	-0.028* (0.005)
20	Side Salad	-0.001* (0.005)	-0.01* (0.004)	-0.01* (0.004)	-0.015* (0.004)	-0.035* (0.006)	-0.014* (0.003)	0.039* (0.007)	-0.013* (0.005)	-0.008 (0.007)	0.007 (0.005)	-0.047* (0.007)	-0.118* (0.011)	-0.069* (0.008)	-0.041* (0.006)	-0.083* (0.009)	0.028* (0.003)	0.007* (0.002)	0.002 (0.002)	-0.006* (0.002)	-0.296* (0.01)	-0.005* (0.003)
21	Baked Potato	-0.016* (0.006)	-0.026* (0.006)	-0.024* (0.006)	-0.008 (0.005)	-0.021* (0.007)	-0.038* (0.005)	0.073* (0.009)	-0.005 (0.007)	-0.029* (0.01)	-0.066* (0.009)	-0.119* (0.012)	-0.286* (0.017)	-0.17* (0.014)	-0.026* (0.007)	0.072* (0.009)	0.04* (0.003)	-0.009* (0.003)	-0.034* (0.004)	-0.013* (0.002)	-0.01* (0.004)	-0.414* (0.011)
22	No-buy	0.156* (0.006)	0.086* (0.004)	0.08* (0.004)	0.099* (0.004)	0.147* (0.006)	0.04* (0.003)	0.246* (0.01)	0.083* (0.005)	0.2* (0.008)	0.107* (0.005)	0.092* (0.005)	0.208* (0.009)	0.13* (0.006)	0.076* (0.004)	0.256* (0.01)	0.103* (0.004)	0.064* (0.003)	0.048* (0.002)	0.031* (0.002)	0.085* (0.003)	0.082* (0.003)

Note: Numbers in parentheses are standard errors. *Indicate significance at the 5%-level or above

To further translate such differences in choice behaviors across dining setting into more tangible terms, we calculated the nutritional composition of the average order. To do so, we used the Nutritionix website (Link) to derive the calories, fat content, carbohydrates, protein, and cholesterol content for each of the 21 items[12]. Following Caputo and Lusk (2022), we then multiplied the probability of ordering each item with the five nutritional components, which provided us with their average impact on the nutritional composition of the order. Based on this we determined that the average order in the *Restaurant* setting contains around 1767kcal and the average order in the *Delivery* setting had 2105 kcal (see Table 1.7). Hence, respondents in the *Delivery* setting ordered meals with on average 19% more calories indicating that frequent food delivery orders are detrimental to the overall calorie intake.

Table 1.7 Nutritional Composition of the average order in the *Restaurant* and *Delivery* setting

	***Restaurant* Setting**	***Delivery* Setting**
Calories (in kcal)	1767.61	2105.01
Protein (in g)	73.04	87.91
Total Fat (in g)	100.66	116.62
Carbohydrates (in g)	142.09	176.16
Cholesterol (in mg)	226.03	261.14

The 2020-2025 Dietary Guidelines for Americans recommend 1800 to 2800kcal for moderately active adults depending on age and gender (U.S. Department of Agriculture and U.S. Department of Health and Human Services 2020). Thus, in both settings, the average meal almost covers the recommended amount. Correspondingly, the average order in the *Restaurant* setting had about 73g of protein and 142g of carbohydrates. In comparison, in the *Delivery* setting the average order contained 87g of protein and 176g of carbohydrates. The daily nutritional goals

[12] We used the serving sizes suggested by the website for the different dishes in our menu. Table A1.4 in the Appendix reports nutritional make-up of each item and the corresponding serving size.

summarized in the dietary guidelines for a 19–30-year-old female are 46g of Protein and 130g of carbohydrates, while they are 52g of protein and 130g of carbohydrates for a 19-30-year-old male[13]. This means that the average meal in both settings substantially exceeds the recommended daily intake, which highlights the importance of considering FAFH consumption in the design and evaluation of food policies.

7. The effect of a red meat tax on demand and policy implications

The basket-based approach permits sufficient flexibility to evaluate the impact of various policies on demand and preferences as also shown in Caputo and Lusk (2022). We capitalize on this flexibility to assess the effects of a tax on red meat products. Red meat products have been classified as probably carcinogenic by the World Health Organization (WHO) (WHO 2015) and its production is associated with substantial detrimental effects on the environment (see e.g., Smil 2002; Nguyen et al, 2010). Springmann et al. (2018) proposed that instead of regulating the products through direct interventions like limiting or banning the consumption, a tax could represent an alternative market-based approach. Based on their calculations, a (non-processed) red meat tax would have to be about 20% in high income countries to lead to substantial declines in red meat attributable deaths and health costs. However, their analysis does not incorporate an analysis of how such a tax would affect the consumption of other products.

We employ the same approach used to derive the elasticities above to measure the impact of a 20% tax on all red meat products in the experiment (beef burger, steak, ribs) in line with the estimations of Springmann et al. (2018). We not only estimate these results for the pooled sample

[13] 19-30 years was chosen as it has the highest recommended consumption of calories and other macronutrients, meaning the presented difference is on the conservative end.

in both studies, but also separately for low- and high- income respondents[14]. The subsequent percentage changes in demand are highlighted in Table A1.5 in the Appendix. The results demonstrate that the tax impacts the three taxed products differently, with a disproportionately low impact of the tax on beef burger demand. We also find that the impact on the demand for all products varies across income groups and settings, with a mostly more pronounced effect of the tax on respondents with a lower income.

Given these results, it was of particular interest to us to assess the welfare effect of the tax. Specifically, we were interested in assessing whether the tax would indeed be regressive, and if so, how the extent of regressivity changes as the tax rate changes. To answer this question, we re-estimated the demand changes at different tax rates (i.e., 1% to 30% in1% increments for both low- and high-income individuals). We then translated the changes in demand across all items into the compensating variation (CV) to understand the welfare effects of this change[15]. In doing so, we set the estimated CV values relative to the average order price for the respective income groups[16] across the two dining settings to allow for better comparability between the two income groups (see Figure 3).

As can be seen from Figure 3, in relative terms there is barely any difference in the *Restaurant* setting between the two income groups. At a hypothetical 20% tax, the CV required to return to the initial average level of utility is equal to 7.31% of the initial average order cost among low-income consumers relative to 7.30% among high income consumers. Even at the highest tax

[14] To derive the tax impact for the two groups, we re-estimated the initial MVL model separately for high- and low-income respondents and then employed the new coefficient estimates to derive the tax impact via the same process employed for the pooled sample.

[15] In this case, the CV can be understood as the additional dollar amount a respondent would need to pay to return to the original utility. In the derivation of it we followed the approach laid out by Small and Rosen (1981) and applied by Caputo and Lusk (2022).

[16] The average order price was $28.50 and $24.31 for high- and low-income respondents in the *Restaurant* setting, respectively. In the *Delivery* one it was $29.66 and $27.06.

rate (30%), the difference is only 0.09% (10.51%-10.42%). This suggests that the tax is only minorly regressive in a restaurant dine-in setting. In the *Delivery* setting, on the other hand, we find a very pronounced difference between the two income groups, with low-income consumers being substantially more affected by a tax on red meat products than high-income consumers. The trendlines depicted in Figure 2 indicate that the higher the tax the bigger the extent of the tax regressivity: at a tax rate of 6% the CV amounts to 2.05% of the average meal order price for high income respondents and 3.06% of low-income respondents; at 20% the difference has grown to almost 3% (9.40%-6.45%) and at a tax of 30% it is more than 4% (13.31%-9.29%).

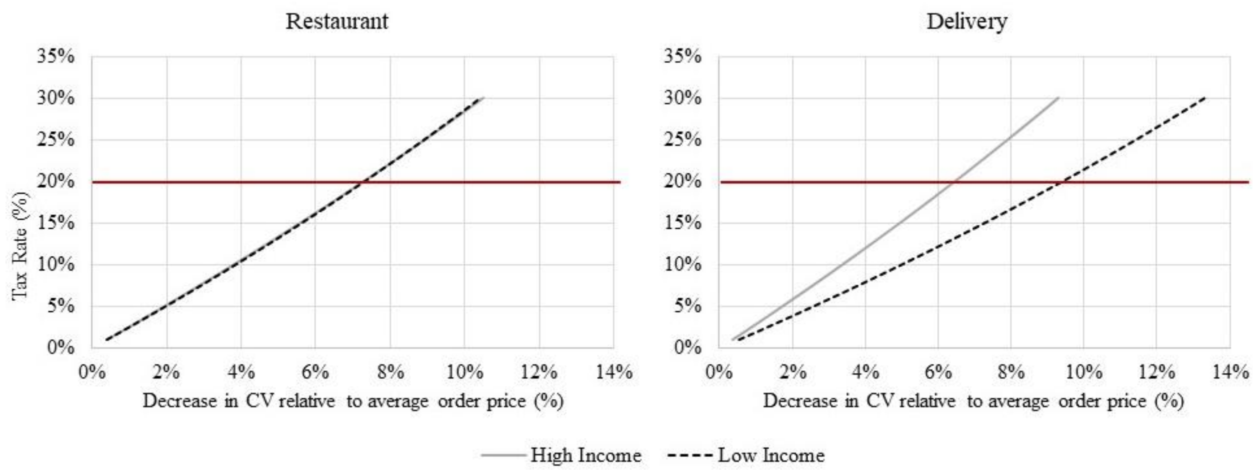

Figure 1.3 Estimated CV to compensate for a red meat tax relative to the average meal price in the respective income groups.

This aligns with previous studies who found that taxes levied on food items tend to be regressive (see e.g., Leicester and Windmeijer 2004; Chouinard et al. 2007; Cornelsen and Carreido 2015; Madden 2015), as also discussed in Lusk and McCluskey (2018) and Caputo and Just (2022).

However, it should also be considered that we assumed a somewhat linear relationship between an increasing tax rate and consumer behavior. As noted by Lusk (2014) consumers might not notice that a tax is being applied or its impact might be dispersed between producers and consumers. This could particularly be the case for relatively low tax rates, meaning we could find a stronger effect as tax rates increase. Nevertheless, our results serve to illustrate that the tax impact and the associated regressivity is setting dependent. These differences across settings should be considered during the policy process. The recent increases in food delivery orders could have significant dietary and subsequent health implications. Obesity affects more than 42% of the U.S. population (CDC 2021) and creates significant societal costs for example in terms of health care expenses (CDC 2019). This has led to some researchers classifying obesity as an externality (see e.g., the Caputo and Just 2022 for a recent discussion of this issue). Should policy makers decide to intervene in FAFH consumption instead of leaving it to the market to mitigate this situation they need to take the heterogeneous nature of FAFH into consideration when choosing an approach. As we show, a (red meat) tax-based approach might result in a lower consumption of meat options, but also reduce the demand for certain plant-based options such as salad or broccoli depending on the order setting considered. Likewise, it will affect consumers with different socio-demographics in different ways. Especially in a food delivery setting the tax is regressive in nature as it more thoroughly burdens low-income consumers.

Recent literature has shown that more passive approaches like providing a nutri-score to online shoppers can lead to healthier choices by consumers (Jansen et al. 2021). Similarly, studies like Ellison et al. (2013, 2014a,b) demonstrated that traffic lights and calorie labeling are effective in reducing the total calories ordered in an in-restaurant dining setting without significant negative effects on restaurant revenues. Thus, a more stringent approach to nutritional labeling could be explored as a policy option to improve the dietary quality of FAFH orders. On the other hand, we also need to consider how these changes in consumption patterns affect producers of different commodities. To elaborate, around 60% of beef is consumed away from home (California Beef Council 2021). As we showed in our results, high-quality cuts such as steaks are selected significantly more often in the *Restaurant* setting than they are in the *Delivery* setting, while items such as beef burgers are popular in either setting. Producers and processors will likely need to adapt to these changes to maximize their profits and meet the demand of consumers.

8. Conclusion

The significant relevance of FAFH for consumer diets in today's world is undeniable. Yet, while FAFH consumption is evolving with a growing share of food being ordered for delivery, research on FAFH consumption disaggregated by dining setting is still lacking. Detailed insights into consumer preferences for FAFH are also lacking despite their relevance in understanding how recent market developments and policies impact demand.

We targeted this gap in the literature by utilizing two different experimentally designed settings (i.e., in-restaurant dining vs. food delivery) to analyze the impact dining settings have on choice behavior and decision-making. As part of this analysis, we used a cutting-edge experimental procedure, the FM-BBCE. This approach enabled us to a) identify the substitution and complementarity patterns between various food types (meat versus plant-based food) and courses (appetizers, entrees, and side dishes), and b) determine the demand and welfare impact of a 20% red meat across the two settings.

We find that preferences for the different items vary significantly across socio-demographics and the two settings. Items in the *Restaurant* setting have a significantly higher own- and cross-price elasticity and a lot of items acting as demand substitutes in this setting are complements in the *Delivery* setting. Correspondingly, we observe that the implementation of a red meat tax would affect the two settings in different ways. For example, while the relative welfare impact of the tax barely differs for low- and high-income consumers in the *Restaurant* setting across different tax rates, we find that such a tax would be highly regressive in a delivery setting. Such differences are particularly important as we also observe that the average meal composed by respondents in the *Delivery* setting has a significantly higher content of calories, protein, fat, carbohydrates, and cholesterol than the average meal in the *Restaurant* setting.

While our results generate important insights for producers, agribusinesses, and policy makers, they should also be viewed under the lens of certain limitations inherent to the design. Specifically, we cannot exclude the possibility of hypothetical bias given that the choices made were non-consequential for respondents. We also did not incorporate components such as tips, taxes, or fees in our experimental design which could have an impact on respondent's choices. Future studies might want to examine how results differ if the experiment is non-hypothetical or also incorporates additional charges. Similarly, additional studies might want to look at how choices alter depending on the company one is in when consuming FAFH or the cuisine that is being considered. We further suggest that future work tests how results change if respondents are given the option to select different quantities of items or choose predetermined entrée & side combinations with the option to substitute the latter for alternative options. We also encourage the exploration of alternative policy measures and their impact on the order composition, such as carbon or fat taxes. Related to that, one might then extend the assessment of the nutritional composition by also looking at micronutrients of the different dishes. Lastly, the panel structure of the derived data permits the analysis of the data with traditional demand system models, which means future research might want to combine secondary data on FAH consumption with experimental data on FAFH data derived via the FM-BBCE to gain more detailed insights on total food consumption patterns.

APPENDIX

APPENDIX

Tables

Table A1.1 Item-specific price level

Item	**Price Levels**		
Appetizers			
Mozzarella Sticks	$5.00	$9.00	$13.00
Spinach Artichoke Dip	$6.00	$10.00	$14.00
Cauliflower Wings	$7.00	$11.00	$15.00
Onion Rings	$4.00	$8.00	$12.00
Chicken Wings	$7.00	$11.00	$15.00
Avocado Toast	$7.00	$11.00	$15.00
Entrees			
Beef Burger	$7.00	$12.00	$17.00
Plant-Based Burger	$10.00	$15.00	$20.00
Chicken Sandwich	$10.00	$15.00	$20.00
Caesar Salad	$9.00	$14.00	$19.00
Salmon	$15.00	$20.00	$25.00
Steak	$15.00	$20.00	$25.00
Ribs (full rack)	$15.00	$20.00	$25.00
Fettucine Alfredo (Vegetarian)	$10.00	$15.00	$20.00
Medium Pizza	$11.00	$16.00	$21.00
Sides			
Fries	$3.00	$5.00	$7.00
Mac and Cheese	$3.00	$5.00	$7.00
Broccoli	$2.00	$4.00	$6.00
Bread	$2.00	$4.00	$6.00
Side Salad	$3.00	$5.00	$7.00
Baked Potato	$3.00	$5.00	$7.00

Table A1.2 Cross-Utility Effect Estimates from MVL Model – *Restaurant* Setting

		Change in Utility of Purchasing																			
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Mozzarella Sticks																				
2	Spinach Artichoke Dip	-0.949* (0.077)																			
3	Cauliflower Wings	-0.921* (0.098)	-1.184* (0.105)																		
4	Onion Rings	-0.641* (0.069)	-0.796* (0.087)	-1.102* (0.122)																	
5	Chicken Wings	-0.291* (0.069)	-0.335* (0.078)	-0.267* (0.093)	-0.469* (0.081)																
6	Avocado Toast	-0.622* (0.114)	-0.544* (0.112)	0.208 (0.105)	-0.398* (0.125)	-0.567* (0.122)															
7	Beef Burger	1.02* (0.054)	0.41* (0.071)	-0.193 (0.103)	1.474* (0.058)	0.304* (0.069)	-0.605* (0.134)														
8	Plant-Based burger	1.111* (0.078)	1.674* (0.076)	1.77* (0.087)	0.678* (0.098)	0.801* (0.086)	1.21* (0.105)	-2.337* (0.114)													
9	Chicken Sandwich	0.743* (0.063)	0.635* (0.073)	1.109* (0.077)	0.985* (0.07)	0.706* (0.07)	0.461* (0.103)	-2.769* (0.09)	-1.602* (0.105)												
10	Caesar Salad	0.412* (0.074)	0.554* (0.076)	0.868* (0.084)	0.298* (0.085)	0.556* (0.079)	0.886* (0.097)	-1.749* (0.096)	-1.199* (0.122)	-1.115* (0.091)											
11	Salmon	0.683* (0.077)	0.626* (0.083)	0.131 (0.103)	0.689* (0.085)	0.543* (0.086)	0.432* (0.113)	-1.991* (0.099)	-1.12* (0.117)	-1.907* (0.117)	-1.009* (0.102)										
12	Steak	0.59* (0.062)	0.835* (0.065)	0.372* (0.082)	0.769* (0.068)	0.672* (0.067)	0.277* (0.098)	-2.305* (0.077)	-1.142* (0.09)	-1.718* (0.081)	-0.843* (0.08)	-1.978* (0.097)									
13	Ribs (full rack)	0.492* (0.08)	0.694* (0.088)	0.652* (0.097)	0.837* (0.083)	0.574* (0.083)	0.586* (0.116)	-2.127* (0.098)	-0.911* (0.111)	-1.089* (0.089)	-0.933* (0.108)	-1.799* (0.134)	-1.665* (0.092)								
14	Fettucine Alfredo	0.674* (0.083)	0.782* (0.085)	0.26* (0.113)	0.317* (0.103)	0.409* (0.099)	0.553* (0.122)	-2.057* (0.124)	-1.22* (0.138)	-1.192* (0.11)	-0.864* (0.101)	-1.891* (0.148)	-1.82* (0.12)	-1.222* (0.138)							
15	Medium Pizza	1.195* (0.059)	0.386* (0.077)	0.304* (0.097)	0.698* (0.071)	0.902* (0.069)	0.469* (0.109)	-0.974* (0.07)	-0.262* (0.09)	-0.68* (0.08)	-0.875* (0.095)	-0.58* (0.091)	-0.589* (0.074)	-0.545* (0.094)	-0.988* (0.115)						
16	Fries	0.843* (0.048)	0.21* (0.062)	0.093 (0.078)	0.138* (0.055)	0.622* (0.06)	0.18* (0.096)	2.094* (0.047)	1.059* (0.074)	1.276* (0.055)	-0.139* (0.07)	0.214 (0.08)	1.068* (0.058)	1.079* (0.069)	-0.396* (0.096)	0.202* (0.06)					
17	Mac and Cheese	0.726* (0.061)	1.087* (0.064)	0.64* (0.083)	0.344* (0.071)	1.112* (0.064)	0.333* (0.108)	0.785* (0.064)	1.337* (0.077)	0.931* (0.066)	-0.077* (0.084)	0.31 (0.091)	0.776* (0.068)	0.881* (0.081)	-0.061 (0.103)	0.335* (0.07)	-1.37* (0.064)				
18	Broccoli	0.084 (0.065)	0.504* (0.064)	1.239* (0.068)	0.118 (0.07)	0.204* (0.072)	0.531* (0.087)	0.234* (0.07)	0.41* (0.085)	0.649* (0.066)	0.373* (0.069)	1.524* (0.065)	0.971* (0.06)	0.844* (0.078)	0.601* (0.079)	-0.306* (0.082)	-1.335* (0.068)	-0.883* (0.077)			
19	Bread	0.732* (0.066)	0.662* (0.072)	0.39* (0.096)	0.79* (0.071)	0.642* (0.074)	0.444* (0.105)	0.036 (0.076)	-0.218* (0.109)	-0.686* (0.102)	1.042* (0.07)	0.609* (0.084)	0.387* (0.073)	0.093 (0.098)	1.242* (0.078)	0.58* (0.073)	-0.479* (0.072)	-0.202* (0.082)	-0.45* (0.078)		
20	Side Salad	0.007 (0.052)	0.206* (0.056)	0.316* (0.068)	0.119 (0.056)	0.258* (0.059)	0.482* (0.078)	0.288* (0.051)	0.529* (0.071)	0.265* (0.057)	-0.878* (0.073)	0.885* (0.059)	0.88* (0.05)	0.543* (0.065)	0.451* (0.067)	0.277* (0.057)	-1.308* (0.051)	-1.006* (0.065)	-0.568* (0.053)	-0.004 (0.06)	
21	Baked Potato	0.08 (0.064)	0.133* (0.067)	0.074 (0.082)	-0.022 (0.069)	0.405* (0.068)	0.669* (0.087)	0.274* (0.067)	0.183* (0.094)	0.536* (0.068)	0.023 (0.072)	0.659* (0.072)	1.966* (0.053)	1.082* (0.073)	-0.04 (0.089)	-0.405* (0.08)	-1.768* (0.072)	-0.997* (0.078)	-0.249* (0.059)	0.308* (0.067)	-0.341* (0.05)

Note: Numbers in parentheses are standard errors. * indicate significance at the 5%-level or above.

Table A1.3 Cross-Utility Effect Estimates from MVL Model – *Delivery* Setting

		Change in Utility of Purchasing																			
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Mozzarella Sticks																				
2	Spinach Artichoke Dip	-0.93* (0.075)																			
3	Cauliflower Wings	-0.883* (0.082)	-0.71* (0.089)																		
4	Onion Rings	-0.281* (0.057)	-0.645* (0.084)	-0.615* (0.09)																	
5	Chicken Wings	-0.308* (0.057)	-0.305* (0.071)	-0.318* (0.077)	-0.346* (0.065)																
6	Avocado Toast	-0.441* (0.101)	-0.388* (0.11)	0.25* (0.096)	-0.525* (0.119)	-0.485* (0.104)															
7	Beef Burger	1.027* (0.049)	0.463* (0.071)	0.355* (0.079)	1.342* (0.053)	0.294* (0.057)	-0.078 (0.112)														
8	Plant-Based burger	1.263* (0.073)	1.861* (0.075)	1.319* (0.086)	0.553* (0.091)	0.877* (0.075)	1.331* (0.105)	-1.685* (0.098)													
9	Chicken Sandwich	0.827* (0.054)	0.73* (0.068)	1.37* (0.065)	0.825* (0.06)	0.555* (0.058)	1.062* (0.086)	-1.656* (0.066)	-1.221* (0.088)												
10	Caesar Salad	0.128 (0.072)	0.699* (0.076)	0.792* (0.08)	0.303* (0.079)	0.453* (0.072)	1.01* (0.093)	-0.79* (0.081)	-1.09* (0.12)	-0.592* (0.078)											
11	Salmon	0.715* (0.082)	0.503* (0.093)	0.735* (0.094)	0.262* (0.097)	0.32* (0.089)	0.258* (0.122)	-0.666* (0.095)	-0.514* (0.116)	-0.976* (0.099)	-0.026 (0.097)										
12	Steak	0.561* (0.061)	0.922* (0.069)	0.683* (0.077)	0.808* (0.065)	0.942* (0.06)	0.184* (0.103)	-0.936* (0.069)	-0.736* (0.09)	-0.917* (0.071)	-0.426* (0.081)	-0.487* (0.092)									
13	Ribs (full rack)	0.183* (0.077)	0.158* (0.09)	0.801* (0.084)	0.556* (0.079)	0.689* (0.072)	0.699* (0.103)	-0.883* (0.085)	-0.462* (0.104)	-0.599* (0.08)	-0.162* (0.091)	-0.222* (0.103)	-0.361* (0.08)								
14	Fettucine Alfredo	0.563* (0.08)	0.689* (0.089)	0.568* (0.098)	0.529* (0.088)	0.52* (0.083)	0.308* (0.125)	-0.517* (0.091)	-0.776* (0.129)	-0.824* (0.098)	0.286* (0.087)	-0.58* (0.123)	-0.87* (0.103)	0.02 (0.101)							
15	Medium Pizza	0.757* (0.049)	0.149* (0.069)	0.242* (0.073)	0.344* (0.058)	1.05* (0.051)	0.233* (0.094)	-0.52* (0.055)	-0.501* (0.082)	-0.427* (0.06)	-0.27* (0.071)	-0.307* (0.088)	-0.46* (0.066)	-0.49* (0.079)	-0.312* (0.082)						
16	Fries	0.721* (0.045)	-0.119 (0.065)	-0.059 (0.069)	0.375* (0.051)	0.63* (0.051)	-0.284* (0.096)	2.056* (0.044)	0.634* (0.073)	1.233* (0.05)	0.098 (0.068)	0.164* (0.087)	0.593* (0.059)	0.311* (0.073)	-0.346* (0.088)	-0.094* (0.05)					
17	Mac and Cheese	0.652* (0.053)	1.039* (0.06)	0.154* (0.073)	0.164* (0.062)	0.69* (0.055)	-0.112 (0.1)	0.405* (0.058)	0.937* (0.071)	0.768* (0.057)	0.005 (0.075)	0.222* (0.09)	0.733* (0.061)	0.846* (0.071)	0.104 (0.088)	-0.082 (0.058)	-0.658* (0.055)				
18	Broccoli	0.186* (0.064)	0.697* (0.067)	1.086* (0.066)	-0.008 (0.074)	0.127* (0.068)	0.594* (0.089)	0.16 (0.071)	0.477* (0.085)	0.907* (0.061)	0.456* (0.072)	1.48* (0.076)	0.826* (0.066)	0.556* (0.078)	0.968* (0.081)	-0.424* (0.072)	-0.929* (0.068)	-0.482* (0.069)			
19	Bread	0.663* (0.064)	0.124 (0.084)	0.219 (0.088)	0.448* (0.072)	0.199* (0.072)	0.38* (0.109)	0.291* (0.071)	0.059 (0.102)	0.094 (0.077)	0.727* (0.077)	0.641* (0.095)	0.611* (0.075)	0.288* (0.091)	1.443* (0.079)	0.646* (0.063)	-0.083 (0.068)	0.209* (0.071)	-0.083 (0.08)		
20	Side Salad	0.048 (0.051)	0.128 (0.063)	0.056 (0.068)	0.282* (0.055)	0.262* (0.053)	0.347* (0.085)	0.225* (0.053)	0.355* (0.076)	0.389* (0.055)	-0.066 (0.067)	0.758* (0.075)	0.952* (0.055)	0.754* (0.065)	0.764* (0.071)	0.673* (0.046)	-0.579* (0.05)	-0.433* (0.058)	-0.454* (0.063)	-0.001 (0.065)	
21	Baked Potato	0.256* (0.06)	0.038 (0.072)	-0.198* (0.079)	0.1 (0.067)	0.017 (0.065)	0.56* (0.089)	0.12* (0.066)	0.024 (0.091)	0.44* (0.064)	0.646* (0.069)	1.084* (0.078)	1.531* (0.058)	1.22* (0.068)	0.207 (0.089)	-0.291* (0.066)	-0.76* (0.063)	-0.196* (0.064)	0.218* (0.063)	0.141* (0.074)	-0.141* (0.057)

Note: Numbers in parentheses are standard errors. * indicate significance at the 5%-level or above.

Table A1.4 Nutritional Composition of the Menu Items

Item	Serving Size	Calories (in kcal)	Total Fat (in g)	Carbohydrates (in g)	Protein (in g)	Cholesterol (in mg)
Appetizers						
Mozzarella Sticks	6 sticks	606	34.2	46.8	27.6	66
Spinach Artichoke Dip	1 cup	456	38.4	19.2	12	84
Cauliflower Wings	1 serving	520	29	58	8	35
Onion Rings	1 serving	1260	57	171	15	0
Chicken Wings	1 serving	650	33	49	39	105
Avocado Toast	1 piece	189	11	20	3.8	0
Entrees						
Beef Burger	1 piece	540	27	40	34	122
Plant-Based burger	1 serving	410	18	38	25	0
Chicken Sandwich	1 serving	468	21	39	30	65
Caesar Salad	3 cups	481	40	23	10	36
Salmon	1 fillet	468	28	0	50	143
Steak	12 oz	1050	91	0	55	240
Ribs (full rack)	1 serving	1160	79	51	57	260
Fettucine Alfredo	2 cups	1186	73	106	28	200
Medium Pizza	1 pizza	958	35	120	41	61
Sides						
Fries	1 medium serving	365	17	48	4	0
Mac and Cheese	1 cup	510	29	39	24	96
Broccoli	1 serving	100	8	6	3	20
Bread	1 serving	120	1	23	4	0
Side Salad	1 cup	85	7.2	3.7	2.2	5.4
Baked Potato	1 potato	161	0.2	37	4.3	0

Table A1.5 Predicted changes in quantity demanded as per effect of a tax (20% price increase) on red meat items

	% Change of quantity demanded following a 20% increase in the price of the beef burger, the steak, and ribs					
	Restaurant			**Delivery**		
From 20% price increase on red meat items	Pooled Sample	Low Income	High Income	Pooled Sample	Low Income	High Income
Appetizer						
Mozzarella Sticks	-3.18%	-4.29%	-1.94%	-3.96%	-4.50%	-3.03%
Spinach Artichoke Dip	-3.28%	-4.82%	-1.18%	-4.45%	-4.68%	-3.05%
Cauliflower Wings	0.79%	1.28%	0.57%	-3.92%	-3.39%	-3.24%
Onion Rings	-5.23%	-6.51%	-3.68%	-6.72%	-7.26%	-4.13%
Chicken Wings	-3.39%	-2.06%	-3.85%	-5.44%	-3.78%	-7.10%
Avocado Toast	-0.12%	0.01%	0.19%	-3.80%	-2.58%	-3.12%
Entrée						
Beef Burger	-9.64%	-12.15%	-6.94%	-10.18%	-10.34%	-10.22%
Plant-Based burger	3.53%	7.25%	1.46%	-0.38%	2.15%	-0.23%
Chicken Sandwich	7.91%	9.46%	6.13%	1.24%	1.84%	2.05%
Caesar Salad	7.33%	8.39%	5.81%	-0.91%	-0.26%	0.28%
Salmon	10.44%	10.34%	9.50%	-4.54%	-3.92%	-2.25%
Steak	-23.60%	-28.31%	-18.17%	-22.96%	-24.44%	-21.16%
Ribs (full rack)	-25.40%	-29.59%	-19.88%	-25.09%	-26.22%	-22.94%
Fettucine Alfredo	11.60%	13.26%	9.15%	-1.74%	-1.23%	0.13%
Medium Pizza	2.63%	3.65%	2.08%	2.11%	3.24%	1.47%
Side						
Fries	-4.10%	-4.46%	-4.20%	-3.59%	-3.60%	-3.20%
Mac and Cheese	-2.82%	-4.36%	0.06%	-4.99%	-4.19%	-5.04%
Broccoli	-1.71%	-2.14%	0.50%	-5.55%	-5.09%	-3.09%
Bread	-1.20%	-0.14%	-1.06%	-6.07%	-7.22%	-3.57%
Side Salad	-1.22%	-1.36%	-0.25%	-5.18%	-5.34%	-3.23%
Baked Potato	-8.10%	-7.54%	-6.99%	-8.69%	-9.30%	-6.50%
No Purchase	19.76%	21.22%	15.57%	14.20%	15.63%	11.03%

Figures

Please imagine you are going to a restaurant to have dinner.

In what follows we will present you with **nine choice questions**, where you will be asked to **put together a meal order** resembling what you would typically order if you were to go to a restaurant.

The **dishes that we present to you resemble what you would typically find on a restaurant** and they **remain the same in each of the nine questions**. However, their **price in each question changes**. All other attributes not mentioned here are assumed to be the same.

When making a decision on what to order, please keep in mind that you stated earlier that your **usual weekly** expense for meals **eaten in restaurants** is **$100** and you spent **$25** on the **last meal** you **ate in a restaurant.**

How to answer the questions:

For each of the nine questions that follow, please **compose an order corresponding to what you would be most likely to order if presented with the items at their respective prices,** which are indicated underneath the images.

Click on the items you would like to order at the indicated prices in **whatever combination you wish**. You can choose as many dishes as you would like in each category (Appetizer, Entrees, Sides). If you no longer want a previously selected item, click on it again to undo the selection.

If you do not want any of the options presented, please click "I would not order any of these Appetizers/Entrees/Sides" in the respective category.

At the bottom of the menu, you are presented with the **total price** of your order.

Please imagine you are ordering food to be delivered for dinner.

In what follows we will present you with **nine choice questions**, where you will be asked to **put together a meal order** resembling what you would typically order if you were to order food for delivery.

The **dishes that we present to you resemble what you would typically find on a delivery menu** and they **remain the same in each of the nine questions**. However, their **price in each question changes**. All other attributes not mentioned here are assumed to be the same.

When making a decision, please keep in mind that you stated earlier that your **usual weekly** expense for meals **ordered for delivery from restaurants** is **$100** and you spent **$25** on the **last meal** you **ordered for delivery from a restaurant.**

How to answer the questions:

For each of the nine questions that follow, please **compose an order corresponding to what you would be most likely to order if presented with the items at their respective prices,** which are indicated underneath the images.

Click on the items you would like to order at the indicated prices in **whatever combination you wish**. You can choose as many dishes as you would like in each category (Appetizer, Entrees, Sides). If you no longer want a previously selected item, click on it again to undo the selection.

If you do not want any of the options presented, please click "I would not order any of these Appetizers/Entrees/Sides" in the respective category.

At the bottom of the menu, you are presented with the **total price** of your order.

Figure A1.1 FM-BBCE Choice Exercise Instructions – *Restaurant* vs. *Delivery*

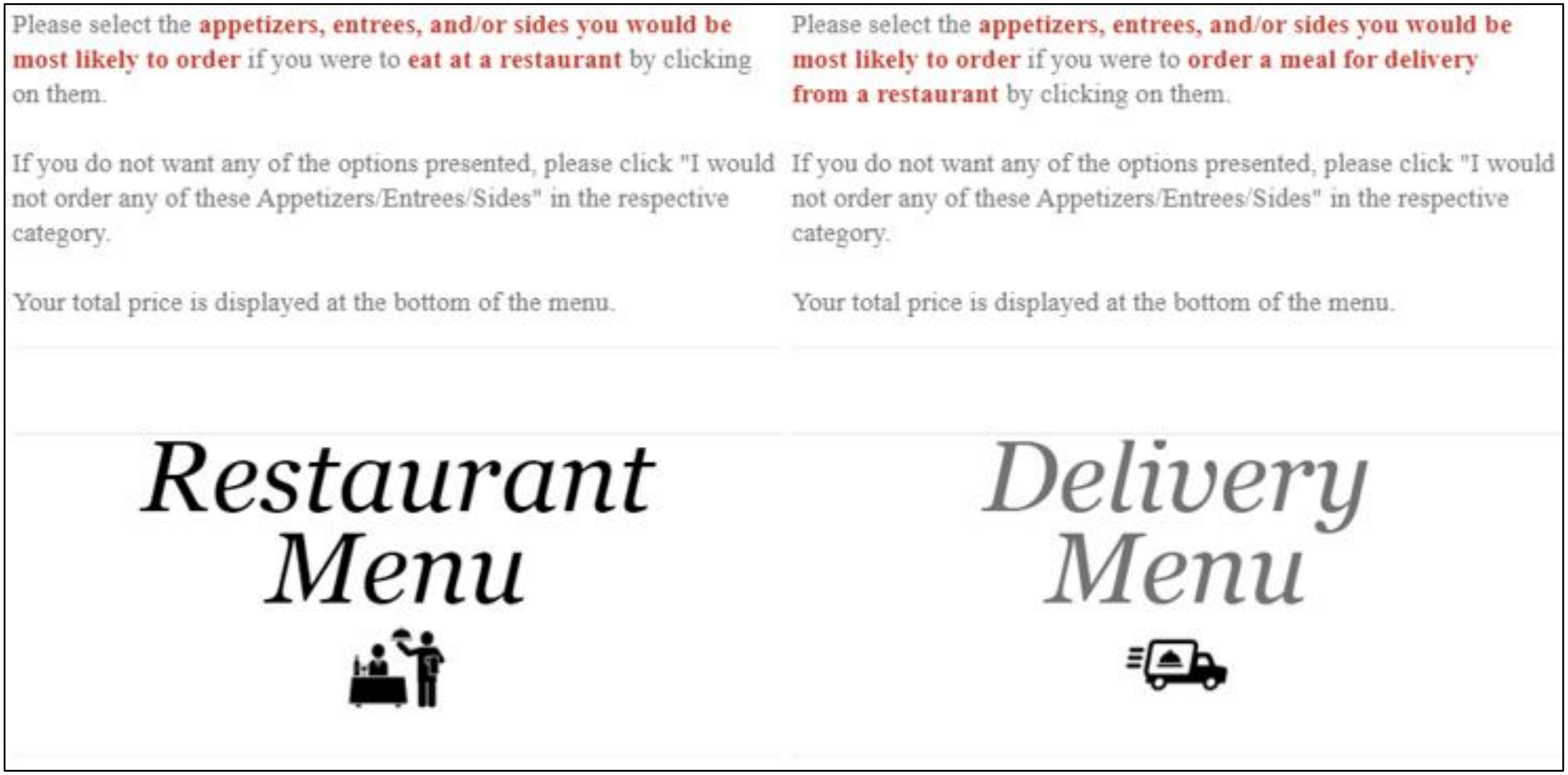

Figure A1.2 FM-BBCE Choice Question Introduction – *Restaurant* vs. *Delivery*

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CHAPTER 2: A REFERENCE PRICE INFORMED EXPERIMENT TO ASSESS CONSUMER DEMAND FOR BEEF WITH A REDUCED CARBON FOOTPRINT

1. Introduction

Agriculture accounts for about half of the land use in the U.S. (EPA 2022a). While these activities are necessary to supply society with food and other inputs, they can also have harmful consequences for the environment (Ibid.). One area that has received particular attention is livestock production. For example, a 2022 New York Times op-ed video specifically called out the beef industry for contributing significantly to climate change through methane emissions generated during the ruminant digestion (Semple et al. 2022).

In light of this, and partially motivated by the growing public pressure and consumer demand for sustainable food options (The Economist Intelligence Unit2021), the market is responding by developing production methods of meat alternatives that, for example, do not contain animal products or address some of the negative environmental effects occurring throughout the supply chain. For instance, in late 2021 the USDA approved a low carbon beef verification scheme (USDA AMS 2022). The certification can be applied to cattle which has been raised with at least 10% less emissions than the industry baseline according to the Low Carbon Beef Scoring Tables (USDA AMS 2022). Yet, a change in production practices that qualify farmers for such a verification is likely to be associated with additional operational costs, which need to be offset by a market premium if a wide-scale adoption of the label is to take place.

Indeed, some studies have shown consumers value sustainability labels on products, especially on meat products (see e.g., Van Loo et al. 2014). But others, found that respondent's WTP for a premium for food traded with carbon footprint labels varies in magnitude and across products, socio-demographic groups, as well as geographic regions (Li et al. 2016; Rondoni and

Grasso 2021). It now remains to be seen whether beef products falling under the new verification scheme will succeed in the food market. We address this question by assessing consumer preferences and demand for beef labeled to have a lower carbon footprint . In doing so, we also evaluated the potential market performance of this novel labeling program relative to other widely available production claims on beef products, such as the USDA-certification for organic and animal welfare certified products, (Beef Checkoff 2021; Animal Welfare Institute 2021) as well as beef produced with conventional methods.

There is a dearth of market data on lower carbon footprint certified beef product. Hence, to achieve this objective we used an online discrete choice experiment (DCE) on ribeye selection administered to 777 U.S. consumers. One of the main challenges when designing a DCE is to use a range of price levels that cover actual market prices since the latter often fluctuate over time and across locations, especially for certain food products like meat (Debelle and Lamont 1997; Hill 2004; Piot-Lepetit 2011; Mghenyi et al. 2011). To illustrate, the weighted average price for a branded boneless ribeye steak in the first week of August 2021 was $14.04 in the Northeast of the US compared to $9.77 in the Southeast (USDA 2021). Correspondingly, during that week the national weighted average price for the same cut was $13.19 compared to a price of $8.62 during the same week in the previous year. Such significant market price variation for ribeye steak across time and space adds an additional degree of difficulty in demand analyses based on experimental data. For instance, how should researchers incorporate such market price variations in DCEs scenarios?

To reflect actual market prices in DCEs, researchers typically use price levels that cover the real price range, or by limiting it within their design, irrespective of actual price fluctuations (Caputo and Scarpa 2022). Such practices raise concerns regarding how price range impacts stated choice behavior. Indeed, past DCE studies found that different price vectors and price ranges affect choice outcomes (Carlsson and Martinsson 2008; Mørkbak et al. 2010; Kragt 2013; Aravena et al. 2014; Su et al. 2017; Contini et al. 2019; Lemos et al. 2022) and that external pricing information increase reference price uncertainty (Caputo et al. 2018a; 2020). Therefore, as a second objective of this study, we test a novel design we termed Reference-Price-Informed (*RP-Informed*) design. The *RP-Informed* design incorporates individual's reference prices into DCEs, thus reflecting what consumers experience in actual food markets. We postulate that the *RP-Informed* design leads to less price uncertainty among respondents and produces more conservative demand estimates as prices better correspond with respondent's expectations, thus increasing choice realism. We test these hypotheses by asking respondent's to report their reference price and further separating our respondents into one of three treatments: (1) an experimental design using four prices that cover the range of prices available in the market, (2) a design covering the same range but employing eight price levels, and (3) a four-price-level design in which respondents are presented with prices covering either the upper or lower half of the market price range, in accordance with their individual reference price (i.e., the *RP-Informed* design).

Our results project a very small market share of the low-carbon ribeye (3% - 4%), which is consistent across all tested treatments and models. A reference-dependent model and a model accounting for uncertainty improve the model fit relative to a basic MXL in all treatments. The results also suggest that the reference price informed design captures a lot of respondent's uncertainty. Our results also hold in a robustness test, where we assessed the model fit and simulated market share for a fourth treatment in which respondents saw price levels that contrasted their internal reference price.

Taken together, results from our study provide three contributions to the existing food choice and choice modeling literatures. First, from an empirical perspective we provide fresh insights on consumer preferences and demand for an emerging product (beef with a reduced carbon footprint) which is of relevance in society's efforts to mitigate the climate impact of agriculture. The derived estimates can be useful to producers and marketers faced with input, production, pricing, and marketing decisions. Likewise, policymakers can build upon our results to inform their decision-making on whether and how to support the development of such emerging products or the farmers involved in their production. Secondly, our study complements the existing reference price related literature by providing a simple way to incorporate reference prices into the experimental design. As discussed above, studies have already shown the substantial influence that reference prices can have on respondent's choice behavior in non-market valuation studies. Our design goes a step further than the existing literature by recognizing that prices and subsequently reference prices vary over time and across locations, which can lead to pricing biases in food experiments when ignored. Beyond just food marketing and agricultural economics, the proposed experimental procedure can be applied in a wide spectrum of fields. It allows researchers to more realistically design (food) DCEs. The use of more realistic designs is particularly important in economic environments where inflation or policy changes can rapidly alter market prices, as witnessed during the 2021/2022 record inflationary period for food products (USDA ERS 2022). Our proposed design ensures that respondents are presented with prices aligning with their expectations. This approach in turn improves the external validity of the conducted studies, and thus serves policy makers and stakeholders along the value chain who rely on the accuracy of scientific results in their decision-making processes. Lastly, we generate insights into how consumers make food choices under market conditions in which market prices conform to respondents' internal reference prices, and when they fail to conform. This can be used by producers, marketers, and policy makers to evaluate how potential price changes might affect their demand beyond just the products of interest.

The remainder of the chapter is organized as follows: in the next section we provide an overview over the existing literature, followed by a description of the experimental procedures, which includes a description of the data analysis process used. We then discuss the results in section 4 and conduct a robustness test in section 5. We conclude in section 6.

2. Reference prices in the literature: A Background

Prospect theory (Kahneman and Tversky 1984; Tversky and Kahneman 1991) for which Kahneman was awarded the Nobel prize in economics in 2002, states that consumers perceive losses and gains differently, i.e., the loss of a given quantity is felt more harshly than its gain. Whether something is perceived as a loss in a purchasing situation heavily depends on a consumer's price expectation. According to Hicks (1939) and Oliver and Winer (1987), a consumer's price expectation is predominantly formed by three key factors: *"(1) non-economic factors (e.g., political events, psychological factors), (2) economic but non-price factors (e.g., supply and demand), and (3) actual past and present price experiences.*" (Oliver and Winer, 1987 pg. 478). Particularly the past price experiences can form price expectations or reference prices, which constitute "*an internal standard against which observed prices are compared*" (Kalyanaram and Winer 1995, pg. G161), i.e., whether the purchase of the product would constitute a loss or a gain in utility terms.

Several theoretical and empirical studies utilizing secondary data sources like scanner data have clearly demonstrated the effects of reference prices on consumer demand (Winer 1986; Kalyanaram and Winer 1995; Mazumdar et al. 2005) and shopping behavior (Briesch et al. 1997;

Neumann and Böckenholt 2014), suggesting that reference-price-dependence plays a critical role in predicting decision makers' choice behavior. For example, Winer (1986) and Briesch et al. (1997) showed that including the reference price in a model enhances the model's ability to predict consumer behavior. Comparing two stimulus-based (external) reference models and three memory-based (internal) reference models the authors look at four different products (coffee, peanut butter, laundry detergent and tissues), and find that all models outperform that of not integrating the reference price for all products. Further, they observe that the memory-based price relying on the past prices paid for the specific brand surpasses with regards to the operationalization of the reference price. However, like many studies looking at reference prices Briesch et al. (1997) utilized secondary data. While secondary data is suitable when exploring the data for well-established products, it has several drawbacks when it comes to novel products or products still unavailable in the market.

Reference price effects are also largely documented in the experimental economics literature, especially within the realms of non-market valuation methods (see for example Adaval and Monroe 2002; Hess et al. 2006; Hu et al. 2006; Drichoutis et al. 2008; Wolk and Spann 2008; Rose and Masiero 2010; Day et al. 2012; Ahmad 2015; Caputo et al. 2018a & 2020; Contini et al 2019). Within the realm of DCEs, Hess et al. (2006) looked at consumer preferences for transportation options by providing respondents with a reference commute in comparison to two alternative routes in the context of a DCE. Running costs and toll costs were included as attributes, thus respondents were externally provided with a reference price. Their results show that reference points have a significant influence on preference formation. Within the food choice environment Hu et al. (2006) also included reference prices within their analysis of a DCE but in contrast to the above study the authors did not provide their respondents with an artificial reference price. Rather, they asked them what their typical expenditure on bread was . The authors paid particular attention to whether the price levels in the choice task alternatives represented a gain or a loss for the respondents in comparison to the stated reference price. Results show that in line with prospect theory (Kahneman and Tversky 1984; Tversky and Kahneman 1991) particularly the coefficient for perceived losses relative to the reference price was significant. More recent food DCE studies have also demonstrated that reference price formation is affected by market price information that consumers experience in actual shopping situations (Caputo et al. 2018a).

This finding raises several questions regarding the way DCE are designed. For instance, how do consumers adjust their choice behavior relative to the price levels they are presented with in the experimental design? Does the range or number of price levels matter? Does this change depend on their internal reference price? If so, should researchers select price levels to reflect individuals reference prices? Hensher et al. (2015) stressed that the correct determination of attribute levels is highly complex and it actively impacts on how respondents answer the choice questions. For example, in a 2006 study Hensher found that with regards to reference points related to traffic experiences, respondents adjusted their choice behavior and observation of additional attributes if the attribute level deviated from their reference levels.

3. Experimental Procedures and Sampling

3.1 Design and Experiments

To find an answer to the above questions we designed a DCE focused on choices between ribeye steaks. We selected this product for three main reasons. First, in the U.S. red meat consumption exceeds 220lbs per person per year (Widmar 2021), with ribeye steaks being one of the most frequently chosen cuts (USDA AMS 2021; Beef Checkoff 2020). Second, cattle production is also a major contributor to the emission of methane in agriculture due to enteric fermentation (EPA

2022b). Lastly, in late 2021, the USDA approved a USDA verified program for low carbon beef, i.e., beef which over its lifetime emits at least 10% less greenhouse emissions than the industry baseline (USDA AMS 2022). Taken together, these reasons make (low carbon) ribeye steak the ideal focal product of this study.

The experimental design was developed following existing food DCE studies, while also exploring how endogenously varying the price vector to reflect individual's reference prices in DCEs influences food choice behavior. In the food choice literature, the vast majority of DCE studies are designed with four price levels (see Caputo and Scarpa 2022 for a detailed discussion), although the use of more price levels is not unheard of, particularly in certain areas such as wine research (e.g., Tait et al. 2019). To reflect this, we implemented the following designs: A standard design with four price levels that are spread out to cover the range of existing prices in U.S., which we named *WIDE-4*; and a standard design with eight price levels that are spread out to cover the same wide range of existing prices as *WIDE-4*, named *WIDE-8*. To further explore whether and how experimentally designed price levels and ranges influence choice behavior and reference price formation, we implemented a third design, which presented respondents with price levels corresponding to their reference price. Respondents with a reference price equal to or below $20.49 were presented with four price level covering the lower half of the prices used in *WIDE-4*, while respondents with a reference price above $20.49[17], saw four price level which envelope the upper half of the prices used in *WIDE-4*. We named this treatment *RP-Informed.*

[17] As this study is exploratory, we defined the threshold of $20.49 (which is the average of the price levels we used) ex-post. Numerous thresholds were tested and assessed (e.g., the average price of the lower price range, the average reference price, etc.) with results remaining consistent across the cutoffs. We selected the threshold of $20.49 due to its suitability and easy applicability in future studies. In future studies Researchers can simply take the average of their price levels as the cutoff for an automatic assignment to a low price or high price group respective to their reference price during the data collection phase. In our current study respondents who do not meet the criteria set for the *RP-Informed* treatment fall into the below discussed fourth treatment used as a robustness check.

In all the treatments (*WIDE-4, WIDE-8,* and *RP-Informed*), respondents were asked to report their reference price prior to the DCE exercise. Similarly to the wording used by Caputo et al. (2018a, 2020), we asked respondents *"What price would you expect to pay per pound for a ribeye steak of your choice in a store?"*. The assignment to one of the three treatments was random. Aside from the different price level utilized in the treatments, the choice questions did not differ in terms of instructions, wording, or imaging (Figure A2.1 in the Appendix displays an example of a choice question). Respondents could choose between four purchase alternatives (conventional ribeye, ribeye with a lower carbon footprint, USDA organic ribeye, or animal welfare certified ribeye) meaning we used a labeled choice experiment. A no-purchase option was included to increase choice realism.

The price levels were selected in accordance with available market prices. We utilized the prices reported in the weekly National Retail Report on Beef published by the USDA (USDA AMS 2021) as well as a review of prices found in different grocery store outlets across the country to inform our price level selection. Given its currently very limited availability in the U.S. market, we matched the price level of ribeye steak with a lower carbon footprint to those of USDA organic and Animal Welfare Certified ribeye. Table A2.1 in the Appendix reports the selected price levels across treatments for the different ribeye options in price per lb.

Given that we have four alternatives in our DCE, a full factorial design would require $4^4 = 256$ choice questions for the treatments with four price levels and $8^4 = 4096$ choice questions for the wide price range treatment with eight price levels. Subsequently, using a simultaneous fractional factorial design[18] we reduced the number of choice questions per product to only 16

[18] The simultaneous design creates attribute combinations in which the prices of an alternative are uncorrelated with the prices of the other alternatives in the experiment.

questions split into two separate blocks for all treatments using the Ngene software program (ChoiceMetrics 2018).

Beyond the DCEs and reference price related questions above, the survey further contained questions on different socio-demographics as well as questions about steak consumption habits.

3.2 Survey Implementation and Data

The survey was implemented within the survey platform Qualtrics (https://www.qualtrics.com) with management of the data collection done through Dynata (https://www.dynata.com/) a leading provider of survey samples. To ensure that the sample approximately matched the US population in terms of age, gender, education, and income we integrated quotas on participation for age, income, and gender at the beginning of the survey. Respondents had to be at least 18 years of age to participate. An additional qualification for their participation was that they had consumed ribeye in the last three months. This resulted in the collection of 583 completed responses.

The overall sample is widely in line with the U.S. census recorded population means (see Table A2.2 in the Appendix). The median age in our sample (50 years) is above the national median (38.2 years) (U.S. Census Bureau 2020), which we attribute to the age restriction imposed on our sample. In line with other food choice experiment studies (e.g., Loureiro and Umberger 2007), we also note a higher share of respondents with a college degree than the U.S. average (national average of 37.9%, U.S. Census Bureau 2022). Across all samples the average reference price was about $12.24 which is below the national average price for boneless ribeye ($13.08) at the time of the data collection (November/December 2021) (USDA AMS 2022). Meanwhile, the average of the lowest (highest) price respondents expect to find in 90% of the stores is $10.02 ($13.65).

3.3 Research Hypotheses and Empirical Strategies

Our experimental set up allows us to formulate and empirically test three research hypotheses. They all relate to how endogenously varying price information across DCE experiments affects consumer food choice behavior.

Our first research hypothesis relates to how presenting consumers with a high variance of observed market prices influences their purchasing behavior. Earlier studies found that price vectors and their range influence respondent's choice behavior (Carlsson and Martinsson 2008; Mørkbak et al. 2010; Kragt 2013; Aravena et al. 2014; Su et al. 2017; Contini et al. 2019; Lemos et al. 2022). Other studies also demonstrated that a higher reference price uncertainty increases the probability of respondents choosing the "none" option in food DCEs (Caputo et al. 2018a). Presenting respondents with a price vector and range that more closely align with their reference price might signal the validity of their prior beliefs and thus reduce uncertainty. Therefore, we hypothesize that providing narrower price ranges that correspond to respondent's reference price will result in a lower selection frequency of the opt-out option than when the experimentally designed price vector covers a wide range that does not take respondent's reference price into consideration; That is: we will see a higher probability of selecting the opt-out option in the *WIDE4* and *WIDE8* treatments compared to the *RP-Informed* treatment (**H1**). To test this hypothesis, we first estimate a mixed logit model (MXL) for panel data (Train 2009) (*Model 1 – Single Price)* and then use the estimates from the model to calculate the choice shares of the various products alternatives and the "opt-out" option. In the MXL the choice probabilities of choosing alternative j is:

[1] $$\mathrm{P}\{j\} = \int_{\tilde{\alpha}_n} \prod_{t=1}^{T} \frac{e^{V_{njt}}}{\sum_j e^{V_{njt}}} f(\tilde{\alpha}_n | \mu, \Omega) d\tilde{\alpha}_n$$

where V_{njt} is the observed portion of the utility; $f(\tilde{\alpha}_n|\mu,\Omega)$ is the probability density function of the random coefficients; μ is the vector of the *J-1* estimate means; and Ω is the variance-covariance matrix.

We express the observed portion of the utility, V_{njt}, as follows:

[2] $$V_{njt}=\alpha_n\, PRICE_{njt} + \ ASC_{nj};$$

where α_n is the price coefficient representing the marginal utility of money, $PRICE_{jt}$ is a vector of price levels posted for alternative j in choice task t during the DCE exercise; ASC_{nj} is an alternative-specific constant for *J-1* product alternatives representing the purchase options available in our study (conventional, lower carbon, organic, and animal welfare certified ribeye) with the constant of the opt-out option normalized to zero for identification purpose. The distribution of the ASC is assumed to be normal, while the price coefficient is assumed to follow a constrained triangular distribution. We then employ the estimates from [1] to compute the unconditional choice (market) shares of the various product alternatives and the opt-out-option. This was done via parametric bootstrapping following the procedures illustrated in Krinsky and Robb (1986) and applied by for example Chang et al. (2009) and Caputo et al. (2018b).

Our second research hypothesis (**H2**) concerns the effects of reference prices on choice behavior. In line with previous studies such as Caputo et al. (2018a, 2020) we postulate that accounting for reference price effects leads to an increased model fit. To test this hypothesis, we estimate a second MXL model assuming reference-price dependence (*Model 2- Reference-Price*). The systematic portion of the utility is expressed as follows

[3] $$V_{njt} = ASC_j + \beta(p_{jt} - \tilde{r}_n)I_{r_{nj}<p_{jt}} + \gamma(p_{jt} - \tilde{r}_n)I_{r_{nj}>p_{jt}}$$

where $I_{r_{nj}<p_{jt}}$ is an indicator function equaling one if the reference price is lower than the posted price and zero otherwise, while $I_{r_{nj}>p_{jt}}$ equals one if the reference price is higher than the posted price. Correspondingly β and γ are the respective price coefficients if $\left(p_{jt} - \tilde{r}_n\right)$ is positive (i.e., the respondent experiences a loss relative to his reference price) or negative (i.e., the respondent experiences a gain). The self-reported reference price is represented by $\tilde{r}_n$.

We then compared *Model 2 – Reference-Price* with the choice model only assuming a single price effect (*Model 1 – Single-Price*). We expect *Model 2-Reference-Price* to better explain choices than *Model 1 – Single-Price* in all treatments. Following prospect theory (Kahneman and Tversky 1979) we thus expect that respondents will perceive losses and gains relative to the prices that they are presented with, even in the *RP-Informed* treatment meaning *Model 2* will be more appropriate to capture respondent's preferences.

Closely aligned with **H2** is our third hypothesis (**H3**) that the reference price informed design leads to a reduction in uncertainty among respondents. Research suggests that respondents tend to tie their choices to the price levels that they are presented with (see e.g., Gracia et al. 2011; Ladenburg & Olsen 2006; Su et al. 2017; Lemos et al. 2022). A disconnect between those price levels and their reference price might lead to more uncertainty. To test this hypothesis, we will estimate a third model in which we integrate uncertainty in line with the derivation detailed in Caputo et al. (2020) (*Model 3 – Uncertainty*). We can represent the expected utility of alternative j, as follows (We omit the t-subscripts for clarity):

$$[4] \quad E\left[V_{nj}\right] = ASC_j + \beta\Phi(\theta)\left\{p_j - \bar{r}_n + \eta_n\left[\frac{\phi(\theta)}{\Phi(\theta)}\right]\right\} + \gamma\left(1 - \Phi(\theta)\right)\left\{p_j - \bar{r}_n - \eta_n\left[\frac{\phi(\theta)}{1-\Phi(\theta)}\right]\right\}$$

where Φ represents the cumulative distribution function of the standard normal distribution and ϕ is the corresponding probability density function. Correspondingly, β and γ are the respective price coefficients if $(p_j - \tilde{r}_n)$ is positive (i.e., the respondent experiences a loss relative to his reference price) or negative (i.e., the respondent experiences a gain). The mean subjective reference price is denoted by $\bar{r}_n$ and η_n represents the standard deviation of the subjective reference price. Lastly, $\theta = (p_j - \bar{r}_n)/\eta_n$[19].

We then compare the fit of *Model 2 – Reference-Price* with the fit of *Model 3-Uncertainty* using model fit criteria such as the log-likelihood function, the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC). In addition, we use the Vuong-test (Vuong 1989) to determine which of the three models provides the best specification[20] for the data. An insignificant Vuong statistic for the *RP-Informed* treatment would support **H3**. Implications of these three research hypotheses are further discussed in terms of market shares, implied demand curves, and elasticities.

4. Results

We begin by focusing on our first hypothesis (**H1**), i.e., the share of the no-buy option is higher in the *WIDE-4* and *WIDE-8* treatments than in the *RP-Informed* treatment. From the simulated unconditional market shares from the MXL model in Figure 2.1 we note that only about 26% of consumers are predicted to opt-out of purchasing ribeye steaks in the *RP-Informed* treatment compared to 39% and 43% in the *WIDE-4* and *WIDE-8* treatments, which validates our **H1** research hypothesis. This result is in line with the findings in Caputo et al. (2018a): a decrease in reference price variability leads to a decrease in the no-buy selection. It also corresponds to the

[19] See Caputo et al. (2020) for an explanation of the derivation and interpretation of the equation.

[20] The appropriate test for our non-nested hypothesis is the one laid out in Vuong (1989). The test uses the Kullback-Leibler information criterion where the average difference in the log-likelihood of the two competing models (Model 1 vs Model 2, Model 1 vs. Model 2, Model 2 vs. Model 3) is tested against the null hypothesis that the difference is zero. A detailed breakdown of the derivation can be found in Henscher et al. (2015).

conclusions made by Rose et al. (2008) who advocated for reference price informed designs in DCEs.

The predicted market shares also reveal that irrespective of the treatment, the conventionally produced ribeye steak alternative has the highest market share. This aligns with other surveys finding that only about 25% of consumers purchased beef with specific production method claims (Beef Checkoff 2021). In fact, without differentiating by cut and in terms of volume, beef with such claims (e.g., grass fed, natural/naturally raised, organic and antibiotic free) constitutes only about 3% of all beef sales (NielsenIQ 2021) Among the alternatives with a special production claim in our DCE, the lower carbon alternative is the least preferred option. In contrast, the organic alternative is generally the most preferred production claim in all treatments followed closely by the animal welfare certified steak. Our results are in line with the findings by Van Loo et al. (2014) who found that consumers had the highest preference for animal welfare related claims on eggs over claims such as the carbon footprint label. They also resonate with the results by Li et al. (2016) who found that less than a quarter of respondents would pay more for climate friendly beef production practices. The difference in preferences could be induced by a lack of familiarity with the production methods: past studies have shown the positive impact that a greater product familiarity can have on purchase decisions (see e.g., Park & Lessig 1981).

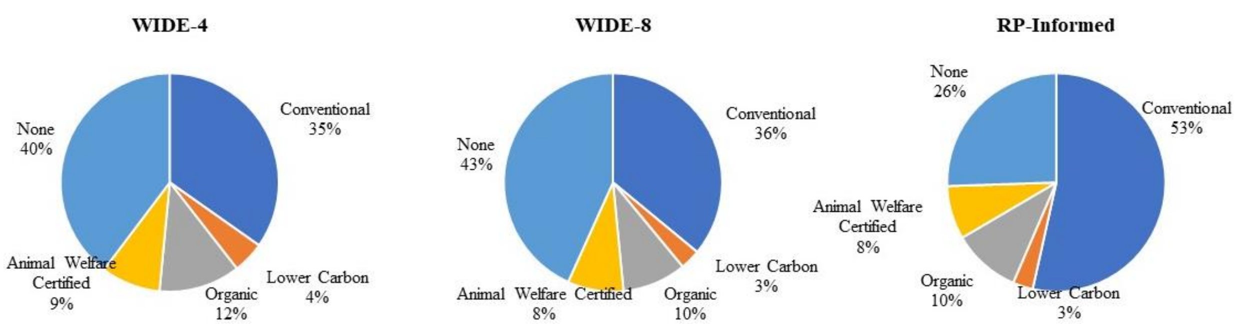

Figure 2.1 Unconditional Market Share of the available alternatives across treatments

While we might be able to explain the low market share of the lower carbon alternative relative to the other options, the results shown in Figure 2.1 also raise the question of what might cause the decrease in the share of the no-buy alternative across treatments. One explanation could be a decrease in uncertainty for respondents facing experimental price levels that reflect their internal reference price. Indeed, reference price uncertainty is found to affect food choices, including the probability of opting out from purchasing anything (Caputo et al. 2018a, 2020). To further explore this, as discussed in the methods section, we estimated two additional choice models: a MXL model which accounts for reference price effects (*Model 2-Reference-Price*) and a MXL model integrating reference price uncertainty (*Model 3-Uncertainty*). As laid out above, we hypothesize (**H2**) that Model 2 will lead to an increase in model fit relative to Model 1 for all treatments. However, we also hypothesize (**H3**) that there will be no significant increase in model fit for the *RP-Informed* treatment when comparing Model 2 and Model 3, as the reference price informed design decreases respondent's potential reference price uncertainty. Table 2.1 reports various model fit criteria (AIC and BIC), as well as the results of the Vuong test (Vuong 1989), which we use to discriminate across models.

Models 2 and 3 fit the data better than model 1 across all treatments as demonstrated by lower AIC and BIC values, and the results of the Vuong test supporting **H2**. Most notably, in line with **H3**, we find a significant increase in model fit for model 3 relative to model 2 for the *WIDE-4* and *WIDE-8* treatments, but no significant difference in the *RP-Informed* treatment. We also note that the slightly better fit in the data from the *WIDE-8* treatment relative to those for the *WIDE-4* treatment indicate that if no reference price assignment is chosen, more price levels might be preferable to fewer. However, in many cases this also requires a larger design, meaning the researcher might have to make trade-offs between design size and model fit.

Table 2.1 Model Fit Comparison across the three models

	WIDE-4	WIDE-8	RP-Informed
Model 1			
Log-Likelihood	-1539.7	-1397.17	-1477.3
BIC/N	1.956	1.862	1.816
AIC/N	2.017	1.921	1.786
# of Parameters		9	
Model 2			
Log-Likelihood	-1484.4	-1361.3	-1433.2
BIC/N	1.892	1.820	1.767
AIC/N	1.946	1.873	1.735
# of Parameters		10	
Model 3			
Log-Likelihood	-1483.5	-1360.7	-1432.1
BIC/N	1.891	1.820	1.766
AIC/N	1.945	1.873	1.733
# of Parameters		10	
Vuong Test*			
Model 1 v 2	**-6.253**	**-5.723**	**-9.054**
Model 1 v 3	**-6.259**	**-5.728**	**-9.055**
Model 2 v 3	**-1.967**	**-2.212**	-0.395
# of Choices (N)	1608	1536	1664

* Bolded values indicate a significant difference at the 5%-level.

To explore whether and how these differences in model fit translate into differences in choice behavior, we now turn our attention to the structural estimates from models 1-3. We do so by briefly discussing the parameter estimates from the models, and then by deriving and examining the demand curves from each of the three models. Table A2.4 in the Appendix reports the parameter estimates from the three models and corresponding standard deviations for the different alternatives across the three models[21]. The estimated price coefficient is negative and significant: as one expects, a price increase induces a decrease in demand. We also find that the loss coefficient

[21] The respective parameter estimates from the Multinomial logistic (MNL) model are reported in Table A2.3

is negative and significant in accordance with previous DCE studies (see e.g., Hu et al. 2006; Caputo et al. 2018a, 2020; Tonsor 2018). In absolute terms in Model 2 the loss coefficient is larger than the gain coefficient, which follows the basic principles of prospect theory that losses are perceived more strongly than gains (Kahneman and Tversky 1979). However, the gain coefficient is positive but only slightly significant. The same result holds in Model 3. Potentially this is due to some consumers perceiving a higher price as a proxy for quality (Rao 2005). In some products, such as wine or olive oil, a higher price might be taken as a signal (in the respondent's mind) for higher quality (Cronley et al. 2005; Roberts and Reagans 2012; Romo-Muñoz et al. 2017). Thus, as long as the price levels of alternatives in the choice task are below the respondent's reference price the alternatives are perceived as a gain, and respondents might be willing to choose the alternative with a higher price.

We now turn our attention to the demand curves and elasticities derived from the estimates of models 1-3[22]. We focus on the demand curves estimated for the lower carbon ribeye (see Figure 2.2). What can clearly be seen is that the estimated demand curves differ substantially across the three treatments demonstrating the impact that the price vector selection has on choice behavior. Across our models, we derive the most conservative estimates in the *RP-Informed* treatment, which could suggest that the reference price informed experimental design leads to a reduction of bias induced by respondents anchoring their choices to the price levels they are presented with (Brzozowicz and Krawczyk 2022). We also find that the demand curves increase in steepness as we move from Model 1 to Model 3 reflecting the decline in elasticity estimates.

[22] The demand curves and elasticities were derived from the estimates of models 1-3 as well as the parametric bootstrapping. For the demand curves, we focused on the lower carbon alternative. The price of the other three alternatives was held constant at the average price across treatments and respective price levels, while the price of the lower carbon alternative varied. This approach aligns with previous studies such as Lusk and Tonsor (2016) and Van Loo et al. (2020).

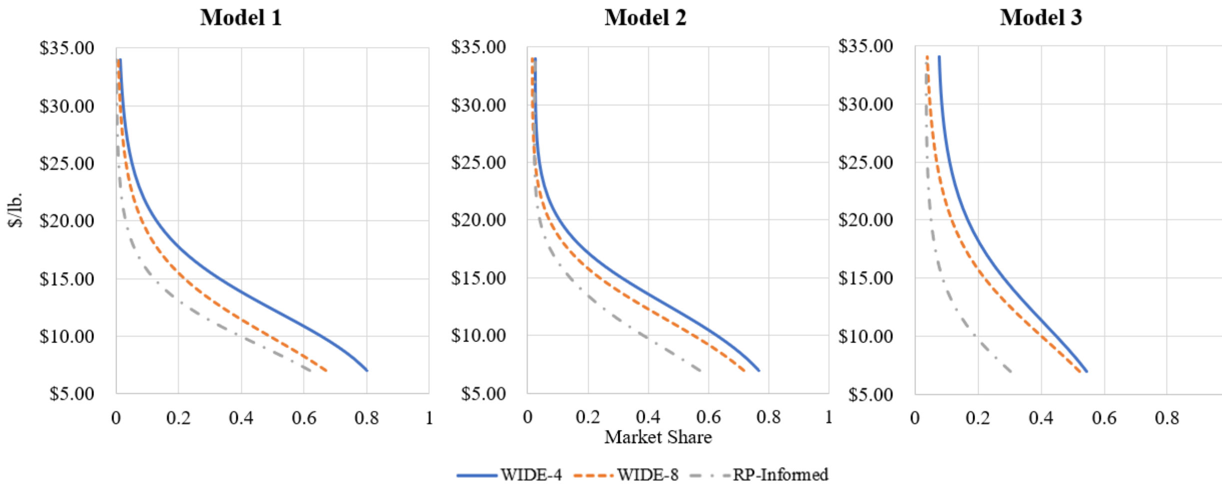

Figure 2.2 Implicit Demand Curves for the Lower Carbon Ribeye

This evidence is also reflected by the own-price elasticities, which are reported in Table A2.5 in the Appendix. They reveal that estimates of demand elasticity decrease as we move from model 1 to model 3. This aligns with the results by Caputo et al. (2020). In addition, we see that the inferred elasticities vary substantially across treatments. For example, across all models the own-price elasticity of the conventional option varies between -0.747 (Model 3) to -1.134 (Model 1) in the *RP-Informed* treatment, while it is substantially more elastic in the other two treatments.

To summarize, our results indicate that assigning respondents to experimental designs with price levels which reflect more closely their reference prices will result a) in a lower market share of the no-buy option, b) a higher model fit, and c) more conservative demand estimates.

5. Robustness Check

To assess the robustness of our results we also collected the data needed to create a counterfactual to the *RP-Informed* treatment. To do so we created another treatment ex-post, which we call the *UNMATCHED* treatment. In this treatment respondents with a reference price above (below) the $20.49 cutoff, saw the low-price (high-price) vector employed in the *RP-Informed* treatment, i.e., they were assigned to prices not aligned with their internal reference price. 194 respondents were assigned to this treatment (See Tables A2.6 and A2.8 in the Appendix for the demographics and parameter estimates, respectively[23]). Following the same procedure explained above we derived the unconditional market shares, which are reported in Figure 2.3.

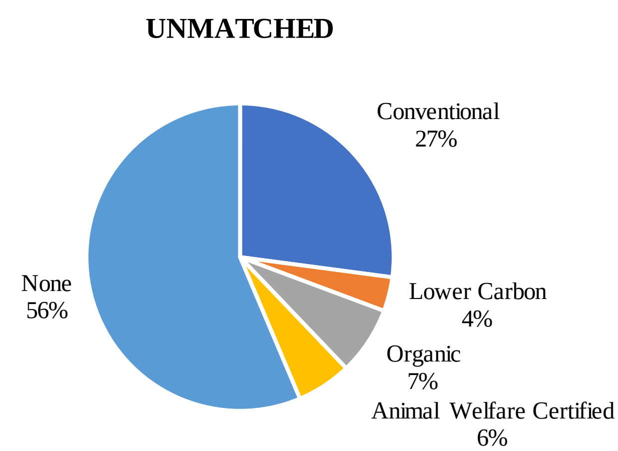

Figure 2.3 Unconditional market share of the available alternatives in the UNMATCHED treatment.

As can be seen we have a substantially lower market share of the conventional ribeye, while the predicted share of the no-buy option exceeds that of the other treatments by at least 13%. This result corroborates **H1** and again demonstrates how the selection of inadequate price vectors can affect choice behavior. Looking at the model fit of models 1-3 for this treatment, we surprisingly see that the model fit overall is better than that of other treatments (see Table A2.9 in the Appendix). However, this might be attributable to the high selection of the opt-out option in this treatment (53%). Nevertheless, in line with **H2** we find a significant increase in model fit when

[23] The respective MNL parameter estimates are reported in Table A2.7.

going from Model 1 to models 2 and 3. Likewise, in line with **H3,** we also find that the model fit increases significantly in Model 3 relative to Model 2.

6. Conclusion

Within the agricultural field, animal production, in particular beef production, is one of the main emitters of climate damaging gasses (EPA 2022b) leading to widespread concern across the public worldwide (Semple et al. 2022). Partially motivated by this, and by concerns related to the contribution of animal production to climate change, the USDA has introduced a certification scheme for beef with a reduced carbon footprint (USDA AMS 2022). In our study, we assessed consumer preferences and demand for ribeye steak that falls under such a scheme, relative to steak from alternative production methods widely available in food markets: organic, animal welfare certified, conventional.

We surveyed 777 U.S. respondents on their ribeye steak consumption preferences using a DCE. While applied widely in the food choice literature (see Caputo and Scarpa 2022 a review) especially when assessing consumer preferences and demand for novel food items, questions about DCEs' external validity remain, especially regarding how researchers include price information that are able to mirror actual market price variations. Our study adds to the existing choice modeling literature by introducing a reference price informed design. Using a between sample approach, we split our experiment into four treatments that varied by the underlying experimental design: a four (eight) price-level treatment with a price vector covering the available market range named *WIDE-4* (*WIDE-8*), a four price-level treatment where respondents saw prices covering either the lower or upper half of the market price range in line with their reference price (*RP-Informed*), and a treatment where respondents saw the lower or upper half of prices not in line with their reference price (*UNMATCHED*), which served as a robustness check. In doing so, we could assess whether a reference price informed design (i.e., the *RP-Informed*) accounts for reference price effects and reduces reference price uncertainty. In the analysis of our data, we tested three separate models to help us answer this question: a basic MXL model (*Model 1 - Single-Price*), a reference-dependent MXL model (*Model 2 - Reference-Price*), and a model incorporating reference price uncertainty (*Model 3 – Uncertainty*).

Across all treatments we find that respondents clearly prefer all other alternatives to the lower carbon ribeye. So, the verification scheme might not lead to the intended market response. This is re-affirmed when looking at the predicted unconditional market share, where the lower carbon alternative is predicted to not exceed 4%. When comparing the different treatment with one another we find that the highest share of consumers is predicted to opt-out of purchasing anything in the *UNMATCHED* treatment (56%). In contrast, we measure the lowest opt-out market share for the *RP-Informed* treatment (26%), which is an indicator for the level of uncertainty present in the sample (Caputo et al. 2018a, 2020). We find a significantly better model fit for models 2 and 3 relative to Model 1, but no significant improvement in fit when comparing Model 2 and Model 3 for the *RP-Informed* treatment. In all other treatments a significant improvement in fit can be found when going from Model 2 to Model 3. Moreover, the implicit demand curves for the lower carbon ribeye reveal that the most conservative estimates are derived by following the approach used in the *RP-Informed* treatment, which could indicate that the design minimizes anchoring-induced biases.

Taken together these results suggest that a reference price informed experimental design produces more conservative results. The application of such design is of particular value when considering goods or services with a wide price range such as wine, seafood products, other meat products, etc. Likewise, it can be of use when goods and market environments are affected by processes such as rapid inflation or policy changes that impact the market prices. As shown by Poken et al. (2022), the historic 2022 food price inflation had varying impacts across locations particularly for meat products. Our proposed *RP-Informed* design can capture differences in choice behavior resulting from those geographic differences and their impact on respondent's reference prices. Empirically, we also highlight that the lower carbon verification scheme might not be able to capture a relevant market share and subsequently premium to offset potential increases in costs that fall upon producers in their effort to comply with the scheme's requirements.

Nevertheless, we suggest that this topic be explored using other products and applications in future studies to test the robustness of our findings. Since we relied on primary data for our assessment, we also suggest that future studies should consider the adoption of non-hypothetical experiments and/or compare our results to secondary data sources such as scanner data.

APPENDIX

APPENDIX

Tables

Table A2.1 Price levels employed in the Experimental Designs

	WIDE-4	**WIDE-8**	**RP-Informed**	
			Low prices	High prices
Conventional	$6.99, $12.99, $18.99, $24.99	$6.99, $9.99, $11.99, $14.99, $16.99, $19.99, $21.99, $24.99	$6.99, $8.99, $10.99, $12.99	$18.99, $20.99, $22.99, $24.99
Lower Carbon/ Organic/ Animal Welfare Certified	$15.99, $21.99, $27.99, $33.99	$15.99, $18.99, $20.99, $23.99, $25.99, $28.99, $30.99, $33.99	$15.99, $17.99, $19.99, $21.99	$27.99, $29.99, $31.99, $33.99

Table A2.2 Sample Demographics

	Description[a]	Pooled	Treatments		
			WIDE-4	**WIDE-8**	**RP-Informed**
Female	1 if female; 0 if male	0.45	0.41	0.50	0.50
Age	Age in years (Median)	50	51	47	52
College	1 if obtained college degree; 0 otherwise	0.46	0.48	0.48	0.43
Low Income	1 if household income below \$75,000; 0 otherwise	0.60	0.59	0.54	0.66
Reference Price	Mean reference price in treatment	\$12.24	\$12.52	\$12.17	\$12.04
Highest Reference Price	Highest expected reference price in 90% of stores	\$13.65	\$13.71	\$13.63	\$13.61
Lowest Reference Price	Lowest expected reference price in 90% of stores	\$10.02	\$9.78	\$9.96	\$10.31
Price > Reference Price	1 if price of item > reported reference price; 0 otherwise	0.68	0.67	0.69	0.63
Price = Reference price	1 if price of item = reported reference price; 0 otherwise	0.003	0.004	0.003	0.006
Respondents per Treatment		583	192	183	208

[a] Values presented are the mean unless indicated otherwise.

Table A2.3 MNL Parameter estimates Model 1-Model 3 across treatments

Parameters	**Model 1 – Single Price**			**Model 2 - Reference-Price**			**Model 3 – Uncertainty**		
	WIDE-4	*WIDE-8*	*RP-Informed*	*WIDE-4*	*WIDE-8*	*RP-Informed*	*WIDE-4*	*WIDE-8*	*RP-Informed*
Conventional	2.48*	2.16*	1.83*	1.41*	1.10*	1.84*	1.41*	1.10*	1.84*
	(0.12)	(0.12)	(0.15)	(0.09)	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)
Lower Carbon	2.17*	1.37*	-0.31	0.93*	0.21	1.00*	0.93*	0.21	1.00*
	(0.17)	(0.20)	(0.25)	(0.13)	(0.14)	(0.21)	(0.13)	(0.14)	(0.21)
Organic	2.92*	2.31*	0.88*	1.69*	1.15*	2.22*	1.69*	1.15*	2.22*
	(0.17)	(0.18)	(0.23)	(0.12)	(0.12)	(0.19)	(0.12)	(0.12)	(0.19)
Animal Welfare	2.67*	2.13*	0.52*	1.40*	0.97*	1.83*	1.40*	0.97*	1.83*
	(0.17)	(0.18)	(0.24)	(0.12)	(0.12)	(0.19)	(0.12)	(0.12)	(0.19)
Price	-0.15*	-0.13*	-0.06*						
	(0.01)	(0.01)	(0.01)						
Loss				-0.19*	-0.15*	-0.25*	-0.19*	-0.16*	-0.26*
				(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Gain				0.01	-0.01	-0.04	0.01	0.00	-0.03
				(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)

Table A2.4 Parameter estimates Model 1-Model 3 across treatments

Parameters		**Model 1 – Single Price**			**Model 2 - Reference-Price**			**Model 3 – Uncertainty**		
		WIDE-4	*WIDE-8*	*RP-Informed*	*WIDE-4*	*WIDE-8*	*RP-Informed*	*WIDE-4*	*WIDE-8*	*RP-Informed*
Conventional										
	Mean	5.54*	5.85*	7.45*	2.79*	2.60*	3.21*	2.80*	2.61*	3.21*
		(0.28)	(0.32)	(0.46)	(0.19)	(0.22)	(0.26)	(0.19)	(0.22)	(0.26)
	SD	1.54*	1.85*	2.90*	1.38*	1.96*	2.49*	1.38*	1.96*	2.45*
		(0.16)	(0.20)	(0.26)	(0.16)	(0.21)	(0.24)	(0.16)	(0.21)	(0.22)
Lower Carbon										
	Mean	5.89*	5.33*	7.28*	2.55*	1.96*	2.05*	2.57*	1.97*	1.95*
		(0.32)	(0.41)	(0.59)	(0.21)	(0.28)	(0.32)	(0.21)	(0.28)	(0.32)
	SD	0.01	1.09*	0.84*	0.85*	0.88*	1.35*	0.85*	0.88*	1.26*
		(0.26)	(0.24)	(0.34)	(0.26)	(0.26)	(0.33)	(0.26)	(0.25)	(0.30)
Organic										
	Mean	6.37*	6.61*	8.55*	3.12*	3.03*	3.12*	3.13*	3.04*	3.35*
		(0.38)	(0.39)	(0.58)	(0.27)	(0.26)	(0.32)	(0.28)	(0.26)	(0.33)
	SD	1.54*	1.22*	1.15*	1.67*	1.65*	2.01*	1.67*	1.65*	2.07*
		(0.23)	(0.24)	(0.22)	(0.24)	(0.26)	(0.29)	(0.23)	(0.26)	(0.33)
Animal Welfare										
	Mean	6.27*	6.37*	8.19*	2.90*	2.89*	3.18*	2.91*	2.90*	3.13*
		(0.34)	(0.39)	(0.57)	(0.23)	(0.27)	(0.32)	(0.23)	(0.27)	(0.31)
	SD	1.00*	1.35*	1.24*	1.48*	1.73*	1.57*	1.48*	1.73*	1.58*
		(0.21)	(0.26)	(0.24)	(0.20)	(0.25)	(0.27)	(0.20)	(0.25)	(0.25)
Price										
	Mean	-0.33*	-0.37*	-0.49*						
		(0.02)	(0.02)	(0.03)						
	SD	0.33*	0.37*	0.49*						
		(0.02)	(0.02)	(0.03)						
Loss										
	Mean				-0.49*	-0.55*	-0.63*	-0.50*	-0.56*	-0.65*
					(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)
	SD				0.49*	0.55*	0.63*	0.50*	0.56*	0.65*
					(0.03)	(0.04)	(0.05)	(0.03)	(0.04)	(0.05)
Gain										
	Mean				0.08*	0.04	0.07*	0.09*	0.05	0.08*
					(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.04)
	SD				0.08*	0.04	0.07*	0.09*	0.05	0.08*
					(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.04)

Notes: Numbers in brackets indicate standard errors. * indicate a significance at the 5%-level or above.

Table A2.5 Own-price Elasticities of the three models across treatments.

	WIDE-4	WIDE-8	RP-Informed
Model 1			
Conventional	-2.056	-1.945	-1.134
Lower Carbon	-4.454	-4.443	-5.018
Organic	-3.414	-3.676	-3.866
Animal Welfare Certified	-3.874	-3.740	-4.100
Model 2			
Conventional	-1.875	-1.859	-0.747
Lower Carbon	-3.450	-3.767	-4.114
Organic	-3.184	-3.308	-3.180
Animal Welfare Certified	-3.287	-3.324	-3.368
Model 3			
Conventional	-1.319	-1.276	-0.777
Lower Carbon	-1.200	-1.829	-1.531
Organic	-1.106	-1.487	-1.202
Animal Welfare Certified	-1.130	-1.485	-1.295

Table A2.6 Sample demographics *UNMATCHED* treatment

Variable	Description[a]	UNMATCHED
Female	1 if female; 0 if male	0.50
Age	Age in years (Median)	49
College	1 if obtained college degree; 0 otherwise	0.40
Low Income	1 if household income below $75,000; 0 otherwise	0.61
Reference Price	Mean reference price in treatment	$13.03
Highest Reference Price	Highest expected reference price in 90% of stores	$13.63
Lowest Reference Price	Lowest expected reference price in 90% of stores	$9.69
Price > Reference Price	1 if price of item > reported reference price; 0 otherwise	0.72
Price = Reference price	1 if price of item = reported reference price; 0 otherwise	0.000
Respondents per Treatment		194

[a] Values presented are the mean unless indicated otherwise.

Table A2.7 MNL Parameter Estimates Model 1-Model 3 *UNMATCHED* treatment

Parameters	**Model 1 – Single Price**	**Model 2 - Reference-Price**	**Model 3 – Uncertainty**
Conventional	2.79*	0.57*	0.57*
	(0.30)	(0.12)	(0.12)
Lower Carbon	2.43*	-0.42*	-0.42*
	(0.43)	(0.21)	(0.21)
Organic	3.24*	0.38*	0.38*
	(0.42)	(0.18)	(0.18)
Animal Welfare	2.98*	0.13	0.13
	(0.42)	(0.19)	(0.19)
Price	-0.17*		
	(0.01)		
Loss		-0.12*	-0.12*
		(0.01)	(0.01)
Gain		-0.01	-0.01
		(0.01)	(0.01)

Table A2.8 Parameter Estimates Model 1-Model 3 *UNMATCHED* treatment

Parameters		**Model 1 – Single Price**	**Model 2 - Reference-Price**	**Model 3 – Uncertainty**
Conventional				
	Mean	6.56*	3.85*	3.85*
		(0.58)	(0.38)	(0.38)
	SD	2.52*	2.27*	2.27*
		(0.29)	(0.27)	(0.27)
Lower Carbon				
	Mean	6.21*	3.58*	3.57*
		(0.73)	(0.54)	(0.53)
	SD	1.65*	1.56*	1.55*
		(0.35)	(0.42)	(0.42)
Organic				
	Mean	7.66*	4.90*	4.90*
		(0.67)	(0.46)	(0.46)
	SD	0.60	1.11*	1.11*
		(0.50)	(0.32)	(0.30)
Animal Welfare				
	Mean	7.18*	4.47	4.47*
		(0.70)	(0.47)	(0.46)
	SD	1.16*	1.14*	1.13*
		(0.33)	(0.32)	(0.31)
Price				
	Mean	-0.39*		
		(0.03)		
	SD	0.39*		
		(0.03)		
Loss				
	Mean		-0.54*	-0.55*
			(0.04)	(0.04)
	SD		0.54*	0.55*
			(0.04)	(0.04)
Gain				
	Mean		0.15*	0.16*
			(0.03)	(0.03)
	SD		0.15*	0.16*
			(0.03)	(0.03)

Notes: Numbers in brackets indicate standard errors. * indicate a significance at the 5%-level or above

Table A2.9 Model fit comparison, *UNMATCHED* treatment

	UNMATCHED
Model 1	
Log-Likelihood	-1192.73
BIC/N	1.525
AIC/N	1.549
# of Parameters	9
Model 2	
Log-Likelihood	-1184.58
BIC/N	1.574
AIC/N	1.539
# of Parameters	10
Model 3	
Log-Likelihood	-1183.77
BIC/N	1.573
AIC/N	1.538
# of Parameters	10
Vuong Test*	
Model 1 v 2	**-3.225**
Model 1 v 3	**-3.239**
Model 2 v 3	**-3.750**
# of Choices (N)	1552

Figures

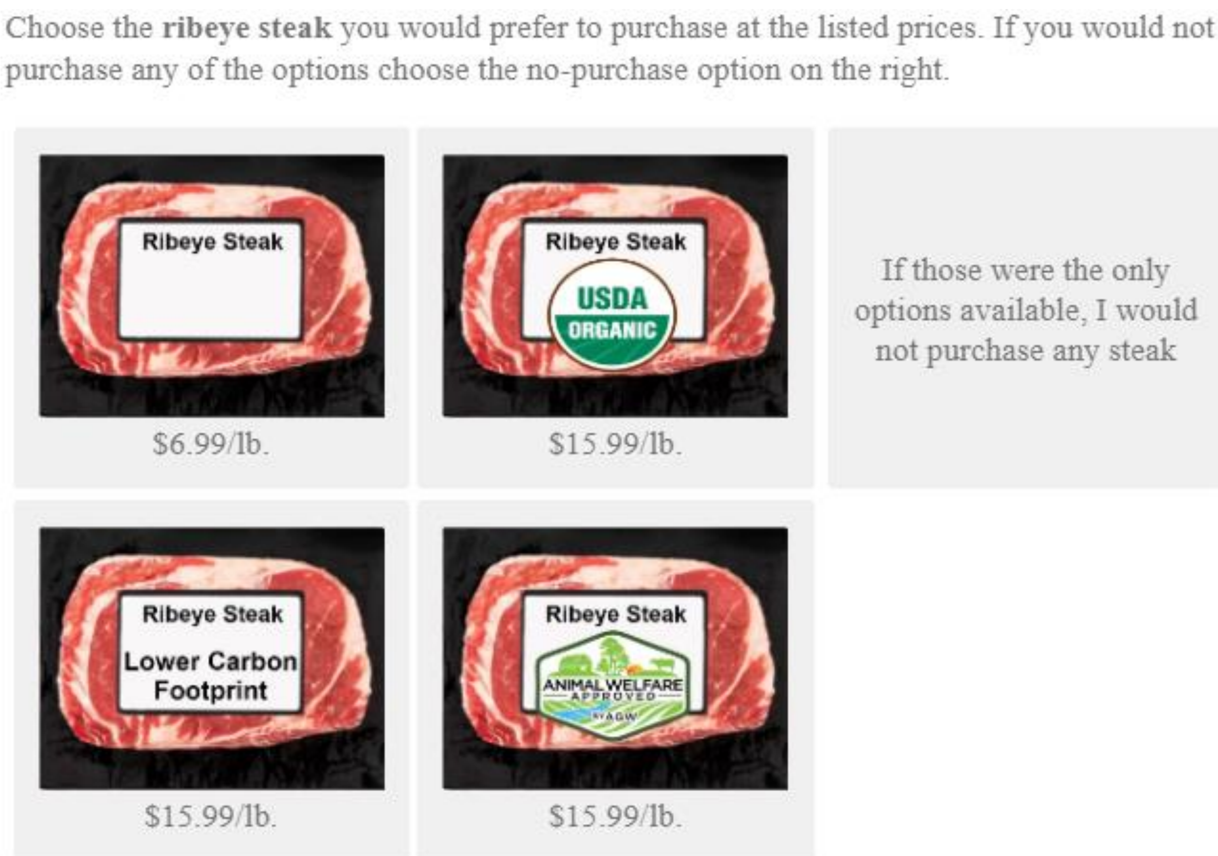

Figure A2.1 Example of a choice question

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CHAPTER 3: TOO LONG, DIDN'T READ – AN INVESTIGATION OF CONSUMER SENSITIVITY TO INFORMATION TREATMENTS

1. Introduction

Within agriculture, animal production is one of the main sources of greenhouse gas emissions (Environmental Protection Agency (EPA) 2022). In the U.S., enteric fermentation[24] of farm animals accounts for 27% of all greenhouse gas emissions in the agricultural sector. About 97% of this type of methane emissions stem from beef (72%) and dairy cattle (25%) (EPA 2022)- with the emissions having increased about 7% since 1990. These emissions do not only represent a threat to the climate, but the production of these gasses also result in energy losses in cattle, thus negatively impacting production (Arndt et al. 2016).

As a result, continuous efforts are made to reduce the total emissions in cattle. For example, early research has focused on practices to adjust dairy cow's feed composition to decrease the emissions of methane (Roque 2019). However, such adjustments on a wide scale would likely require substantial adjustments along the supply chain and affect other factors such as feed efficiency and subsequently the financial bottom line. More recently, researchers have called for using gene-editing as an alternative approach to reducing the methane produced by cattle (Giddings et al. 2020; Recchia et al. 2021). While this approach has the potential to reduce the cattle's emissions significantly without affecting other parameters, it also remains to be seen whether food products derived from gene-edited cows will find acceptance among consumers.

Previous studies showed that consumers do not strictly differentiate between gene-editing and genetic modification, which traditionally has been viewed negatively relative to other available

[24] Enteric fermentation refers to a process that naturally occurs in the digestive system of animals where bacteria break down organic matter resulting in the production of different GHG like CO_2 and in particular methane (CH_4) (FAO n.d.).

alternative production methods (Caputo et al. 2020b, 2022, Yunes et al. 2021). Hence, if perceived similarly, consumers might reject for example milk from gene-edited cows leading to a market failure of the application. Indeed, several studies find that gene-edited products are often still discounted relative to other alternatives already available in the market for both plant- and animal-based products (see e.g., Caputo et al. 2020b, 2022; Muringai et al. 2020; Kilders and Caputo 2021; Marette et al. 2021; Ortega et al. 2022; Ufer et al. 2022). Yet, consumer acceptance of new food technologies is application dependent (Caputo et al. 2020b), highlighting the need to assess the acceptance of new gene-editing applications on an individual basis rather than treating them as a homogenous group.

Earlier studies have determined consumer acceptance of gene-edited products under the lens of for example different labeling standards (Caputo et al. 2022), different geographic or cultural contexts (Yang and Hobbs 2020b; Marette et al. 2021; Ortega et al. 2022), or animal welfare considerations (Kilders and Caputo 2021; Ufer et al. 2022). With this study we add to this growing literature by assessing consumer preferences for milk from cows that were gene-edited (henceforth referred to as gene-edited milk) to produce less methane relative to conventional and organic milk. We conducted an online survey of about 1850 U.S. consumers. Using a discrete choice experiment (DCE) format, we asked respondents to choose between conventional milk, organic milk, and gene-edited milk to determine how the gene-edited alternative is valued relative to other existing animal-based milk alternatives. By doing so, we explore preferences for a new gene-editing application within the dairy space.

We also take into consideration that different studies demonstrated that the overall acceptance of gene-edited products is affected by information provided to consumers (see e.g., Shew et al. 2018, Caputo et al. 2020b, 2022, Yang and Hobbs 2020; Kilders and Caputo 2021, Ortega et al. 2022). These studies belong to a range of works that have integrated information provision beyond mere instructions into their design. Often this is done in the form of different information treatments meant to explore how respondents adjust their choice behavior once they are confronted with certain facts. Most of these studies suggest that respondent's preferences and willingness to pay (WTP) do indeed change with the provision of additional information. Yet, the way information was conveyed in most of these studies was forced; respondents did not get to select whether they want to see the information or not, and how they saw this information. In a real context, consumers can typically choose whether they want to actively access information on a topic as well as the type of medium (e.g., text, video, etc.). Both aspects are likely to affect the external validity of the results. In studies where respondents did have the option to opt into accessing information (e.g., Bell et al. 2017; Caputo et al. 2022), no counterfactual was created. This means it is difficult to identify what share of the effect is attributable to the information given to respondents and what is attributable to the inherent differences between information seekers and non-seekers.

Addressing this issue, our study randomly assigned respondents into three treatments which altered the way information is conveyed. Respondents in the *Control* treatment were not shown any additional information and proceeded directly to the choice experiment. Respondents in the *Forced* group were randomly assigned to see additional information on using gene-editing to reduce methane production in cows either via text or via video. This is irrespective of whether they wanted to see the additional information or not. Lastly, respondents in the *Select* group could choose whether they wanted to see additional information on the same topic and which type of medium they would prefer to use to access the information: a text, or a video. This approach allowed us to assess the impact of additional information on consumer preferences for gene-edited milk and evaluate whether the impact of the provided information differed between a text and video format. Moreover, the design also allows us to examine how choice behavior of survey respondents might change if 1) they can choose to access information relative to not receiving any information or being forced to see information and 2) how the information medium or format might impact potential differences.

Our analysis finds that respondents discount gene-edited milk relative to conventional and organic milk, but their WTP increases when exposed to information highlighting the benefit of the technology. There is no significant difference in whether a text or a video is used, although texts are chosen more frequently as an information medium by respondents who were allowed to choose. Our results also show a higher impact of information on the mean marginal WTP among information seekers compared to non-seekers. Interestingly, information seeking as a factor is more relevant when considering gene-edited milk relative to conventional milk than an organic alternative. Likewise, giving respondents the option to see the information positively affects their marginal WTP. Taken together our results imply that the use of forced information treatments in DCE might yield choice outcomes not comparable with what could be observed in a real-life setting.

Findings from this study offer several contributions to the food choice literature. To begin with, from an empirical perspective our examination of demand patterns and consumer preferences for milk from gene-edited cows generated insights for producers and processors on the market viability of such an application. Likewise, policymakers can use our findings in their decision-making processes concerning the regulation of gene-edited products. In addition, we showed how respondent's self-selection into receiving information and the impact of those decisions influences subsequent choice behavior. In contrast to existing studies which allowed respondents to self-select into receiving information or not (Bell et al. 2017), we tested how self-selection differs when using different vehicles for the information provision (written text vs. video) and examined which vehicle is preferred by respondents. This approach provides a more in-depth understanding of the different consumer segments. We supplement this with an analysis, of how the process of choosing to receive information (either via written text or video) then affects respondent's choice behavior. Combined, these results can be used by researchers to design more effective information treatments.

2. Background

2.1 Information Treatments in DCE

DCEs are widely applied within the research world and their external validity for applications in the agricultural and food marketing field have been widely established (See Caputo and Scarpa for a review). DCEs present a convenient method to measure preferences and reactance of producers, processors, and consumers towards a wide range of issues. These issues include among many others, food production methods and new food technologies (see e.g., Mørkbak and Nordström 2009; Van Loo et al. 2011; Koistinen et al. 2013; Bazzani et al. 2017; Ortega et al. 2020; Caputo 2020; Caputo et al. 2013, 2020b, 2022; Kilders and Caputo 2021), place of origin (Aprile et al. 2012; Rihn et al. 2016; Vroegindewey et al. 2021), nutrition and health claims (Van Wezemael et al. 2014), as well as more methodological and behavioral concepts such as time preferences (De Marchi et al. 2016) reference prices (Caputo et al. 2018, 2020a), and inattention measures (Malone and Lusk 2018a,b, 2019; Sandorf 2019) among others.

Many of the studies on consumer valuation for new food technologies incorporate information treatments, where respondents are exposed to different forms of information intended to elicit some kind of reaction/response. Examples from DCE studies in different areas of agriculture and food marketing using information treatments are listed in Table A3.1 in the Appendix.

Most of these studies found a significant change in respondent's choice behavior in response to the information they were provided with (see e.g., Papoutsi et al. 2015; Ortega et al. 2015; Czajkowski et al. 2016). Specifically concerning gene-edited food, studies found that providing information on the technology as well as the benefits that can be generated leads to a significant increase in respondent's WTP compared to a no-information control group (Caputo et al. 2020b, 2022; Kilders and Caputo 2021; Ortega et al. 2022). However, as illustrated in these works, this effect is dependent on receiving information that goes beyond just information on the technicalities of the production method. The 2022 report by Caputo et al. also showed that participants who opted-into seeing additional information had a significantly higher acceptance of gene-edited products than those who did not.

Like many others, the information in the underlying experiments of the above studies was delivered in a written format. While certainly convenient and omnipresent in today's world, research has also shown that text comprehension and effectiveness is affected by a multitude of factors including the length/detail of the text (Andreassen and Bråten 2010) as well as the style (Zumbach and Mohraz 2008) that is used to convey the information. In fact, some studies employing DCE, have tested how these aspects can affect respondent's WTP. For example, in two different treatments Shew et al. (2018) presented respondents from the US, Australia, Belgium, France, and Canada with either short or long information on conventional, gene-edited, and genetically modified rice. Interestingly, their results differ between countries, with the longer information treatment resulting in a smaller discount for the genetically engineered alternatives in the USA and Australia, but not the other three countries. Still targeting gene-editing, the focus of

Yang and Hobbs (2020) was to evaluate how respondents react to different framing of information. They provided about half of their respondents with information on the use of gene-editing in apples in a more scientific way, while the other was framed in a more narrative way. Their results show that by using a more narrative way to describe the application, negative perceptions of consumers surrounding gene-editing are significantly reduced.

Aside from using written text, some studies have instead used alternative media to convey information to respondents in their survey. For instance, Kilders and Caputo (2021) conducted a choice experiment in which they used four different videos that were presented to respondents prior to the choice questions. Depending on their treatment group respondents were shown a video containing varying levels of information on gene-editing, its differences to genetic modification, and its benefits for animal welfare. Their results show a significant influence of the information on respondent's WTP and the spread of the preference distribution. As the authors point out, previous studies have shown that videos not only affect public opinion and awareness (Kalaitzandonakes et al. 2004) but have also been shown to be effective learning tools (Karpinnen 2005; Merkt et al. 2011).

Klaiman et al. (2016, 2017) used a more mixed approach in their exploration of US consumer's WTP for packaging materials and recyclability products using a DCE. Klaiman et al. (2016) looked at fruit juice drink products and employed a control (i.e., no additional information), an indirect questioning treatment, and a video treatment. Among others their results found a positive effect of the video treatment on respondent's WTP for packaging recyclability relative to the control, while the indirect questioning approach had the opposite effect. Similarly, Klaiman et al. (2017) looked at an on-the-go sandwich container and assigned respondents randomly to a control group or one of two treatments where they were either presented with an infographic or a video on recycling. Compared to the control, the treatments did not have a significant effect on respondent's willingness to clean the container, but respondents in both treatments preferred paper and cardboard packaging over plastic one.

Recently, McFadden et al. (2021), used a within treatment approach, where both an information and a narrative block were shown to respondents in a randomized order. In the information block respondents were presented with written information on how different breeding techniques were similar or distinct from one another. Meanwhile, in the narrative block respondents watched a CBS news clip, that elaborated on how citrus greening effects the citrus industry in Florida. Their results indicate that respondents, who were first exposed to the information in the narrative block perceived gene-editing as less safe than those who first saw the information block. Results from these three studies highlight that videos can serve as an effective measure to deliver information. However, as in most of the previous studies except for Caputo et al. (2022) accessing information in these studies was not voluntary.

2.2 Willful Ignorance and Information Avoidance

Whether consumers purposely avoid information or assimilate information in line with their prior beliefs has been the subject of several earlier studies. For example, Bell et al. (2017) evaluated whether respondents willfully ignore information on animal welfare. Citing guilt avoidance as one motivator, the authors found that around one third of respondents in their online survey chose to rather look at a blank screen than see a picture of the living conditions of a pregnant hog. Golman et al. (2017) discuss different mechanisms people might employ to avoid information, which include physical avoidance, inattention, and a biased interpretation of results. The latter has been found in several studies, where respondent's assessment of given information tended to be significantly biased by their prior beliefs (Lord et al. 1979; Plous 1991; McFadden and Lusk 2015;

Ortega et al. 2020). Relatedly, one of the key motivations behind avoiding information lies in the obligation to act when information is received (Sweeny et al. 2010). This obligation to act might therefore bias the answers of survey respondents that are compelled to see certain information during a survey. Thus, it is important to assess and disentangle what part of the information effect is due to such a bias, and whether it can be alleviated when the information acquisition is voluntary. In the latter case, it is also important to understand how much of the difference is attributable to inherent differences between information seekers and non-seekers or the actual information received.

3. Experimental Procedures and Research Hypotheses

3.1 Product of interest selection

We focus our empirical analysis on consumer preferences for cow's milk. Milk was chosen as a product of interest for two main reasons: 1) it's economic relevance and 2) the potential of the gene-editing application to make measurable changes in the climate impact of dairy cows. On average 0.33 cup-equivalents of milk are consumed per person per day in the U.S. (Stewart et al. 2021) contributing to the about $49 billion in direct economic impact that milk production has in the U.S. (International Dairy Food Association 2021). However, in the U.S., dairy cows are also responsible for about 25% of total methane emissions stemming from animal agriculture (EPA 2022). Researchers are now exploring pathways to use gene-editing to reduce how much methane cows produce and release (Pszczola et al. 2018; Edick et al. 2020; Recchia et al. 2021). If successful, the application could provide an environmentally beneficial alternative to existing milk without requiring large scale adaptive changes in the dairy supply chain as would be the case if for example cow's feed would be adjusted to reduce the methane production. Producer adoption and the viability of this technology, lies in part on consumer acceptance of the application (Ufer et al. 2019).

3.2 Experiments and DCE Design

To assess whether consumers will indeed accept gene-edited milk, we employed a hypothetical DCE. We asked respondents to choose between three purchase alternatives (organic milk, conventional milk, gene-edited milk) presented at different prices as well as a no-purchase option. We selected organic and conventional milk as alternatives to gene-edited milk as these represent the main differentiation in terms of production method for fluid milk sales (USDA Agricultural Marketing Service (USDA AMS) 2022a, b). We used price levels that were in accordance with the retail milk prices reported by the USDA AMS (2022b) for May 2022 and price research across different retail outlets across the four U.S. census regions. The final prices ranged from \$2.50-\$5.50 for the conventional and gene-edited milk and \$3.50-\$6.50 for the organic option each with \$1 increments between levels. The price levels are summarized in Table A3.2 in the Appendix. This combination of alternatives and price levels would require $4^3 = 64$ choice questions for a full factorial design. To prevent choice fatigue, we employed a simultaneous fractional factorial design which reduced the number of choice tasks to eight per respondent (ChoiceMetrics 2018).

In addition to the instructions shown in each choice question (see Figure 3.1), each respondent also received more detailed instructions prior to the DCE (see Figure A3.1 in the Appendix for a full script) on what to expect as well as a brief cheap talk script to alleviate potential hypothetical bias (Cummings & Taylor 1999; Lusk 2003; Aadland & Caplan 2006).

Figure 3.1 Example of a choice question

While all respondents saw the same choice questions and received the same basic instructions for the DCE questions, we also randomly assigned respondents to one of three experimentally designed treatments[25]. The treatments differed in a) the terms of how information was accessed (*Control*, *Forced* and *Select*) and b) the information medium given to respondents (Video or Text) (see Figure 3.2).

Respondents in the *Control* treatment were not shown any additional information and instead proceeded directly to the choice questions after they were given the instructions, meaning the group served as the baseline of our experiments. Respondents in treatment 2 (*Forced*) were randomly assigned to see additional information either via text or via video after the instructions and prior to the choice experiment. This was irrespective of whether they wanted to see the additional information or not. In both the *Control* and *Forced* treatment, we asked respondents whether they would have chosen to see additional information on gene-editing in dairy cows after the choice questions to have an ex-post control of who would classify as an information seeker

[25] The assignment to the treatments was random. However, we doubled the probability of being assigned to the *Select* treatment to collect enough responses for each information access and medium choice (none, video, text).

and who would be a non-seeker. Lastly, respondents in treatment 3 (*Select*) could not only choose whether to see the provided information, but also choose which type of medium they would prefer to use to access the information, a text or a video.

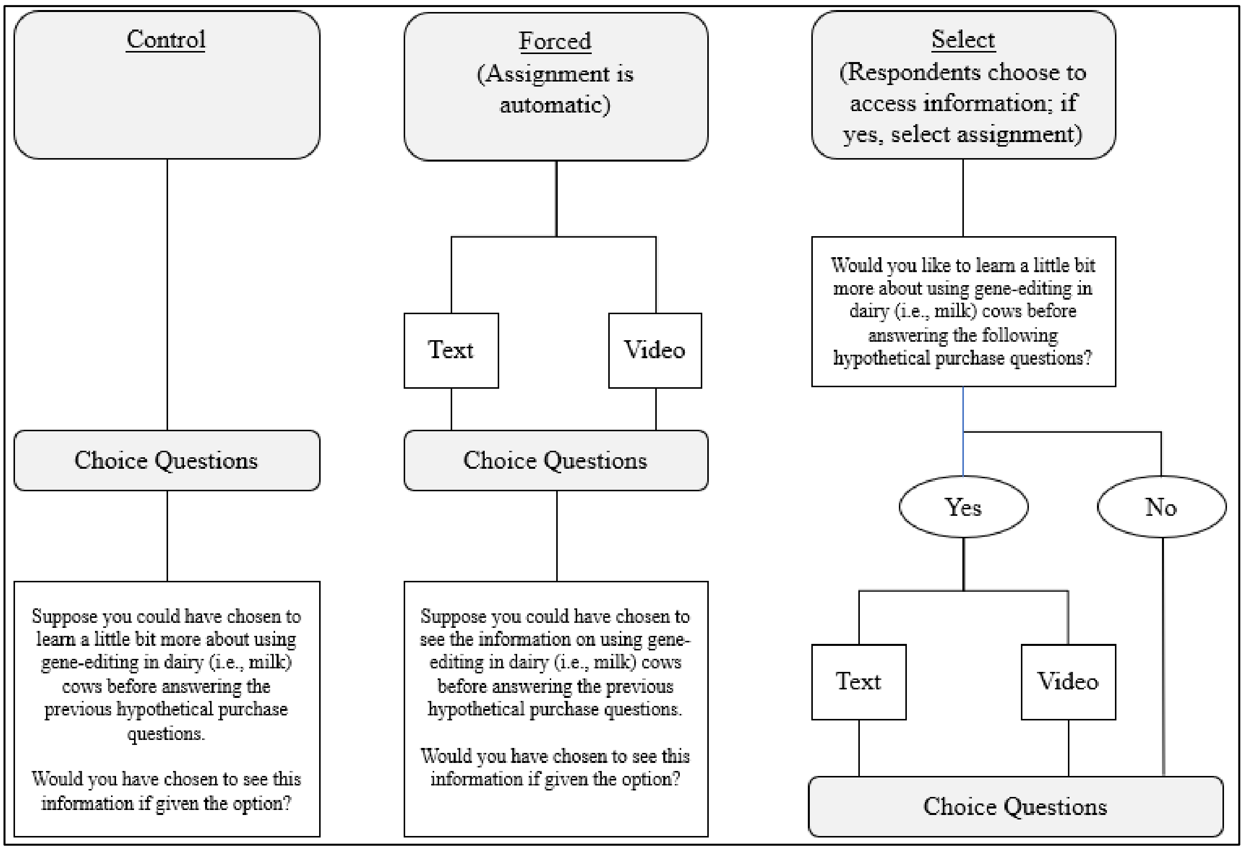

Figure 3.2 Study design and treatments

The information script[26] was modeled after the work by Lusk et al. (2004) and Ortega et al. (2020) in that the technology itself and how it works was not specifically explained, with the emphasis being on the issue and the benefit. We also used a more narrative style of language in line with the results by Yang and Hobbs (2020). The same script was used for the voice over in

[26] The full script of the information can be found in Figure A3.2 in the Appendix.

the video, which used an animated explainer style to support the script[27]. Explainer style videos have seen a rise in usage both in educational as well as business settings and have been shown to be effective in conveying information to consumers (Krämer & Böhrs 2017, 2018).

Beyond the choice questions, we also incorporated questions on respondent's consumption habits and knowledge about gene-editing, their socio-demographics, etc.

3.3 Research Hypotheses

Our experimental setting allows us to test four distinct hypotheses. We first hypothesize (**H11**) that providing information on potential emission benefits of gene-editing to respondents, will lead to an increase in average WTP, irrespective of the medium (text or video). This hypothesis follows from results of previous studies that found a positive impact of benefit information on consumers' WTP for gene-edited products (Shew et al. 2018, Caputo et al. 2020b, 2022, Yang and Hobbs 2020; Kilders and Caputo 2021, Ortega et al. 2022). We assess this by comparing respondent's WTP for gene-edited milk in the *Control* ($WTP^{Control}$) treatment with that in the *Forced* treatment ($WTP^{Forced}_{Video\,\&\,Text}$) with the later consisting of pooled responses from individuals who see the video and text:

$$H_{01}: \left(WTP^{Control} - WTP^{Forced}_{Video\,\&\,Text}\right) \geq 0$$

$$H_{11}: \left(WTP^{Control} - WTP^{Forced}_{Video\,\&\,Text}\right) < 0$$

Our second hypothesis builds directly on the argument used for **H11** as we hypothesize to find a higher WTP for gene-edited milk among respondents in the *Select* treatment compared to the *Control* treatment (**H12**). While respondents also had the option to opt-out of receiving

[27] The video can be found under the following link: https://tinyurl.com/46efpar4 and was created by a professional graphic designer.

information, we anticipate seeing a majority of respondents opting into receiving information in line with previous studies (Bell et al. 2017; Caputo et al. 2022), which we assume will lead to an increase in mean WTP for the gene-edited milk ($WTP^{Select}_{Video,Text\ \&\ Opt-out}$):

$$H_{02}: \left(WTP^{Control} - WTP^{Select}_{Video,Text\ \&\ Opt-out}\right) \geq 0$$
$$H_{12}: \left(WTP^{Control} - WTP^{Select}_{Video,Text\ \&\ Opt-out}\right) < 0$$

In our third hypothesis we focus on a comparison between the *Forced* and the *Select* treatment. Specifically, we predict that by granting respondents the autonomy to opt-into receiving additional information, the information will have a more sizable effect (expressed in terms of changes in WTP) than when information is forced upon respondents (**H13**). Previous studies have shown that learning is more effective when the learner is given autonomy over the learning process (see Dickinson 1995 for a review). Hence, we assume that the autonomy to opt-into information is associated with a greater effect of the technology information on consumer acceptance. We focus on respondents in the *Select* treatment who chose to either watch the video or read the text and compare their WTP for the gene-edited alternative ($WTP^{Select}_{Video\&Text}$) with the mean WTP for the gene-edited milk in the *Forced* treatment ($WTP^{Forced}_{Video\&Text}$).

$$H_{03}: \left(WTP^{Forced}_{Video\&Text} - WTP^{Select}_{Video\&Text}\right) \geq 0$$

$$H_{13}: \left(WTP^{Forced}_{Video\&Text} - WTP^{Select}_{Video\&Text}\right) < 0$$

In doing so, we can disentangle what share of the effect is due to the actual information given vs. the inherent differences between the two groups and the provided autonomy.

Lastly, for our fourth hypothesis (**H14**) we narrow the effect of information even further down. We hypothesize that using a video will have a stronger effect on consumer preferences compared to using a text. This follows from the results by McFadden et al. (2021) who compared a written text with a CBS news clip. It is also motivated by the existing literature, which shows a great efficacy of explainer style videos in conveying information (Krämer & Böhrs 2017, 2018). To test this hypothesis, we compare respondent's mean WTP for gene-edited milk when they saw the video (WTP_{Video}) versus when they read the text (WTP_{Text}) in both the *Forced* and the *Select* treatment:

$$H_{04}: (WTP_{Video} - WTP_{Text}) \geq 0$$

$$H_{14}: (WTP_{Video} - WTP_{Text}) < 0$$

4. Data Analysis

DCEs build upon random utility theory (McFadden 1973; Hanemann 1984) and Lancaster's (1966) new approach to consumer theory, meaning they follow the assumption that the utility of a good is the sum of the utilities derived from the different attributes composing it. In line with these seminal papers, we assume that the utility function can therefore be represented as:

$$U_{njt} = V_{njt} + \varepsilon_{njt} \qquad (1)$$

U_{njt} represents the utility of respondent n for alternative j in choice task t. It is composed of the systematic component of the utility V_{njt} and the unobserved error term ε_{njt}.

To analyze the underlying data and disentangle what is represented in (1) we used a basic mixed logit model (MXL) (Train 2009) with utilities specified in the WTP-space as demonstrated in equation (2):

$$U_{njt} = \lambda_n\left(-Price_{jt} + ASC_j\right) + \varepsilon_{njt} \qquad (2)$$

where the common price/scale factor is given by $\lambda_n = \alpha_n/\mu_n$[28]. The continuous variable $Price_{jt}$ is populated with the corresponding price levels for each alternative and ASC_j is the alternative-specific constant for milk type j, which represents the estimated WTP values for the conventional, organic, and gene-edited milk. Lastly, ε_{njt} represents the extreme value type I distributed error term. By estimating the model in WTP space we avoid scale effects across treatments that would be present in models with utilities specified in preference space (Train & Weeks, 2005; Scarpa et al. 2008; Scarpa & Willis, 2010). This approach has been shown to be more appropriate for comparisons across treatments (Caputo et al. 2017) and prevents an overestimation of consumer's WTP (Hole & Kolstad, 2012).

To explore our above hypotheses, we estimate a MXL model for each information treatment (*Control*, *Forced*, and *Select*), and a MXL model for each information subgroup (Video or Text) in the *Forced* and *Select* treatment resulting in a total of eight estimated models[29]. Using the estimates from the MXL model in WTP space we also derived marginal WTPs following the same approach as in Lusk and Schroeder (2004).

5. Results

The survey was implemented in Qualtrics, who also handled the data collection[30]. The sample targeted respondents who were above 18 years of age, had purchased cow's milk in the past three months, and were responsible for at least half of the household's grocery shopping. In total we collected 1850 complete responses across the three treatments. Table A3.3 in the Appendix reports

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[28] μ_n represents the Gumble scale parameter of individual n while the random price coefficient is given by α_n. We define $\lambda_n = -exp(v_n)$ where v_n represents a latent random factor underlying the respective coefficient. We assume v_n to be normally distributed, meaning that $-\lambda_n$ is log-normally distributed (see Train and Weeks 2005 section 4.2, or Scarpa et al. 2008 for further details). This permits us to achieve a negative range of variation of the price coefficient.

[30] The pre-registration protocol of the survey can be found here: https://aspredicted.org/MVC_XN2.

the basic socio-demographic characteristics of our sample, which is mostly in accordance with the general U.S. census population with a few exceptions. For example, in contrast to the median age of the U.S. population (38.2 years) as reported in the 2020 census (U.S. Census Bureau 2020), the median age of our sample was slightly higher (46 years) likely since the sample only consists of adults of 18 years and older.

In terms of information access, in the *Select* treatment (where respondents could choose whether to see the information and the medium) around 62% of respondents choose to access the information. The share of information seekers is slightly lower than in the study by Bell et al. (2017), which might be due to the punishment given to respondents who were willingly ignorant in the previous study. Nevertheless, our sample does correspond to the study by Caputo et al. (2022) where about 60% of respondents chose to see additional information on production methods (including gene-editing) prior to the DCE. The result highlights that most respondents are indeed interested in receiving more information about gene-editing. Among the information seekers, a larger share of respondents chose to see the text (37%) rather than the video (24%) indicating a clear preference for the text medium over the video. We also find that the share of information seekers in the *Select* treatment is lower than in the *Forced* and *Control* treatments, suggesting that some respondents might overstate their willingness to see information if the question is asked after the DCE.

Tables A3.4 and A3.5 in the Appendix reports the estimates from a basic Multinomial Logistic model as well as the MXL models, which were all specified in WTP space. The significant standard deviations of the product alternatives indicate the presence of substantial heterogeneity in preferences, which aligns with prior studies on consumer acceptance of milk in general (Kim et al. 2018a,b) and more specifically gene-edited milk Kilders and Caputo (2021). The mean estimates from the MXL-WTP model represent the population mean total WTP for conventional, organic, and gene-edited milk products[31]. As the mean of all product alternatives is positive and significant, we can conclude that respondents preferred selecting any of the milk options, including the gene-edited one, over the no-buy alternative. We also find that across all treatments, the WTP is lowest for the gene-edited option, which corresponds to earlier studies that compared gene-edited food products with conventional and organic ones (see e.g., Caputo et al. 2020b, 2022, Edenbrandt et al. 2018). Hence, irrespective of whether respondents receive information they will still discount gene-edited milk relative to other available alternatives. However, the magnitude is mostly smaller than the discount Brooks and Lusk (2013) found for milk from cloned cows.

The estimated total WTP for the conventional and organic alternative is generally higher than the average milk price for the survey month ($4.33, USDA AMS 2022b). Lusk and Schroeder (2004) showed that while respondents tend to overestimate their total WTP in hypothetical DCE, marginal WTP values typically mirror welfare estimates elicited in non-hypothetical settings. Accordingly, we focus the discussion of our results on marginal WTP values[32] (see Table 3.1[33]). The standard errors and respective confidence intervals were constructed using the Krinsky and Robb (1986) bootstrapping method. We then employed the non-parametric test introduced by Poe et al. (2005) to determine whether the differences across treatments and groups were significant.

[31] These total WTP values can be understood as the average dollar amount at which a respondent is indifferent between selecting the respective purchase alternative and not selecting anything (i.e., choosing the no-buy option).
[32] Marginal WTP indicates the dollar amount at which a respondent is indifferent between choosing one of two milk types, a or b.
[33] For the *Forced* treatment, the table reports the estimates derived from the pooled sample (i.e., containing all individuals in the respective information treatment) and the segmented samples (respondents who saw the video or the text). Similarly, for the *Select* treatment the table reports the estimates from the pooled sample, the segmented sample (video, text, or opt-out), as well as the estimates from the sample containing both the video and text group..

Table 3.1 Marginal WTP estimates from the WTP-Space model across treatments and information groups.

	Gene-edited vs. Organic	Gene-edited vs. Conventional	Organic vs. Conventional
Marginal WTP Estimates			
Control	-\$3.45 (0.31)	-\$3.69 (0.26)	-\$0.24 (0.22)
	[-3.47, -3.43]	[-3.71, -3.67]	[-0.25, -0.22]
Forced			
Video & Text	-\$2.02 (0.29)	-\$2.13 (0.23)	-\$0.11 (0.24)
	[-2.04, -2.00]	[-2.14, -2.11]	[-0.12, -0.09]
Video	-\$1.87 (0.37)	-\$1.80 (0.29)	\$0.07 (0.33)
	[-1.89, -1.85]	[-1.82, -1.78]	[0.05, 0 .09]
Text	-\$2.13 (0.43)	-\$2.47 (0.37)	-\$0.34 (0.34)
	[-2.16, -2.11]	[-2.49, -2.45]	[-0.36, -0.32]
Select			
Video, Text & opt-Out	-\$1.94 (0.22)	-\$2.03 (0.19)	-\$0.09 (0.17)
	[-1.95, -1.92]	[-2.04, -2.01]	[-0.10, -0.08]
Video + Text	-\$1.28 (0.23)	-\$0.52 (0.18)	\$0.76 (0.21)
	[-1.29-1.26]	[-0.53-0.51]	[0.75-0.77]
Video	-\$0.93 (0.36)	-\$0.36 (0.31)	\$0.57 (0.33)
	[-0.95, -0.90]	[-0.38, -0.34]	[0.55, 0.59]
Text	-\$1.42 (0.29)	-\$0.61 (0.25)	\$0.81 (0.27)
	[-1.43, -1.40]	[-0.62, -0.59]	[0.79, 0.82]
Opt-out	-\$3.61 (0.54)	-\$4.79 (0.46)	-\$1.18 (0.26)
	[-3.64, -3.57]	[-4.82, -4.76]	[-1.20, -1.17]
Poe Test			
Control vs. $Forced_{Video\,\&\,Text}$	<0.001	<0.001	0.345
Control vs. $Select_{Video,Text\,\&\,Opt-out}$	<0.001	<0.001	0.297
$Forced_{Video\,\&\,Text}$ vs. $Select_{Video\,\&\,Text}$	0.021	<0.001	0.004
$Forced_{Video}$ vs. $Forced_{Text}$	0.319	0.077	0.194
$Select_{Video}$ vs. $Select_{Forced}$	0.149	0.266	0.712

Note: Numbers in round brackets are standard errors. Numbers in square brackets are 95% confidence intervals. Both were derived via Krinsky and Robb (1986) bootstrapping

As can be noted from Table 3.1[34], the marginal WTP values for the gene-edited option relative to both the organic and conventional milk products are negative and significant. However, substantial differences in consumer valuation for gene-edited milk are found across treatments. To illustrate, we first focus on the marginal WTP for gene-edited milk from the pooled samples across three main treatments: $Control$, $Forced_{Video\,\&\,Text}$ and $Select_{Video,Text,\&\,Opt-out}$. We find that respondent's marginal WTP for the gene-edited milk relative to both the organic and conventional alternatives is indeed higher in the $Forced_{Video\,\&\,Text}$treatment (-\$2.02 and -\$2.13) compared to the $Control$ (-\$3.45 and -\$3.69). The Poe-test confirms the significance of these differences ($p<0.001$). This evidence supports **H11**.

The positive impact of information is also observable in the comparison of the between the $Control$ treatment and the marginal WTP estimates from the pooled sample in the $Select_{Video,Text,\&\,Opt-out}$treatment which validates **H12**. The marginal WTP for the gene-edited alternative relative to both other options is over \$1.50 higher in the $Select_{Video,Text,\&\,Opt-out}$treatment compared to the $Control$ ($p<0.001$ in Poe-test). Hence, in coherence with previous studies (Shew et al. 2018; Caputo et al. 2020b, 2022; Yang and Hobbs 2020; Kilders and Caputo 2021; Ortega et al. 2022) we observe that providing consumers with information on the benefits of the technology leads to an increase in the mean marginal WTP for gene-edited milk products.

Next, we explore the differences between the $Forced_{Video\,\&\,Text}$ and $Select_{Video\,\&\,Text}$ treatment and thus turn our attention to our third hypothesis (**H03)**, i.e., the marginal WTP for the

[34] We did not find a substantial premium for the organic option over the conventional milk which contradicts several experimental studies (see e.g., Kim et al. 2018a,b) but does align with the results derived from scanner data by Lusk (2011).

gene-edited option is higher in the $Select_{Video\ \&\ Text}$treatment compared to the $Forced_{Video\ \&\ Text}$treatment, irrespective of whether they see the information via the video or the text. This process allows us to see how much of the observed increase in WTP relative to the $Control$ is attributable to the actual information given to respondents and what is a result of inherent differences between information seekers and non-seekers. When comparing these two treatments (Figure 3.3.), we consider the full sample in the $Forced$ treatment ($Forced_{Video\ \&\ Text}$), while only people who selected to see the information either via video or text (i.e., information seekers) in the $Select$ treatment are considered ($Select_{Video\ \&\ Text}$).

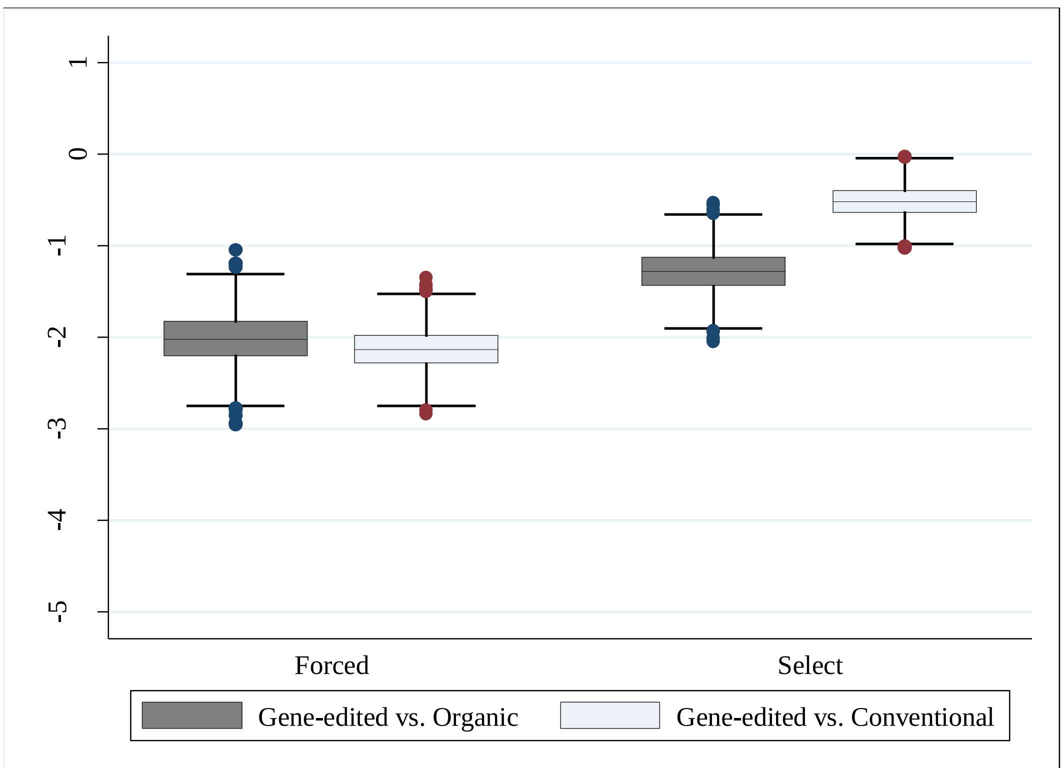

Figure 3.3 Marginal WTP of the gene-edited milk relative to the organic and conventional milk, $Forced_{Video\ \&\ Text}$vs. $Select_{Video\ \&\ Text}$

The marginal WTP of the gene-edited milk relative to both the conventional (p<0.001 in Poe-test) and organic (p<0.03 in Poe-test) milk is significantly higher in

$Select_{Video\,\&\,Text}$treatment than in the $Forced_{Video\,\&\,Text}$treatment. This finding allows us to reject **H03** and implies that there is a substantial difference between letting respondents choose to access information compared to just giving it to them, which aligns with previous studies on the effect of autonomy on knowledge assembly (Dickinson 1995).

To further explore the differences between the $Forced_{Video\,\&\,Text}$and $Select_{Video\,\&\,Text}$treatment, we now turn our attention to our fourth hypothesis. We do so by focusing on the marginal WTP for the gene-edited milk relative to the organic and conventional alternatives segmented by the medium that the respondents saw (see Figure 3.4). Again, this analysis only contains the information seekers in the *Select* treatment ($Select_{Video\,\&\,Text}$).

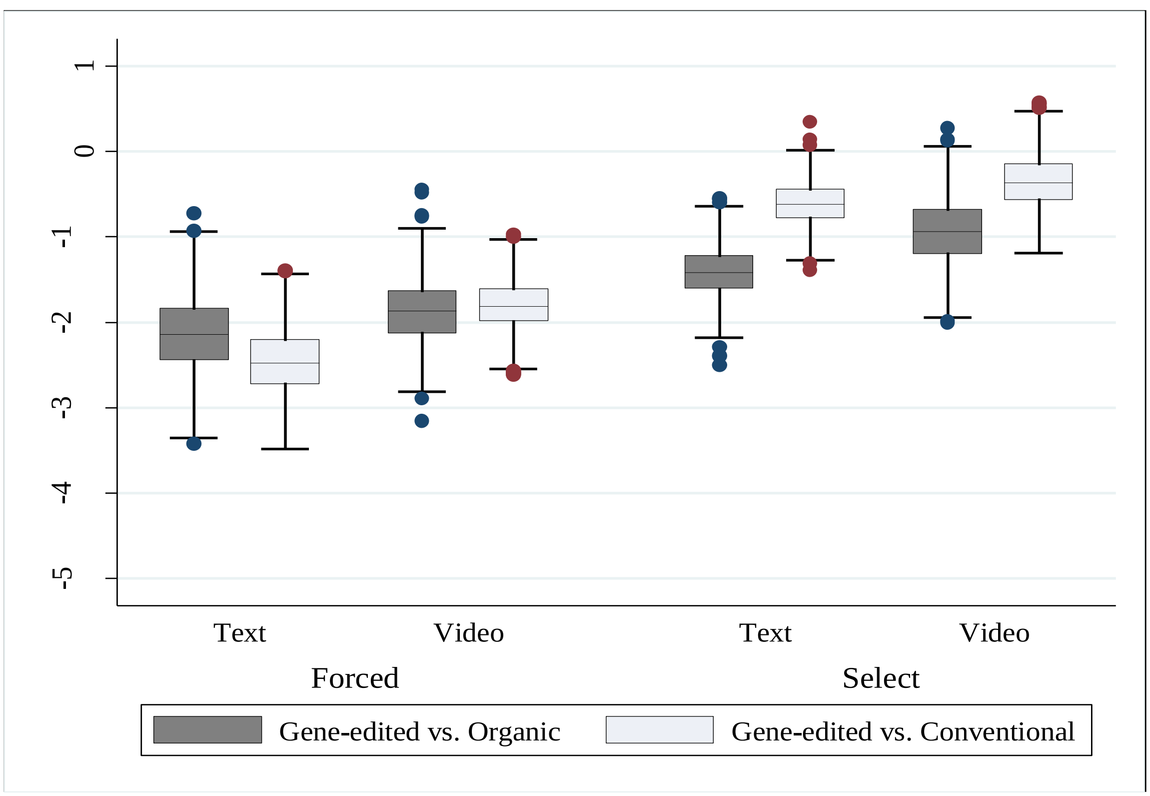

Figure 3.4 Marginal WTP of the gene-edited milk relative to the organic and conventional milk, $Forced_{Video\,\&\,Text}$ vs. $Select_{Video\,\&\,Text}$ across mediums

We find that the mean marginal WTP for the gene-edited milk is higher when respondents saw the video (-\$1.87 and -\$1.80) compared to the text (-\$2.13 and -\$2.47) in the $Forced_{Video\,\&\,Text}$ treatment. However, the Poe-test is not significant for the marginal WTP of the gene-edited milk relative to the organic milk (p=0.32), and only significant at the 10% level for the comparison with the conventional milk (p=0.08). Hence, our estimates do not allow us to reject **H04**. This result also holds when looking at the same groups in the $Select_{Video\,\&\,Text}$ treatment: Even though the mean marginal WTP for the gene-edited vs. organic milk is \$0.48 higher for respondents who saw the video relative to seeing the text, and \$0.26 higher for the gene-edited vs. conventional marginal, the Poe-test is not significant for either at conventional levels (p=0.15 and p=0.27, respectively). Thus, our results contradict the findings by McFadden et al. (2021) that a stronger reaction is elicited when using a video in a DCE compared to a text.

6. Preferences by Information Seeker Status and the Influence of Demographics

6.1 Preferences by Information Seeker Status

Given the above results, we take a closer look at the differences between information seekers and non-seekers in the $Forced$ and $Select$ treatments. As discussed in the experimental procedure section, respondents in the $Forced$ treatment were asked whether they would have wanted to see additional information on gene-editing in cows irrespective of the treatment they were randomly allocated to. The inclusion of this question allows us to assess whether behavior differs between information seekers and non-seekers in both the $Forced$ and $Select$ treatments.

We re-estimated the data of the *Forced* and *Select* treatments segmented by respondents who indicated that they would want to see additional information (information seekers) ($Forced_{Seekers}$ & $Select_{Seekers}$) vs. those who did not (non-information seekers) ($Forced_{Non-seekers}$ & $Select_{Non-seekers}$). The results of this estimation are reported in Table

A3.7[35] in the Appendix. For brevity, we focus our discussion on respondent's marginal WTP using boxplots that were generated from the bootstrapped values (Krinsky and Robb 1986).

Looking at the boxplots for the four groups ($Forced_{Non-seekers}$, $Select_{Non-seekers}$, $Forced_{Seekers}$ & $Select_{Seekers}$) (see Figure 3.5) we can see that information seekers generally have a higher marginal WTP for the gene-edited option relative to non-information seekers. This finding mirrors the results of Dickinson (1995) suggesting that autonomy of gathering knowledge has a positive impact on the effect of information. We observe that there are no significant differences in marginal WTP for the gene-edited milk between information seekers and non-seekers when considering the product relative to the organic option (p=0.60). Yet, the difference between the two groups is significant for the marginal WTP of the gene-edited milk compared to the conventional one. Thus, the results suggest that information seeking might mainly serve in the preference formation for gene-edited milk relative to conventional milk and not organic milk. We also note that the heterogeneity in preferences appears to be substantially more pronounced among non-seekers than seekers across all treatments. Potentially, this relates back to the findings in earlier studies that consumers seek out information to confirm prior beliefs (Lord et al. 1979; Plous 1991; McFadden and Lusk 2015).

[35] Table A3.6 reports the corresponding results of the MNL.

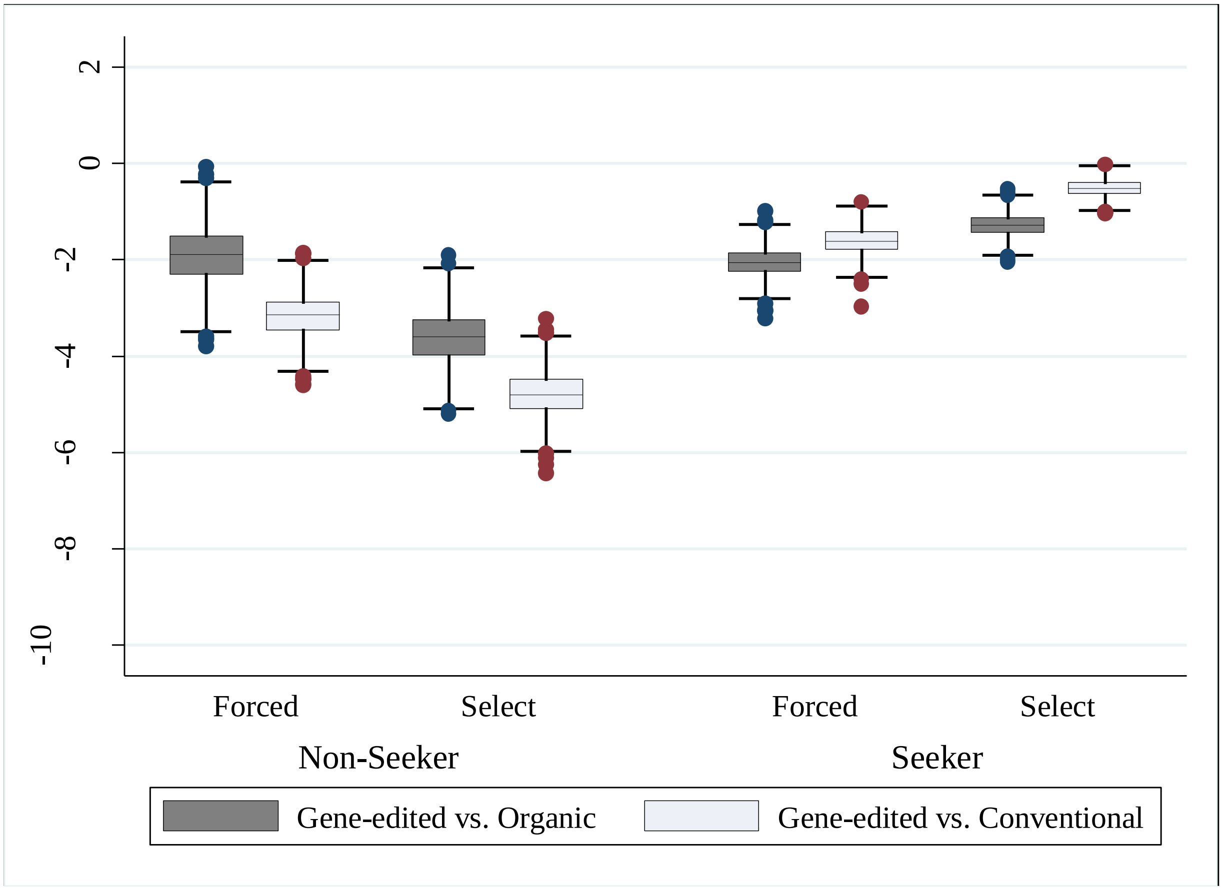

Figure 3.5 Marginal WTP of the gene-edited milk relative to the organic and conventional milk, $Forced_{Non-seekers}$, $Select_{Non-seekers}$, $Forced_{Seekers}$ & $Select_{Seekers}$.

Moreover, comparing information seekers in the $Forced$ and $Select$ treatments, we find that the marginal WTP for the gene-edited alternative is substantially higher in the group that got to choose to access the information ($Select_{Seekers}$) vs. the one that did not get this option ($Forced_{Seekers}$) even though the latter would have chosen to see the information. The Poe-test confirms the significance of these results (p<0.02). This not only confirms that providing respondents with the autonomy to access information positively impacts their WTP but also suggests that autonomy itself is an influencing factor beyond the characteristic of being an information seeker or not.

6.2 The Influence of Demographics on the Information Seeker Status and Selection of Information Medium

Seeing the stark influence that the information seeking status has on preferences, we also wanted to assess whether there are socio-demographic differences between information seekers and non-seekers. We estimated a Probit model with the information seeking status as the dependent variable and the respondents in the $Select_{Video,Text,\&\ Opt-out}$ treatment as our selected sample[36] for this analysis. We also estimated a second Probit model for all respondents who chose to access information in the $Select_{Video,Text,\&\ Opt-out}$ treatment ($Select_{Video\ \&\ Text}$) with the medium as our dependent variable (choosing the text was the baseline). The results are summarized in Table 3.2 and highlight that there are several significant differences across demographics. For example, looking at the information seeking status, we see that the older respondents are, the less they are interested in seeking out additional information, which aligns with findings of other studies on information acquisition (Schaninger and Sciglimpaglia 1981). Likewise, respondents living in rural or suburban areas are less interested in accessing additional information than respondents living in urban areas. At the 10% level we find that females are more likely to seek out information, while respondents with a low income are less likely to do so. Our results align with previous studies, which found a positive association between income and information acquisition (see e.g., Schaninger and Sciglimpaglia 1981). Income was also significant at the 10% level in the second Probit model, where the positive coefficient indicates that respondents are more likely to select the video than the text if they had a low income. At the 5% level, age was also significant with older respondents seeming to prefer the video over the text.

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[36] Respondents in the *Control* and *Forced* treatment were excluded as the information seeking question was asked ex-post of the DCE meaning no there was no actual follow-though.

Table 3.2 Results Probit model

Variable	Coefficient	
	Probit 1: Information Seeking	Probit 2: Video
Female	0.17*	-0.09
	(0.10)	(0.13)
Low income	-0.16*	0.22*
	(0.10)	(0.12)
Age	-0.01***	0.01**
	(0.00)	(0.00)
College	0.12	0.00
	(0.10)	(0.12)
Respondent lives in rural area	-0.35***	-0.01
	(0.13)	(0.16)
Respondent lives in suburban area	-0.33***	-0.07
	(0.10)	(0.12)
Respondent ever worked on farm	-0.11	-0.03
	(0.11)	(0.15)
Constant	1.24***	-0.65***
	(0.21)	(0.25)
Observations	935	576

Note: Numbers in brackets indicate standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

7. Conclusion

Gene-editing could represent a pathway to reduce the climate impact of agriculture without negatively affecting production parameters, product quality, and animal welfare. Nevertheless, it remains to be seen whether such products will find acceptance among consumers. In this study we explored this question in the context of consumer preferences for milk from cows that were gene-edited to produce less methane and explore the effects of information on consumer acceptance.

We employed a DCE in which 1850 U.S. respondents had the option to choose between milk from gene-edited cows, conventional milk, organic milk, and a no-buy option. Using a between-subject design we segmented our respondents into three treatments: a control, a treatment where they randomly saw a video or a text explaining how gene-editing cows could reduce the methane they emit, and a treatment where respondents could choose whether they wanted to access the information and if so whether they wanted to see a text or a video. This approach permitted us to explore a) if providing benefit information increases respondent's WTP for gene-edited milk, b) if videos have a stronger effect than text, and c) if giving respondents the autonomy to see information influences their choice behavior over forcing them to see the information. We note that most food choice studies on consumer valuations (which employ information treatments) force respondents to read some sort of information related to the technology.

We find that respondents have a lower WTP for the gene-edited milk relative to other milk options (conventional and organic). Nevertheless, we also find clear evidence that information on the potential benefits of gene-editing can increase consumer's marginal WTP for gene-edited milk relative to the alternatives. When respondents get to choose, 62% opt-into seeing information, while the rest remains willfully ignorant in line with earlier studies (Bell et al. 2017; Caputo et al. 2020). Those choosing to access the information prefer a text over a video, but there is no significant difference across the two mediums in terms of how they impact respondents marginal WTP for the gene-edited milk. Importantly, we find that the effectiveness of said information does however vary between respondents who can be classified as information seekers and non-seekers, with the latter being generally less responsive to it. These results lead us to our main finding, that using forced information treatments in DCE are likely to lead to choice outcomes which diverge from consumer behavior in a real-life setting. Our results also suggest that information seeking itself is more relevant in the preference formation for gene-edited milk relative to conventional milk than organic. Lastly, an assessment of the effect of socio-demographics on respondents' information seeker status and the preferred information medium revealed that some variables like age and area of residence are significantly associated with changes in the respective variables.

Our study, while comprehensive, has a number of shortcomings. For example, we only assess respondents' responses to different information settings for a single product and gene-editing application. Caputo et al. (2020b) showed that consumer preferences for gene-edited food and benefit information are product dependent. Future studies could therefore assess whether the results hold for other products and applications. Similarly, it would be of interest to assess consumer preferences for gene-edited products in the context of a basket-based approach to see whether and how respondents make trade-offs between gene-edited foods and other alternatives when making multiple simultaneous choices as in Caputo and Lusk (2022). Moreover, in the context of information sensitivity other studies might also explore the role of attention to the provided information and survey responses in general.

Despite these limitations, our study is able to inform the market potential of gene-edited milk which can be used by producers, processors and policymakers. Likewise, our findings on how information delivery can influence choice behavior can be used in future studies to design choice experiments more realistically and thus provide better accurate information to industry stakeholders.

APPENDIX

APPENDIX

Tables

Table A3.1 Summary of selected studies using DCEs and information treatments

	Topic	**Findings**
Written Text		
Ahn and Lusk (2021)	Consumers response towards different reasons for price hikes/ size bans for sugar sweetened beverages was examined.	The information treatments resulted in significant heterogeneity in responses, with no clear trend.
Britwum & Yiannaka (2019)	The impact of gain and loss message framing on consumer's WTP for technologies/interventions contributing to food safety was evaluated.	The highest impact on respondent's WTP was elicited in the information treatments employing loss-framed messages.
Burton and Rigby (2012)	Examination of attitudes and preferences of Australian consumers toward beef derived from animals bred using stem cell technologies. Four information treatments phrased the information about the technology using different keywords.	Wording of the information affected the utility and corresponding variance associated with the different attributes significantly.
Caputo et al. (2020b)	Determination of consumer's WTP for different gene-edited food products when providing information on the different production methods and consumer, environmental, and farmer benefits.	Respondent's sensitivity to information is dependent on the product. Generally, the provision of benefit information in combination with information on the production methods led to an increase in the marginal WTP.
Caputo et al. (2022)	Assessment of consumer's WTP for gene-edited and genetically modified lettuce under different disclosure option. Respondents could opt-into learning more about the production methods of the included alternatives. Also, information on the benefits of gene-editing and genetic modification was provided prior to a second set of choice questions.	Significant differences in preferences exist between information seekers and non-seekers, with the former displaying a generally higher acceptance of gene-editing.

Table A3.1 (cont'd)

Chowdhury et al. (2011)	Analysis of Ugandan consumer's WTP for biofortified sweet potato. Treatments varied whether nutritional information was provided and whether choices were real or hypothetical.	Information on the sweet potatoes nutrition only resulted in a marginal premium compared to not providing information.
Czajkowski et al. (2016)	Analysis of the effect information provision has on the mean and the variance of individual-specific scale parameters. The empirical application concerned biodiversity conservation programs.	Giving respondents more positively framed and complete information was correlated with a higher mean relative scale and lower scale variance.
Ortega et al. (2015)	Evaluation of the effects of media headlines on consumer preferences for food safety, quality and environmental attributes	Media headlines were found to have a statistically significant effect on consumer preferences and WTP for product characteristics.
Ortega et al. (2020)	Prediction of consumers responsiveness to given information on genetic modification based on their preference uncertainty.	Individuals with a higher degree of uncertainty are more responsive to the information.
Papoutsi et al. (2015)	Evaluation of the impact information on fiscal policies can have on parent's food choices for their kids in the context of a fat tax and/or a thin subsidy.	Providing information augments the effect of the fiscal intervention in terms of selecting healthier food items.
Shew et al. (2018)	Provision of either name-only descriptions or more extensive information on different production method to analyze consumer's WTP for gene-edited, and genetically modified rice. The survey was conducted in the US, Australia, Belgium, France, and Canada.	Results are country dependent. The longer information treatment caused a smaller discount for the genetically engineered alternatives in the USA and Australia, but not in the other three countries.

Table A3.1 (cont'd)

Weir et al. (2021)	Analysis of the impact of positive, negative, and balanced information concerning genetic modification (GM) on the demand of organic, Non-GM, GM-fed and GM salmon.	WTP for GM salmon was reduced in all treatments. Moreover, positive information also resulted in a reduction of WTP for organic, and Non-GM salmon, while negative information increased WTP for organic salmon. Balanced information led to a reduced WTP for all alternatives.
Yang and Hobbs (2020)	Comparison of using logical-scientific versus narrative information to provide consumers information about gene-editing.	Using a more narrative style helps to reduce respondent's negative perceptions of biotechnologies.
Written Text and Graphics		
Cao et al. (2021)	Assessment of consumer preferences for eggs from different production systems. Respondents were either given only basic information on different metrices concerning housing conditions of chickens or also provided with additional information on living conditions evaluated via stars.	Consumers with less purchase experience respond more strongly to the information compared to more experienced consumers.
Lusk (2003)	Analysis of consumer's WTP for golden rice in the context of using cheap talk. Respondent's either saw a statement of the author or a one-page advertisement for the rice.	WTP of respondents did not differ significantly between the two information treatments.
Van Loo et al. (2020)	Analysis of consumer's preferences for farm-raised meat, lab-grown meat, and plant-based meat alternatives when exposed to different sets of information.	Providing information on the environment or technology had only minor effects on the conditional market share but reduced the share of respondent's selecting a buying option.

Table A3.1 (cont'd)

Written Text and Videos		
Klaiman et al. (2016)	Assessment of US consumer's WTP for packaging materials and recyclability of fruit juice drink products. Outside of the control group, treatments entailed either indirect questioning or a video on recycling.	Indirect questioning led to a reduction of respondent's WTP for recyclability, while the video increased the WTP relative to the control.
McFadden et al. (2021)	Consumer's acceptance of different biotechnologies targeting citrus greening were assessed. Randomly respondents either first saw scientific information on the technologies or a CBS newsclip, which represented a narrative format.	Respondents perceive the biotechnologies as less safe when first exposed to more narrative information, respondents.
Other		
Kilders and Caputo (2021)	Evaluation of US consumer's WTP for milk from gene-edited cows. Information was provided in several treatments via video providing different combinations of information on gene-editing, how it differs to GM, and/or its animal welfare implications	Particularly animal welfare information led to an increase in respondent's WTP. The spread of the preference distribution increased as more information is provided.
Klaiman et al. (2017)	Test of the effectiveness of information on recycling behavior related to on-the-go sandwich container. Respondents that were not in the control group were either shown an infographic or a video on recycling.	Willingness to clean the container was not affected by the information, but both the infographic and the video led to respondent's generally preferring the paper and cardboard packaging over the plastic one.
Caputo (2020)	Assessment of South Korean consumer's preferences for irradiated beef. Respondents not in the control saw a video on food safety, which depending on the treatment stood alone, was combined with positive information, combined with negative information, or combined with both.	Consumers acceptance of food irradiation increased with the provision of information on food safety and corresponding benefit statements of irradiation.

Table A3.2 Price level used in the DCE

Alternative	Price Level
Conventional & Gene-edited Milk	\$2.50, \$3.50, \$4.50, \$5.50
Organic Milk	\$3.50, \$4.50, \$5.50, \$6.50

Table A3.3 Sample Demographics

	Description[a]	Treatment			
		Pooled	Control	Forced	Select
Female	1 if female; 0 if male	0.52	0.53	0.50	0.52
Age	Age in years (Median)	46	44	46	47
Low Income	1 if household income below $75,000; 0 otherwise	0.58	0.53	0.60	0.60
College	1 if obtained college degree; 0 otherwise	0.49	0.55	0.50	0.46
Information Access					
Opt-out	1 if respondent saw no additional information; 0 otherwise	0.44	1.00	0.00	0.38
Video	1 if respondent saw the video; 0 otherwise	0.24	0.00	0.50	0.24
Text	1 if respondent saw the text; 0 otherwise	0.31	0.00	0.50	0.37
Information Seeker	1 if respondent (would have) wanted to see additional information; 0 otherwise	0.67	0.71	0.74	0.62
# of Respondents		1850	463	452	935

[a] Values presented are the mean unless indicated otherwise.

Table A3.4 MNL model estimates across treatments and information groups

Variable	**Control**		**Forced**				**Select**		
		Video & Text	Video	Text	Video, Text & Opt-Out	Video & Text	Video	Text	Opt-out
Organic	3.825*	3.773*	4.052*	3.526*	3.729*	4.203*	4.011*	4.341*	3.705*
	(0.12)	(0.12)	(0.17)	(0.17)	(0.08)	(0.10)	(0.17)	(0.15)	(0.15)
Conventional	3.791*	3.742*	3.939*	3.576*	3.690*	3.754*	3.597*	3.870*	4.203*
	(0.11)	(0.10)	(0.15)	(0.14)	(0.07)	(0.10)	(0.15)	(0.13)	(0.13)
Gene-edited	1.731-	2.774*	3.104*	2.467*	2.861*	3.591*	3.510*	3.657*	1.730*
	(0.11)	(0.10)	(0.15)	(0.14)	(0.07)	(0.1)	(0.15)	(0.13)	(0.13)
Price	-0.568*	-0.527*	-0.542*	-0.513*	-0.485*	-0.476*	-0.478*	-0.475*	-0.621*
	(0.02)	(0.02)	(0.03)	(0.0.3)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)

Table A3.5 MXL model estimates in WTP-Space across treatments and information groups

Variables	**Control**	**Forced**				**Select**			
		Video & Text	Video	Text	Video, Text & Opt-Out	Video & Text	Video	Text	Opt-out
Organic									
Mean	5.70*	5.88*	6.01*	5.71*	6.14*	7.01*	6.50*	7.23*	4.98*
	(0.18)	(0.19)	(0.25)	(0.28)	(0.14)	(0.19)	(0.29)	(0.24)	(0.23)
SD	3.18*	2.95*	2.80*	3.09*	3.28*	3.37*	3.50*	3.32*	3.03*
	(0.20)	(0.20)	(0.27)	(0.29)	(0.16)	(0.20)	(0.32)	(0.24)	(0.23)
Conventional									
Mean	5.94*	5.98*	5.95*	6.04*	6.21*	6.25*	5.92*	6.43*	6.16*
	(0.13)	(0.15)	(0.21)	(0.22)	(0.11)	(0.14)	(0.22)	(0.19)	(0.15)
SD	2.03*	2.24*	2.08*	2.39*	2.35*	2.06*	2.17*	2.02*	2.11*
	(0.13)	(0.15)	(0.21)	(0.22)	(0.11)	(0.15)	(0.23)	(0.22)	(0.15)
Gene-edited									
Mean	2.25*	3.86*	4.14*	3.58*	4.20*	5.75*	5.58*	5.83*	1.38*
	(0.24)	(0.19)	(0.24)	(0.29)	(0.15)	(0.16)	(0.24)	(0.20)	(0.43)
SD	2.54*	2.75*	2.50*	2.91*	3.10*	2.62*	2.64*	2.59*	3.12*
	(0.30)	(0.22)	(0.28)	(0.35)	(0.17)	(0.18)	(0.28)	(0.23)	(0.44)
Price Scale Parameter									
Mean	1.18*	1.14*	1.22*	1.06*	1.10*	0.96*	1.04*	0.91*	1.51*
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
SD	1.18*	1.14*	1.22*	1.06*	1.10*	0.96*	1.04*	0.91*	1.51*
	(0.02)	(0.02)	(0.03)	(0.03)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
Model Statistics									
LL	-2827.21	-2919.18	-1408.67	-1506.56	-5907.25	-3868.39	-1485.78	-2381.10	-1851.09
Obs/Choices	3704	3616	1800	1816	7480	4608	1816	2792	2872
Par	7	7	7	7	7	7	7	7	7
BIC/N	1.542	1.630	1.594	1.688	1.588	1.692	1.665	1.726	1.308
AIC/N	1.53	1.618	1.573	1.667	1.581	1.682	1.644	1.711	

Notes: Numbers in brackets indicate standard errors. * indicate a significance at the 5%-level or above

Table A3.6 MNL estimates across treatments and information seekers and non-seekers

Variables	Forced		Select	
	Seeker	Non-Seeker	Seeker	Non-Seeker
Organic	3.941*	3.640*	4.203*	3.705*
	(0.14)	(0.25)	(0.10)	(0.15)
Conventional	3.675*	4.339*	3.754*	4.203*
	(0.12)	(0.22)	(0.10)	(0.13)
Gene-edited	2.962*	2.494*	3.591*	1.730*
	(0.12)	(0.21)	(0.1)	(0.13)
Price	-0.501*	-0.682*	-0.476*	-0.621*
	(0.024)	(0.05)	(0.02)	(0.03)

Table A3.7 MXL model estimates in WTP-Space across treatments and information seekers and non-seekers

Variables		**Forced**		**Select**	
		Seeker	Non-Seeker	Seeker	Non-Seeker
Organic					
	Mean	6.49*	4.40*	7.01*	4.98*
		(0.21)	(0.36)	(0.19)	(0.23)
	SD	2.92*	2.70*	3.37*	3.03*
		(0.23)	(0.36)	(0.20)	(0.23)
Conventional					
	Mean	6.05*	5.66*	6.25*	6.16*
		(0.19)	(0.22)	(0.14)	(0.15)
	SD	2.32*	1.90*	2.06*	2.11*
		(0.18)	(0.26)	(0.15)	(0.15)
Gene-edited					
	Mean	4.43*	2.48*	5.75*	1.38*
		(0.21)	(0.40)	(0.16)	(0.43)
	SD	2.68*	2.52*	2.62*	3.12*
		(0.25)	(0.43)	(0.18)	(0.44)
Price Scale Parameter					
	Mean	1.00*	1.97*	0.96*	1.51*
		(0.02)	(0.06)	(0.02)	(0.03)
	SD	1.00*	1.97*	0.96*	1.51*
		(0.02)	(0.06)	(0.02)	(0.03)
Model Statistics					
LL		-2280.43	-585.567	-3868.39	-1851.09
Obs/Choices		2680	936	4608	2872
Par		7	7	7	7
BIC/N		1.722	1.302	1.692	1.308
AIC/N		1.707	1.266	1.682	1.294

Notes: Numbers in brackets indicate standard errors. * indicate a significance at the 5%-level or above

Figures

In what follows, we will present you with **8 choice questions.** In each of these choice questions (displayed on individual pages) we will ask you to choose between **three types of milk** offered at **different price levels**. You can also select a no-purchase option. For each question, we want to know which milk (if any) you would be most likely to buy.

The types of milk are presented...

- **...without any label ("conventional milk"),**
- **...with the USDA organic label ( ),**
- **...with an indication that the milk comes from gene-edited cows ("gene-edited milk")**.

All other characteristics of the milk that are not reported in the choice questions are similar across the products and in line with your preferences (e.g., in terms of the fat content). The options are the **same size (1 Gallon)**.

Please answer as honestly as possible and in a manner that you think would truly reflect how you would actually shop. Do not choose a higher priced option unless you would really pay the higher price in the grocery store. Click to proceed.

Figure A3.1 Choice Experiment Instructions provided to each respondent

REDUCING METHANE PRODUCTION IN DAIRY COWS

When thinking about cows, you might also think about the milk they produce. However, when creating this source of proteins, high-quality fat, minerals and vitamins cows also produce something else you might not necessarily expect: Methane.
Methane is a gas that contributes tremendously to global warming. Cows produce the gas during their digestive process and release it in the form of burps or farts. Indeed, dairy cows are responsible for about 25% of this type of methane emissions in the United States.

Researchers are now using gene-editing, a new addition to the biotechnology toolbox, to reduce how much methane cows produce. This process has the potential to benefit the environment without detrimental effects to the cow.

When answering the next questions, please keep in mind that some of the milk products you have the option to hypothetical buy have been gene-edited to reduce how much methane cows produce.

Figure A3.2 Information script shown to respondents in the DCE who were assigned/chose to the Text information.

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