JOURNAL of FOOD DISTRIBUTION RESEARCH

Volume 54 / Issue 3 / November 2023



Published by

FDRS
FOOD DISTRIBUTION RESEARCH SOCIETY

http://www.fdrsinc.org

Food Distribution Research Society

2023 Officers and Directors

Journal of Food Distribution Research
Volume 54, Issue 3
November 2023

ISSN 0047-245X

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Online Grocery Shopping Practices and Intentions Shaped by Pandemic-era Experiences

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Abstract

This study examines impacts of COVID-19 on preferences for and changes in grocery shopping methods. Fifty-five percent of respondents indicated they would not continue online grocery shopping in the coming year. However, analyses suggest those who initiated online grocery shopping during the pandemic are more likely to shop online in the future. Age, income, education level, money spent grocery shopping online, and previous online grocery shopping behavior were statistically significant in the model of future intentions to shop online. This work provides an understanding of drivers of online grocery shopping, which is of interest to retailers and policy makers.

Keywords: consumer behavior; food preferences; grocery; household decision making; online shopping

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Introduction

Shopping for food and household essentials has changed dramatically over the past several years, partially due to natural evolution of consumer behaviors. Additionally, change was instigated and/or accelerated by behaviors/adaptations to mitigate exposure risks and accommodate stay-at-home practices or caregiving responsibilities during the COVID-19 era. Early in the pandemic and upon concerns of supply disruption or shortages, consumers stockpiled grocery items (Acosta, 2020; Dou et al., 2020; Melo, 2020). During 2020 and 2021 consumers spent less time and money dining out (restaurants or food service facilities) and cooked more meals at home (Bender et al., 2022; Ko, Son, and Kim, 2022). In addition, consumers shopped for food and household consumables less frequently in response to stay-at-home orders (or personal desire) to reduce frequency of potential exposure (Ellison et al., 2020; Kowitt and Lambert, 2020; Melo, 2020; Jensen et al., 2021). Instead, consumers shifted their food expenditures to food delivery services or online grocery shopping (Redman, 2020).

The consumers' shift to online grocery shopping during 2020 and 2021 in response to COVID-19 risks resulted in an increase in online grocery sales. One study found that 45% of consumers are buying more groceries online since the start of COVID-19 (Redman, 2021). Jensen et al. (2021) found that 37% of respondents who have shopped online in 2020 were first-time online shoppers. Online grocery sales in the United States exceeded $35 billion in 2022 and are projected to reach $36.3 billion in 2023 (IBIS World, 2023). The annualized growth rate of online grocery sales in the United States is estimated at 15.1% for 2018-2023 (IBIS World, 2023). Considering the gradual growth of online grocery sales before the pandemic, COVID-19 was a situational factor leading shoppers to adopt online grocery shopping much more rapidly than would have been predicted otherwise. Online grocery sales took a giant leap of 54% from $18.5 billion in 2019 to $28.4 billion in 2020 (IBIS World, 2023). They rose by only 11% from $16.6 billion to $18.5 billion between 2018 and 2019 (IBIS World, 2023).

Prior to 2020, many consumers did not actively adopt online grocery shopping due to concerns of freshness not being guaranteed (Hand et al., 2009; Singh, 2019; Kvalsvik, 2022), dissatisfaction from the fact that immediate product possession is not possible (Rohm and Swaminathan, 2004; Hand et al., 2009; Singh, 2019), the missing experiences of touching and feeling products (Pechtl, 2003), concern about substitution to unsuitable items (Hand et al., 2009), and/or picking wrong items or receiving items close to expiration dates (Hand et al., 2009). Mistrust of online grocery product quality kept online grocery shopping one of the least popular e-commerce segments (Kvalsvik, 2022) despite the supply side technological improvements (Mason, 2019)[1] compared to other product categories such as travel, fashion, electronics, and books/music (Nielson, 2018).

[1] The continuous growth and optimistic anticipation of online grocery shopping are attributed to recent technological advances in artificial intelligence, big data analytics, machine learning and/or robotics (Mason, 2019). The technologies help overcome such challenges that prior online grocers used to face as managing highly perishable products, differing temperature regimes (chilled, frozen, and ambient), keeping proper stock levels, food waste minimization, wide variation in consumers' tastes, accurate item picking for orders placed in a basket, and last mile delivery (Mason, 2019).

Research has been conducted to examine internal and external triggers in the adoption (and disadoption) of online grocery shopping practices. Internal triggers often cover customers' demographics, attitudes, and perceptions. Younger shoppers are more likely to shop for groceries online due to their familiarity with technology compared to older shoppers (Farag et al., 2007; Van Droogenbroeck and Hove, 2018; Etumnu et al., 2019). Findings are inconsistent regarding gender. Some studies suggest a positive relationship between being female and online grocery shopping adoption (Jaller and Pawha, 2020), while others find the opposite (Farag et al., 2007; Etumnu and Widmar, 2020). Households with younger children may prefer to shop for groceries online (Hansen, 2005; Melis et al., 2016; Etumnu et al., 2019; Jaller and Pawha, 2020) because grocery shoppers with children may find that grocery shopping is more challenging with children in tow (Jensen et al., 2021). Household income has a positive effect on online grocery shopping (Hansen, 2005). Additionally, full-time employment (Van Droogenbroeck and Hove, 2018) and a higher level of education (Etumnu et al., 2019; Jaller and Pawha, 2020) had positive effects on online grocery shopping. Distance from the nearest brick-and-mortar grocery store also affects consumers' willingness to shop online, albeit ambiguously (Melis et al., 2016; Germain, 2020; Jensen et al., 2021). Melis et al. (2016) found that the farther grocery shoppers live from a brick-and-mortar grocery store, the more likely they are to spend a larger share of their grocery budget at online grocery websites. On the other hand, Jensen et al. (2021) pointed out that this finding may not hold true for more rural areas where there are challenges delivering the last mile(s).

External triggers, such as situational factors driving consumers to kick off their online grocery shopping, have also been explored. Previously studied triggers included having a baby, developing health or mobility problems, and sudden uncontrollable events (Hand et al., 2009; Kvalsvik, 2022). Hand et al. (2009) found that situational factors, such as the birth of a child or family circumstances, motivated shoppers to buy groceries online. Kvalsvik (2022) focused more on aging and unfavorable health conditions as situational factors that limit mobility and found that adoption of online grocery shopping among older adults is a result of complicated tradeoffs.

After overcoming the initial hurdle to try online grocery shopping, whether the experience(s) keep consumers shopping online when situational factors resolve is an open question (Hand et al. 2009; Sreeram, Kesharwani, and Desai, 2017; Singh, 2019; Grashuis and Skevas, 2020; Jensen et al., 2021). Jensen et al. (2021) found that slightly more than half of respondents planned to shop online after the pandemic. Conversely, Grashius and Skevas (2020) suggested that many online shoppers may return to brick-and-mortar grocery stores when the pandemic subsides. Hand et al. (2009) mainly investigated situational factors; finding that many shoppers who adopted online grocery shopping for the first time (because of situational factors) discontinued shopping online once the triggering situation disappeared.

Previous studies mainly investigated how internal factors, such as age, income, and the presence of children in the household, influence consumers' decision to adopt online grocery shopping (Melis et al., 2016; Van Droogenbroeck and Hove, 2017; Etumnu et al., 2019; Jaller and Pawha, 2020). Now, even though consumers persisted with online grocery shopping during the acute phases of the pandemic, it is unclear if they will continue to shop online after other COVID-19-era practices are discontinued. This study evaluates the COVID-19 pandemic as one situational factor that limited public mobility, leading consumers to adopt online grocery shopping, and investigates online grocery shoppers' intention to continue shopping online. This study follows Jensen et al. (2021), Grashius and Skevas (2020), and Hand et al. (2009) in the sense that it investigates shoppers' intention to continue online shopping after a certain situational trigger, the COVID-19 pandemic, disappears. Understanding shoppers' future online grocery shopping intentions and factors behind their decision would provide insights for online grocery retailers to improve the quality of online grocery services.

Methods

Data Collection and Survey Instrument

An online survey was created and hosted using the Qualtrics online survey platform (Qualtrics, 2021). The survey instrument was approved by university IRB. Kantar, an opt-in online panel hosting company, was used to obtain survey respondents. They were required to be 18 years or older. No other exclusionary criteria were included. The proportion of respondents were matched to the 2019 U.S. census (U.S. Census Bureau, 2019a; U.S. Census Bureau, 2019b) using Quotas set in Qualtrics. Targeted demographics included sex, age, education, income (U.S. Census Bureau, 2019a), and U.S. region of residence (U.S. Census Bureau, 2019b). Once a quota category was met, additional respondents from that category were not allowed to continue past the demographic section of the survey. Although the focus of this work is grocery shopping, in order to ensure a representative sample, grocery shopping behavior was not an exclusionary criterion. Data collection took place from January 13, 2021, through January 23, 2021. The test of proportions was used to compare the proportion of respondents in each of the targeted demographic categories to the U.S. census (Acock, 2018). There were 2,250 respondents who entered the survey, and 1,819 respondents completed the demographic section of the survey, which included gender, age, income, household makeup, income, education, as well as region, state, and county of residence. There were 972 respondents who were within the demographic quotas. Of those, 929 respondents completed the survey. The rurality of the respondents was determined using the 9 categories outlined in the USDA rural-urban continuum codes (USDA-ERS, 2020). For example, a code of 1 indicates a county in a metro area with a population of 1 million or more; 4 indicates an urban population of 20,000 or more adjacent to a metro area; and 9 indicates a completely rural county or an urban population of less than 2,500 not adjacent to a metro area. For this analysis we use two categories: metro counties and nonmetro counties. Metro counties included the rural urban continuum codes from 1–3, and nonmetro includes the rural urban continuum codes 4–9 (USDA-ERS, 2020).

In addition to demographic questions, respondents were asked about their dining and grocery shopping behavior and preferences. The survey instrument is available in Appendix A. Questions included the frequency of dining out, which was defined as either take-out or in-restaurant settings. Individual participation in obtaining food was also collected and answer choices ranged from the respondent having a primary role to the respondent having no role in procuring food or household items. The main focus of the paper was determining frequency and motivation for online grocery shopping. Respondents were asked the amount of time and money spent online grocery shopping as well as the specific method. Online grocery shopping methods included buying groceries online, pick up in store; pick up retailer curbside; delivery by retailer; delivery by third-party food service; and delivery by mail service. Finally, respondents were asked their future expectations for online grocery shopping and why they do, or do not, grocery shop online.

Statistical Testing and Econometric Modeling

The test of proportions was used to compare demographics within the respondent involvement with food procurement categories for the table included in the Appendix (Acock, 2018). The test of proportions was also used to compare the percentages of respondents for time and money expenditures for in-store grocery shopping and online grocery shopping.

Logit Model of COVID-19-induced Online Shopping

A logit model was used to determine the relationship between demographics and beginning to shop online during the COVID-19 pandemic. A logit model was specified because the belief that participants would shop online was a binary response (Greene, 2012). The model estimated was as follows:

$$\begin{aligned} ShopOnlineCOVID = {} & \beta_1 Female + \beta_2 Age1824 + \beta_3 Age2534 + \beta_4 Age3554 + \\ & \beta_5 Age5565 + \beta_6 Income024 + \beta_7 Income2549 + \beta_8 Income5074 + \beta_9 Income7599 + \\ & + \beta_{10} EducationNoHigh + \beta_{11} EducationHigh + \beta_{12} EducationNoBach + \\ & \beta_{13} EducationBach + \beta_{14} Northeast + \beta_{15} South + \beta_{16} Midwest + \beta_{17} Metro + \beta_{18} Child + \\ & \beta_{19} Veg + \beta_{20} HouseholdSize + \varepsilon \end{aligned} \tag{1}$$

where *ShopOnlineCOVID* is a binary variable indicating the respondent began shopping online during COVID-19. *Age1824*, *Age2534*, *Age3554*, and *Age5565* are age binary variables using the census age categories and in reference to the age category of 65-plus. *Income024* (\$0-\$24,999), *Income2549* (\$25,000-\$49,999), *Income5074* (\$50,000-\$74,999), and *Income7599* (\$75,000-\$99,999) are income binary variables using the census income categories and in reference to the income category of more than \$100,000. The education binary variables are *EducationNoHigh* (did not graduate from high school), *EducationHigh* (graduated from high school, did not attend college), *EducationNoBach* (attended college, no degree earned), *EducationBach* (attended college, Associate's or Bachelor's degree earned), and are in reference to attended college, graduate or professional degree earned. Regions of residence binary variables are *Northeast*, *South*, and *Midwest*. Regional binary variables are in reference to the region West. *Child* indicates the respondent has at least one child in the household. *Veg* indicates the respondent has a vegan or vegetarian family member in the household. *HouseholdSize* is a continuous variable indicating the number of adults and children in the household.

Logit Model of Respondents' Future Online Shopping

A logit model was used to determine the relationship between demographics, previously shopping online, and the respondent's belief they would shop online in the 12 months following January 2021. A logit model was specified because the belief that they would shop online was a binary response (Greene, 2012). The model estimated was as follows:

$$ShopOnlineFuture = \beta_1 Female + \beta_2 Age1824 + \beta_3 Age2534 + \beta_4 Age3554 +$$

$$\beta_5 Age5565 + \beta_6 Income024 + \beta_7 Income2549 + \beta_8 Income5074 + \beta_9 Income7599 +$$

$$+\beta_{10} EducationNoHigh + \beta_{11} EducationHigh + \beta_{12} EducationNoBach +$$

$$\beta_{13} EducationBach + \beta_{14} Northeast + \beta_{15} South + \beta_{16} Midwest + \beta_{17} Metro + \beta_{18} Child +$$

$$\beta_{19} Veg + \beta_{20} HouseholdSize + \beta_{21} PrimaryShopper + \beta_{22} FemalePrimaryShopper +$$

$$\beta_{23} ObtainsFood + \beta_{24} FemaleObtainsFood + \beta_{25} PlacesOnlineOrder +$$

$$\beta_{26} FemalePlacesOnlineOrder + \beta_{27} MoneyStore100199 + \beta_{28} MoneyStore200plus +$$

$$\beta_{29} TimeStore60149 + \beta_{30} TimeStore150plus + \beta_{31} MoneyOnline100199 +$$

$$\beta_{32} MoneyOnline200plus + \beta_{33} TimeOnline60149 + \beta_{34} TimeOnline150plus +$$

$$\beta_{35} OnlinePreCOVID + \beta_{36} OnlineCOVID + \beta_{37} PickUp + \beta_{38} Delivered + \varepsilon \quad (2)$$

where *ShopOnlineFuture* indicates the respondent stated their household would shop online in the 12 months following January 2021. The demographic variables are as described in equation 1. *PrimaryShopper* is a binary variable indicating the respondent selected "they have the primary role in selecting the food and household items." *FemalePrimaryShopper* is an interaction term between female and primary shopper. *ObtainsFood* is a binary variable indicating the respondent selected they "obtained the food and household items in-store." *FemaleObtainsFood* is an interaction term between female and obtains food. *PlacesOnlineOrder* is a binary variable indicating the respondent "places the order online for food and household items." Binary variables for in-store spending include *MoneyStore100199* (spends between \$100 and \$199 in-store) and *MoneyStore200plus* (spends more than \$200 in store). The reference category for spending in store is \$0–\$99. Binary variables for time spent in-store include *TimeStore60149* (spends between 60 and 140 minutes) and *TimeStore150plus* (spends more than 150 minutes in store). The reference category for spending in store is \$0–\$99. Binary variables for online spending include *MoneyOnline100199* (spends between \$100 and \$199 in-store) and *MoneyOnline200plus* (spends more than \$200 in store). The reference category for spending online is \$0–\$99. Binary variables for time spent online include *TimeOnline60149* (spends between 60 and 140 minutes) and *TimeOnline150plus* (spends more than 150 minutes in store). The reference category for spending online is \$0–\$99. Previous shopping behavior is represented by the binary variables

OnlinePreCOVID (shopped online before COVID) and *OnlineCOVID* (began shopping online during COVID, but not before). Previous shopping is in reference to never shopped online. *PickUp* is a binary variable indicating the respondent had picked up online groceries in the past. *Delivered* is a binary variable indicating the respondent had online groceries delivered in the past. ε is the error term.

Results and Discussion

The demographics of the sample of survey respondents closely matched the U.S. population as described in the U.S. census (see Table 1). Statistical differences were found in age, with the 18–24 and 25–34 categories representing a smaller percentage of the sample than the population. The age categories 34–44 and 55–65 years old represented a larger percentage of the sample than the population. The percentage of the sample who did not graduate from high school (2%) was statistically lower than the population (11%). The percentage of the sample with education categories—attended college, associate's or bachelor's degree earned (34%), and graduate or professional degree earned (15%)—were statistically higher than the U.S. population (29%, 13%). A lower percentage of respondents were from the West (18%) when compared to the U.S. population (24%). Only 8% of respondents self-reported as vegetarian, while 4% of respondents self-reported as vegan.

Table 1. Demographic Information (n = 929)

Demographic Variable	**Percentage of Respondents**	**U.S. Census[2]**
Gender		
Male	46	49
Female	54	51
Age		
18–24	8$^{\Psi}$	12
25–34	13$^{\Psi}$	18
35-44	19$^{\Psi}$	16
45–54	16	16
55–65	20$^{\Psi}$	17
65 +	23	21
Income		
$0–$24,999	19	18
$25,000–$49,999	22	20
$50,000–$74,999	16	17
$75,000–$99,999	13	13
$100,000 and higher	29	31
Education		
Did not graduate from high school	2$^{\Psi}$	11
Graduated from high school, did not attend college	27	27
Attended college, no degree earned	21	21
Attended college, associate's or bachelor's degree earned	34$^{\Psi}$	29
Attended college, graduate or professional degree earned	15$^{\Psi}$	13

Table 1. Continued

Demographic Variable	Percentage of Respondents	U.S. Census[2]
Region of residence		
Northeast	18	17
South	41	38
Midwest	22	21
West	18 ᴪ	24
Rurality		
Metro	74	
Non metro	26	
Household make-up	Average number	
Adults (over 18 years) *n* = 911[1]	2.04	
Children ages 0–4 *n* = 751	0.16	
Children ages 5–10 *n* = 764	0.26	
Children ages 11–15 *n* = 768	0.24	
Children ages 16–18 *n* = 743	0.13	
Vegetarianism		
Self	8	
A member of household	5	
A close friend or family member is	9	
Veganism		
Self	4	
A member of household	5	
A close friend or family member is	7	

Notes: ᴪIndicates the percentage of respondents is statistically different than the U.S. census at the 0.05 level.
[1]Not all respondents indicated their household makeup, n is as given.
[2] U.S. Census Bureau, 2019a; U.S. Census Bureau, 2019b

Regarding the role the participants played in selecting food and household items, 68% indicated that they had a primary role, while 29% indicated they assisted, in selecting food and household items (see Figure 1). Just under a quarter (24%) = of respondents indicated they obtain the food and household items in-store. Online grocery ordering was reported by 9% of respondents , and 7% used curbside pick-up for the food and household items. Only 4% of respondents had no role in procuring food or household items. An additional breakdown of demographics and food procurement is available in Appendix B.

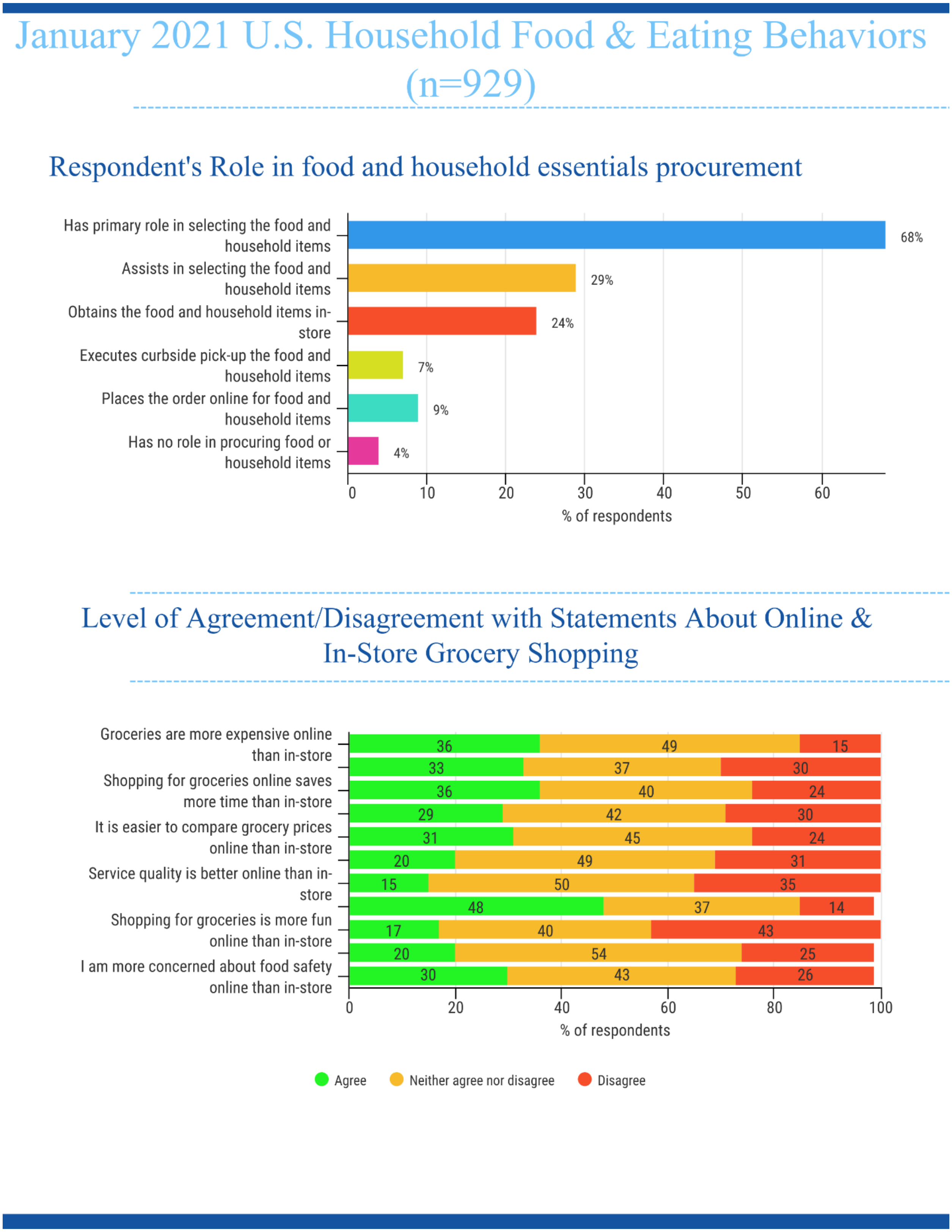

Figure 1. Food Procurement and Eating Behaviors by U.S. Households in 2021

A high percentage (42%) of respondents indicated they spent 30–59 minutes grocery shopping in-store during an average week since March 2020 (see Table 2). March 2020 was selected as a focal point, as this was around the time most people became aware of the prevalence of COVID-19 in the United States. Of the respondents who indicated they grocery shopped online, 51% spent less than 30 minutes. Approximately a third (34%) of respondents indicated they spent between \$50–\$99 in-store grocery shopping, and 26% indicated they spent between \$100–\$149. There were 41% of respondents who indicated they spent less than \$50 on online groceries. There are several potential explanations for the differences in time and money spent shopping online when compared to in-store. Respondents spent both less money and time shopping online. This finding could be reflective of the number of items purchased, as well as the ease of online shopping. Future research should include questions regarding the specific items purchased to further analyze spending behavior online.

Table 2. Estimated Time and Money the Household Spends on Online Grocery Shopping and In-store Grocery Shopping

	In-store Grocery Shopping	**Online Grocery Shopping**
Time spent	*n* = 887	*n* = 492
Less than 30 mins	17 Ψ	51 Ψ
30 mins to 59 mins	42 Ψ	25 Ψ
60 mins to 89 mins	23 Ψ	12 Ψ
90 mins to 119 mins	8	6
120 mins to 149 mins	6 Ψ	3 Ψ
150 mins to 179 mins	2	1
180 mins and above	2	2
Money spent	*n* = 882	*n* = 477
Less than \$50	15 Ψ	41 Ψ
\$50 to \$99	34 Ψ	22 Ψ
\$100 to \$149	26 Ψ	18 Ψ
\$150 to \$199	13 Ψ	9 Ψ
\$200 to \$249	7	6
More than \$250	5	4

Note: Ψ Indicates the percentage of respondents is statistically different (< 0.05) between the in-store grocery shoppers and online grocery shoppers.
This table shows the estimated time and money spent by household in an average week since March 2020. Online grocery shopping includes ordering via an app, website, or via phone for pick up in-store or curbside, or for delivery. Percentage of self-reported respondents who shopped in that way. (*N* is given in table.)

Of the respondents who bought groceries online and picked them up in a retail store (n = 274), a high percentage did so at least once a week (44%) or at least once in three months (41%) (see Table 3). For those who buy groceries online and pick them up at the retailer curbside (n = 311), a high percentage did so at least once in three months (48%). The same percent of respondents (n = 275) also indicated they bought groceries online and had them delivered by the retailer at least once a month. High percentages of respondents who bought groceries online and had them delivered by a third-party food service (n = 236) did so at least once a week (39%) or at least once a month (40%). There were 48% of respondents who buy groceries online and have them delivered by mail service (n = 272) do so at least once in three months.

Table 3. Online Grocery Shopping Type and Frequency

	At Least Once a Week	At Least Once in Three Months	At Least Once in the Past Year
Buy groceries online, pick up in retailer store (n = 274)	44	41	15
Buy groceries online, pick up at retailer curbside (n = 311)	38	48	14
Buy groceries online, delivery by retailer (n = 275)	38	48	14
Buy groceries online, delivery by third-party food service (n = 236)	39	40	21
Buy groceries online, delivery by mail service (n = 272)	34	48	18

Note: Percentage of respondents who participate in that type of online shopping. N given in table.

Just over half (55%) of respondents indicated they would not online shop in the 12 months after January 2021, which is consistent with Grashius and Skevas (2020) and Hand et al. (2009). Jensen et al. (2021) found that 58% of respondents plan to continue online grocery shopping regardless of pandemic conditions. Table 4 specifies reasons why 55% of respondents indicated they would not shop online in the 12 months after January 2021. A high percentage of respondents (65%) indicated the reason they would not shop online was because they like to see and choose products in person before buying them. About half (52%) of respondents would not shop online because they enjoy shopping for groceries in store. "I do not like paying charges for delivery/curbside" was selected as a reason to not shop online by 31% of participants. Surprisingly, only 1% of respondents indicated they would not shop online due to limited internet access. This finding may be reflective of increases in rural broadband (Smith, 2023), as well as the prevalence of cellular data.

Table 4. Reasons Why Respondents Indicated They Would Not Online Shop

Reason for Not Online Shopping	Percentage of Respondents
I like to see and choose products in person before buying them.	65
I enjoy shopping for groceries in-store.	52
I do not like paying charges for delivery/curbside.	31
I do not like to plan my grocery shopping in advance.	9
I find it inconvenient waiting for a delivery.	15
My favorite/preferred grocery retailer does not offer this service in my area.	3
Online grocery shopping is not available from any retailer in my area.	2
I find picking up an order at the store inconvenient.	7
Previous bad experience with online grocery shopping.	5
I have limited internet access.	1
I do not trust online grocery retailers.	18
Other reasons(s)	4

Note: This table represents a period over 12 months after January 2021. Percentage of respondents, multiple selections allowed. N = 513.

Level of agreement/disagreement with statements about online and in-store grocery shopping (see Figure 1) may provide some insights surrounding intentions of not continuing online grocery shopping after the situational factor occurred—COVID-19. Agreement with negative statements about online grocery shopping, such as "Groceries are more expensive online than in-store" and "I am more concerned about food safety online than in-store" may motivate a return to in-store shopping. Despite the belief by some that groceries are more expensive online, respondents spent less money online grocery shopping. This finding could be a result of purchasing fewer items, or there may be some shoppers who find discounts or purchase only lower cost items online. Disagreement with such positive statements about online grocery shopping as, "Service quality is better online than in-store" and "Shopping for groceries is more fun online than in-store" would also suggest a desire to return to in-store experiences. Even though respondents agree that it is easier to compare grocery prices online than in-store, the results suggest that consumers are still wary of the quality of some food items and the service from online grocers.

On the other hand, 45% of respondents indicated they would shop online in the 12 months after January 2021. Table 5 illustrates why 45% of the respondents would continue to shop for groceries online. Half (50%) of respondents indicated they shop online to lessen contact with other people due to COVID-19 or related health concerns. These respondents may be looking to return to stores after the pandemic subsides further. There were 46% percent of respondents who indicated online shopping saves them time, while 38% indicated it helps avoid lines. Online shopping lets them order groceries "anytime from anywhere" was reported by 35% of respondents, and 26% indicated it was easy to choose the delivery time.

Table 5. Reasons Why Respondents Indicated They Would Online Shop

Reason for Online Shopping	Percentage of Respondents
I can order groceries anytime from anywhere.	35
I can easily choose the delivery time.	26
It helps me avoid lines/queues.	38
It allows me to compare prices easily.	22
It is easier for me to search for grocery items online.	25
I have access to more stores and grocery items.	17
I have physical constraints.	10
I dislike grocery shopping in stores.	10
It saves me time.	46
I can avoid impulse buying.	22
To lessen contact with other people due to COVID-19 or related health concerns.	50
Other reasons	8

Note: This table represents a period over 12 months after January 2021. Percentage of respondents, multiple selections allowed. $N = 416$

Logit Model of COVID-19-induced Online Shopping

Surprisingly, few demographics were statistically significant in the logit model of COVID-19-induced online shopping. Gender, age, income, education level, household size, region of residence, and rurality were not statistically significant (see Table 6). Having a child increased the likelihood of starting to shop online during COVID-19 (marginal 2.42). Previous studies recorded that shoppers may find it more challenging to grocery shop at brick-and-mortar stores with young children, which would increase the appeal of online shopping (Hansen, 2005; Melis et al., 2016; Etumnu et al., 2019; Jaller and Pawha, 2020; Jensen et al., 2021). The COVID-19 vaccine was available later for children, starting with those aged 5–11 on November 2, 2021 (Kates, Tolbert, and Rouw, 2021). This delay may have been the catalyst for some families to shop online in order to minimize children's exposure. Respondents with a vegan or vegetarian in the household were also more likely to begin shopping online during COVID-19. Pymnts (2023) found that 50% of meat eaters indicated they would not purchase meat online. This, coupled with the ease of shipping dry goods and potential refrigeration and delivery availability concerns, may make vegan/vegetarian purchases easier.

Table 6. Logit Model of Respondents Who began Online Shopping during the COVID-19 Pandemic $N = 929$.

Independent variables	**Coefficient**	**Robust SE**	**Marginal**
Female	0.240	0.196	0.031
Age			
18–24	0.026	0.440	0.003
25–34	0.447	0.375	0.057
35–44	0.438	0.345	0.056
45–54			
55–65	0.065	0.339	0.008
65+	Omitted	Omitted	Omitted
Income			
$0–$24,999	-0.175	0.318	-0.022
$25,000–$49,999	0.079	0.277	0.010
$50,000–$74,999	0.112	0.287	0.014
$75,000–$99,999	0.025	0.290	0.003
$100,000 or greater	Omitted	Omitted	Omitted
Education			
Did not graduate from high school	0.061	0.575	0.008
Graduated from high school, did not attend college	-0.469	0.338	-0.060
Attended college, no degree earned	-0.377	0.324	-0.048
Attended college, associate's or bachelor's degree earned	-0.194	0.286	-0.025
Attended college, graduate or professional degree earned	Omitted	Omitted	Omitted
Region of residence			
Northeast	0.067	0.316	0.009
South	0.188	0.269	0.024
Midwest	-0.030	0.312	-0.004
West	Omitted	Omitted	Omitted
Lives in a metro area	-0.059	0.217	-0.007

Table 6. Continued

Independent variables	Coefficient	Robust SE	Marginal
Has children	0.711**	0.296	0.091**
Vegetarian or vegan in the family	0.938***	0.230	0.120***
Household size	-0.075	0.093	-0.010
Constant	-1.952	0.445	

Note: * statistically significant at the 0.10 level, **0.05 level, ***< 0.0001 level. Model is statistically significant at < 0.001, pseudo R squared 0.0766. [1]Omitted indicates the dummy variable category used as the reference category.

Logit Model of Belief That Households Will Shop Online in the Future

Varying degrees of the restricted model of shopping online in the future are available in Appendix C. In the logit model of belief that respondents' households will shop online in the 12 months following January 2021, results are somewhat different from previous studies (see Table 7). Gender was not statistically significant. Respondents aged 45–54 were more likely to shop online (marginal 0.074) when compared to those 65 and older. Prior research found that older people were less likely to shop online (Etumnu et al., 2019; Van Droogenbroeck and Hove, 2018; Farag et al., 2007). This finding may be attributed to technological barriers and/or a need for more social interaction while shopping in brick-and-mortar stores (Hand et al., 2009; Kvalsvik, 2022). Jensen et al. (2021) presents somewhat different results; they found that for each additional year in age, the probability of planning to shop online in the future increases by 0.4%. Older shoppers may appreciate online grocery shopping due to difficulties with transportation or health-related issues.

Table 7. Logit Model of Respondent's Belief Their Household Will Shop Online

Independent Variables	Coefficient	Robust SE	Marginal
Female	0.123	0.590	0.011
Age			
18–24	0.169	0.704	0.015
25–34	0.105	0.460	0.009
35–44	0.159	0.361	0.014
45–54	0.861**	0.316	0.074**
55–65	0.006	0.293	0.001
65+	Omitted	Omitted	Omitted
Income			
$0–$24,999	-0.154	0.435	-0.013
$25,000–$49,999	-0.350	0.352	-0.030
$50,000–$74,999	-0.675*	0.374	-0.058*
$75,000–$99,999	0.735**	0.360	0.063**
$100,000 or greater	Omitted	Omitted	Omitted
Education			
Did not graduate from high school	-1.668	1.050	-0.144
Graduated from high school, did not attend college	-0.633	0.394	-0.055
Attended college, no degree earned	-0.213	0.358	-0.018

Table 7. Continued

Independent Variables	Coefficient	Robust SE	Marginal
Attended college, associate's or bachelor's degree earned	-0.498*	0.298	-0.043*
Attended college, graduate or professional degree earned	Omitted	Omitted	Omitted
Region of residence			
Northeast	0.013	0.380	0.001
South	0.116	0.368	0.010
Midwest	0.295	0.387	0.025
West	Omitted	Omitted	Omitted
Lives in a metro area	0.124	0.273	0.011
Has children	-0.224	0.391	-0.019
Vegetarian or vegan in the family	-0.050	0.418	-0.004
Household size	0.042	0.107	0.004
Is the primary shopper	0.572	0.407	0.049
Interaction of female and primary shopper	-0.371	0.613	-0.032
Obtains the food in store	0.246	0.413	0.021
Interaction of female and obtains the food in store	-0.872	0.564	-0.075
Places the online order	-0.120	0.887	-0.010
Interaction of female and places the online order	2.239**	1.093	0.193**
Money spent grocery shopping in store			
$0–$99	Omitted	Omitted	Omitted
$100–$199	0.026	0.272	0.002
Greater than $200	0.579	0.578	0.050
Time spent grocery shopping in store			
0–30 minutes	Omitted	Omitted	Omitted
60–149 minutes	0.030	0.263	0.003
150 minutes and greater	-1.195	0.874	-0.103
Money spent grocery shopping in online			
$0–$99	Omitted	Omitted	Omitted
$100–$199	0.742*	0.417	0.064*
Greater than $200	2.595**	1.305	0.224**
Time spent grocery shopping online			
0-30 minutes	Omitted	Omitted	Omitted
60-149 minutes	0.801	0.518	0.069
150 minutes and greater	-1.652	1.155	-0.142
Previous online shopping behavior			
Never shopped online	Omitted	Omitted	Omitted
Shopped online before COVID	2.154***	0.270	0.186***
Began shopping online during COVID, but not before	2.073***	0.395	0.179***

Table 7. Continued

Independent Variables	Coefficient	Robust SE	Marginal
Picked up online groceries in the past	1.521***	0.295	0.131***
Had online groceries delivered in the past	1.770***	0.253	0.153***
Constant	-3.206***	0.626	

Note: * statistically significant at the 0.10 level, **0.05 level, *** < 0.0001 level
This table presents a period over the 12 months after January 2021. $N = 929$. Model is statistically significant at <0.001, pseudo R squared 0.5766.
[1]Omitted indicates the dummy variable category used as the reference category.

Respondents with an income of $50,000–$74,999 were less likely to shop online (marginal -0.058), and those with an income of $75,000–$99,999 were more likely to shop online (marginal 0.063) when compared to those with an income of $100,000 or greater. This finding was less clear than prior studies that found household income had a positive impact on online grocery shopping (Hansen, 2005). Curbside pickup and the SNAP program for lower income shoppers can be used online, which may mitigate some barriers those with lower income face when shopping online (Day, 2020; USDA-FNS, 2020). Curbside pickup options did not incur extra delivery cost (Redman, 2020; Jensen et al., 2021) in many cases in 2021, due to many stores waiving curbside fees during the pandemic. Waived delivery fees also may have also served to level the online shopping playing field.

Attending college and associate's or bachelor's degree earned decreased the probability the respondent would continue to shop online (marginal -0.498) when compared to those who attended college and obtained a graduate or professional degree. Previous studies present similar results that show grocery shoppers with higher education levels would continue to shop online (Van Droogenbroeck and Hove, 2018; Etumnu et al., 2019; Jaller and Pawha, 2020; Jensen et al., 2021).

Rurality and region of residence were insignificant in our model. Previous studies were split on the benefits of online shopping for those in rural communities. Very remote shoppers may incur extra costs for delivery, or delivery may not be available (Jensen et al., 2021). Conversely, if rural consumers are far from brick-and-mortar stores but within reach of delivery services for online groceries, rurality may increase online grocery shopping (Melis et al., 2016). The lack of significance of rurality in our model may be reflective of the dichotomy in terms of usefulness for rural shoppers found in previous research.

Surprisingly, having a child did not increase the probability of continuing to shop online in the future. It is possible that other shopping behavior variables included in the model, such as spending and previously shopping online, are better indicators of shopping behavior than the simple presence of children in the household. Similarly, despite previous studies indicating people would not buy meat online (Pymnts, 2023), having a vegetarian or vegan in the family did not increase the likelihood of shopping online. Even heavy meat eaters could be buying other non-meat products online and simply reserving meat purchases for in-store shopping trips. Household size was also not statistically significant. Further research asking respondents specifics regarding product type and purchasing frequency online could shed more light on this issue.

Being the primary shopper, being the person who obtains food in the store, and placing the online order were not statistically significant. However, the interaction term between female and placing the online order was statistically significant, and being a female who placed the online order increased the likelihood of shopping online in the future (marginal 0.193). This information may be of use to those developing marketing surrounding online shopping.

The amount of time and money spent grocery shopping in store was not statistically significant. However, spending \$100–\$199 (marginal 0.064) and spending greater than \$200 (marginal 0.224) increased the likelihood of shopping online in the future, compared to spending \$0–\$99. Time spent grocery shopping online was not statistically significant. For retailers with online shopping platforms, focusing on retention of lower dollar customers or understanding their preferences could be an avenue to increase online shopping participation.

Respondents who shopped online before COVID-19 were more likely to shop online in the future (marginal 0.186) when compared to those who never shopped online. Similarly, those who began shopping online during COVID-19, but not before, were more likely to shop online in the future (marginal 0.179), suggesting the pandemic, a situational factor, might have led consumers to initiate online grocery shopping. Positive experiences with online grocery shopping during the pandemic may be expanding their intention of shopping online to the near future. Prior studies suggest somewhat different results where situational factors introduced online grocery shopping to consumers, resulting in shoppers who do not plan to continue online grocery shopping after the pandemic is no longer a threat (Hand et al., 2009; Grashius and Skevas, 2020; Jensen et al., 2021). There is a consensus that the COVID-19 pandemic in 2020 led consumers to adopt online grocery shopping for the first time, but there is disagreement on whether online grocery shopping will continue post-pandemic. Results from prior studies (Yeo, Goh, and Rezaei, 2017; Singh, 2019; Singh and Söderlund, 2020), in combination with our result that 55% of respondents will not continue shopping for groceries online, show that a consumer's intention to continue shopping online may be a direct result of their online shopping experience during the pandemic. Other respondents may be satisfied with their online grocery shopping experience during their first experience during the pandemic and will continue procuring grocery items online. Additionally, respondents who picked up groceries purchased online in the past (marginal 0.131), and those who had online groceries delivered in the past (marginal 0.153) were more likely to shop online in the future. This finding may indicate that consumers enjoy the ease of choosing the items online, with the actual method of obtaining the groceries being a secondary personal preference.

Conclusion

Although online grocery shopping had grown prior to 2020, it grew gradually, and many consumers were hesitant due to concerns regarding freshness, dissatisfaction from delayed possession of products, and the desire to touch and feel grocery items (Pechtl, 2003; Rohm and Swaminathan, 2004; Singh, 2019; Kvalsvik, 2022). The COVID-19 pandemic, a situational factor, accelerated the adoption of online grocery shopping by consumers who wanted to avoid exposure and alleviate related health threats (Hand et al., 2009; Kvalsvik, 2022).

Predictions of consumers' intention to continue online grocery shopping initiated by the pandemic are not consistent in previous studies (Hand et al., 2009; Grashius and Skevas, 2020; Jensen et al., 2021). This study explored COVID-19 as a situational factor that led shoppers to purchase groceries online and furthered understanding by examining intentions to continue to shop for groceries online after 12 months. In the model "began shopping online during COVID," only having children in the household and having a vegan/vegetarian in the household were statistically significant. This study finds that those who started shopping for groceries online during the pandemic were more likely to say they will continue to do so in the future. Gender, region, rurality, having children, having a vegetarian/vegan in the family, household size, shopping role, money spent in-store, and time spent in-store and online were not statistically significant in the model for future intentions of online grocery shopping. Statistically significant variables were age, income, education level, money spent grocery shopping online, and previous online grocery shopping behavior. In addition to prior studies that examine what and how internal and external factors lead shoppers to online grocery shopping, a better understanding of drivers of continuous online grocery shopping would be of interest not only to the grocery retailing industry but also to policy makers. Retailers may not consider the sudden rise of online grocery shopping during COVID-19 as a continuous shopping behavior after the pandemic subsides when evaluating business strategies.

This cross-sectional study should be interpreted within the context of the data collection timing and survey's focus. Future research should consider discrepancies in preferences across food categories in terms of perishability, such as packaged breakfast cereals and snacks, processed deli items, or fresh fruits and vegetables. In addition, consumers' online grocery shopping experiences could be examined to find what factors keep them purchasing groceries online after their initial adoption during COVID-19. It would be advantageous to monitor online grocery shopping for a longer time period after the pandemic subsides. As health concerns continue to lessen, it is expected that more "normal" online versus in-person shopping patterns may emerge compared to those observed in this research during a time where the most acute phases may have subsided, but health concerns impacting everyday activities were still widespread.

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Appendix A. Survey Instrument

I am:

- o Male
- o Female

I am _____ years old.

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

Please enter the number of household members - including adults and children - within each age bracket currently living in your household. Please include yourself in the count.

	Total number of household members
Adults (over 18 years)	
Children ages 0 to 4 years	
Children ages 5 to 10 years	
Children ages 11 to 15 years	
Children ages 16 to 18 years	

My annual pre-tax, household income is:

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

The best description of my educational background is:

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

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

- o Northeast
- o West
- o South
- o Midwest

State and county of residence was asked using a drop-down menu based on the previous response to region. The full list of counties was not included for brevity.

Do you participate in obtaining food and household essentials for your household in any of the following ways? (Check All That Apply)

- I have the primary role in selecting the food and household items
- I assist in selecting the food and household items
- I obtain the food and household items in-store
- I curbside pick up the food and household items
- I place the order online for food and household items
- I have no role in procuring food or household items

How much time would you estimate that your household spends on online grocery shopping and in-store grocery shopping in an average week since March 2020? Note that online grocery shopping includes ordering via an app, website, or via phone for pick up in-store or curbside, or for delivery.

	Amount of time spent per week							
	Less than 30 mins	30 mins to 59 mins	60 mins to 89 mins	90 mins to 119 mins	120 mins to 149 mins	150 mins to 179 mins	180 mins and above	None
In-store grocery shopping								
Online grocery shopping								

How much would you estimate your household spends on groceries in an average week since March 2020? Note that online grocery shopping includes ordering via an app, website, or via phone for pick up in store or curbside, or for delivery.

	Amount of money spent per week					
	Less than $50	$50 to $99	$100 to $149	$150 to $199	$200 to $249	More than $250	None

In-store grocery shopping expenses	○	○	○	○	○	○	○
Online grocery shopping expenses	○	○	○	○	○	○	○

Q2.4 Which of the following best describes your household's use of online grocery services, including ordering online and picking up curbside or in-store, during COVID-19? (Select All That Apply)

- I do none of my grocery shopping online
- I do a small amount of my grocery shopping online (e.g. less than one-quarter)
- I do some of my grocery shopping online (e.g. between a quarter and a half)
- I do most of my grocery shopping online (i.e. between a half and three quarters)
- I do almost all of my grocery shopping online (between three quarters and all of it)
- I started shopping for groceries online during COVID-19 but had not done so before
- I greatly increased my online shopping for groceries due to COVID-19
- My grocery shopping behaviors did not change due to COVID-19
- I spend more money at the grocery store in an average week due to COVID-19

How often does your household use each of the following online grocery shopping delivery methods during COVID-19?

	At least once a week	At least once in three months	At least once in the past year	Never
Buy groceries online, pick up in retailer store				
Buy groceries online, pick up at retailer curbside				
Buy groceries online, delivery by retailer				
Buy groceries online, delivery by third party food service				

Buy groceries online, delivery by mail service	

Does your household expect to buy groceries online in the next 12 months? Note that online grocery shopping includes ordering via an app, website, or via phone for pick up in store or curbside, or for delivery.

- Yes
- No

Displayed if household did not purchase groceries online

Which of the following are reasons why you do not expect to buy groceries online in the next 12 months.

- I like to see and choose products in person before buying them
- I enjoy shopping for groceries in-store
- I do not like paying charges for delivery/curbside
- I do not like to plan my grocery shopping in advance
- I find it inconvenient waiting for a delivery
- My favorite/preferred grocery retailer does not offer this service in my area
- Online grocery shopping is not available from any retailer in my area
- I find picking up an order at the store inconvenient
- Previous bad experience with online grocery shopping
- I have limited internet access
- I do not trust online grocery retailers
- Other reasons(s) ____

Displayed if household did purchase groceries online

- Which of the following are the reasons why you expect to buy groceries online in the next 12 months? Please select all that apply.
- I can order groceries anytime from anywhere
- I can easily choose the delivery time
- It helps me avoid lines/queues
- It allows me to compare prices easily
- It is easier for me to search for grocery items online
- I have access to more stores and grocery items
- I have physical constraints
- I dislike grocery shopping in stores
- It saves me time
- I can avoid impulse buying
- To lessen contact with other people due to COVID-19 or related health concerns
- Other reasons ____

To what extent do you agree or disagree with the following statements regarding online and in-store grocery shopping

	Agree	Neither agree nor disagree	Disagree
Groceries are more expensive online than in-store			
Shopping for groceries is more convenient online than in-store			
Shopping for groceries online saves more time than in-store			
It is easier to search for grocery items online than in-store			
It is easier to compare grocery prices online than in-store			
Grocery retailers have a lot more varieties online than in-store			
Service quality is better online than in-store			
Shopping online for groceries is safer during COVID-19 than shopping in-store			
Shopping for groceries is more fun online than in-store			
Online reviews are more helpful for buying groceries online than in-store			
I am more concerned about food safety online than in-store			

Appendix B

Ways Respondent Participates in food and Household Essentials in their Household by Demographic. Multiple Selections Permitted (n = 929)

	Selects food and household items	Assists in selecting food and household items	Obtains items in store	Places the order online	Executes curbside pick-up	Has no role in procuring food or household items
Gender						
Male n = 429	59a[1]	36a	28a	8a	8a	5a
Female n = 500	76b	23b	20b	9a	6a	4a
Age						
18–24 n = 79	37b	52a	30a	16a	14a	6a
25–34 n = 122	70ac	29b	21a	7b	8ab	7a
35–44 n = 181	72ac	29b	25a	11ab	10a	3a
45–54 n = 152	76c	22b	20a	9ab	7ab	7a
55–65 n = 183	72ac	25b	24a	7b	4b	3a
65+ n = 212	67a	30b	24a	6b	4b	3a
Income						
\$0–\$24,999 n = 181	70a	28a	15a	7a	7a	6a
\$25,000–\$49,999 n = 202	69a	27a	19ab	10a	6a	3a
\$50,000–\$74,999 n=154	72a	26a	25bc	7a	5a	4a
\$75,000–\$99,999 n=118	67a	31a	30c	8a	7a	3a
\$100,000 and higher n = 274	65a	32a	29c	9a	9a	5a
Education						
Did not graduate from high school n = 20	70ab	27a	23a	8a	7a	4a
Graduated from high school, did not attend college n = 250	62a	32a	20a	10a	9a	6ab
Attended college, no degree earned n = 200	70ab	27a	23a	8a	7a	4b
Attended college, associate's or bachelor's degree earned n = 318	71b	29a	26a	8a	5a	4b
Attended college, graduate or professional degree earned n = 141	72b	28a	26a	10a	7a	4b
Region of residence						
Northeast n = 171	73a	28a	26a	5a	6a	5a
South n = 382	68a	27a	23a	9ab	8a	4a
Midwest n = 208	67a	34a	20a	8ab	7a	4a
West n = 168	65a	29a	27a	13b	8a	5a

Note: 1 Mismatched letters indicate the percentage within that participation method and demographic category are statistically different at the 0.05 level. For example, the percentage of men who selected food and household items was statistically different than the percentage of women

Appendix C

Varying degrees of the restricted logit model of respondent's belief their household will shop online in the 12 months after January 2021. *N* = 929. All models were statistically significant. Pseudo R Squared: Model A 0.0974, Model B 0.1219, Model C 0.5766

	Model A		Model B		Model C	
Independent variables	**Coefficient**	**Robust SE**	**Coefficient**	**Robust SE**	**Coefficient**	**Robust SE**
Female	-0.099	0.147	-0.033	0.152	0.123	0.590
Age						
18–24	1.334***	0.302	0.968**	0.340	0.169	0.704
25–34	1.750***	0.258	1.284***	0.287	0.105	0.460
35–44	1.519***	0.231	1.164***	0.258	0.159	0.361
45–54	1.200***	0.241	0.991***	0.250	0.861**	0.316
55–65	0.296	0.234	0.240	0.236	0.006	0.293
65+	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Income						
$0–$24,999	-0.317	0.246	-0.228	0.259	-0.154	0.435
$25,000–$49,999	-0.158	0.218	-0.105	0.225	-0.350	0.352
$50,000–$74,999	-0.240	0.221	-0.230	0.229	-0.675*	0.374
$75,000–$99,999	0.578**	0.241	0.442*	0.247	0.735**	0.360
$100,000 or greater	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Education						
Did not graduate from high school	-0.903*	0.524	-0.931*	0.561	-1.668	1.050
Graduated from high school, did not attend college	-0.707**	0.262	-0.704**	0.266	-0.633	0.394
Attended college, no degree earned	-0.285	0.252	-0.319	0.258	-0.213	0.358
Attended college, associate's or bachelor's degree earned	-0.530**	0.221	-0.534**	0.226	-0.498*	0.298
Attended college, graduate or professional degree earned	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Region of residence						
Northeast	-0.395*	0.237	-0.391	0.244	0.013	0.380
South	0.002	0.196	-0.014	0.204	0.116	0.368
Midwest	-0.141	0.229	-0.116	0.235	0.295	0.387
West	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
Lives in a metro area	0.072	0.169	0.080	0.173	0.124	0.273
Has children			0.630	0.228	-0.224	0.391
Vegetarian or vegan in the family			0.992	0.219	-0.050	0.418
Household size			-0.082	0.069	0.042	0.107
Is the primary shopper					0.572	0.407
Interaction of female and primary shopper					-0.371	0.613

Note: * statistically significant at the 0.10 level, **0.05 level, ***< 0.0001 level
[1]Omitted indicates the dummy variable category used as the reference category.

Appendix C. Continued

	Model A		Model B		Model C	
Independent variables	**Coefficient**	**Robust SE**	**Coefficient**	**Robust SE**	**Coefficient**	**Robust SE**
Obtains the food in store					0.246	0.413
Interaction of female and obtains the food in store					-0.872	0.564
Places the online order					-0.120	0.887
Interaction of female and places the online order					2.239**	1.093
Money spent grocery shopping in store						
$0–$99					Omitted	Omitted
$100–$199					0.026	0.272
Greater than $200					0.579	0.578
Time spent grocery shopping in store						
0–30 minutes					Omitted	Omitted
60–149 minutes					0.030	0.263
150 minutes and greater					-1.195	0.874
Money spent grocery shopping online						
$0–$99					Omitted	Omitted
$100–$199					0.742*	0.417
Greater than $200					2.595**	1.305
Time spent grocery shopping online						
0–30 minutes					Omitted	Omitted
60–149 minutes					0.801	0.518
150 minutes and greater					-1.652	1.155
Previous online shopping behavior						
Never shopped online					Omitted	Omitted
Shopped online before COVID					2.154***	0.270
Began shopping online during COVID, but not before					2.073***	0.395
Picked up online groceries in the past					1.521***	0.295
Had online groceries delivered in the past					1.770***	0.253
Constant	-0.514*	0.308	-0.462	0.352	-3.206***	0.626

Note: * statistically significant at the 0.10 level, **0.05 level, ***< 0.0001 level
[1]Omitted indicates the dummy variable category used as the reference category.

Journal of Food Distribution Research
Volume 54, Issue 3, pp. 30–65

A Comparison of Demand System Models Peculiar to a Granular Array of Dairy Products

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Abstract

Demand interrelationships for eight dairy categories—margarine and plant-based milk alternatives—were estimated using the Quadratic Almost Ideal Demand System (QUAIDS) and the Barten Synthetic Model (BSM), based on data derived from Nielsen covering the period January 2010 to November 2015. The own-price elasticities, with few exceptions, were in the elastic range. Those derived from the BSM typically were larger than those derived from the QUAIDS. All products considered were necessities. The BSM discerned more statistically significant compensated cross-price elasticities than the QUAIDS. Most of the statistically significant cross-price elasticities from the demand models were positive, indicative of substitutability among the products.

Keywords: dairy products, plant-based milk, Nielsen Homescan panel, QUAIDS, Barten Synthetic Model

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Introduction

The U.S. dairy market was valued at $103 billion in 2020 and is projected to reach $137 billion by 2026, growing at a compound annual growth rate of nearly 5% from 2020 to 2026 (United States Dairy Market Report, 2021). According to the International Dairy Foods Association (IDFA), the incremental contribution of the U.S. dairy industry to the U.S. economy in 2021 was $753 billion (Dykes, 2021). In addition, the U.S. dairy industry supports slightly more than 3 million jobs and contributes 3.5% of the U.S. GDP. Further, dairy products play a key role in the American diet as they contain vital nutrients for the health and maintenance of the human body. Notable nutrients include calcium, vitamin D, protein, and potassium (Bailey et. al, 2010; U.S. Department of Agriculture, 2021). The U.S. Department of Agriculture suggests that diets containing 3 cups of dairy products per day can improve bone mass and bone health (U.S. Department of Agriculture, 2021). In sum, the U.S. dairy industry is not only vital to the health of the U.S. economy but also vital to the health of Americans.

On a per capita consumption basis, the major dairy products in the United States include fluid milk, cheese, butter, yogurt, and ice cream. Based on data from the Economic Research Service, U.S. Department of Agriculture (USDA-ERS, 2023), consumption of fluid milk has been declining steadily from 196 pounds per person annually in 2000 to 134 pounds per person annually in 2021. Consumption of cheese (including both natural cheese and processed cheese) on the other hand has been rising steadily from 29.5 pounds per person annually in 2000 to 38.4 pounds per person annually in 2021. As well, annual per capita consumption of butter has increased sharply since 2000, from 4.5 pounds to 6.5 pounds. Annual per capita consumption of yogurt rose monotonically from 6.5 pounds to 14.9 pounds over the period 2000 to 2014 but has leveled off since then from 13.4 pounds to 14.4 pounds. Finally, annual per capita consumption of ice cream has experienced a decline since 2000 from 22.7 pounds to 18.4 pounds.

Based on per capita consumption patterns previously described, notable changes are evident in the demand for dairy products. Additionally, the plant-based milk industry has grown over the last decade, predominantly driven by Millennials, vegan diets, dietary restrictions, and environmental concerns. In this light, the general objective of this study is to investigate demand interrelationships among different categories of dairy products and plant-based alternatives to milk based on monthly time-series data derived from Nielsen for calendar years 2010[1] to 2015. The specific objectives are as follows:

To estimate the Quadratic Almost Ideal Demand Systems (QUAIDS) and the Barten Synthetic Model (BSM) concerning 10 distinct products: (i) flavored milk, (ii) white milk, (iii) non-Greek yogurt, (iv) Greek yogurt, (v) butter, (vi) natural cheese, (vii) processed cheese, (viii) ice cream, (ix) plant-based milk alternatives, and (x) margarine;

[1] Calendar year 2010 was selected as the starting year because the market shares for Greek yogurt and plant-based milk dairy alternatives were extremely small compared to other dairy categories before 2010.

To derive uncompensated and compensated own-price elasticities as well as expenditure elasticities and income elasticities for these products; and

To analyze the substitutability and complementarity among the 10 dairy and alternative products based on compensated cross-price elasticities.

The information gleaned from the empirical findings of this study will be of interest to different stakeholders. Manufacturers and retailers can employ the estimates of own-price and cross-price elasticities in designing revenue-maximizing pricing strategies as well as inventory management and input procurement plans to adequately respond to price changes associated with dairy products. Policy makers can use the empirical findings to design or revise policies that would help them provide oversight to the dairy industry.

This analysis rests on the use of data from the Nielsen Homescan panel over the period January 2010 to November 2015. As such, this analysis serves as a benchmark for future analyses concerning consumption of dairy products and dairy alternatives. Of particular importance is the fact that demand system analyses associated with different dairy categories in the United States were done at least a decade ago (Chouinard et al., 2010; Davis et al., 2010; Davis et al., 2011a; Davis et al., 2011b). Hence, a need exists to update these demand systems models concerning dairy products. To illustrate, plant-based milk alternatives and Greek yogurt were just introduced to the marketplace around 2010. As such, our contribution serves to provide a more up-to-date demand systems analysis for a granular array of dairy products as well as for plant-based milk alternatives currently lacking in extant literature. Further, with the use of two popular demand systems, we provide a check on the robustness of the empirical results.

Demand System Models

Most of the plethora of previous studies concerning the demand for dairy products have focused on individual dairy products, notably fluid milk (Gould, Cox, and Perali, 1990; Cornick, Cox, and Gould, 1994; Gould, 1996; Davis et al., 2009; Alviola and Capps, 2010; Davis et al., 2012; Dharmasena and Capps, 2012; Li, Peterson, and Xia, 2012; Yang and Dharmasena, 2021), cheese (Maynard, 2000), ice cream (Maynard and Veeramani, 2003; Davis et al., 2009), and yogurt (Dharmasena and Capps, 2014; Robinson, 2017; Keller, 2018).

Over the past three decades, demand analyses concerning dairy products have been conducted to investigate the interrelationships among different dairy categories. In the early studies (Huang, 1985; Heien and Wessells, 1988; Heien and Wessells, 1990; Huang, 1993), the demands of different dairy products were estimated along with other food, such as non-dairy beverages, meat, eggs, etc. According to the U.S. Department of Agriculture Dietary Guidelines, dairy has been listed as an independent food group in the U.S. diet system, along with vegetables, fruits, grains, and protein foods, based on their nutrient-dense forms. Consistent with previous studies, we consider a granular set of dairy products in this research, namely flavored milk, white milk,[2] non-

[2] In the dairy market, white milk could be disaggregated into organic milk and conventional milk based on production methods. Alternatively, white milk could be disaggregated into skim milk (0% fat), low-fat milk (1% or

Greek yogurt, Greek yogurt, natural cheese, processed cheese, ice cream, and butter. We also include plant-based milk alternatives and margarine in our research. Additionally, our analysis is dedicated to products of primary interest to the dairy industry.

Importantly, like Maynard and Liu (1999), Maynard and Veeramani (2003), Chouinard et al. (2010), Dharmasena and Capps (2014), Sarker, Koto, and Cassidy (2015), and Yang and Dharmasena (2021), we avoid the data-censoring problem inherent with cross-sectional studies. In this study, we aggregate monthly expenditures and purchases of dairy products and plant-based milk alternatives made by U.S. households over the period January 2010 to November 2015. This approach circumvents the problem of zero observations concerning purchases that are often encountered when using micro-level (household) data.[3]

To investigate interrelationships among dairy products, the most popular demand system model has been variations of the AIDS model (Heien and Wessells 1988; Heien and Wessells 1990; Maynard and Liu, 1999; Cakir and Balagtas, 2010; Davis et al., 2010; Davis, Yen, Dong, and Blayney, 2011b); a few studies also featured the Barten Synthetic Model (Maynard and Liu, 1999; Maynard and Veeramani, 2003; Sarker, Koto, and Cassidy, 2015). Our work differs from previous studies by utilizing both the Quadratic Almost Ideal Demand System (QUAIDS) and the Barten Synthetic Model (BSM) to analyze the interrelationships among 10 dairy products as well as two alternative product categories. The QUAIDS allows quadratic Engel curves, which permits goods to be luxuries at some income levels and necessities at others. At the same time, the BSM provides more flexibility by nesting four widely used demand systems, the Rotterdam Model, the Almost Ideal Demand System (AIDS), the Central Bureau of Statistics (CBS) Model, and the National Bureau of Research (NBR) Model. With the estimation of these respective demand models, we are positioned to check on the robustness of the empirical results.

QUAIDS (Quadratic Almost Ideal Demand System)

QUAIDS was first introduced by Banks, Blundell, and Lewbel (1997). The specification of this model is as follows:

$$w_i = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} \log(p_j) + \beta_i \log\left(\frac{m}{a(p)}\right) + \frac{\lambda_i}{b(p)} \log\left(\frac{m}{a(p)}\right)^2 \quad (1)$$

where:

w_i is the expenditure share on good i,

p_i is the price for good i,

2% fat), and whole milk (3.25% fat) based on the fat content. We used the aggregated white milk category in this research because the prices of these disaggregated milk products were highly correlated.

[3] We recognize and acknowledge that previous studies have found various combinations of demographic variables, such as age, education, race/ethnicity, region, household size, and household income to affect the demand for dairy products. We plan to conduct a future analysis wherein we entertain the use of these sociodemographic variables.

m is the total expenditure,

the price index $\log\left(a(p)\right)$ is specified as

$$\log\left(a(p)\right) = \alpha_0 + \sum_{i=1}^{n} \alpha_i \log(p_i) + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} r_{ij} \log(p_i) \log(p_j), \tag{2}$$

and the price aggregator $b(p)$ is specified as

$$b(p) = \prod_{i=1}^{n} p_i^{\beta_i} \tag{3}$$

To conform to demand theory, the following constraints are imposed:

(1) $\sum_{i=1}^{n} \alpha_i = 1; \sum_{i=1}^{n} \beta_i = 0; \sum_{i=1}^{n} \gamma_{ij} = 0;$ Adding-up condition,

(2) $\sum_{j=1}^{n} \gamma_{ij} = 0; \sum_{i=1}^{n} \lambda_i = 0;$ and Homogeneity condition,

(3) $\gamma_{ij} = \gamma_{ji}$ Symmetry of the Slutsky matrix.

The expenditure as well as uncompensated and compensated price elasticities can be calculated as:

expenditure elasticity for product category i: $\eta_i = \frac{\mu_i}{w_i} + 1$ (4)

uncompensated own-price and cross-price elasticities: $\varepsilon_{ij}^{u} = \frac{\mu_{ij}}{wi} - \delta_{ij}$ (5)

(compensated own-price and cross-price elasticities)[4]: $\varepsilon_{ij}^{c} = \varepsilon_{ij}^{u} + \eta_i w_j$ (6)

where:

$$\mu_i = \frac{\partial w_i}{\partial \log(m)} = \beta_i + \frac{2\lambda_i}{b(p)} \log\left(\frac{m}{a(p)}\right) \tag{7}$$

$$\mu_{ij} = \frac{\partial w_i}{\partial \log(p_j)} = r_{ij} - \mu_i\left(a_j + \sum_{k=1}^{n} \gamma_{jk} \log(p_k)\right) - \frac{\lambda_i \beta_j}{b(p)} \left\{\log\left(\frac{m}{b(p)}\right)\right\}^2 \tag{8}$$

$$\delta_{ij} = \begin{cases} 1, & when\ i = j \\ 0, & when\ i \neq j \end{cases}$$ is the Kronecker delta.

BSM (Barten Synthetic Model)

BSM was first developed by Barten (1993). Matsuda (2005) demonstrated that the BSM is not a mere artificial composite of known differential demand systems. The BSM is specified as follows:

[4] Derived from Slutsky's equation.

$$w_i d\ln q_i = (a_i + \lambda w_i) d\ln Q + \sum_j \left[b_{ij} - \mu w_i \left(\delta_{ij} - w_j\right)\right] d\ln p_j \,, i = 1, \dots, n, \tag{9}$$

where:

w_i is the budget share on good i,

p_i is the price for good i,

q_i is the quantity for good i,

$d\ln q_i$ is the logarithmic differential of the quantity for good i.

In practice, $d\ln q_i \approx \Delta \ln q_i = \ln q_{i,t} - \ln q_{i,t-1}$,

$d\ln Q \equiv \sum_i w_i \, d\ln q_i$ denotes the Divisia volume index,

$\delta_{ij} = \{\begin{matrix} 1, & when\ i = j \\ 0, & when\ i \neq j \end{matrix}$ is the Kronecker delta.

The following constraints are imposed to conform to demand theory:

Adding up: $\sum_{i=1}^{n} b_{ij} = 0$; $\sum_{i=1}^{n} a_i = 1 - \lambda$.

$\sum_{j=1}^{n} b_{ij} = 0$ for homogeneity.

Symmetry: $b_{ij} = b_{ji}$.

Parameters can be restricted to arrive at nested models within the BSM:

(1) $\lambda = 0,\ \mu = 0$ Rotterdam model

(2) $\lambda = 1,\ \mu = 1$ AIDS model

(3) $\lambda = 1,\ \mu = 0$ CBS model

(4) $\lambda = 0,\ \mu = 1$ NBR model

The uncompensated elasticity of good i with respect to the price of good j is:

$$\varepsilon_{ij}^{u} = -\left(\frac{a_i + \lambda w_i}{w_i}\right) w_j + \frac{b_{ij} - \mu w_i (\delta_{ij} - w_j)}{w_i} \tag{10}$$

The expenditure elasticity of good i is:

$$\eta_i = \frac{a_i + \lambda w_i}{w_i} \tag{11}$$

The compensated elasticity of good i with respect to the price of good j is:

$$\varepsilon_{ij}^{c} = \varepsilon_{ij}^{u} + \eta_i w_j \tag{12}$$

Data

The data used in this study correspond to monthly observations of dairy products and plant-based milk alternatives derived from Nielsen Homescan Panel over the period of January 2010 to November 2015.[5] The respective products are partitioned into 10 categories: (i) flavored milk (mainly chocolate milk), (ii) white milk (both organic and conventional white milk), (iii) non-Greek yogurt, (iv) Greek yogurt, (v) butter, (vi) natural cheese, (vii) processed cheese,[6] (viii) plant-based milk alternatives,[7] (ix) ice cream, and (x) margarine. To the best of our knowledge, we provide the first demand systems analysis incorporating Greek and non-Greek yogurt and plant-based milk alternatives among the conventional set of dairy products. Also, this study represents the initial use of the QUAIDS model in investigating interrelationships of demand among dairy products.

In the Nielsen Homescan Panel, the purchasing records are reported for each household over time, including the total amount paid in dollars, the coupon value in dollars, and the quantity purchased in ounces. Initially, all the purchasing records are aggregated over households for the same month; thus, a total of 71 monthly observations are used for further analysis. Second, the aggregated coupon values per month are subtracted from the aggregated total amount paid per month to derive the aggregated monthly expenditures for each of the respective 10 product categories. Subsequently, we derive monthly expenditure and quantity data per household from January 2010 to November 2015. The number of households who purchased these dairy and alternative product categories differs not only over the 10 respective categories but also over the monthly time periods. As such, the expenditure and quantity data are expressed in terms of dollars and ounces purchased per household per month. Then, the monthly unit values, a proxy for retail prices, for each dairy category are derived by dividing monthly expenditure by monthly quantity.

The construction of unit values is consistent with the methodology proposed by Deaton (1987), which allows the use of expenditure and quantity data from household surveys to estimate a system of demand equations. Indeed, as pointed out by Deaton (1988, 1990, 1997) and Niimi (2005), bias associated with the use of unit values may occur. The bias is attributed to quality variation and reporting errors in expenditures and/or quantities (measurement errors). Deaton (1988) suggested

[5] The Nielsen Homescan Panel did not contain purchasing records for the entire month of December 2015. Thus, November 2015 was set as the end of the monthly time-series data in this analysis.
[6] There are various types of cheeses in the dairy market. We used the definition of processed cheese (pasteurized process cheese) from CFR–Code of Federal Regulations Title 21 U.S. Food and Drug Administration to identify and develop the processed cheese category.
[7] Products of two brands, Blue Diamond and Silk, are used to represent plant-based milk alternatives since these two brands had the largest market shares by far in this category over calendar years 2010 to 2015.

that the bias associated with quality variation makes the demand for a commodity appear to be more elastic, overstating the response of quantity to changes in price.

Gibson and Rozelle (2006) suggested that two types of measurement error bias are evident: (i) attenuation bias because unit values are noisy measures of market prices and (ii) bias due to correlated errors in measuring expenditures and/or quantities. In the case of attenuation bias, Gibson and Rozelle (2006) noted that the bias was in the opposite direction to that attributed to quality variation. If so, then the bias due to quality variation and the bias due to attenuation are offsetting to some degree. However, Gibson and Rozelle (2006) also pointed out that the bias due to correlated errors operated in the opposite direction to attenuation bias. Consequently, the bias due to correlated errors reinforces the bias due to quality effects. Importantly, Gibson and Rozelle (2006) documented that the bias associated with quality variation was relatively minor, also consistent with the finding of Deaton (1997). Bottom line, we recognize these issues in using unit values as proxies for retail prices. We operate on the assumption that the biases previously mentioned are negligible.

Next, all the expenditures of the 10 categories per month are summed to derive the total monthly expenditure. We divide monthly expenditure for each product category by total monthly expenditure to obtain the respective budget shares per month. In the end, the dataset for this analysis includes monthly quantities per household (expressed in ounces), unit values (expressed as $/ounce), monthly expenditures per household (expressed in $), and monthly budget shares from January 2010 to November 2015 (71 observations).

Table 1 shows the market penetration for different dairy products from 2010 to 2015. Market penetration is defined as the number of households who purchase the product divided by the number of households who participated in the Nielsen Homescan Panel in various months of the respective calendar years. Plant-based milk alternatives (e.g., almond milk, oat milk, soy milk, rice milk, coconut milk, and so on) and Greek yogurt have gained in popularity. The market penetration of plant-based milk alternatives increased noticeably from 17% to 29% over the period 2010 to 2015. The market penetration of Greek yogurt increased to 54% in 2014 and 2015, from 20% in 2010, and the market penetration of natural cheese rose modestly from 94% to 96% over this period. On the other hand, the market penetration for white milk declined from 94% to 92%, flavored milk decreased from 28% to 21%, ice cream fell from 75% to 71%, processed cheese declined from 90% to 86%, and non-Greek yogurt decreased from 80% to 72% over the period 2010 to 2015. The market penetration of butter rose from 66% to 71%, but the market penetration for margarine declined from 72% to 61% over the period 2010 to 2015.

Table 1. Market Penetration for Different Dairy Products, 2010 to 2015

Year	White Milk	Flavored Milk	Butter	Ice Cream	Natural Cheese	Processed Cheese	Non-Greek Yogurt	Greek Yogurt	PMA[1]	Margarine
2010	94%	28%	66%	75%	94%	90%	80%	20%	17%	64%
2011	94%	26%	67%	72%	94%	89%	78%	35%	19%	72%
2012	93%	25%	69%	71%	95%	89%	75%	44%	21%	65%
2013	93%	23%	71%	72%	95%	88%	72%	53%	23%	61%
2014	92%	21%	70%	72%	95%	87%	73%	54%	28%	59%
2015	92%	23%	71%	71%	96%	86%	73%	54%	29%	61%

Note: [1] The acronym PMA denotes plant-based milk alternatives. This category includes milk alternatives (predominantly almond milk) manufactured by Blue Diamond and Silk.
Source: Nielsen Homescan Panel, calendar years 2010 to 2015.

Table 2 gives descriptive statistics of quantities (ounces), total expenditures ($), budget shares, and unit values ($/ounce) for the 10 product categories, respectively. The amount purchased per household per month is highest for white milk at 213.80 ounces on average, followed by ice cream at 23.71 ounces, natural cheese at 23.64 ounces, and non-Greek yogurt at 22.54 ounces. Monthly purchases of processed cheese per household (9.43 ounces) are more than two times less than monthly purchases of natural cheese on average. Monthly purchases of Greek yogurt per household (6.15 ounces) are nearly four times less than monthly purchases of non-Greek yogurt on average. The monthly purchases of flavored milk, plant-based milk alternatives, butter, and margarine per household are 7.89, 8.28, 7.26, and 9.22 ounces on average, respectively.

The budget shares on average in descending order are as follows: natural cheese 29%, white milk 27%, non-Greek yogurt 10%, processed cheese 9%, ice cream 7%, butter 7%, Greek yogurt 5%, margarine 4%, plant-based milk alternatives 2%, and flavored milk 1%. Meanwhile, the unit values on average over the 71-month period in descending order are as follows: natural cheese 26 cents/ounce, processed cheese 21 cents/ounce, butter 19 cents/ounce, Greek yogurt 18 cents/ounce, non-Greek yogurt 10 cents/ounce, margarine 9 cents/ounce, ice cream 6 cents/ounce, plant-based milk alternatives 5 cents/ounce, flavored milk 4 cents/ounce, and white milk 3 cents/ounce. The monthly total expenditures for the 10 product categories per household are $21.30 on average over the period 2010 to 2015. Nominal income per capita[8] over this period is $39,647 on average.

[8] U.S. Bureau of Economic Analysis, Real Disposable Personal Income: Per Capita [A229RX0], retrieved from the Federal Reserve Economic Database (FRED), Federal Reserve Bank of St. Louis.

Table 2. Summary Statistics of Quantities, Expenditures, Budget Shares, Unit Values, Producer Price Index (PPI), and Disposable Personal Income (DPI), January 2010 to November 2015

		Mean	Std Dev	Minimum	Maximum
Monthly quantities (Ounces)	Flavored milk	7.89	0.91	6.05	10.22
	White milk	213.80	19.79	180.58	274.84
	Non-Greek yogurt	22.54	4.09	14.26	33.06
	Greek yogurt	6.15	3.29	0.56	10.96
	Butter	7.26	2.28	4.93	13.24
	Natural cheese	23.64	4.19	15.64	31.65
	Processed cheese	9.43	1.23	7.61	12.89
	Plant-based milk alternatives	8.28	1.50	5.24	11.63
	Ice cream	23.71	3.89	17.15	33.19
	Margarine	9.22	1.46	7.18	13.52
Budget share	Flavored milk	0.01	0.002	0.01	0.02
	White milk	0.27	0.02	0.21	0.30
	Non-Greek yogurt	0.10	0.02	0.06	0.14
	Greek yogurt	0.05	0.02	0.01	0.08
	Butter	0.06	0.02	0.05	0.13
	Natural cheese	0.29	0.03	0.24	0.33
	Processed cheese	0.09	0.01	0.08	0.12
	Plant-based milk alternatives	0.02	0.003	0.01	0.02
	Ice cream	0.07	0.01	0.05	0.10
	Margarine	0.04	0.01	0.03	0.05
Unit values ($/Ounce)	Flavored milk	0.04	0.00	0.03	0.04
	White milk	0.03	0.00	0.02	0.04
	Non-Greek yogurt	0.10	0.00	0.09	0.10
	Greek yogurt	0.18	0.01	0.16	0.21
	Butter	0.19	0.02	0.15	0.26
	Natural cheese	0.26	0.01	0.24	0.30
	Processed cheese	0.21	0.01	0.19	0.23
	Plant-based milk alternatives	0.05	0.00	0.04	0.05
	Ice cream	0.06	0.00	0.05	0.07
	Margarine	0.09	0.01	0.08	0.10
Expenditure ($)	Total expenditure	21.30	1.83	17.04	25.25
Ppi (dec 2000 = 100)	Producer price index	105.92	0.97	103.90	107.20
Per capita Income ($)	Disposable personal income (dpi)	39,647	1193	37,573	41,933

Estimation Issues

Various issues are addressed during the estimation of the respective demand system models: (i) autocorrelation or serial correlation; (ii) endogeneity of total expenditure and prices (unit values); (iii) stationarity; and (iv) seasonality.

Autocorrelation

Because time-series data are used in this research, the presence of serial correlation is considered using the Ljung-Box test (Ljung and Box, 1978; Box et al., 2015) to check on the presence/absence of serial correlation in each of the respective equations of the QUAIDS and the BSM. In general, the respective models assuming the presence of autocorrelation may be specified as follows:

$$y_{it} = f(x_{it}, \beta) + \sum \rho_k (y_{it-k} - f(x_{it-k}, \beta)) + \sum_{s=1}^{11} \theta_s D_s + \epsilon_{it}, \tag{13}$$

where k is the number of lag terms, y_{it} represents the budget share of product category i in period t for the QUAIDS, and y_{it} represents the budget share times the logarithm of the differential of the quantity of product category i for period t for the BSM. $f(x_{it}, \beta)$ is the functional form from equation (1) for the QUAIDS and the function form from equation (9) for the BSM (Berndt and Savin, 1975; Dharmasena and Capps, 2012; Hovhannisyan and Gould, 2014). Upon estimation of the respective models, the Ljung-Box statistics indicate the presence of first-order autoregression processes of disturbance terms (AR(1)) in the QUAIDS, but the absence of any autocorrelation whatsoever in the BSM. The reason for this finding is attributed to the fact that the BSM is expressed in terms of logarithmic differences and not levels, unlike the QUAIDS, which involves levels of budget shares. Owing to adding up, the estimation of a common ρ across the QUAIDS is necessary to mitigate the issue of serial correlation.

Endogeneity

The second issue centers attention on the endogeneity of total expenditure and prices in the QUAIDS and in the BSM.[9] Because total expenditure is defined as the sum of expenditures of each product category, it is reasonable to consider this term endogenous. Following Dhar, Chavas, and Gould (2003) and Lakkakula, Schmitz, and Ripplinger (2016), we specify the auxiliary equation for the total expenditure to deal with the endogeneity issue as follows:

$$\ln m_t = f\,(\ln DPI_t\,, lags\ of \ln m) \tag{14}$$

where $\ln m_t$ is the logarithm of total expenditure at period t, $\ln DPI_t$ is the logarithm of disposable income at period t, and $lags\ of \ln m$ represent the lags of the logarithm of total expenditure. The instrument variables used in this equation are also like those used in the works of Attfield (1985), Capps et al. (1994), and Dharmasena and Capps (2012). To select the optimal lags of $\ln m$ as the instrumental variables, we considered criteria such as AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), adjusted R^2, and Root Mean Square Error (RMSE). Lag lengths of two and three months had similar values associated with these criteria. As exhibited in Table 3, based on the principle of parsimony, a lag of order 2 for $\ln m$ was used in the instrumental variable regression.

[9] In the BSM model, the logarithmic differential of the price $\mathrm{d}\ln p_i$ is used. In practice, $\mathrm{d}\ln p_i \approx \Delta \ln p_i = \ln p_{i,t} - \ln p_{i,t-1}$.

Table 3. Instrumental Variable Estimation Results Concerning Total Expenditure and Prices

Total Expenditure		
Explanatory Variables	**Estimate**	***p*-value**
constant	-4.17	0.14
log (DPI)$_t$	0.48	0.10
log (Total Expenditure)$_{t-1}$	0.35	0.00
log (Total Expenditure)$_{t-2}$	0.36	0.00
Goodness-of-Fit	R^2	0.66
	Adjusted R^2	0.65
	RMSE	0.05
	Durbin Watson	2.16

Log(Flavored Milk Price)			Log(Unflavored Milk Price)		
Explanatory Variables	**Estimate**	***p*-value**	**Explanatory Variables**	**Estimate**	***p*-value**
constant	-2.08	0.26	constant	-8.13	0.06
log (PPI)$_t$	0.31	0.40	log (PPI)$_t$	1.50	0.09
log (own price)$_{t-1}$	**0.80**	**0.00**	log (own price)$_{t-1}$	**0.68**	**0.00**
Goodness-of-Fit	R^2	0.78	Goodness-of-Fit	R^2	0.65
	Adjusted R^2	0.77		Adjusted R^2	0.65
	RMSE	0.02		RMSE	0.05
	Durbin-Watson	1.94		Durbin-Watson	1.92

Log(Non-Greek Yogurt Price)			Log(Processed Cheese Price)		
Explanatory Variables	**Estimate**	***p*-value**	**Explanatory Variables**	**Estimate**	***p*-value**
constant	**-5.29**	**0.02**	constant	**-6.05**	**0.02**
log (PPI)$_t$	**1.00**	**0.02**	log (PPI)$_t$	**1.21**	**0.03**
log (own price)$_{t-1}$	**0.75**	**0.00**	log (own price)$_{t-1}$	**0.74**	**0.00**
Goodness-of-Fit	R^2	0.88	Goodness-of-Fit	R^2	0.83
	Adjusted R^2	0.87		Adjusted R^2	0.83
	RMSE	0.02		RMSE	0.02
	Durbin-Watson	1.99		Durbin-Watson	2.04

Log(Plant-based Alternative Milk Price)			Log(Butter Price)		
Explanatory Variables	**Estimate**	***p*-value**	**Explanatory Variables**	**Estimate**	***p*-value**
constant	**-8.00**	**0.00**	constant	-8.32	0.06
log (PPI)$_t$	**1.43**	**0.00**	log (PPI)$_t$	1.71	0.07
log (own price)$_{t-1}$	**0.57**	**0.00**	log (own price)$_{t-1}$	**0.78**	**0.00**
Goodness-of-Fit	R^2	0.69	Goodness-of-Fit	R^2	0.76
	Adjusted R^2	0.68		Adjusted R^2	0.76

Table 3. Continued

Log(Plant-based Alternative Milk Price)			Log(Butter Price)		
Explanatory Variables	**Estimate**	***p*-value**	**Explanatory Variables**	**Estimate**	***p*-value**
	RMSE	0.02		RMSE	0.05
	Durbin-Watson	2.02		Durbin-Watson	1.97

Log(Natural Cheese Price)			Log(Margarine Price)		
Explanatory Variables	**Estimate**	***p*-value**	**Explanatory Variables**	**Estimate**	***p*-value**
constant	0.91	0.50	constant	1.18	0.68
log $(PPI)_t$	-0.23	0.44	log $(PPI)_t$	-0.34	0.57
log (own price)$_{t-1}$	**1.13**	**0.00**	log (own price)$_{t-1}$	**0.84**	**0.00**
log (own price)$_{t-2}$	-0.06	0.76	log (own price)$_{t-2}$	**-0.35**	**0.03**
log (own price)$_{t-3}$	-0.20	0.12	log (own price)$_{t-3}$	**0.34**	**0.01**
Goodness-of-Fit	R^2	0.88	Goodness-of-Fit	R^2	0.61
	Adjusted R^2	0.87		Adjusted R^2	0.59
	RMSE	0.02		RMSE	0.04
	Durbin-Watson	2.06		Durbin-Watson	2.05

Log(Greek Yogurt Price)			Log(Ice Cream Price)		
Explanatory Variables	**Estimate**	***p*-value**	**Explanatory Variables**	**Estimate**	***p*-value**
constant	3.38	0.14	constant	**-9.69**	**0.00**
log $(PPI)_t$	1.62	0.26	log $(PPI)_t$	**1.94**	**0.00**
log (PPI)t-1	**-4.65**	**0.01**	log (own price)$_{t-1}$	**1.18**	**0.00**
log (PPI)t-2	2.23	0.13	log (own price)$_{t-2}$	**-0.41**	**0.00**
log (own price)$_{t-1}$	**0.80**	**0.00**			
Goodness-of-Fit	R^2	0.89	Goodness-of-Fit	R^2	0.98
	Adjusted R^2	0.88		Adjusted R^2	0.97
	RMSE	0.02		RMSE	0.01
	Durbin-Watson	1.97		Durbin-Watson	2.06

Note: Based on critical values associated with the Durbin-Watson tests, there is not enough evidence to support the existence of serial correlation at the 5% significance level in the respective auxiliary regressions.
Source: Calculations by the authors.

Zhen et al. (2013) argued that using data at the household level makes the issue of price endogeneity inconsequential since purchase decisions typically do not influence market price. However, this analysis rests on the use of data aggregated over households. To mitigate the issue of price (or unit value) endogeneity, following Dhar, Chavas, and Gould (2003) as well as Lakkakula, Schmitz, and Ripplinger (2016), we use reduced-form equations of prices p_{it} (see equation]15]); the natural log of price p_{it} of each product category is regressed on the natural log of the Producer Price Index (PPI) for all commodities, $\ln \mathrm{PPI}_t$ or its lags, as well as lags of the prices of the respective dairy categories. The use of the PPI in this analysis is reflective of supply-side variation in prices and, thus, is most likely to be exogenous. To support this contention, producer price indices were used as instruments in Lakkakula, Schmitz, and Ripplinger (2016).

$$\ln p_{it} = \Gamma\,(\ln \mathrm{PPI}_t\,, \text{lags of PPI, and lags of} \ln p) \tag{15}$$

Like the situation for total expenditure, we used AIC, BIC, adjusted R^2, and RMSE to determine the optimal lags of the instrumental variables, detailed estimation results from equation (15) are shown in Table 3.

To check on the endogeneity of prices and total expenditure, we implement the Durbin–Wu–Hausman (DWH) test. The null hypothesis suggests that the parameter estimates are consistent without accounting for endogeneity (Dhar, Chavas, and Gould, 2003). The test statistic H is computed as follows,

$$H = (\beta - \beta_{IV})'\big(\mathrm{var}(\beta) - \mathrm{var}(\beta_{IV})\big)^{-1}(\beta - \beta_{IV}), \tag{16}$$

where β is the vector of estimated coefficients without controlling for price and expenditure endogeneity, β_{IV} is the vector of estimated coefficients after controlling for endogeneity, and the term $\mathrm{var}(\beta) - \mathrm{var}(\beta_{IV})$ is the difference between the respective variance-covariance matrices. The statistic H is asymptotically distributed as a chi-squared statistic, with degrees of freedom equal to the number of positive diagonal elements of the differenced variance-covariance matrices. The DWH test results are presented in Table 4.

Table 4. Goodness-of-fit Metrics, Durbin-Watson Statistics, and DWH Test Results for the QUAIDS and the Barten Synthetic Model (BSM)

	Category	**R-Squared**	**Adj R-Sq**	**Durbin-Watson**
QUAIDS	Flavored milk	0.95	0.94	2.55
	White milk	0.97	0.96	2.71
	Non-Greek yogurt	0.99	0.98	2.49
	Greek yogurt	0.99	0.98	2.03
	Butter	0.92	0.89	2.36
	Natural cheese	0.98	0.97	2.17
	Processed cheese	0.97	0.96	2.54
	Plant-based milk Alternatives	0.90	0.86	1.74
	Ice cream	0.98	0.97	2.19
	Margarine	0.98	0.97	2.12

Table 4. Continued

	Category	R-Squared	Adj R-Sq	Durbin-Watson
	DWH Test	Degree of Freedom	Chi-squared statistic	p-value
		182	453	0.00
BSM	Flavored milk	0.89	0.85	2.01
	White milk	0.94	0.91	2.30
	Non-Greek yogurt	0.93	0.91	2.00
	Greek yogurt	0.89	0.85	1.55
	Butter	0.86	0.81	1.61
	Natural cheese	0.97	0.96	1.67
	Processed cheese	0.96	0.95	2.54
	Plant-based milk Alternatives	0.80	0.72	1.70
	Ice cream	0.90	0.86	1.95
	Margarine	0.95	0.93	2.25
	DWH Test	Degree of Freedom	Chi-squared statistic	p-value
		156	375	0.00

Notes: Based on critical values associated with the Durbin-Watson tests, there is not enough evidence to support the existence of serial correlation at the 5% significance level in the respective equations.
The demand systems were re-estimated by dropping the equations associated with flavored milk to obtain the goodness-of-fit metrics for ice cream.

Stationarity

According to Matsuda (2006), unless linearly approximated, nonlinear systems including the QUAIDS are not amenable in dealing with nonstationary variables. As such, to handle the nonstationarity issue and to reduce any difficulties in estimation, we linearized the translog price index ln $a(\boldsymbol{p})$ as follows,

$$\ln a(\boldsymbol{p}) = \sum_i w_{it-1} \ln p_{it} \tag{17}$$

In essence, we used Stone's index to replace ln $a(\boldsymbol{p})$. To avoid any contemporaneous correlation among the budget shares in Stone's price index and the budget shares as associated with the dependent variables in the QUAIDS model, we modified the Stone index by lagging the budget shares by one period as depicted in equation (17). To preserve nonlinear Engel curves (available upon request), the Cobb-Douglas price aggregator $b(\boldsymbol{p})$ in the QUAIDS was kept and used in the estimation.

Seasonality

Seasonal patterns likely are evident in monthly purchases of the respective product categories. To capture possible seasonality, we included 11 monthly dummy variables in the QUAIDS and the BSM. December serves as the base or reference category for seasonality.

Empirical Results

SAS 9.4 was used to estimate the demand system models based on the iterated seemingly unrelated regression procedure (ITSUR). The equation associated with ice cream was dropped to avoid the singularity of the variance-covariance matrix due to the adding-up constraint. Since two lags of total expenditure and up to three lags of own prices are used in the instrumental regression to circumvent the issue of endogeneity, the number of observations available for use was 68.[10]

Goodness-of-Fit

The goodness-of-fit metrics R^2, adjusted R^2, Durbin-Watson statistics, and DWH test results for the QUAIDS and the BSM are shown in Table 4. For the QUAIDS, the R^2 of all the other categories were above 0.90. The Durbin-Watson statistics ranged from 1.74 to 2.71, indicative of white noise after the AR(1) correction. For the BSM, the R^2 measures ranged from 0.80 (plant-based milk alternatives) to 0.97 (natural cheese). The Durbin-Watson Statistics ranged from 1.55 to 2.54, indicative of the presence of white noise or random patterns in the residuals. The Durbin-Wu-Hausman statistics are statistically significant for both models, which confirm the presence of endogeneity of prices and total expenditure.

Estimated Parameters

In Tables 5 and 6, we exhibit the estimated parameters and associated p-values for the QUAIDS and the BSM, respectively. The level of significance chosen for this analysis is 0.05. For the QUADIS, 15 out of 55 gamma parameters γ_{ij}, 6 out of 10 alpha parameters α_i, and 5 out of 10 beta parameters β_i, were statistically different from zero. Five out of 10 lambda parameters λ_i are significantly different from zero individually, and these parameters were jointly significantly different from zero based on the chi-squared test (see Table 5). These findings then reflect the presence of quadratic Engel curves. Because of the significance and joint significance of the λ_i parameters, the QUAIDS was statistically superior to the AIDS.

The estimate of the first-order autocorrelation is specified as rho, and this estimated coefficient of 0.97 was statistically different from zero. Based on joint chi-squared tests, seasonality was evident for all product categories except plant-based milk alternatives. For flavored milk, white milk, non-Greek yogurt, and Greek yogurt, the month with the highest purchase was February, and the month associated with the lowest purchase was December. For natural cheese, the month with the highest purchase was January; the month with the lowest purchase was February. In contrast, the purchases

[10] For the BSM, 67 observations were used due to log differences of quantities, prices, and total expenditure.

for butter, margarine, and processed cheese were highest in December and were lowest in February. Purchases of ice cream were highest in June and lowest in December.

For the BSM, 23 out of 55 beta parameters β_{ij} and 9 out of 10 alpha parameters α_i were significant at the 5% level. In addition, lambda λ and mu μ were statistically significant at the 5% level individually. As mentioned previously, the BSM nests four different models by imposing constraints on λ and μ. The joint test results for the four null hypotheses associated with λ and μ presented in Table 6 indicate that all the respective nested models were not supported by the data. Concerning seasonality, like the QUAIDS, all product categories except plant-based milk alternative revealed seasonal patterns based on joint chi-squared tests. The month associated with the highest purchases for flavored milk, white milk, non-Greek yogurt, and Greek yogurt was February, and the months associated with the lowest purchases were May, March, January, and January, respectively. Households purchase more butter in November and purchased less in February. Regarding cheese (both natural cheese and processed cheese), the month with the highest purchases was January, and the month with the lowest purchases was February. Purchases of ice cream were highest in June and lowest in November.

Table 5. Parameter Estimates, Standard Errors, and *p*-values for the QUAIDS

	Parameters	Estimates	Std Err	*p*-value		Parameters	Estimates	Std Err	*p*-value
Gamma	g11	0.00	0.00	0.19	Gamma	g710	-0.01	0.02	0.66
	g12	0.00	0.02	0.80		g88	**-0.02**	**0.01**	**0.02**
	g13	0.00	0.02	0.85		g89	0.01	0.01	0.47
	g14	0.01	0.01	0.31		g810	-0.01	0.01	0.41
	g15	0.00	0.01	0.79		g99	-0.02	0.02	0.46
	g16	0.01	0.01	0.69		g910	0.01	0.02	0.79
	g17	0.00	0.00	0.28		g1010	-0.03	0.02	0.16
	g18	0.00	0.00	0.41					
	g19	0.00	0.00	0.62	Alpha	a1	**-0.07**	**0.03**	**0.01**
	g110	0.00	0.01	0.86		a2	-0.10	0.30	0.73
	g22	-0.24	0.13	0.08		a3	**-0.67**	**0.29**	**0.03**
	g23	**-0.46**	**0.09**	**0.00**		a4	-0.15	0.16	0.33
	g24	0.13	0.08	0.11		a5	**1.39**	**0.43**	**0.00**
	g25	**0.21**	**0.08**	**0.01**		a6	**0.55**	**0.25**	**0.04**
	g26	**0.30**	**0.15**	**0.05**		a7	**0.32**	**0.13**	**0.02**
	g27	-0.02	0.07	0.81		a8	-0.06	0.05	0.19
	g28	0.01	0.04	0.86		a9	**-0.40**	**0.14**	**0.01**
	g29	-0.05	0.07	0.48		a10	0.19	0.10	0.06
	g210	**0.11**	**0.04**	**0.01**	Beta	b1	0.00	0.02	0.98
	g33	**-0.53**	**0.16**	**0.00**		b2	**-0.36**	**0.06**	**0.00**
	g34	**0.22**	**0.10**	**0.04**		b3	**-0.44**	**0.08**	**0.00**
	g35	**0.26**	**0.09**	**0.01**		b4	0.15	0.09	0.08
	g36	**0.40**	**0.13**	**0.00**		b5	**0.21**	**0.08**	**0.01**
	g37	0.03	0.07	0.69		b6	**0.32**	**0.10**	**0.00**
	g38	0.01	0.04	0.79		b7	0.01	0.07	0.87
	g39	-0.06	0.07	0.36		b8	0.01	0.04	0.77
	g310	**0.13**	**0.05**	**0.01**		b9	-0.03	0.07	0.63
	g44	-0.11	0.06	0.10		b10	**0.13**	**0.04**	**0.00**
	g45	-0.09	0.05	0.11	Lambda	L1	0.00	0.00	0.95
	g46	**-0.15**	**0.07**	**0.04**		L2	**0.10**	**0.03**	**0.00**
	g47	-0.02	0.03	0.41		L3	**0.12**	**0.03**	**0.00**
	g48	0.01	0.02	0.57		L4	-0.04	0.02	0.07
	g49	0.04	0.03	0.15		L5	**-0.07**	**0.02**	**0.00**
	g410	-0.04	0.03	0.12		L6	**-0.09**	**0.04**	**0.03**
	g55	-0.19	0.10	0.06		L7	0.00	0.02	0.94
	g56	**-0.16**	**0.07**	**0.03**		L8	0.00	0.01	0.78
	g57	0.01	0.04	0.87		L9	0.01	0.02	0.51
	g58	0.00	0.02	0.95		L10	**-0.03**	**0.01**	**0.00**
	g59	0.02	0.04	0.60					
	g510	**-0.07**	**0.03**	**0.02**		**rho**	**0.97**	**0.00**	**0.01**
	g66	**-0.42**	**0.19**	**0.03**					
	g67	0.05	0.06	0.39					
	g68	0.00	0.04	0.92		**Joint test for Lambda**	**Chi-sq stat**	***p*-value**	
	g69	0.05	0.06	0.45					
	g610	-0.08	0.04	0.08					
	g77	**-0.05**	**0.02**	**0.00**					
	g78	0.01	0.01	0.54					
	g79	0.01	0.01	0.46			**61.12**	**0.00**	

Table 5. Continued

	Parameters	Estimates	Std Err	*p-value*		Parameters	Estimates	Std Err	*p-value*
Seasonality	m11[1]	0.001	0.00	0.00		m61	0.017	0.00	0.00
	m12	0.004	0.00	0.00		m62	-0.010	0.01	0.08
	m13	0.002	0.00	0.00		m63	-0.005	0.00	0.14
	m14	0.002	0.00	0.00		m64	-0.006	0.00	0.10
	m15	0.001	0.00	0.00	Natural	m65	-0.001	0.00	0.81
Flavored	m16	0.002	0.00	0.00	cheese	m66	-0.004	0.00	0.31
milk	m17	0.002	0.00	0.00		m67	-0.005	0.00	0.15
	m18	0.002	0.00	0.00		m68	-0.002	0.00	0.52
	m19	0.002	0.00	0.00		m69	0.003	0.00	0.46
	m110	0.002	0.00	0.00		m610	-0.003	0.00	0.39
	m111	0.002	0.00	0.00		m611	-0.003	0.00	0.46
	m21	0.012	0.00	0.00		m71	-0.001	0.00	0.60
	m22	0.030	0.00	0.00		m72	-0.024	0.00	0.00
	m23	0.005	0.00	0.14		m73	-0.011	0.00	0.00
	m24	0.010	0.00	0.00		m74	-0.015	0.00	0.00
White milk	m25	0.013	0.00	0.00	Processed	m75	-0.008	0.00	0.00
	m26	0.013	0.00	0.00	cheese	m76	-0.009	0.00	0.00
	m27	0.012	0.00	0.00		m77	-0.010	0.00	0.00
	m28	0.013	0.00	0.00		m78	-0.009	0.00	0.00
	m29	0.011	0.00	0.00		m79	-0.012	0.00	0.00
	m210	0.009	0.00	0.01		m710	-0.007	0.00	0.00
	m211	0.013	0.00	0.00		m711	-0.009	0.00	0.00
	m31	0.007	0.00	0.01		m81	0.000	0.00	0.71
	m32	0.043	0.00	0.00		m82	0.002	0.00	0.24
	m33	0.018	0.00	0.00		m83	0.001	0.00	0.18
	m34	0.018	0.00	0.00	Plant-based	m84	0.002	0.00	0.12
Non-Greek	m35	0.014	0.00	0.00	milk alterna-	m85	0.001	0.00	0.40
yogurt	m36	0.017	0.00	0.00	tives (PMA)	m86	0.002	0.00	0.08
	m37	0.015	0.00	0.00		m87	0.001	0.00	0.26
	m38	0.013	0.00	0.00		m88	0.001	0.00	0.18
	m39	0.018	0.00	0.00		m89	0.001	0.00	0.38
	m310	0.018	0.00	0.00		m810	0.001	0.00	0.47
	m311	0.012	0.00	0.00		m811	0.001	0.00	0.34
	m41	0.005	0.00	0.03		m91	0.005	0.00	0.01
	m42	0.023	0.00	0.00		m92	0.012	0.00	0.00
	m43	0.009	0.00	0.00		m93	0.015	0.00	0.00
	m44	0.012	0.00	0.00		m94	0.015	0.00	0.00
Greek	m45	0.009	0.00	0.00		m95	0.012	0.00	0.00
yogurt	m46	0.011	0.00	0.00	Ice cream	m96	0.019	0.00	0.00
	m47	0.010	0.00	0.00		m97	0.015	0.00	0.00
	m48	0.009	0.00	0.00		m98	0.014	0.00	0.00
	m49	0.011	0.00	0.00		m99	0.004	0.00	0.03
	m410	0.009	0.00	0.00		m910	0.006	0.00	0.00
	m411	0.007	0.00	0.00		m911	0.004	0.00	0.04
Butter	m51	-0.037	0.00	0.00		m101	-0.009	0.00	0.00
	m52	-0.071	0.01	0.00		m102	-0.010	0.00	0.00
	m53	-0.030	0.00	0.00		m103	-0.005	0.00	0.00
	m54	-0.031	0.00	0.00		m104	-0.007	0.00	0.00
	m55	-0.034	0.00	0.00		m105	-0.007	0.00	0.00
	m56	-0.042	0.00	0.00	Margarine	m106	-0.009	0.00	0.00
	m57	-0.033	0.00	0.00		m107	-0.007	0.00	0.00
	m58	-0.034	0.00	0.00		m108	-0.006	0.00	0.00
	m59	-0.032	0.00	0.00		m109	-0.005	0.00	0.00
	m510	-0.029	0.00	0.00		m1010	-0.006	0.00	0.00
	m511	-0.024	0.00	0.00		m1011	-0.004	0.00	0.00

Table 5. Continued

		Chi-Squared Stat	*p*-value
Joint test for seasonality			
	Flavored milk	48.15	0.00
	White milk	60.01	0.00
	Non-Greek yogurt	177.14	0.00
	Greek yogurt	69.01	0.00
	Butter	183.10	0.00
	Natural cheese	81.36	0.00
	Processed cheese	189.10	0.00
	PMA	7.60	0.74
	Ice cream	441.89	0.00
	Margarine	156.76	0.00

Note: Bold numbers indicate significance at the 5% level.
[1] The subscript number represents dairy categories: (1) flavored milk (mainly chocolate milk), (2) white milk (contains both organic and conventional white milk), (3) non-Greek yogurt, (4) Greek yogurt, (5) butter, (6) natural cheese, (7) processed cheese, (8) plant-based milk alternatives (PMA), (9) ice cream, and (10) margarine.
Source: Estimation done via the use of SAS 9.4.

Table 6. Parameter Estimates, Standard Errors, and *p*-values for the BSM

	Parameters	Estimates	Std Err	*p*-value		Parameters	Estimates	Std Err	*p*-value
Beta	**b11**	0.01	0.00	0.08	Alpha	**a1**	**-0.01**	**0.00**	**0.00**
	b12	**-0.01**	**0.00**	**0.00**		**a2**	**-0.23**	**0.04**	**0.00**
	b13	0.00	0.00	0.42		**a3**	**-0.08**	**0.02**	**0.00**
	b14	0.00	0.00	0.56		**a4**	**-0.06**	**0.01**	**0.00**
	b15	0.00	0.00	0.07		**a5**	0.03	0.03	0.36
	b16	0.00	0.00	0.92		**a6**	**-0.14**	**0.04**	**0.00**
	b17	0.00	0.00	0.39		**a7**	**-0.04**	**0.01**	**0.01**
	b18	0.00	0.00	0.09		**a8**	**-0.02**	**0.00**	**0.00**
	b19	**-0.01**	**0.00**	**0.02**		**a9**	**-0.05**	**0.01**	**0.00**
	b110	**0.02**	**0.00**	**0.00**		**a10**	**-0.02**	**0.01**	**0.00**
	b22	**0.26**	**0.03**	**0.00**	Lambda	**L**	**1.62**	**0.13**	**0.00**
	b23	**-0.05**	**0.01**	**0.00**	mu	**mu**	**1.72**	**0.15**	**0.00**
	b24	**-0.04**	**0.01**	**0.00**					
	b25	0.01	0.01	0.49					
	b26	**-0.10**	**0.01**	**0.00**	**Joint test**	**H_0:**	**Chi-sq stat**	***p*-value**	
	b27	**-0.03**	**0.01**	**0.00**	Rotterdam	**L=0,mu=0**	**321.08**	**0.00**	
	b28	**-0.01**	**0.00**	**0.01**	AIDS	**L=1,mu=1**	**51.99**	**0.00**	
	b29	**-0.03**	**0.01**	**0.00**	CBS	**L=1,mu=0**	**171.3**	**0.00**	
	b210	**-0.01**	**0.00**	**0.00**	NBR	**L=0,mu=1**	**196.32**	**0.00**	
	b33	0.00	0.02	0.98					
	b34	**0.03**	**0.01**	**0.04**					
	b35	**0.04**	**0.01**	**0.00**					
	b36	-0.01	0.01	0.47					
	b37	**0.03**	**0.01**	**0.01**					
	b38	-0.01	0.01	0.23					
	b39	**-0.04**	**0.02**	**0.01**					
	b310	0.01	0.01	0.21					
	b44	-0.03	0.02	0.11					
	b45	0.02	0.01	0.10					

Table 6. Continued

	Parameters	Estimates	Std Err	*p*-value		Parameters	Estimates	Std Err	*p*-value
	b46	-0.01	0.01	0.46					
	b47	0.01	0.01	0.65					
	b48	0.01	0.01	0.12					
	b49	0.01	0.01	0.29					
	b410	0.01	0.01	0.41					
	b55	**-0.11**	**0.03**	**0.00**					
	b56	**0.04**	**0.01**	**0.00**					
	b57	0.00	0.01	0.59					
	b58	0.00	0.00	0.41					
	b59	0.01	0.01	0.25					
	b510	**-0.01**	**0.00**	**0.02**					
	b66	0.03	0.04	0.49					
	b67	**0.04**	**0.01**	**0.01**					
	b68	0.01	0.01	0.21					
	b69	0.00	0.02	0.85					
	b610	0.01	0.01	0.22					
	b77	**-0.04**	**0.02**	**0.02**					
	b78	0.01	0.01	0.26					
	b79	0.02	0.01	0.13					
	b710	**-0.03**	**0.01**	**0.00**					
	b88	-0.01	0.01	0.34					
	b89	0.00	0.01	0.84					
	b810	0.00	0.00	0.60					
	b99	0.02	0.02	0.32					
	b910	**0.01**	**0.01**	**0.05**					
	b1010	**0.26**	**0.03**	**0.00**					
Seasonal-ity	**m11**	0.000	0.000	0.08	Natural cheese	**m61**	**0.018**	**0.002**	**0.00**
Flavored	**m12**	**0.001**	**0.000**	**0.01**		**m62**	**-0.015**	**0.003**	**0.00**
milk	**m13**	0.000	0.000	0.11		**m63**	0.000	0.002	0.94
	m14	0.000	0.000	0.08		**m64**	**-0.008**	**0.002**	**0.00**
	m15	**-0.001**	**0.000**	**0.01**		**m65**	0.003	0.002	0.16
	m16	0.000	0.000	0.14		**m66**	**-0.004**	**0.002**	**0.05**
	m17	**0.000**	**0.000**	**0.04**		**m67**	-0.001	0.002	0.39
	m18	0.000	0.000	0.28		**m68**	-0.001	0.002	0.56
	m19	**0.000**	**0.000**	**0.02**		**m69**	0.003	0.002	0.06
	m110	**0.000**	**0.000**	**0.03**		**m610**	0.001	0.002	0.66
	m111	**0.001**	**0.000**	**0.00**		**m611**	-0.003	0.002	0.13
White milk	**m21**	-0.001	0.002	0.72	Processed cheese	**m71**	**0.009**	**0.001**	**0.00**
	m22	**0.012**	**0.003**	**0.00**		**m72**	**-0.010**	**0.002**	**0.00**
	m23	**-0.012**	**0.002**	**0.00**		**m73**	-0.002	0.001	0.15
	m24	0.004	0.003	0.11		**m74**	**-0.008**	**0.001**	**0.00**
	m25	-0.004	0.002	0.11		**m75**	0.002	0.001	0.12
	m26	0.000	0.002	0.86		**m76**	0.001	0.001	0.19
	m27	-0.004	0.002	0.07		**m77**	0.000	0.001	0.65
	m28	0.001	0.002	0.58		**m78**	-0.001	0.001	0.63
	m29	-0.001	0.002	0.79	Plant-based	**m79**	**-0.002**	**0.001**	**0.05**
	m210	**-0.007**	**0.002**	**0.00**	milk alter-	**m710**	**0.004**	**0.001**	**0.00**
	m211	0.000	0.002	0.92	natives	**m711**	0.000	0.001	0.83
Non-Greek	**m31**	**-0.009**	**0.002**	**0.00**	(PMA)	**m81**	-0.001	0.000	0.16
yogurt	**m32**	**0.020**	**0.003**	**0.00**		**m82**	0.001	0.001	0.17

Table 6. Continued

	Parameters	Estimates	Std Err	*p*-value		Parameters	Estimates	Std Err	*p*-value
	m33	0.002	0.002	0.40	Alter-natives	**m83**	0.000	0.000	0.96
	m34	0.004	0.002	0.06		**m84**	**0.002**	**0.001**	**0.00**
	m35	-0.003	0.002	0.16		**m85**	-0.001	0.000	0.15
	m36	-0.002	0.002	0.40		**m86**	0.001	0.000	0.09
	m37	-0.003	0.002	0.09		**m87**	-0.001	0.000	0.13
	m38	**-0.003**	**0.002**	**0.05**		**m88**	0.001	0.000	0.15
	m39	0.001	0.002	0.46		**m89**	0.000	0.000	0.88
	m310	0.000	0.002	0.85		**m810**	0.000	0.000	0.29
	m311	**-0.004**	**0.002**	**0.02**		**m811**	0.000	0.000	0.51
Greek yogurt	**m41**	**-0.004**	**0.001**	**0.01**	Ice cream	**m91**	**-0.004**	**0.001**	**0.00**
	m42	**0.013**	**0.002**	**0.00**		**m92**	-0.004	0.002	0.06
	m43	0.001	0.002	0.63		**m93**	**0.005**	**0.001**	**0.00**
	m44	**0.006**	**0.002**	**0.00**		**m94**	**0.007**	**0.001**	**0.00**
	m45	0.000	0.001	0.79		**m95**	**0.003**	**0.001**	**0.02**
	m46	0.000	0.001	0.74		**m96**	**0.008**	**0.001**	**0.00**
	m47	0.000	0.001	0.78		**m97**	**0.005**	**0.001**	**0.00**
	m48	0.000	0.001	0.99		**m98**	**0.003**	**0.001**	**0.01**
	m49	0.002	0.001	0.20		**m99**	**-0.007**	**0.001**	**0.00**
	m410	-0.001	0.001	0.39		**m910**	**-0.005**	**0.001**	**0.00**
	m411	-0.002	0.001	0.15		**m911**	**-0.007**	**0.001**	**0.00**
Butter	**m51**	-0.005	0.004	0.24	Margarine	**m101**	**-0.003**	**0.001**	**0.00**
	m52	**-0.016**	**0.006**	**0.02**		**m102**	-0.001	0.001	0.19
	m53	0.005	0.005	0.29		**m103**	0.001	0.001	0.25
	m54	-0.006	0.005	0.29		**m104**	**-0.002**	**0.001**	**0.00**
	m55	0.001	0.005	0.85		**m105**	**-0.001**	**0.001**	**0.05**
	m56	-0.002	0.004	0.57		**m106**	**-0.002**	**0.001**	**0.01**
	m57	0.005	0.004	0.22		**m107**	0.000	0.001	0.69
	m58	0.001	0.004	0.83		**m108**	0.000	0.001	0.60
	m59	0.001	0.004	0.73		**m109**	0.001	0.001	0.07
	m510	**0.010**	**0.004**	**0.02**		**m1010**	0.000	0.001	0.49
	m511	**0.013**	**0.004**	**0.00**		**m1011**	**0.002**	**0.001**	**0.00**

Seasonality		**Chi-squared stat**	***p*-value**
	Flavored milk	**42.00**	**0.00**
	White milk	**46.51**	**0.00**
	Non-Greek Yogurt	**103.62**	**0.00**
	Greek yogurt	**71.19**	**0.00**
	Butter	**27.04**	**0.00**
	Natural cheese	**149.50**	**0.00**
	Processed cheese	**147.68**	**0.00**
	Plant-based milk alternatives	16.49	0.12
	Ice cream	**225.61**	**0.00**
	Margarine	**100.49**	**0.00**

Note: Bold numbers indicate significance at the 5% level.
Source: Estimation done via the use of SAS.9.4.

Comparison of Elasticities Across Models

The uncompensated, compensated price elasticities and expenditure elasticities were calculated based on equations (4), (5), and (6) for the QUAIDS and based on equations (10), (11), and (12) for the BSM. Note that the respective elasticities depend not only on the estimated parameters but also on prices, total expenditure, and budget shares. The compensated price elasticities as well as the expenditure and income elasticities calculated at the sample means for the QUAIDS and the BSM are presented in Tables 7 and 8, respectively. In Table 9, we compare the compensated own-price elasticities and income elasticities between the QUAIDS and the BSM. The uncompensated own-price and cross-price elasticities are available from the authors upon request.

Table 7. Compensated Own-Price and Cross-Price Elasticities as well as Expenditure and Income Elasticities for the QUAIDS

Good *i* / Good *j*	Flavored Milk	White Milk	Non-Greek Yogurt	Greek Yogurt	Butter	Natural Cheese	Processed Cheese	PMA	Ice Cream	Margarine	Expenditure Elasticity	Income Elasticity
Flavored milk	**-1.31**	-0.27	0.32	**0.50**	0.13	0.39	-0.29	-0.16	-0.13	-0.08	**1.04**	0.50
White milk	**0.25**	**-0.38**	0.05	**0.23**	**0.34**	**0.29**	**0.17**	**0.25**	0.19	**0.25**	**1.00**	0.48
Non-Greek yogurt	**0.12**	**-0.48**	**-1.33**	**0.54**	**0.50**	**0.55**	0.31	0.06	-0.23	-0.04	**0.87**	0.42
Greek yogurt	**0.18**	-0.10	**1.07**	**-1.92**	-0.12	-0.43	-0.33	**0.34**	**0.64**	0.15	**1.04**	0.50
Butter	0.05	0.24	0.26	-0.15	**-1.66**	0.46	**0.37**	0.11	-0.03	0.15	0.60	0.29
Natural cheese	**0.30**	**0.30**	**0.42**	**0.20**	**0.36**	**-1.26**	**0.50**	**0.31**	**0.35**	**0.37**	**0.99**	0.47
Processed cheese	**0.08**	-0.15	**0.37**	-0.04	0.03	**0.69**	**-1.51**	**0.17**	0.27	0.01	**1.16**	0.56
PMA	-0.11	-0.18	-0.07	0.82	0.20	0.33	0.30	**-2.17**	0.41	-0.41	**1.07**	0.52
Ice cream	0.06	-0.16	-0.26	**0.53**	-0.08	0.31	0.17	0.18	**-1.09**	-0.02	**1.17**	0.56
Margarine	0.04	0.04	-0.16	0.24	-0.30	**0.53**	-0.21	-0.13	0.04	**-0.85**	**1.33**	0.64

Note: Bold numbers indicate significance at the 5% level.
Source: Calculations by the authors.

Table 8. Compensated Own-Price and Cross-Price Elasticities As Well As Expenditure and Income Elasticities for the BSM

Good *i* / Good *j*	Flavored Milk	White Milk	Non-Greek Yogurt	Greek Yogurt	Butter	Natural Cheese	Processed Cheese	PMA	Ice Cream	Margarine	Expenditure Elasticity	Income Elasticity
Flavored milk	**-1.28**	-0.08	-0.07	0.17	**0.32**	**0.54**	0.01	-0.28	**-0.53**	**1.25**	**0.63**	0.30
White milk	0.00	**-0.29**	0.02	**-0.05**	**0.15**	**0.15**	**0.06**	0.01	0.01	0.02	**0.78**	0.38
Non-Greek yogurt	-0.01	0.05	**-1.53**	**0.31**	**0.47**	**0.43**	**0.52**	-0.06	-0.26	**0.15**	**0.88**	0.42
Greek yogurt	0.05	**-0.29**	**0.64**	**-2.23**	**0.45**	0.30	0.27	0.23	0.46	0.18	**0.48**	0.23
Butter	**0.07**	**0.60**	**0.74**	**0.33**	**-3.18**	**1.13**	0.10	0.08	0.29	-0.08	**2.07**	0.99
Natural cheese	**0.03**	**0.14**	**0.15**	0.05	**0.26**	**-1.12**	**0.29**	**0.06**	**0.11**	**0.10**	**1.16**	0.56
Processed cheese	0.00	**0.18**	**0.57**	0.14	0.07	**0.90**	**-1.96**	0.11	**0.28**	**-0.22**	**1.23**	0.59
PMA	-0.21	0.09	-0.33	0.61	0.27	**0.96**	0.55	**-2.07**	0.22	-0.04	**0.56**	0.27
Ice cream	**-0.10**	0.05	-0.38	0.33	**0.28**	**0.44**	**0.38**	0.06	**-1.26**	**0.27**	**0.87**	0.41
Margarine	**0.44**	0.12	**0.39**	0.23	-0.14	**0.73**	**-0.53**	-0.02	**0.48**	**-1.21**	**1.12**	0.54

Note: Bold numbers indicate significance at the 5% level. Source: Calculations by the authors.

Table 9. Comparison of Compensated and Uncompensated Own-Price Elasticities as well as Income Elasticities between the QUAIDS and the BSM

		QUAIDS	**BSM**
Uncompensated own-price elasticity	Flavored milk	-1.32	-1.29
	White milk	-0.64	-0.51
	Non-Greek yogurt	-1.42	-1.63
	Greek yogurt	-1.97	-2.25
	Butter	-1.70	-3.32
	Natural cheese	-1.55	-1.46
	Processed cheese	-1.62	-2.08
	PMA	-2.19	-2.08
	Ice cream	-1.17	-1.32
	Margarine	-0.90	-1.25
Compensated own-price elasticity	Flavored milk	-1.31	-1.28
	White milk	-0.38	-0.29
	Non-Greek yogurt	-1.33	-1.53
	Greek yogurt	-1.92	-2.23
	Butter	-1.66	-3.18
	Natural cheese	-1.26	-1.12
	Processed cheese	-1.51	-1.96
	PMA	-2.17	-2.07
	Ice cream	-1.09	-1.26
	Margarine	-0.85	-1.21
Income elasticity	Flavored milk	0.50	0.30
	White milk	0.48	0.38
	Non-Greek yogurt	0.42	0.42
	Greek yogurt	0.50	0.23
	Butter	0.29	0.99
	Natural cheese	0.47	0.56
	Processed cheese	0.56	0.59
	PMA	0.52	0.27
	Ice cream	0.56	0.41
	Margarine	0.64	0.54

Compensated Own-Price Elasticities

As expected, the compensated own-price elasticities for both demand systems were negative, statistically significant at the 5% level.[11] Both systems satisfied the negativity condition from the demand theory. In both models, compensated own-price elasticities were greater than 1 for most product categories except white milk and margarine in the QUAIDS, and white milk only in the BSM. As such, households were quite sensitive to changes in prices except for white milk.

[11] The standard errors were obtained using the delta method.

For the QUAIDS, the compensated own-price elasticities ranged from -0.38 (white milk) to -2.17 (plant-based milk alternatives). In the case of the BSM, the compensated own-price elasticities ranged from -0.29 (white milk) to -3.18 (butter). Compared to the QUAIDS, the BSM results in larger compensated own-price elasticities in magnitude for most of the categories, including non-Greek yogurt, Greek yogurt, processed cheese, ice cream, margarine, and butter. To illustrate, the compensated own-price elasticities for butter from the QUAIDS model and the BSM model were -1.66 and -3.18, respectively.

Expenditure and Income Elasticities

The expenditure elasticities for both demand systems were not only positive but also statistically significant at the 5% level, except for butter in the QUAIDS. We derived the income elasticities using equation (18) as follows:

$$IE_i = \frac{\%\Delta \text{ Total Expenditure}}{\%\Delta \text{ Income}} \times \frac{\%\Delta \text{ Quantity Demanded}_i}{\%\Delta \text{ Total Expenditure}} = 0.48 \times \varepsilon_i, \tag{18}$$

where IE_i is the income elasticity for product category i, ε_i is expenditure elasticity derived from equations (4) and (11), 0.48 is the estimated coefficient from equation (14), and %Δ represents the percentage change.

For the respective demand system models, all product categories in both models were estimated to be necessities. The income elasticities for the QUAIDS ranged from 0.29 (butter) to 0.64 (margarine). The income elasticities for the BSM ranged from 0.23 (Greek yogurt) to 0.99 (butter).

Compensated Cross-Price Elasticities

In the QUAIDS, 34 out of 90 compensated cross-price elasticities were statistically significant at the 5% level. Non-Greek yogurt was a complement to white milk. But the remaining 33 statistically significant cross-price elasticities were positive, indicative of substitution relationships among the product categories.

Flavored milk was a substitute for white milk, non-Greek yogurt, Greek yogurt, natural cheese, and processed cheese, while white milk was a substitute for natural cheese. Non-Greek yogurt was a substitute for Greek yogurt, natural cheese, and processed cheese, while Greek yogurt was a substitute for flavored milk, white milk, non-Greek yogurt, natural cheese, and ice cream. Butter was a substitute for white milk, non-Greek yogurt, and natural cheese. Natural cheese was a substitute for white milk, non-Greek yogurt, processed cheese, and margarine. Processed cheese was a substitute for white milk, butter, and natural cheese. Ice cream was a substitute for white milk, Greek yogurt, and natural cheese. Plant-based milk alternatives were a substitute for white milk, Greek yogurt, natural cheese, and processed cheese. In the QUAIDS, substitutability between margarine and butter was not evident, but margarine was a substitute for white milk and natural cheese.

In the BSM, 45 out of 90 compensated cross-price elasticities were statistically significant at the 5% level. Six of these statistically significant compensated cross-price elasticities were negative, indicative of complementary relationships. Thirty-nine of these statistically significant cross-price elasticities were positive, indicative of substitution relationships among the product categories. Consequently, the BSM was able to discern more statistically significant compensated cross-price elasticities than the QUAIDS.

Flavored milk and ice cream were complements, Greek yogurt and white milk were complements, while processed cheese and margarine were complements. Flavored milk was a substitute for butter, natural cheese, and margarine. White milk was a substitute for butter, natural cheese, and processed cheese. Not unexpectedly, non-Greek yogurt and Greek yogurt were substitutes. Non-Greek was also a substitute for butter, natural cheese, processed cheese, and margarine. Additionally, Greek yogurt and butter were substitutes. Not surprisingly, natural cheese and processed cheese were substitutes. Further, natural cheese was a substitute for flavored milk, white milk, non-Greek yogurt, plant-based milk alternatives, ice cream, and margarine. Butter was a substitute for flavored milk, white milk, non-Greek yogurt, Greek yogurt, natural cheese, and ice cream. Processed cheese was a substitute for white milk, non-Greek yogurt, and ice cream. Plant-based milk alternatives were a substitute for natural cheese. Ice cream was a substitute for natural cheese, processed cheese, and margarine.

The similarity of the own-price and cross-price elasticities between the respective models is indicative of the robustness of the findings. However, notable differences were observed across the two models in some instances, such as the compensated own-price elasticity for butter and the income elasticities for butter, Greek yogurt, and plant-based milk alternatives. Unlike the BSM, the QUAIDS model captured the presence of quadratic Engel curves, and its nonlinear property required more iterations to deal with estimation issues. According to findings from Pashardes (1993), Moschini (1995), and Barnett and Seck (2008), the application of Stone's Price Index to linearize the model could cause estimation bias.

Standard multivariate regression model selection criteria, such as Likelihood Ratio, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC), are not applicable to compare the performance between these two models due to the different dependent variables. In general, the findings from the two popular models are robust and provide estimation ranges for the respective elasticities gleaned from this analysis.

The set of products associated with our analysis is unique among corresponding studies in the extant literature. In Table 10, we compare the results from our study with previous research. Our own-price elasticities for white milk were estimated to be less than 1, different from the findings of Davis et al. (2010), but consistent with the findings of Maynard and Liu (1999). Our own-price elasticities for butter were greater than 1, inconsistent with Maynard and Liu (1999), but in accord with Yen, Kan, and Su (2002) and Davis et al. (2010), though greater in magnitude especially in the BSM model. Our own-price elasticities for natural cheese, processed cheese, margarine, and ice cream were in accord with those reported by Davis et al. (2009, 2010, 2011a, and 2011b).

Finally, our own-price elasticities for plant-based milk alternatives were much greater in magnitude than those reported by Yang and Dharmasena (2021).

Table 10. Comparison of Models, Data, Dairy Products, Compensated Own-Price Elasticities, and Income/Expenditure Elasticities with Previous Studies

Study	Model	Data	Dairy Products	Own-price Elasticity	Income / Expenditure Elasticity
Our study	QUAIDS; BSM[a] models	Time-series data, Monthly Nielsen Homescan data 2010–2015	Flavored milk	-1.31 (-1.28[a])	0.50 (0.30[a])
			White milk	-0.38 (-0.29[a])	0.48 (0.38[a])
			Non-Greek yogurt	-1.33 (-1.53[a])	0.42 (0.42[a])
			Greek yogurt	-1.92 (-2.23[a])	0.50 (0.23[a])
			Butter	-1.66 (-3.18[a])	0.29 (0.99[a])
			Natural cheese	-1.26 (-1.12[a])	0.47 (0.56[a])
			Processed cheese	-1.51 (-1.96[a])	0.56 (0.59[a])
			PMA	-2.17 (-2.07[a])	0.52 (0.27[a])
			Ice cream	-1.09 (-1.26[a])	0.56 (0.41[a])
			Margarine	-0.85 (-1.21[a])	0.64 (0.54[a])
Maynard and Liu (1999)	Double-log model/ Linearized AIDS model[c]/ NBR[d]	Time series data, weekly Nielsen Homescan data 1996–1998	White milk	-0.54 (-0.63[c], -0.78[d])	
			Flavored milk	-1.41 (-1.40[c], -1.47[d])	
			Chunk cheese	-2.18 (-1.96[c], -3.03[d])	
			Sliced cheese	-1.64 (-1.72[c], -2.08[d])	
			Snack cheese	-0.58 (-1.68[c], -0.99[d])	
			Shredded cheese	-1.35 (-1.70[c], -2.66[d])	
			Butter	-0.63 (-0.19[c], -2.33[d])	
			Ice cream	-0.88 (-0.65[c], -1.65[d])	
			Frozen yogurt	-1.31 (-1.49[c], -1.64[d])	
			Frozen novelties	-2.99 (-3.39[c], -3.18[d])	
Yen et al. (2002)	A censored translog demand system	Cross-sectional data, the 1987–1988 Nationwide Food Consumption Survey	Butter	-1.13	1.00
			Margarine	-0.99	1.00
Davis et al. (2009)	A censored translog demand system	Cross-sectional data, 2005 Nielsen Homescan	Bulk ice cream	-1.00	1.01
			Ice milk	-1.28	0.84
			Ice cream novelties	-1.96	0.50
Davis et al. (2010)	Censored AIDS model	Cross-sectional data, 2007 Nielsen Homescan	Bulk ice cream	-0.91	1.01
			Sherbet/ice milk	-1.21	0.93
			Refrigerated yogurt	-1.19	1.00
			Frozen yogurt	-1.26	1.00
			Drinkable yogurt	-1.73	0.96
			Whole milk	-1.70	0.77
			Reduced-fat milk	-1.57	1.14

Table 10. Continued

Study	Model	Data	Dairy Products	Own-price Elasticity	Income / Expenditure Elasticity
			Canned milk	-1.32	1.06
			Natural cheese	-1.73	1.04
			Processed cheese	-0.99	0.85
			Cottage cheese	-1.68	1.10
			Butter	-1.87	0.97
			Margarine	-0.95	0.94
Davis et al. (2011)	Censored AIDS model	Cross-sectional data, 2006 Nielsen Homescan	Natural cheese	-1.84	1.05
			Cottage cheese	-2.59	1.13
			Processed cheese	-1.63	0.94
			Grated cheese	-2.25	1.02
			Shredded cheese	-3.77	0.82
			Other cheese	-1.55	0.98
Davis et al. (2012)	AIDS model	Cross-sectional data, 2007 Nielsen Homescan	Whole milk	-1.48	0.96
			1% milk	-1.40	0.99
			2% milk	-1.39	1.02
			Skim milk	-3.24	1.01
			Whole flavored milk	-2.52	1.23
			1% flavored milk	-2.39	1.19
			2% Flavored Milk	-3.82	1.23
			Skim flavored milk	-1.94	1.37
			Other milk	-1.07	1.00
Robinson (2017)	Single equation estimation[e]/ Seemingly unrelated regression[f]	Time series data, weekly Nielsen Homescan 2009-2011	Chobani yogurt	-1.77[e] (-2.64[f])	0.48[e] (2.89[f])
			Dannon yogurt	-1.42[e] (-1.43[f])	-1.36[e] (2.34[f])
			Yoplait yogurt	-0.41[e] (-0.37[f])	0.11[e] (1.98[bf])
			Stonyfield yogurt	-0.79[e] (-0.86[f])	-4.06[e] (1.64[bf])
			Private label yogurt	-0.14[e] (-0.19[f])	0.99[e] (0.38[bf])
Yang and Dharmasena (2021)	Hedonic BSM model	Time series data, Monthly Nielsen Homescan 2004-2015	Almond milk	-0.12	3.60
			Soy milk	-0.25	10.07
			Rice milk	-0.01	2.31
			2% milk	-0.11	0.83
			1% milk	-0.15	1.14
			Fat-free milk	-0.14	0.57
			Whole milk	-0.12	0.55

Concluding Remarks

In this study, the QUAIDS and the BSM were utilized to investigate the demand for 10 products related to the dairy industry based on monthly time-series data through January 2010 to November 2015, derived from Nielsen Homescan Panels. Issues such as serial correlation, endogeneity of total expenditure and prices, stationarity, and seasonality were addressed during the estimation process. In general, the empirical results were robust for the most part across the respective models.

In both models, seasonality was evident for all dairy categories except for plant-based milk alternatives. Concerning compensated own-price elasticities, both models revealed that the demands for the respective dairy products were elastic except for white milk. In the QUAIDS model, the demand for margarine was inelastic, while the BSM revealed the opposite. The own-price elasticities derived from the BSM were larger than those derived from the QUAIDS in general. Hence, the appropriate strategy for stakeholders in the dairy industry in downstream markets to increase revenue in the short run is to lower prices. For white milk, the appropriate strategy to increase revenue is to raise prices, holding all other factors constant.

Divergences of the expenditure elasticities were evident for Greek yogurt, butter, and plant-based milk alternatives across the models. Nevertheless, for the respective demand system models, all product categories were necessities. As such, changes in income are not likely to provide notable impacts on the demand for the products in question.

The BSM was able to discern more statistically significant compensated cross-price elasticities than the QUAIDS. Across the respective models, most of the statistically significant cross-price elasticities were positive, indicative of substitution relationships among the products considered in this analysis. In the QUAIDS, white milk, Greek yogurt, and plant-based milk alternatives were substitutes. But this finding was not evident in the BSM. Going forward, additional work needs to consider the substitutability of these key products.

Several takeaways are evident from this research. To better understand the demand for dairy products, it is necessary to disaggregate into various segments and to consider plant-based milk alternatives. This disaggregation more accurately captures the reality of what consumers face when shopping at various retail outlets. A fundamental economic principle associated with own-price elasticities is that the greater the number of substitutes for any product, the greater the magnitude of the own-price elasticity. Based on the substitution relationships previously described among the various products considered in this analysis, the magnitudes of the estimated own-price elasticities reported are consistent with this economic principle.

Indeed, for future research, the set of dairy products could be expanded to include white milk and flavored milk delineated by fat type (fat-free, 1%, 2%, and whole), organic milk, cottage cheese, and specific types of natural and processed cheeses as well as specific types of plant-based milk alternatives. Potential issues, however, with this expansion include degrees-of-freedom and degrading collinearity. In addition, including the prices of other desserts in the demand equation for ice cream might be worthwhile.

A statistical comparison of the empirical results based on multivariate regression model selection criteria is inapplicable due to the different dependent variables across the two models. We plan to conduct a comparison between the two models using the cross-validation technique in machine learning to evaluate the performance of the models as a future study.

Our study does not capture the impact of sociodemographic characteristics of households. For future work, we plan to use the Exact Affine Stone Index (EASI) model developed by Pendakur (2009) to examine the impacts of the sociodemographic characteristics of different households. In this way, we are positioned to replicate our analysis at the household level and not aggregate across households.

Further, the data indigenous to our study cover the period January 2010 to November 2015. To conduct a further check on the robustness of the results, it is worthwhile to update the analysis with more recent data, particularly to capture the impact of the pandemic on the demand for the dairy products considered in this analysis. Finally, our study fails to address the impacts of branded or generic advertising on the demands for the respective products. Hence, additional research incorporating these expenditures merits consideration. The issue with this suggestion for future research is the availability of generic and branded advertising expenditures.

Despite these limitations, we provide a definitive more up-to-date picture of demand interrelationships among dairy products and plant-based milk alternatives (primarily almond milk) currently lacking in the extant literature. Moreover, the general similarity of the empirical results from the two widely different demand system models provides more confidence in the findings. Going forward, we recommend continued use of the QUAIDS and the BSM in considering demand interrelationships among dairy products using time-series data. Finally, our analysis serves as a baseline for future research in updating the estimation of these demand interrelationships.

Disclaimer

The researchers' own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC, and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at the University of Chicago, Booth School of Business. The conclusions drawn from the Nielsen data are those of the researcher and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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Journal of Food Distribution Research
Volume 54, Issue 3, pp. 66–77

In-field Food Waste in California Strawberry Production: An Analysis of Harvester Extraction Rates

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Abstract

In this paper, we report on the collection and analysis of two years of "harvest efficiency" data from commercial strawberry farms in California. Harvest efficiency refers to the percentage of total ripe berries that are successfully harvested from the field and has implications for assessing food waste, the relative attractiveness of robotic harvest innovations, and management decisions related to field sanitation and pest management. Results indicate that within the sampled farms, between 12% and 39% of the total strawberries produced were left in the field, with production practices and the time of year significantly affecting this rate.

Keywords: harvest efficiency, specialty crops, food waste, automation

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Introduction

The California strawberry industry produces roughly 90% of the total U.S. production of strawberries and generates more than $3 billion per year at the farm-gate (USDA-NASS, 2023). Strawberry harvest is labor intensive, accounting for roughly a third of the total cost of production and employing 50,000 to 60,000 workers per year across the state (Bolda et al., 2021). In this context, the efficient management and execution of harvest operations has clear implications for farm profitability, but also relates to issues of food waste, effective Integrated Pest Management (IPM) strategies, and the relative attractiveness of advances in robotic harvest technology.

In a typical California strawberry production system, berries are picked for fresh market sale every three or four days and packed directly into plastic clamshell containers in the field. This schedule must be sustained over the duration of the growing season or fruit may overripen and become unmarketable. In the early season, there may be light fruit volume and more than enough harvest workers, but growers may find it difficult to secure enough labor to keep up with their harvest schedule in peak production periods. Harvest workers are typically paid on a piece-rate basis, and while their productivity in terms of trays (and thus dollars) per hour is closely tracked, the accuracy or thoroughness of a harvest crew's work is difficult to systematically monitor.

In this paper, we report on the extraction rate or "harvest efficiency" of manual strawberry harvest crews in California during the 2019 and 2020 crop years and estimate the relationship between the quantity of fruit left behind by harvest crews and key attributes of the production system and field conditions. This analysis establishes a baseline on a previously unexplored component of strawberry harvest management and in-field food waste. Our goal in this paper is to foster discussion and motivate future research on the relationship between fruit left in the field and pest and disease pressure, the optimal incentive structure and harvest management practices to maximize farm profitability, and how the strawberry industry can most efficiently incorporate advances in harvest automation.

Although we are aware of no published studies that measure the percentage of strawberries left in the field by harvest workers, the topic has been explored in other specialty crops, and strawberry harvest management has been a topic of considerable research in the agricultural economics and sociology literature. Ampatzidis and Whiting (2013) assess how manual harvest in sweet cherry is impacted by tree architecture. Hill and Burkhardt (2021) and Hamilton et al. (2022) explore issues related to strawberry harvest productivity, but focus on the trays of harvested fruit per worker hour rather than the percentage of fruit successfully harvested. Delbridge (2021) analyzes the economic feasibility of robotic harvesters in strawberry production and shows that the rate of fruit extraction relative to that of human crews is critical for the success of robotic systems. The perspective of the strawberry harvest worker is explored by Soper (2020), who shows that compensation structure incentivizes harvest speed above other considerations, and that harvesters prefer to pursue work in tidy fields with larger berries.

The current paper makes three main contributions. First, we document the severity of the fruit loss problem during the harvest stage of strawberry production. Many growers and harvest managers are not fully aware of the quantity of fruit that is left behind because it is difficult and costly to monitor and verify the work of harvesters. Second, this study will help motivate further research on the impact that the presence of decaying fruit has on pest pressure in strawberry systems. Both insect pests and disease can flourish in the presence of rotting fruit, though there is little understanding of how significantly current harvest practices may contribute to pest losses.

While this study does not directly assess pest damage, the data and analysis presented here can serve as a baseline for future trials aimed more directly at improving field sanitation and identifying the optimal level of harvest labor input in strawberry production. Finally, this study will contribute to the evolving discussion around the prospect of robotic strawberry harvest. The performance of both human and automated harvesters depends on field conditions that vary across farms and throughout the growing season, and a richer understanding of harvest efficiency will inform choices about how to best integrate robotic harvest technology and human crews.

The paper proceeds as follows: we first describe typical strawberry harvest systems and the ways in which the current systems impact incentives of the worker, the farm manager, and the markets for fresh and processed berries. Second, we describe the methods used to collect data on harvest efficiency during the 2019 and 2020 study periods. Third, we present a simple econometric analysis used to identify the relationship between different production attributes and the percentage of fruit not harvested. We then present the results of the data collection and analysis, and close with a discussion of the implications of the study and specific suggestions for future research.

Background

Harvest labor management is a complex part of the strawberry production system, and harvest managers must continually consider shifting labor markets, field conditions, and fluctuations in fresh and processing market prices. Harvest workers are typically paid a piece rate per tray of harvested fruit, and managers are under pressure to harvest enough area so as not to fall behind their harvest schedule. Keeping up with the flow of ripe fruit becomes particularly difficult during peak production times when it can be challenging for managers to secure their desired number of workers. The compensation structure incentivizes fast work on the part of harvest crews, and some fruit is inevitably overlooked and left in the field. The degree of in-field food waste has not been widely known, as data on abandoned fruit are not routinely gathered.

At some point in the season, growers may switch from harvest for the fresh market to the processed market. While fresh market fruit brings in a higher price than processing fruit, the aesthetics and quality must be pristine, and a smaller proportion of ripe fruit is suitable for sale. A switch to the processed fruit market is often accompanied by a shift in wage structure from piece-rate pay to hourly pay, which decreases the incentive to pick quickly at the same time that the lower quality requirements increases the volume of fruit that is saleable.

Marketable fruit that is missed during a harvest pass represents a significant loss of potential revenue. Missed fruit also rots in the field, leading to pest and disease pressure, ultimately reducing the marketable yields achieved later in the production season (Bolda et al., 2023). Proper field sanitation, defined here as the removal of diseased or pest-infested fruit, is recommended as a critical cultural control method within IPM programs and, in some cases, can prevent new disease infections from occurring or keep existing infections or infestations from worsening (Goodhue et al., 2011; Dara, 2015; Bolda et al., 2023). Field sanitation is the leading method of managing diseases such as Rhizopus and Botrytis fruit rots, as well as insect infestations such as spotted wing drosophila (Bolda et al., 2023). Both fruit rots and spotted wing drosophila infest fruits that are at approximately 80%–100% berry maturity, and any infested berries missed during the harvest pass or follow-up sanitation passes can lead to further infestations on ripening fruit (Baena et al., 2022; Bolda et al., 2023). Even missing a few infested berries can lead to new infestations as spotted wing drosophila, for example, can have up to 10 continuous generations a year and lay 350 eggs per female.

Despite the benefits of field sanitation for the sake of disease and pest prevention, growers do not often pay harvest workers to remove diseased or pest-damaged fruit and there is little incentive for a harvester to reduce their piece-rate volume to keep their assigned rows tidy. Moreover, pest pressure can be spread unevenly across a field in “hot spots,” making it unfair to those harvesters who face a greater amount of infested fruit than other workers in their harvest crew. Therefore, many of the diseased, mushy, moldy, or infested strawberries are left on the plants. In this context, it is important to understand how much fruit is being missed by harvest crews, and how the harvest efficiency may vary across fields and time.

The prospect of commercially viable robotic harvest technologies for in-field strawberry production makes an improved understanding of harvest efficiency even more critical. Robotic harvest systems that are currently in the testing and refinement stage in commercial strawberry operations tend to miss more fruit than human workers, with the harvest efficiency lower in fields with larger, more densely placed plants. There are persistent concerns that robotic harvest systems leave too much fruit in the field, that supplementing robots with human harvesters will be too costly, and that robotic harvesters are less effective later in season when the labor supply is most constrained (Delbridge, 2021).

The field structure of commercial strawberry farms in California varies across the region and can include two, three, or four rows of plants together in a single planted bed. Plants tend to become bushier over the course of the growing season, which can make it harder for pickers to quickly spot berries on the plant. Individual cultivars also vary in the amount of vegetative growth and may impact the speed and accuracy of the harvest crew. As an example of differences in field conditions that harvest crews may face, the images in Figure 1 show typical scenes from early and mid-season fields.

Figure 1. Pictures of a four-row production system in Santa Maria, CA in late January (left) and a two-row production system in Salinas, CA in July (right).

Data Collection

In this paper, we describe results from two separate periods of data collection on the harvest efficiency of California strawberry production systems. The first data collection period, carried out during eight weeks from June to August of 2019, took place in Santa Maria, CA. Data were collected from two production locations, both growing the “Monterey” cultivar under conventional management. A research assistant visited the fields in the afternoon, and the farm’s harvest manager indicated which block would be harvested the following morning. The research assistant marked off four plots of 48 plants each and counted the number of berries on each plant, distinguishing between ripe berries that were marketable, ripe berries that were not suitable for the fresh market, berries that were past ripe, and berries that were “pink” or underripe. The next morning, after the pickers harvested the target block, the research assistant returned and re-counted the number of berries in each of these categories from the same plants.

Harvest efficiency, or the percentage of ripe berries successfully harvested, is the metric of primary interest in this study. Correctly categorizing fruit as ripe (rather than overripe or underripe) and distinguishing between marketable or unmarketable fruit is critically important in evaluating harvest efficiency and the value of missed fruit. Ripe fruit is deemed unmarketable generally if it is undersized, deformed because of poor pollination or other physiological defect, or impacted by pest or decay. Before data collection started on each production location, the harvest manager met with researchers to explain the instructions that were given to pickers regarding fruit classification and size, and a test sample was categorized and then confirmed by the harvest manager.

In 2020, a second, larger effort was initiated and managed by the California Strawberry Commission (CSC). Once again, harvest data were collected on a per-plant basis from eight production locations in Santa Maria, CA, and seven production locations in Watsonville, CA, representing production of three different cultivars under conventional management (“Monterey”, “Cabrillo”, and “Fortaleza”). Fields in Santa Maria are typically planted with four rows per bed, and fields in Watsonville are typically planted with two rows per bed. Both systems are represented in the data from 2020. The data collection process in 2020 was similar to that of 2019, with a few exceptions. In 2020 the total number of ripe berries was counted before harvest, but the pre-harvest count did not attempt to distinguish between marketable and unmarketable fruit. Rather, total counts of ripe fruit were recorded, and all remaining ripe fruit was picked by the research assistants following the harvest pass. The fruit that remained in the field after harvest was classified as marketable or unmarketable and counted. Underripe and overripe fruit was ignored. This process was repeated 49 times from June 16 to October 28 across the 15 locations. As with the 2019 effort, harvest managers verified the classification of berries as marketable or unmarketable before data collection began.

Empirical Analysis

Improved understanding of harvest efficiency in strawberry production systems can contribute to more accurate analyses of new developments in robotic harvest technology, the design of more effective employee compensation regimes, studies of food waste, and the impact of pest and disease pressure on production and profitability outcomes. The overall level of abandoned or missed fruit is of major interest, but so too are the effects of the production system (two-row versus four-row) and cultivar on harvest efficiency and the way that harvest efficiency evolves as field conditions change over the course of the growing season. To this end, we estimate a linear relationship between the fruit left in the field as a percentage of total pre-harvest fruit loads, and independent variables representing management under two-row or four-row systems (as commonly utilized in Watsonville and Santa Maria, respectively), strawberry variety, week of year to account for changes in the plant structure and field conditions over the course of the growing season, and whether growers harvest for both the fresh and processing markets, which impacts picker compensation and behavior. Our empirical model also controls for the year of the data collection to account for potential differences in data collection procedures.

We estimate a pooled OLS model using a simple linear framework as follows:

$$FNH_{it} = \beta_0 + \boldsymbol{\beta X_{it}} + \epsilon_{it} \tag{1}$$

where FNH_{it} represents the percentage of total berries that are not harvested for producer *i* at time *t*, and $\mathbf{X_{it}}$ is a vector of explanatory variables specific to each producer and sampling event.

We anticipate that a four-row production system results in more crowded beds, more obscured fruit, and a higher rate of fruit left in the field than in a two-row system. Different strawberry varieties have differences in plant structure and growth patterns, and it is possible that the robust plant growth seen with the Monterey variety increases the percentage of ripe fruit missed by harvesters. As such, we include a binary variable distinguishing Monterey from other varieties and expect a coefficient estimate with a positive sign. We would expect the week of the year to have a positive relationship with the percentage of fruit left behind, as strawberry plants get larger with more foliage obscuring the fruit as the growing season progresses. It is considered a best management practice to instruct pickers to remove all ripe fruit from the field, regardless of whether processing fruit is also collected for sale. However, in cases in which processing fruit is also collected and sold, pickers may be incentivized to harvest more fruit and we would expect a negative sign on the parameter for the binary "fresh market" variable.

Table 1. Sample Sizes and Percentages of Missed Fruit across Two Seasons of CA Strawberry Harvest for Two-Row and Four-Row Plantings

	N			**Avg. Ripe Berries per Plant**		**Avg. % Ripe Berries Not Harvested**		
	Locations	**# of obs.**	**Plants per obs.**	**Pre-harvest**	**Post-harvest**	**Market-able**	**Unmarket-able**	**Total**
4-row 2019	2	11	192	2.21	0.88	19.8%	58.2%	38.7%
4-row 2020	8	26	160	2.64	0.71	*	*	29.6%
2-row 2020	7	23	160	3.10	0.38	*	*	12.2%

Note: *Marketable and unmarketable berries were not differentiated in pre-harvest counts in 2020.

Results

Figure 2 presents the percentage of abandoned fruit, including both marketable and unmarketable berries for each data collection date in both the 2019 and 2020 study years. This figure shows that the percentage of missed fruit increased over the course of the growing season, was higher in the four-row beds than in two-row beds, and was found to be consistently higher during the 2019 study year. In the four-row production system sampled in 2019, 39% of all ripe berries, including 20% of the production suitable for the fresh market and 58% of unmarketable fruit, was left in the field (see Table 1). The harvest efficiency was higher in the 2020 study year, with 30% of all ripe berries left behind in the four-row system, and only 12% left behind in the 2020 two-row system (see Table 1). Because pre-harvest counts did not distinguish between marketable and unmarketable fruit in the 2020 study year, it is not possible to compare the harvest efficiency in marketable and unmarketable fruit separately.

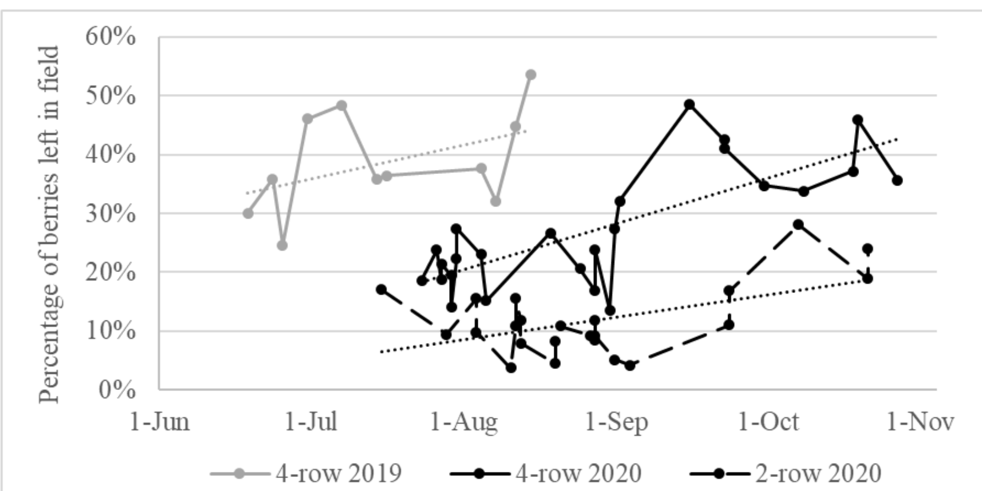

Figure 2. The percentage of berries left in the field over the course of the growing season for each cropping system and data collection year. Includes total berries (marketable and unmarketable) and all growers and cultivars.

In addition to a general decrease in harvest efficiency over the course of the growing season, the underlying data also show meaningful variability across farms. Figure 3 presents the average percentage of fruit left in the field for each individual farm over the growing season, with separate data series for the 2019 four-row, 2020 four-row, and 2020 two-row farms. Total fruit loss percentages range from 9.1% to 16.4% in the two-row system in 2020, 19.8% to 34.9% in the four-row system in 2020, and 37.7% to 42.5% in the four-row system in 2019. This variation across farms and years could be due to differences in harvest management strategies, including picker instructions regarding field sanitation, pay structure, and field conditions. It is also important to emphasize that these numbers count all ripe fruit, including berries that are not suitable for sale in the fresh market.

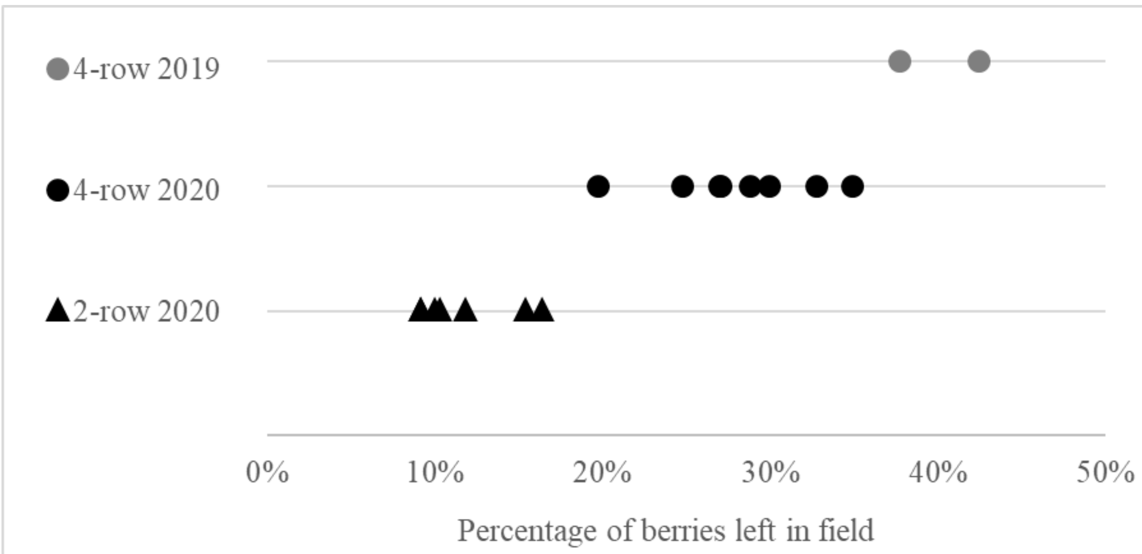

Figure 3. The average percentage of total berries left in the field for each cooperating grower over the course of the growing season. Each data series reflects a different row-spacing and data-collection year combination.

Table 2 presents the parameter estimates from two alternative specifications of the econometric model. Model 1 is the simplest model, including the percentage of total fruit not harvested as a linear function of the year of data collection, whether the data come from a two-row or four-row production system, the week of the calendar year in which data were collected, and a constant term. The regression results confirm what we visually detect in Figures 2 and 3. The two-row planting system common in the Watsonville region is associated with a 16 percentage point reduction in missed fruit relative to the four-row system most common in the Santa Maria area. The coefficient on the “week number” variable indicates that each passing week of the growing season is associated with an increased fruit loss of 1.8 percentage points, likely due to deteriorating field conditions and larger plants. Finally, there is a large difference between the harvest efficiency data collected in the 2019 effort relative to the data collected in 2020. All else equal, the 2019 crop year is associated with a level of missed fruit that is 21 percentage points higher than the 2020 crop year.

Model 2 includes two additional binary variables. The first is the "fresh market" variable, indicating whether harvest managers instructed crews to collect only the fruit that is suitable for the fresh market (= 1) or if fruit for the juice market is also harvested (= 0). The second binary variable indicates whether the field is planted with the Monterey cultivar (= 1) or one of the other cultivars (= 0). The sign and statistical significance of each variable included in Model 1 is maintained in Model 2. Neither the "Monterey" nor the "fresh market" variable are found to have a significant effect on the percentage of fruit left in the field, and the overall model fit declines slightly relative to that of Model 1 as measured by the adjusted R2.

Table 2. Regression Results from Two Linear Models of the Percentage of Berries Not Harvested in CA Strawberry Fields during 2019 and 2020 Crop Years

	(1) Fruit Not Harvested	**(2) Fruit Not Harvested**
Constant term	-0.363*	-0.355**
	(0.14)	(0.13)
Two-row system	-0.164***	-0.143***
	(0.02)	(0.03)
Week number	0.018***	0.019***
	(0.00)	(0.01)
2019 study year	0.213***	0.240***
	(0.03)	(0.05)
Fresh market		-0.025
		(0.03)
Monterey		-0.022
		(0.05)
N	60	60
Adj. R-squared	0.676	0.670
Model F	41.176	24.911

Note: Standard errors are in parentheses *** p < .01, ** p < .05, * p < .1

Limitations

There are a number of limitations that must be kept in mind when interpreting these results. As previously discussed in the data section, the pre-harvest counts in 2020 did not distinguish between marketable and unmarketable fruit. This precludes us from extrapolating the results of this analysis to an industry-wide estimate of the market value of in-field food waste. Although the collected data show that the post-harvest proportions of marketable and unmarketable fruit were similar in both years, we cannot estimate with certainty how much fruit destined for the valuable fresh market was lost. Thus, further in-field data collection would be necessary for more robust analysis of picker compensation schemes or other research questions that depend critically on the market value of abandoned fruit.

Another limitation is that the data from the 2020 growing season include 15 different growers, and each grower and individual harvest manager may place a different level of emphasis on field sanitation when interacting with harvest crews. These management factors are difficult to account for with a small dataset, and the variability that we see in harvest efficiency across farms cannot be attributed to management and other potential causes (e.g., field conditions) separately. Although growers have a strong interest in these harvest efficiency results because of their potential to inform management changes, a different experimental design would be required to identify the effectiveness of different harvest management strategies and incentive structures.

Finally, the difference in harvest efficiency rates between the 2019 and 2020 data collection processes warrants further attention. While the data collection efforts were managed by different groups, and the data collected by different individuals, neither the data collection processes nor the harvest systems were substantially different in the two years. A potential explanation could be that overripe or underripe berries were miscategorized in 2019 and were rightly passed over by the harvest crew. This finding would inflate the percentage of fruit perceived as "missed" in 2019. However, not only did research assistants confirm their categorization process with harvest managers at the beginning of the season, a closer look at the primary data suggests that miscategorization is not a likely explanation.

The 2020 data show a pre-harvest average of 3.1 and 2.6 berries per plant in the two-row and four-row systems, respectively (see Table 1). After the harvest pass, the plants in the 2020 two-row system had an average of 0.3 berries remaining, and plants in the 2020 four-row system had an average of 0.7 berries remaining. The data from 2019 show considerably more fruit remaining on the plants after harvest (0.88 berries per plant), but only 2.2 ripe berries per plant in the pre-harvest count. That is, fewer berries were recorded on each plant prior to harvest in 2019 than in 2020, suggesting that miscategorization of underripe or overripe fruit in 2019 is an unlikely explanation for the difference in results.

Conclusions

With this study we present the first assessment of "harvest efficiency" (defined as the percentage of ripe berries that is successfully harvested) in California strawberry production and show that a significant amount of fruit is routinely missed in harvest operations. High rates of missed fruit in human harvest passes are relevant to questions involving the relative attractiveness of robotic harvest systems and the pest and disease dynamics observed in strawberry production. Although a robust analysis of the value of in-field food waste in California strawberry production is beyond the scope of this study, our results can provide some guidance on the scale of the issue. In calendar year 2020, roughly 1.7 billion pounds of conventional strawberries were produced in California (USDA-AMS, 2023). If we apply the more conservative harvest efficiency rates for two-row and four-row plantings from the 2020 data collection year to corresponding regional production volumes, we estimate that approximately 200 million pounds of conventional strawberries suitable for the fresh market were left in the field in 2020. The volume of unmarketable berries passed over by harvest crews would be nearly three times that amount.

Discussions with strawberry growers indicate that these results are surprising and warrant further study. If we assume profit maximizing behavior, growers are signaling that they believe the current harvest management systems and compensation structures are economically efficient. That is, the additional cost required to adopt a slower, more careful harvest would be greater than the value of the resulting increase in harvested fruit. The results presented here may lead to reconsideration of current practices, as the volume of missed fruit is greater than many have previously assumed.

While we have contributed to the understanding of harvest efficiency levels in California strawberry production, it is unknown how much indirect damage, through additional pest and disease pressure, the abandoned and rotting fruit may cause over the course of the growing season. Future studies on IPM methods in strawberry production may focus on setting a “threshold” of fruit that is acceptable to be left in the field. This type of guidance, common in pest management extension and outreach efforts, is meant to provide growers with an achievable target that could improve economic outcomes, lower fruit waste, and align with best practices for pest control. Establishing such guidance is difficult for two reasons. First, research trials aimed at quantifying the relationship between harvest efficiency and pest pressure require large blocks and labor intensive treatment and data collection efforts. Second, differences in growing practices, crop value (within and across growing seasons), and variation in disease or insect resistance across cultivars could make a meaningful threshold difficult to establish.

The harvest efficiency results that we present in this paper can be seen as somewhat positive for the prospect of robotic harvest technology in strawberries. Preliminary analysis of robotic harvest systems assumed harvest efficiency rates that were much lower than those achieved by human harvest crews (Delbridge, 2021). Our results suggest that robotic systems may not be as far behind as previously understood. However, we find that manual harvest efficiency is highest in two-row plantings and early in the production season, which are also the conditions under which robotic harvesters are likely to perform best. Further study will be needed to assess the feasibility of continually improving robotic systems and how they can most effectively supplement human labor.

Acknowledgements

The authors would like to acknowledge the data collection support of the California Strawberry Commission, participation of cooperating strawberry growers, and research assistance provided by Kale Varvel and Luis Isaiah Valdez.

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Journal of Food Distribution Research
Volume 54, Issue 3, pp. 78–101

Marketing Strategy Selection for Small-Scale Fruit and Vegetable Growers: Lessons from the Mid-Southern United States

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Abstract

This study uses primary data analysis to investigate market outlet choices of small-scale fruit and vegetable growers in the Mid-South region. Factors such as distance to market, marketing costs, sales volume, and production methods significantly influence growers' decisions. Policy implications include the need for industry-specific guidelines and networking opportunities for wholesalers, streamlined regulatory processes, support for local sourcing by restaurants, and support for educational efforts. Overall, this study sheds light on the market outlet choices of small-scale fruit and vegetable growers, offering guidance for policy makers to foster the success of these growers in the Mid-South and beyond.

Keywords: small-scale growers, market outlet choices, Mid-Southern United States, K-means cluster analysis

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Introduction

Local food growers face the dual imperative of producing quality products and identifying profitable markets to sell products before they spoil. It is impossible to overstate the importance of the second part of this dual mandate, as it directly affects the growers' profitability and the availability of fresh, adequate produce for consumers. Perhaps with the recent experiences of supply shortages at the retail level during the COVID-19 pandemic, diverse and growing consumer concerns toward overseas or large-scale production systems give locally produced food a comparative advantage as local food systems can generate economic benefits for the community (Maples et al., 2013; Miller et al., 2019). Identifying why certain growers choose a specific marketing strategy is critical to the viability and continued access to fresh local produce. Indeed, once growers successfully harvest agri-food products on a farm, the choice of market outlet can dictate the selling price and what kind of product quality and quantity standards growers must meet. Hence, growers' marketing channel decisions have become as significant and intricate as production decisions concerning product quality and costs to ensure customer satisfaction (Krafft et al., 2015; Jablonski et al., 2022).

Local governments and communities make many efforts to sustain small-scale fruit and vegetable growers; these efforts reflect in the subsidies, loans, education, and market information made available to farmers by the U.S. Department of Agriculture, Small and Mid-Sized Farmer Resources (USDA, 2023) and other regional organizations. In Northwest Arkansas, for example, the Walton Personal Philanthropy Group and the Northwest Arkansas Land Trust support local farmers from food cultivation to commercialization, including facilitating access to education, land, technical expertise, and financial resources for established and emerging farmers; these organizations also strive to enhance farmers' access to outlets, product certification, and processing services (Northwest Arkansas Food Systems, n.d.). Such philanthropic activities benefit consumers, growers, grocery stores, and wholesalers. The latter gain access to local supplies that may be less prone to supply disruptions in comparison to sourcing internationally. As such, the marketing stage is of utmost importance for growers since it is how they recoup the resources invested in the production process, create local employment, and provide consumers access to fresh produce (Hall, 2002; Andreatta and Wickliffe, 2005).

This work examines market outlet choices of small-scale fruit and vegetable growers, with gross cash farm income less than $350,000 (USDA-NASS, 2023), by identifying common traits that constitute how they think about their marketing channel selection. By identifying these traits, decision makers can better understand the factors influencing growers' market outlet choices. Specifically, we examine revenue, marketing cost, production, and demographic factors by detailing reasons for including these variables in our description of the survey conducted. A comprehensive understanding of these traits is important, as attempts to increase locally grown healthy food alternatives in retail outlets for access by consumers that do not frequent farmers' markets, buy on-farm, or participate in community supported agriculture (CSA), hinges on a better understanding of barriers to producer adoption of wholesaling. At the same time, intermediaries benefit from knowing what services they may need to offer to encourage small-scale growers to become larger volume growers that supply to them.

By examining the underlying decision-making process of small-grower marketing channel choices and associated opportunities, we seek to contribute to the food distribution strategy literature. The remainder of the article is organized as follows. First, we connect the background literature on small farm marketing strategy literature to a stylized map of localized agri-food supply chains. We then describe our methods, which involve multinomial logistic modeling and k-means cluster analysis to classify responses from a grower survey of small farms in the Mid-South. The third section provides results indicating that small-scale grower marketing strategies are clustered into three groups. The final section concludes with implications from our current study, along with a discussion of recommendations for future research.

Background

Farmers have many direct-to-consumer and intermediary marketing options, and making a good choice(s) is the key to success (Uva, 2002; Park, Mishra, and Wozniak, 2014). For many growers, direct marketing is a way to brand their product, collect direct consumer feedback, and evaluate their advertising effectiveness (Hunt, 2007). Direct marketing is often the first step for beginning growers (Bauman, McFadden, and Jablonski, 2018; Jablonski et al., 2022). Further, norms and standards that different customers desire and are willing to pay for vary by market outlet. These standards have cost and revenue implications and impact market outlet choice (Hardesty and Leff, 2010). The decision to determine where to sell the product thus requires knowledge about product certification, packaging standards, and cost of transportation for every outlet so that growers choosing that outlet can meet the needs of customers or intermediaries. Opportunity evaluation is mission-critical for agricultural and food businesses (Bylund and Malone, 2023). Figure 1 provides a stylized example of different aspects of the decision-making process for a local food marketing strategy.

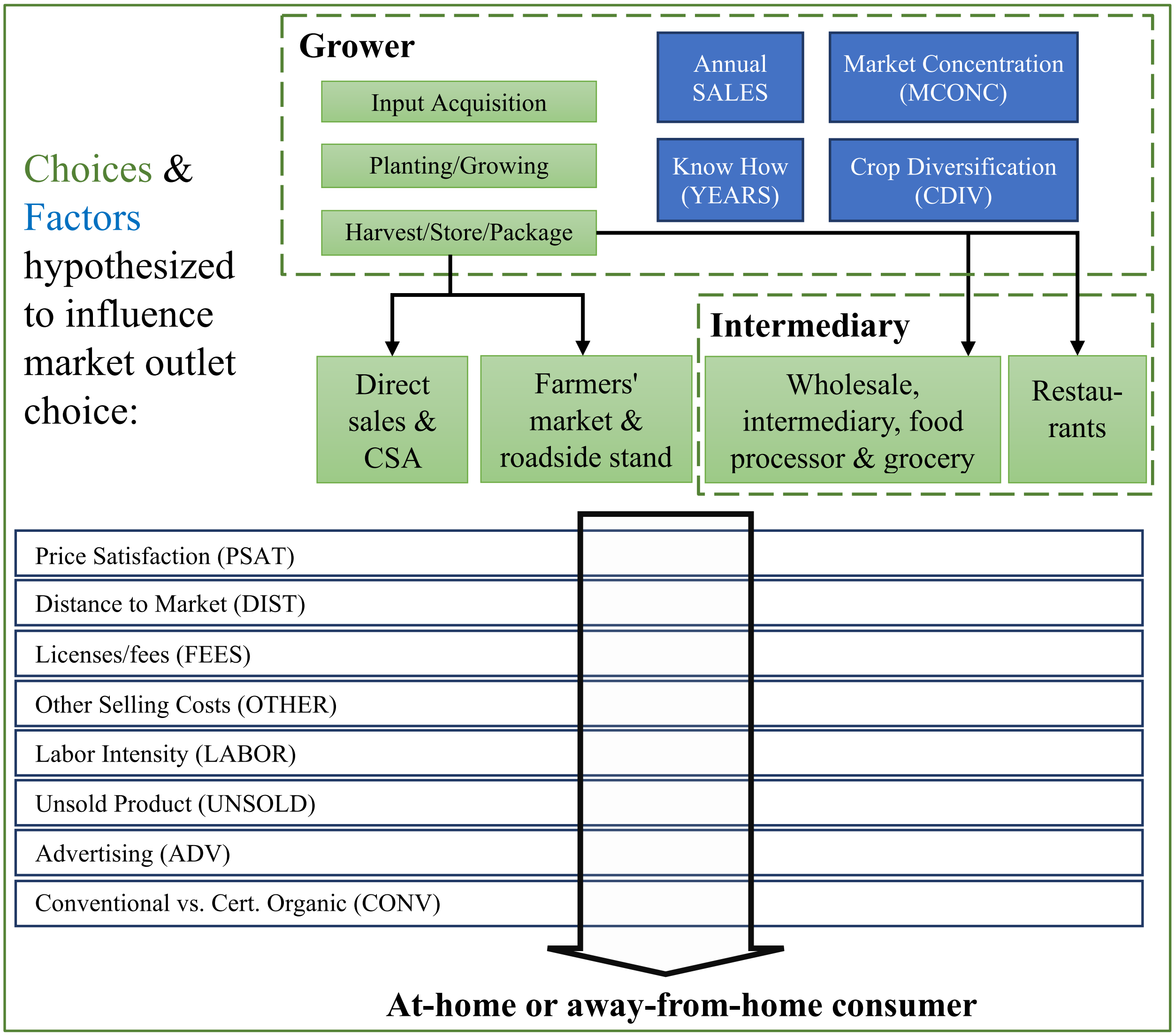

Figure 1. Marketing Outlet Choices and Factors Expected to Drive Market Outlet Choice

Note: See Table 1 for variable name definitions and differences in grower responses across market outlet choice.

Economies of scale are heavily linked to the marketing outlets that might be most appropriate for a grower. Growers can diversify sales by growing various products or focusing on fewer products to meet market outlet-based quantity requirements (Monson, Mainville, and Kuminoff, 2008). Indeed, Bauman, Thilmany, and Jablonski (2019) find that scale, product specialization, and expenditure management significantly affect growers' financial efficiency when using intermediate and direct-to-consumer outlets. Their results suggest that focusing on a few products is a difficult strategy to adopt given the unsteady cash flow associated with this lack of diversification across production season and product, hindering the producer's objective of creating regular income to ensure survival.

While the number of outlets available to growers varies depending on their geographic location, improvements in online marketing have created opportunities for small growers (Hobbs, 2020). Food supply chains are developed through relationships between growers and critical downstream entities, such as supermarkets, restaurants, and wholesale distributors, to foster regional food systems that improve economic outcomes (Maples et al., 2013). Small farmers sell food they grow in farmers' markets organized by local communities to support regional agricultural activity (CSA), and, less commonly, locally grown food is also supplied to wholesale markets for resale to other vendors (Uva, 2002; Hunt, 2007; Monson, Mainville, and Kuminoff, 2008; LeRoux et al., 2010; Low and Vogel, 2011).

Every outlet requires specific product quantity and quality standards, packaging costs, product processing (e.g., cold storage, order picking, washing), travel distance, and licensing and market access fees that impact profitability (Hardesty and Leff, 2010). Wholesale channels, for example, typically require consistent product size and quality, as well as packaging to standardized case weights, which can be a barrier to access for growers, as choosing this channel can lead to additional stress. Wholesaling contracts often stipulate such quantity requirements, leading to a preference for farmers' markets for those growers unable to meet the volume needs of wholesalers.

Regulatory burdens have been well-documented as impediments to the development of regional food systems (Malone and Hall, 2017; Staples, Chambers, and Malone, 2022). As a proxy of difficulty for market access, growers were asked to indicate how many licenses, fees, and certifications are required to sell to a particular market outlet.

Direct marketing via farmers' markets, on-farm sales, and CSAs are often a common way for small-scale growers to commercialize their operations (Uva, 2002; Monson, Mainville, and Kuminoff, 2008). At the same time, CSA channels may require high product volume throughout the production season, with fewer processing and packaging requirements and fewer consumers, which can make this outlet quite profitable (LeRoux et al., 2010). In comparison, direct marketing methods may be less stressful as product availability dictates what products consumers can choose. It is also important to remember that non-quantifiable factors, such as marketing and management skills, are essential in selecting market opportunities and on-farm performance (Park, Mishra, and Wozniak, 2014).

Methods

Data for this study came from an internal review board approved survey (IRB#2008276843) of small-scale fruit and vegetable growers in the Ozark Mountain Region (comprising Arkansas, Southern Missouri, and Eastern Oklahoma). The first e-mail contact occurred on November 14, 2022, with a follow-up reminder on November 28, 2022. The survey closed on December 6, 2022. Approximately 300 fruit, nut, and vegetable farm owners were invited to participate in an online Qualtrics survey. Survey participants were identified by the Center for Arkansas Farms and Foods and University of Arkansas Cooperative Extension agents. As an incentive to participate, respondents were eligible for entry into a random drawing of two coolers valued at less than $500. The survey took 15–25 minutes to complete. Given the rather large set of questions and relatively small grower population, a low response rate was expected. Aside from e-mail contact, the survey was also promoted at extension grower meetings. Using Forcino et al.'s (2015) guidance on requiring at least 58 responses, we wanted to get at least 25 grower responses where each grower was expected to sell to at least two different market outlets for a sample size of 50 or more market outlet choice responses. While this sample may not be representative of all small-scale grower populations, it does allow for a sound discussion of small-scale growers and their marketing behavior in the Mid-South, which can provide marketing and behavioral information for other small-scale producers and regional markets similar to Hunt (2007), which is limited in the literature.

Survey Design

The survey was organized into four parts (Mahamba, 2023). The first section of the survey explored marketing outlet choice, overall sales, and the rationale for choosing a market outlet. Market outlet variables included i) on-farm direct sales and produce sold via CSA; ii) farmers' markets and roadside stands; iii) wholesale, intermediary, food processor, and grocery outlets; and iv) chefs and cooks at restaurants. Since growers often diversify their marketing strategies, we pooled a variable that summed each respondent's total number of market outlets used (*MDIV*). Respondents could also choose "Other" and define alternative outlets, such as food banks, florists, craft fairs, or online sales.

To gain further insight on the revenue side of the profitability equation, we asked about the size of the operation in terms of annual overall produce sales for the farm (*SALES*) to capture scale economies. To measure diversification in marketing channel selection, the ratio of sales by market outlet (*MSALES*) to overall farm sales (*SALES*) or (*MCONC*) provides a more specific measure than the above-mentioned number of marketing channels pursued (*MDIV*).

REASONS was the number of checkmarks a respondent selected to choose a particular market outlet. Reasons ranged from no reason provided (*REASONS* = 0) or choosing a market for the following reasons relative to other market outlet choices: high prices, high customer traffic, least labor intensive, the only choice available, dealing with preferred customers, large sales per customer, and "Other" to allow respondents flexibility to answer this question. A final measure in the revenue category was the level of satisfaction with prices received (*PSAT*).

A second section tracked marketing costs to provide insight into market access and license fees (*FEES)*, personnel at sales events, packaging and labeling costs, market stand, and refrigerated storage requirements (*OTHER*) and a combined variable (*MCOST* = *FEES* + *OTHER*) to capture relative marketing cost differences across each market outlet. More specific measures by market outlet captured advertising expenses (*ADV*) as a percentage of sales and the distance traveled in 10-mile increments to indicate transport cost (*DIST*). Finally, the percentage of unsold produce information was available for all farm sales (*%UNSOLD*), and growers could indicate which of their market outlets were among the worst two in terms of most unsold produce. Multiplying *%UNSOLD* with a binary variable for a market outlet leading to most unsold produce thus added market outlet-specific information to *%UNSOLD* and was labeled *UNSOLD*.

The third section of the survey encompassed measures related to the production methods employed. A respondent could choose whether they followed mainly conventional production methods using herbicides and chemicals (*CONV* = 1), were certified organic, were in the process of certification, were a certified natural grower, or relied on herbicides rarely (*CONV* = 0). The growers were also asked how many crops they grew annually (*CDIV*). Finally, we collected data on location, acreage, and number of employees. Except for labor and acreage, which were deemed unreliable by the authors, please see Table 1 for a summary of these variables across market outlets.

Table 1. Variable Description, Frequency Distribution and Average Response by Market Outlet

	Market Outlet[a]					
	DCSA	FARMER	WIFG	Restaurant	Overall	*P*-value[b] (*n*[c])
SALES[f]						
Avg.	\$48,611A[d]	\$30,104A	\$49,375A	\$58,026A	\$44,855	0.21 (69)
MSALES[g]						
Avg.	\$21,911A	\$15,293A	\$8,002A	\$7,062A	\$14,057	0.29 (69)
MCONC[h]						
Avg.	40.78AB	63.04A	20.89B	24.12B	41.40	< 0.001 (70)
MDIV[i]						
1	11.1[e]	32.0	0.0	0.0	14.3	
2	27.8	32.0	36.8	25.0	31.4	0.14 (70)
3	44.4	28.0	36.8	50.0	37.1	
4	16.7	8.0	26.3	25.0	17.1	
Avg.	2.67AB	2.12B	2.89A	3.00AB	2.57	0.02 (70)
REASONS[j]						
None	5.6	0.0	15.8	12.5	7.1	
1	38.9	28.0	31.6	12.5	30.0	
2	16.7	24.0	36.8	50.0	28.6	
3	33.3	28.0	10.5	12.5	22.9	0.18 (70)
4	5.6	16.0	5.3	0.0	8.6	
5	0.0	0.0	0.0	12.5	1.4	
6	0.0	4.0	0.0	0.0	1.4	
Avg.	1.94A	2.48A	2.89A	2.12A	2.06	0.11 (70)
PSAT[k]						
Not satisfied (-1)	11.1[d]	0.0	15.8	25.0	10.0	*P* = 0.10 (70)
Satisfied (0)	44.4	48.0	68.4	50.0	52.9	
Very satisfied (1)	44.4	52.0	15.8	25.0	37.1	
Avg.	0.33	0.52	0.0	0.0	0.27	na[d]
FEES[l]						
None	70.6[e]	45.8	47.1	62.5	54.6	
1	23.5	37.5	35.3	25.0	31.8	0.85
2	0.0	12.5	11.8	12.5	9.1	(66)
3	5.9	4.2	5.9	0.0	4.6	
Avg.[d]	0.44A	0.75A	0.75A	0.50A	0.64	0.60 (66)

Table 1. Continued

	Market Outlet[a]					
	DCSA	FARMER	WIFG	Restaurant	Overall	*P*-value[b] (*n*[c])
OTHER[m]						
None	35.3	0.0	11.8	25.0	15.2	
1	11.8	4.2	11.8	12.5	9.1	
2	11.8	37.5	35.3	25.0	28.8	0.10
3	11.8	41.7	5.9	12.5	21.2	(66)
4	23.5	12.5	23.5	12.5	18.2	
5	5.9	4.2	11.8	12.5	7.6	
Avg.	1.94A	2.75A	2.56A	2.13A	2.41	0.32 (66)
MCOST[n]						
None	17.7	0.0	11.8	12.5	9.1	
1	17.7	0.0	5.9	12.5	7.6	
2	17.7	20.8	17.7	37.5	21.2	
3	17.7	37.5	17.7	12.5	24.2	
4	17.7	25.0	23.5	12.5	21.2	0.49
5	11.8	12.5	11.8	0.0	10.6	(66)
6	0.0	0.0	0.0	0.0	0.0	
7	0.0	0.0	11.8	12.5	4.6	
8	0.0	4.2	0.0	0.0	1.5	
Avg.	2.39A	3.50A	3.31A	2.63A	3.05	0.18 (66)
ADV[o]						
Avg.[d]	7.33B	15.64A	3.82B	5.25B	9.05	< 0.001 (62)
DIST[p]						
0 (0)	66.7[e]	0.0	0.0	0.0	17.9	
< 10 (10)	11.1	33.3	41.2	25.0	28.4	
11–20 (20)	5.6	25.0	17.7	0.0	14.9	< 0.001 (67)
21–30 (30)	11.1	16.7	5.9	0.0	10.5	
30 + (40)	5.6	25.0	35.3	75.0	28.4	
Avg.	7.8B	23.3A	23.5A	32.5A	20.3	< 0.001 (67)
%UNSOLD[q]						
Avg.	7.36A	6.20A	6.18A	5.00A	6.36	0.74 (66)
UNSOLD[r]						
Avg.	1.67A	2.61A	1.62A	1.25A	1.93	0.83 (66)
CONV[s]						
Yes (1)	16.67	28.0	15.79	0.00	18.57	0.33
No (0)	83.33	72.0	84.21	100.00	81.43	(70)

Table 1. Continued

	Market Outlet[a]					
	DCSA	**FARMER**	**WIFG**	**Restaurant**	**Overall**	***P*-value[b] (*n*[c])**
CDIV[t]						
Avg.	12.17A	13.76A	14.16A	13.76A	13.70	0.81 (70)
YEARS[u]						
Avg.	8.33A	7.98A	9.26A	7.69A	8.39	0.93 (70)

Notes:
[a]DCSA = direct sales to consumers on farm or via CSA, FARMER = farmers' market or roadside stand; WIFG = wholesale, intermediaries, food processors or grocery stores; and RESTAURANT = cooks and chefs.
[b]Pearson's χ^2 level of significance of differences across distribution of answers across market outlet or level of significance from ANOVA using post-hoc analysis with multiple pairwise comparisons.
[c]Number of responses collected for a particular variable.
[d]Averages are as defined in the variable description for categorical data. For numerical responses, compact letter rankings (capital letters) indicate statistically significant differences when a particular market outlet does not share a letter ranking at $P = 0.05$ using analysis of variance.
[e]Numbers in response category rows represent response percentages across variable categories.
[f]SALES = total average annual farm sales (2021 and 2022). See Table 2 for a more meaningful scale variable comparison across growers.
[g]MSALES are total average annual sales (2021 and 2022) by market outlet. Multiplying the overall average of $14,057 by 69 responses leads to $970,000 in annual sales across this set of respondents.
[h]MCONC is the percentage of farm sales dedicated to a single market outlet.
[i]MDIV is the number of market outlets pursued by a grower.
[j]REASONS is the number of reasons checked for picking a market outlet among which are getting the highest price (38.6%), access to high consumer traffic (34.3%), being least labor-intensive (38.6%), the only market available (8.6%), selling to preferred customers (41.4%), largest sales per customer (35.7%), or other (8.6%). (Numbers in parentheses above are the percentage of positive responses for a particular reason.)
[k]PSAT measures satisfaction with prices received. (Numbers in parentheses are used for average.)
[l]FEES represents the number of respondent checks among GAP certification (7.6%), license/fee for market access (19.7%), certified organic requirement (13.6%), naturally grown certification (15.2%), a web site requirement (7.6%), or no requirements (54.5%). (Numbers in parentheses are the percentage of positive responses for a particular requirement/fee given.)
[m]OTHER represents the number of respondent checks among other selling expenses, including workers other than self (37.9%), supplies (e.g., packaging, 77.3%), refrigerated storage (45.5%), labeling/advertising (47.0%), order picking (33.3%), or none (15.2%). (Numbers in parentheses are the percentage of positive responses for a particular selling expense.)
[n]MCOST represents the number of respondent checks summed across *FEES* and *OTHER* as a measure of how expensive it is to access a market outlet.
[o]ADV is the percentage of sales used for advertising by market outlet.
[p]DISTance to market outlet measured in miles. (Numbers in parentheses are used for average.)
[q]%UNSOLD is the percentage of unsold produce that differs by producer and thereby market outlet.
[r]UNSOLD is *%UNSOLD* times a binary variable indicated a market outlet to be either the leading or second highest in terms of unsold produce.
[s]CONVentional production practices include chemical use (yes), whereas the alternative (no) either strictly or mostly avoids the use of chemicals. "No" responses are thereby referred to as organic.
[t]CDIV is the number of different crops grown on farm.
[u]YEARS is the number of years of experience a producer had with fruit and vegetable production.

The final set of questions captured demographic information about growers. Included in this category was a question about years of experience with commercial fruit, nut, or vegetable production (*YEARS*). Other variables included gender, age, ethnicity, education (*EDUC*), and farm income as a percent of household income or relative farm income (*RFI*). See Table 2 for summary statistics related to those variables.

Table 2. Description of Grower Market Outlet Choice, Farm Scale, Demographics, and Relative Importance of Farm Income across Grower Group Clusters

	All[a]	Direct Marketeers	Novice Explorers	Experienced Wholesalers	*P*-value (n)[b]
# of growers	27	12	8	7	na
Market outlet choice and scale of production[c]					
Avg. use per farm					
DCSA	27.3%	25.0%	33.3%	25.9%	0.14 (66)
FARMER	34.8%	54.2%	33.3%	18.5%	
WIFG	25.8%	12.5%	20.0%	40.7%	
RESTAURANT	12.1%	8.3%	13.3%	14.8%	
Avg. # of markets used (MDIV)	2.41	2.00A[b]	1.88A	3.86B	0.003 (27)
Avg. farm sales by market (MSALES)					
DCSA	$21,911	$7,900A	$2,600A	$47,714A	0.09 (18)
FARMER	$15,893	$13,296A	$3,540A	$35,000B	0.004 (23)
WIFG	$8,738	$4,667A	$1,993A	$11,705A	0.39 (17)
RESTAURANT	$7,063	$7,875A	$1,750A	$9,313A	0.77 (8)
Total avg. farm sales (SALES)[d]	$35,741	$20,833A	$5,000A	$96,429B	< 0.001
Gender					
Female	40.7%	50.0%	37.5%	28.6%	0.43 (27)
Male	48.3%	41.7%	37.5%	71.4%	
Other/not specified	11.1%	8.3%	25.0%	0.0%	
Ethnicity					
White	74.1%	66.7%	62.5%	100.0%	0.38 (27)
Amer. Indian or AK native	7.4%	8.3%	12.5%	0.0%	
Asian	7.4%	16.7%	0.0%	0.0%	
Other/not specified	11.1%	8.3%	25.0%	0.0%	
Education					
High school graduate	6.9%	8.3%	0.0%	14.3%	0.59 (27)
Some college	17.2%	16.7%	12.5%	28.6%	
2-yr. degree	20.7%	33.3%	25.0%	0.0%	
4-yr. degree	20.7%	16.7%	25.0%	14.3%	
Master's	24.1%	25.0%	12.5%	42.9%	
PhD	3.4%	0.0%	12.5%	0.0%	
Other/not specified	6.9%	0.0%	12.5%	0.0%	
Age (avg.)[e]	50.4	55.0A	52.9A	40A	0.09 (26)
Years	8.6	9.3A	5A	11.4A	0.24 (27)
Farm income/HH income (RFI)	54.6%	44.1a%	45.7ab%	80.0b%	0.04 (25)

Notes: [a]Statistics pertain to 27 growers (66 obs.) as 2 (4 obs.) lacked responses needed to assign to a grower group.
[b]Pearson's χ^2 level of significance of differences across distribution of answers by grower group or level of significance from ANOVA using post-hoc analysis with multiple pairwise comparisons with *n* observations. Capital letters again indicated statistically significant difference across columns when a letter is not shared at $P < 0.05$.
[c]DCSA = direct sales to consumers on farm or via CSA, FARMER = farmers' market or roadside stand, WIFG = wholesale, intermediaries, food processors or grocery stores, and RESTAURANT = cooks and chefs. [d]The product of average market outlet use, average market outlet farm sales, and average number of markets for a grower group amounts to average farm sales as a measure of scale economy across grower groups.
[e]The age variable was generated from responses to age categories of 18–24 (20), 25–34 (30), 35–44 (40), etc., using the numbers in parentheses. The maximum age category was 75–84 (80) with one response.

Empirical Estimation

Two modeling approaches were employed. First, we estimated a multinomial logit model to analyze whether and to what degree the following factors influenced market outlet choice:

$$OUTLET = f\,(MSALES, MCONC, PSAT, FEES, OTHER, ADV, DIST, UNSOLD, CONV, CDIV, YEARS), \quad (1)$$

where *OUTLET* is one of the four outlet choices with the farmers' market, including roadside stands (FARMER) serving as the baseline market outlet choice, and on-farm, direct and CSA sales (DCSA), wholesale and intermediaries (WIFP), and chefs and cooks (RESTAURANT) serving as alternatives. Other variables are described above and summarized in Tables 1 and 2.

To generate grower profiles, we used k-means clustering, which is a common method in the marketing opportunity identification literature (Malone and Lusk, 2018). The Euclidean distance between a specified number of *k* clusters was minimized among groups' individuals (*j*) using *k*-means cluster analysis (Arabiel and Hubert, 1996; Malone and Lusk, 2018) according to factors (*x*) as follows:

$$\min(distance_x) = \min\sqrt{\textstyle\sum_{j=1}^{9}(x_j - \overline{X_{jk}}\,)^2}\,, \quad (2)$$

where $\overline{X_{jk}}$ is the center of the cluster associated with observations x_j from individuals' responses to a set of questions capturing sales, marketing channel diversification, marketing rationale, marketing cost, production method, and producer experience variables as follows:

$$\mathrm{GG} = \mathrm{g}\ (\mathrm{SALES, MDIV, REASONS, MCOST, ADV, DIST, UNSOLD, CDIV, YEARS}), \quad (3)$$

where GG is the grower group assignment to one of three clusters that would have common, describable characteristics. Please see Tables 1 and 2 for variable name descriptions and statistics.

To be able to plot the data in a spider diagram that would allow easy visual examination of differences across grower groups (GG) with respect to the above variables, we scaled average responses using an index value where 1 (or 100%) represents the maximum value observed for a response variable across all respondents.

Alternative specifications of equations 2 and 3 were pursued and tested for goodness of fit using appropriate statistics and hierarchical clustering to determine the appropriate number of clusters. We also tested individual categorical variables for differences across market outlets using Chi-square tests and analysis of variance (ANOVA) for numeric responses where separate linear models were computed for each response variable in R. For each response variable, the null hypothesis was that there were no significant differences between market outlets. The null hypotheses were evaluated at $P = 0.05$. Post-hoc analysis was computed using multiple pairwise comparisons. Statistical differences between treatment pairs were summarized using a compact letter display.

Results

We received responses from 38 growers, with 29 complete and usable responses. Since, on average, respondents sold to 2.57 different market outlets, we had 70 unique market outlet observations regarding outlet choice. For analysis, we pooled four categories: direct sales and CSA (18 DCSA observations), farmers' market and roadside stand (25 FARMER observations), wholesale, intermediary, food processor, and grocery stores (19 WIFG observations), and chefs and cooks (8 RESTAURANT observations).

Single-Factor Observations about Market Channel Selection

Chi-square and ANOVA tests revealed measures of market diversification both in number (*MDIV*) and percentage of farm sales attributed to a particular market outlet (*MCONC*) to vary by market outlet. Most notable, numerically, was that those selling to farmers' markets and roadside stands (FARMER) tended to sell to fewer other market outlets (Table 1).

On the cost side, advertising expenses (*ADV*) were highest with FARMER markets compared to the other market outlet choices (see Table 1). Finally, the distance for growers to travel to make a sale (*DIST*) was smallest for on-farm and CSA sales (DCSA) as expected since more than half of grower sales were on-farm with some CSA sales that required delivery, thereby leading to an average of 7.8 miles for delivery for this market outlet (see Table 1).

Despite few statistically significant results, given the small number of observations, several interesting numerically different results across market outlet choice stood out (see Table 1). From a revenue perspective, DCSA sales were largest, followed by FARMER sales with wholesale, intermediaries, food processors, grocery stores (WIFG), and RESTAURANT sales two- to three-fold smaller in *MSALES* on average. At the same time, growers were most satisfied with prices received (*PSAT*) using FARMER outlets, followed by DCSA.

While price satisfaction and revenue are important, outlet choice costs also deserve consideration. As expected, licensing, certification, and fee requirements (*FEES*) were least for DCSA and RESTAURANT sales and higher for WIFG and FARMER. Other selling fees like order picking, payroll, refrigerated storage, labeling, and advertising (*OTHER*) again reveal FARMER and WIFG to be more onerous than other market outlet choices, which is also evident in the *MCOST* variable.

Surprisingly, market outlet differences in the number of crops grown on farms were nonexistent. *A priori* expectations were that WIFG growers would grow fewer crops to specialize for sufficient volume and associated cost savings. Looking at a combination of several factors provides a logical explanation later. Statistically insignificant were differences in the percentage of unsold produce, even once multiplied by the binary variable indicating leading unsold produce by outlet. Finally, FARMER sales had the highest percentage of conventionally grown produce, whereas restaurants required organic production. Years of experience with commercial crop production, like the number of crops grown, was also not a distinguishing factor across market outlets.

In sum, the FARMER outlet choice was the costliest but had the highest producer price satisfaction. The highest market-specific sales were achieved using the DCSA and FARMER outlets, suggesting that fruit and vegetable growers interact directly with end consumers, likely to gain marketing feedback from consumers and, to a lesser extent, from WIFG and RESTAURANT sales.

Multivariate Impacts on Market Channel Selection

Table 3 presents the results of the multinomial logit (MNL) regression model (Eq. 1), where marketing outlet was a function of sales, production method, and producer experience variables. With the farmers' market being the baseline market outlet, the multinomial regression on 62 observations resulted in a McFadden R-square, or the coefficient of determination, of 57.4% with several parameter estimates that were statistically significant. The *UNSOLD* variable was dropped from the analysis as it did not contribute to explanatory power.

Table 3. Market Outlet Choice as a Function of Grower Responses to Marketing and Production Response Variables

	Market Outlet[a]								
	DCSA			**WIFG**			**Restaurant**		
Variable	**Robust Coefficient**[b]	**Std. Error**	***P* > z**	**Robust Coefficient**	**Std. Error**	***P* > z**	**Robust Coefficient**	**Std. Error**	***P* > z**
Constant	12.07**	5.21	0.02	1.44	2.90	0.62	1.94	2.75	0.48
MSALES[c]	< 0.01	< 0.01	0.14	< 0.01	< 0.01	0.60	< 0.01	< 0.01	0.38
MCONC	-0.06*	0.03	0.06	-0.07***	0.02	< 0.01	-0.05**	0.02	0.04
PSAT	0.15	1.27	0.90	-2.91**	1.27	0.02	-4.42***	1.58	< 0.01
MCOST	-1.35***	0.54	0.01	-0.21	0.49	0.67	-2.56***	0.87	< 0.01
ADV	-0.13	0.08	0.12	-0.51***	0.21	0.01	-0.18**	0.10	0.05
DIST	-1.75*	0.96	0.07	0.73	0.50	0.15	2.80***	1.12	0.01
CONV	-6.59**	3.08	0.03	-0.70	1.69	0.68	-21.23***	2.57	< 0.01
CDIV	-0.20*	0.12	0.10	0.18**	0.09	0.04	0.36**	0.15	0.02
YEARS	0.02	0.11	0.89	0.18*	0.10	0.09	-0.37	0.28	0.18
Number of observations		62							
McFadden's Pseudo R^2		57.4%							

Notes: [a]The baseline market outlet is the FARMER category with farmers' market or roadside stands in the Ozark Mountain Region, 2022. DCSA = direct sales to consumers on farm and via CSA, WIFG = wholesale, intermediary, food processor, or grocery store, and RESTAURANT = cooks and chefs.
[b]Statistical significance * = 0.1, ** = 0.05, *** = 0.01
[c]Please see variable descriptions in Table 1.

Marginal effects derived from this MNL model are shown in Table 4. A change in any of the variables statistically significantly impacted at least one market outlet choice, as indicated by the bold lettering for marginal effects when statistically significant at $P = 0.05$.

Table 4. Marginal Effects of Grower Marketing and Production Variables on Market Outlet Choice

		Market Outlet[a]			
Variable[b]	**Statistic**	**DCSA**	**Farmer**	**WIFG**	**Restaurant**
MSALES	dy/dx in %[c]	**$1.05 \cdot 10^{-3}$**[d]	$-3.44 \cdot 10^{-4}$	$-3.93 \cdot 10^{-4}$	$-3.10 \cdot 10^{-4}$
	Std. Error	$4.38 \cdot 10^{-6}$	$3.29 \cdot 10^{-6}$	$3.83 \cdot 10^{-6}$	$3.27 \cdot 10^{-6}$
	P > z	0.017	0.297	0.304	0.343
MCONC[e]	dy/dx in %	-0.21	**0.53**	-0.34	-0.03
	Std. Error	$1.98 \cdot 10^{-3}$	$1.07 \cdot 10^{-3}$	$1.97 \cdot 10^{-3}$	$1.07 \cdot 10^{-3}$
	P > z	0.281	< 0.01	0.077	0.80
PSAT	dy/dx in %	14.16	**15.75**	-13.49	**-16.42**
	Std. Error	0.09	0.08	0.08	0.06
	P > z	0.11	0.05	0.08	0.01
MCOST	dy/dx in %	**-8.18**	**10.26**	**11.86**	**-13.95**
	Std. Error	0.03	0.02	0.05	0.04
	P > z	0.01	< 0.01	0.01	< 0.01
ADV[e]	dy/dx in %	0.73	**2.54**	**-4.22**	0.95
	Std. Error	$7.7 \cdot 10^{-3}$	$9.2 \cdot 10^{-3}$	0.02	$7.8 \cdot 10^{-3}$
	P > z	0.345	< 0.01	< 0.01	0.224
DIST[e]	dy/dx in %	**-19.02**	0.70	2.18	16.13
	Std. Error	0.04	0.03	0.04	0.06
	P > z	< 0.01	0.83	0.61	< 0.01
CONV	dy/dx in %	-33.23	**62.09**	**94.62**	**-123.48**
	Std. Error	0.19	0.14	0.16	0.22
	P > z	0.08	< 0.01	< 0.01	< 0.01
CDIV	dy/dx in %	**-2.55**	-0.29	1.10	**1.74**
	Std. Error	$7.4 \cdot 10^{-3}$	$5.2 \cdot 10^{-3}$	$7.8 \cdot 10^{-3}$	$6.7 \cdot 10^{-3}$
	P > z	< 0.01	0.58	0.16	< 0.01
YEARS	dy/dx in %	$-9.7 \cdot 10^{-2}$	$-9.4 \cdot 10^{-2}$	**3.17**	**-2.98**
	Std. Error	$7.0 \cdot 10^{-3}$	$8.4 \cdot 10^{-3}$	0.01	0.02
	P > z	0.89	0.91	< 0.01	0.05

Notes: [a]DCSA = direct sales to consumers on farm or via CSA, FARMER = farmers' market or roadside stand, WIFG = wholesale, intermediaries, food processors, or grocery stores, and RESTAURANT = cooks and chefs.
[b]Please see variable descriptions in Table 1.
[c]For ease of interpretation dy/dx are presented in %. Divide by 100 and standard error to get the *z*-value. For example, targeting a $1,000 increase in market outlet sales increases the likelihood of choosing DCSA by 1% with outcomes for other markets not statistically significant.
[d]Bold lettering adds emphasis to findings that are statistically significant at *P* = 0.05.
[e]The *DIST* variable was modeled as a categorical variable with roughly a 10-mile difference across categories. The marginal effect thus is in increments of 10 miles. Similarly, *MCONC* was modeled as the numeric percentage of total farm sales in a particular outlet as is *ADV* the percent of sales spent on marketing. As such, dy/dx is per 1% increase in market outlet sales concentration or advertising as % of sales. For *MSALES*, *PSAT*, *MCOST*, *CONV*, *CDIV*, and *YEARS* the marginal effect represents a 1-unit change.

On the revenue side, if a producer wanted to increase outlet-specific sales by $1,000, the likelihood that they would choose DCSA increased by 1%. Given DCSA's highest average market-specific sales (see Table 1), this result suggests that growers and consumers may enjoy the farm setting for sales. For those interested in concentrating their sales on a particular market outlet, the choice of the farmers' market outlet showed the only positive marginal effect. Recall that growers selling to the FARMER outlet were least diversified in sales outlets (see Table 1).

For growers interested in increasing their level of satisfaction concerning prices received, the marginal effects analysis suggested selling significantly more using the FARMER outlet at the cost of RESTAURANT sales. DCSA also had a positive marginal effect, whereas WIFG had a negative effect. In sum, and not surprisingly, better pricing can be obtained when selling directly to end consumers.

On the cost side, marketing costs summarized in the *MCOST* variable, rather than specifically in the *FEES* and *OTHER* variables, showed that for growers willing to take on another cost item, they would increase FARMER and WIFG sales at the cost of DCSA and RESTAURANT sales. When analyzed in conjunction with other variables, this finding is now statistically significant, whereas it was not as shown in Table 1, when analyzing the effect of *MCOST* alone. Likely, the effect of one more cost item has a lesser marginal impact for those market channels where the number of marketing costs was already large.

Adding more advertising costs increased the likelihood that growers would sell to the FARMER outlet, decreasing the likelihood of WIFG sales. This increase is likely a function of margin as *PSAT* with FARMER is higher than *PSAT* with WIFG. In other words, greater margins at FARMER than WIFG outlets may offer the opportunity to build a brand name and pursue more sales at farmers' markets and roadside stands.

As DCSA sales required the least, an average of 7.8 miles (see Table 1), adding greater distance (locating the farm farther from consumers or performing CSA delivery at a greater radius) affected this outlet negatively. At the same time, growers drove the furthest (avg. 32.5 miles) to reach restaurants. Future studies might explore whether this is caused by higher margins from institutional buyers such as restaurants, or from the benefits of larger, more consistent sales that a single customer, such as a restaurant, might provide. Regardless, larger distance to end users is expected to lead to more RESTAURANT sales.

On the production side, *CONV*entional production showed a large marginal effect. Increasing ease of production by using chemicals positively impacted both the FARMER and WIFG outlets and negatively affected RESTAURANT sales. RESTAURANT sales were shown to be exclusively organic, indicating that the chefs connected to these growers prefer to add a premium for organic produce to their local offerings on their menus (see Table 1). These results suggest that conventional chemical applications might limit a grower's ability to sell to chefs and cooks. At the same time, FARMER and WIFG sales may allow for chemicals, validating that food-at-home and food-away-from-home local food decisions are driven by unique consumer utility functions (Bazzani et al., 2017; Printezis and Grebitus, 2018). Adding more crop variety impacts RESTAURANT sales positively and DCSA sales negatively. Since crop diversity was statistically insignificant across outlets (see Table 1), this finding may be more relevant when discussing grower type or cluster results in the next section.

Finally, commercial fruit and vegetable production experience showed that increased grower experience reduced the probability of a grower choosing to sell directly to a restaurant. This is not surprising, as more experienced growers also owned larger operations, preferring to specialize on production and to outsource marketing choice to wholesale, intermediaries, food processors, or grocery stores.

Growers Grouped by Similar Characteristics

The k-means cluster analysis grouped growers into sets with similar characteristics. The number of clusters was set to three groups after visual analysis of a dendrogram obtained using hierarchical clustering. Analysis of the dendrogram suggested that four clusters would lead to respondent groups with only one observation and that analysis of only two clusters had a larger within-group sum of squares (WSS) than three respondent groups (see Figure 2). Using a generative AI algorithm, we named each cluster based on its characteristics (OpenAI, 2023).

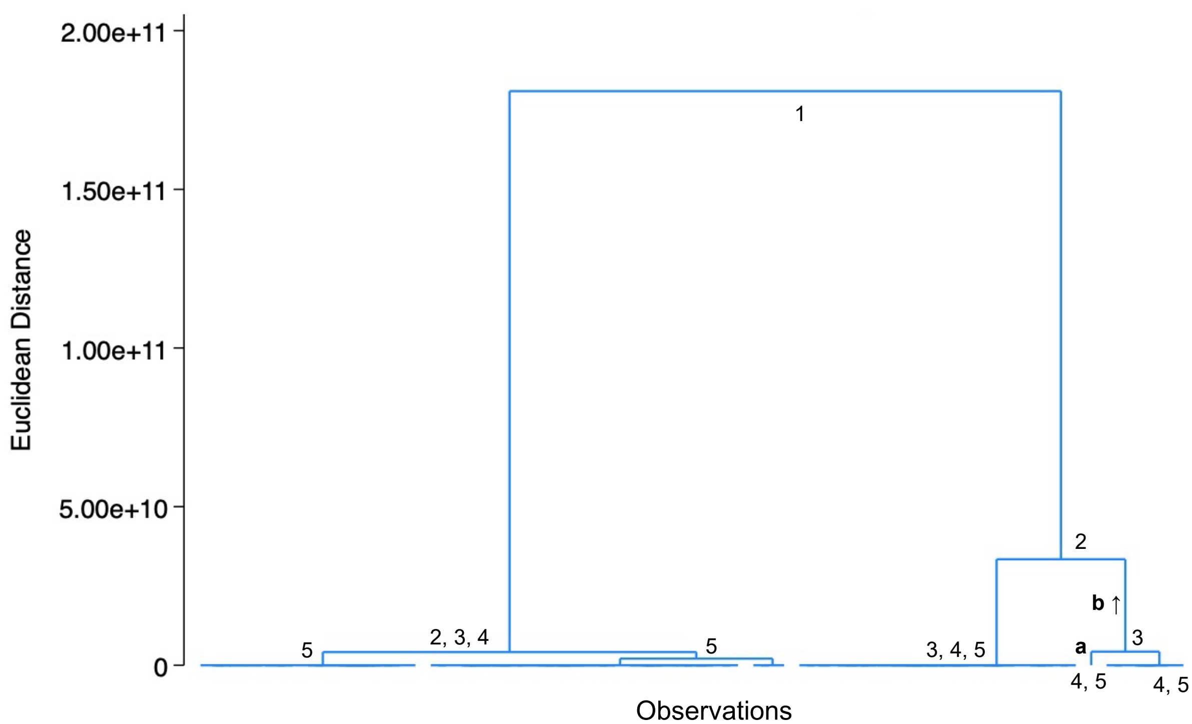

Figure 2. Dendrogram of grower groups employing hierarchical clustering using marketing and production response variables. Four clusters led to groups with few observations or small horizontal bar width (a), and a large increase in within group sum of squares (vertical axis) was observed with two clusters (b). Cluster numbers are shown for each horizontal bar.

Despite significant findings, as shown in Tables 1 and 4, advertising was excluded from Eq. 3 as it had the fewest producer responses and did not change cluster groupings. Using all variables except *ADV* led to producer groups in which cluster differences are portrayed in the top panel of Figure 3. Other descriptive factors across clusters are shown in the bottom panel of Figure 3 and Table 2.

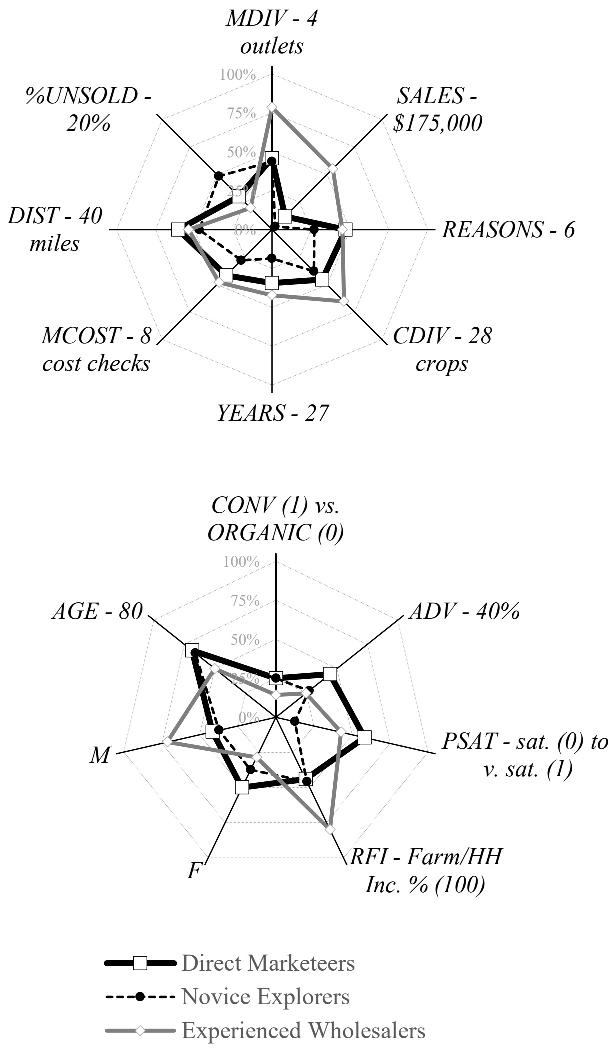

Figure 3. Visual Comparison of Scaled Explanatory Response Variables across Grower Groups (top panel) and Grower Characteristics Not Used for Clustering (bottom panel)

Note: Please see Tables 1 and 2 for variable name definitions. Marker values are scaled to reflect the average response by grower group relative to the overall maximum observed response value reported across all respondents. Maxima are shown for each variable in the graph. For gender variables the maximum would be 100% male or female; for *CONV* the maximum would be 100% conventional production methods that would include use of chemicals. Since the average price satisfaction was 0 = satisfied, the maximum for this variable or 100% responses implies all growers in the group to be very satisfied. Multiplying marker values by the maximum observed values leads to the average response for the grower group.

Group 1 growers with intermediate experience predominantly sold their produce at farmers' markets as a distinguishing feature compared to the second two groups (see Table 2). As such, we deem these individuals to be passionate about selling their products at the farmers' market, so we refer to them as the "Direct Marketeers." This group also invested heavily in advertising their products (see Figure 2). Several factors influenced their selling choices at the farmers' market. They travel the most with the highest price satisfaction and likely enjoy direct consumer interaction. In addition, Direct Marketeers were predominantly female, although not statistically significantly so.

The least experienced growers in Group 2 used the fewest available outlets ($P > 0.05$, Table 2). They advertised sparingly, given both their low farm *SALES* and high reliance on on-farm income as household income. The group's diversity is evident in education achieved, race, and, gender. At the same time, they had the least crop variety, had the most unsold produce, and used conventional production practices as much as the prior group. As such, they appeared least established and also were least satisfied with the prices they received. Hence, we identify them as "Novice Explorers," in part because they did not focus to the same degree on the farmers' market outlet as the Direct Marketeers.

A distinguishing feature of growers in Group 3 was that they identified the most as white males. Numerically, they had the greatest years of production and marketing experience and were statistically significantly the largest farms in terms of sales. Unlike the other groups, they had the lowest use of farmers' markets, although sales using that market outlet were second to DCSA only. Regarding market outlet use, they supplied more heavily to restaurants and WIFG than the above Direct Marketeers and Novice Explorers. In contrast, the fraction of farm sales dedicated to those two outlets still lagged behind DCSA and FARMER outlets. Finally, they used organic production methods the most. These growers also grew a wide range of crops and had the largest marketing costs (*MCOST*) but also the least unsold produce. We refer to them as the "Experienced Wholesalers."

While we had hypothesized that growers, targeting WIFG the most in comparison to the Direct Marketeers and Novice Explorers, would focus on fewer crops to gain sufficient volume, high *CDIV* lowers production and marketing risk while at the same time is likely to lead to a more even or less lumpy distribution of cash flow that would otherwise occur with a more focused or specialized crop production strategy. Enhanced opportunities to manage pests, disease, and weed problems with greater degrees of freedom regarding crop rotation as a function of greater crop variety may also make organic production more attainable, given this group's least observed use of chemicals (*CONV*). Their self-reported satisfaction with prices received was higher than for the Novice Explorers but less than that reported by the Direct Marketeers.

This analysis revealed that WIFG sales increases are difficult to achieve. Growers using these outlets the most had been in business the longest and at the same time were the youngest. Direct, on-farm, and farmers' market sales serve as a base for growers, but they appear insufficient to propel growers to rely on farm sales for most of their household income. On the other hand, using a pronounced strategy to diversify across market channels (high *MDIV*) appears to be a sound risk management strategy that led to low unsold produce, as is a strategy to grow a high diversity of crops. Both require a scale of production that is not quickly achieved.

Relying on consumers to reach the farm (large DCSA sales) lessens producer time spent on delivery (*DIST*) travel. While the largest sales contributor on Experienced Wholesalers farms, this strategy is difficult to achieve as the farms' proximity to consumers, who may need to travel far to reach farms typically located out of town, limits consumer access unless a brand name, desirable farm setting, and consumer willingness to travel exist. Perhaps as a result of those difficulties, Direct Marketeers use farmers' markets extensively to promote their operations by reducing the need for consumers to travel, increasing brand awareness, and using the opportunity to connect with consumers by showcasing their products and building lasting relationships with them. Nonetheless, using the FARMER outlet was demonstrated to be costly regarding producer time invested and may limit sales potential.

Novice Explorers, despite having the lowest *MDIV* score, showed more even pursuit of all market outlet choices (see Table 2). They were also the highest users of conventional production methods. These growers are likely in the process of building name recognition and testing market outlets before scaling up. Their average years of experience suggested that they may not be able to increase in size given both small sales and large reliance on on-farm income in relation to household income as, on average, they had five years of experience in this production and marketing stage. They also had the highest unsold produce, suggesting that their match between production and consumer needs requires attention.

The Experienced Wholesalers strived to grow as much organic produce as possible. Relative to direct consumer-contact outlets, they focused relatively heavily on wholesalers and restaurants. Even still, they had high market-specific sales on-farm and at farmers' markets, and overall, their sales from farming generated 80% of household income on average. Given their longer production experience, these growers invest less heavily in advertising costs as a percent of sales, as they rely on their local name recognition and have a larger advertising budget with high sales. They also spend less time on average transporting produce than the Direct Marketeers, as they may deliver in larger quantities per sale.

Recommendations and Conclusions

This analysis categorized marketing channels and the strategies of fruit and vegetable growers in the Mid-South. Specifically, we identified factors influencing growers' decisions about what outlet to sell their products. Our cluster analysis led to three distinct marketing strategy profiles for fruit and vegetable growers. The first cluster generally targeted farmers' markets as Direct Marketeers. A second cluster, comprised of Novice Explorers, who were least diversified in market outlets pursued, relying on average on 1.88 markets were the least focused on any of the four market outlets. The last cluster used wholesale, intermediary, food processor, and grocery store market outlets and restaurants the most but also had the highest sales across all market outlets, and derived their leading amount of farm sales from DCSA and FARMER outlets.

Our results imply at least two kinds of small-scale fruit and vegetable production systems with unique infrastructure and policy needs. Experienced wholesalers require industry-specific guidelines, often directed by the businesses they sell to or from the growers themselves (Lagoudakis et al., 2020; Staples, Malone, and Sirrine, 2021). They can create opportunities for growers to network with other growers, buyers, and consumers. Through value chain coordination, policy makers might help growers build lasting customer relationships, increasing market share. In addition, local authorities can help remove regulatory barriers that may prevent small growers from accessing specific markets or lessen difficulties associated with regulatory compliance. Local governments can create a more resilient and sustainable food system that benefits growers and consumers by streamlining regulatory processes and providing guidance on compliance requirements. In addition, local governments can encourage restaurants to source ingredients locally by offering tax incentives or other forms of support.

Chi-square analysis indicated that distance to the market matters significantly for market outlet selection. With distance to the market adding fuel and labor constraints, on-farm sales lost adoption likelihood, whereas restaurant sales gained popularity. Locating further from customers reduced on-farm sales, as the consumers' time and cost to travel to the farm increased. At the same time, statistically insignificant and a marginally small result for WIFG suggested that adding farm produce pickup by wholesalers would not be sufficient incentive for growers to use this marketing channel more aggressively. Greater consumer premiums for "localness" are needed for growers to enjoy higher price satisfaction.

At the same time, a policy to promote sales of local produce among less affluent consumers by doubling the value of SNAP dollars for local produce purchases may enhance WIFG sales by making local produce more affordable. Adding less emphasis on distance in defining local production may also assist with marketing efforts by promoting social connectedness to the product (Farris et al., 2019). Extending that social connectedness in a less time-consuming fashion for growers than attending farmers' markets may be a solution.

Assistance with online marketing and social media marketing efforts and building farmer networks and better avenues for further processing of produce as a value-added proposition for consumers and growers may be fruitful as shoppers increase online food shopping. Local efforts of the Center for Arkansas Farms and Foods and the Northwest Arkansas Land Trust aim to educate future growers with production, business, marketing, and legal know how while at the same time assisting with greater access to land that is otherwise difficult to obtain given urban sprawl. The Market Center of the Ozarks, to begin services in 2024, is expected to serve both as a food hub and as a food processing and innovation center to create value-added opportunities. The former is expected to lessen unsold produce and should reduce the number of produce drop-off locations for growers, which helps to lessen distance to market, whereas the latter adds processing and storability in efforts to enhance online marketing potential. This may be especially effective as consumers have grown more accustomed to online purchasing during COVID-19.

This study sets up important next steps for the literature. In addition to standard agronomic concerns, the prior literature indicates that social identity can often play a role in the most profitable crop selection (Moreno and Malone, 2021). Future research would benefit from exploring social identity for growers in the Mid-South. Second, we only focused on small-scale vegetable and fruit growers in parts of Arkansas, Missouri, and Oklahoma, which may limit the applicability of the results to other regions (e.g., California or Oregon where fruit and vegetable growers operate at relatively larger scale and greater degree of automation). In addition, the study may not have considered all relevant variables that may influence growers' market choices, such as farm size in terms of acreage farmed, change in market conditions from year to year, and labor. These possibly omitted variables may limit the ability to draw definitive conclusions about the factors determining grower profiles. Future research efforts could focus on conducting comparative studies with other regions. Those future studies might benefit from a more mixed methods approach, including findings from methods such as focus groups or in-depth interviews, to better understand the motivations and factors influencing growers' market outlet choices as low response rates to complex, online surveys for a small population limit statistical analysis and extension of results beyond the sample.

Growers often need help to track labor force efforts and allocate work hours to different production tasks on the farm versus those incurred to sell produce at or post-farm gate. Farm schools and apprenticeship programs, like the Center for Arkansas Farms and Foods, can and do assist with training future growers with accounting know how to track these costs. Government and industry support to allow for this type of education, which is costly given limited local demand, are needed for long-term investment toward local food supply chains that have a hard time competing on price with large-scale production common with WIFG. A less costly solution may be subsidizing online content at least on business, marketing, and legal curricula that are less location-specific than production training.

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Journal of Food Distribution Research
Volume 54, Issue 3, pp. 102–116

Consumer Perceptions of Craft Breweries in the American South

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Abstract

Regulatory changes related to alcohol consumption in the southern United States led to an increase in the number of craft breweries, whose success depends on consumers' perception of their performance. This research offers insights into which factors impact individuals' awareness and perception of the performance of local breweries. Using data obtained from surveys across 13 communities in the southern United States and probit and ordered probit models, we found that residents of rural communities are less aware and rank performance lower compared to urban residents. Among demographic characteristics, years of residency and gender had a statistically significant impact.

Keywords: Microbreweries, consumer, demand, food systems

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Introduction

The rise of craft beer in the United States over the past 30 years has been remarkable. While the first few craft beer breweries opened across the United States in the 1980s, many states only gained their first craft brewery in the 1990s. As the new millennium approached, the industry grew and evolved rapidly. By 1996, the United States boasted 1,000 craft breweries (Sparhawk, Baldwin, and Storey, 2020), a number that quintupled over the next 20 years. Today, with nearly 9,000 craft breweries in existence, 85% of adults in the United States live less than 10 miles from their nearest brewery (Brewer's Association, 2021b). The near ubiquity of craft breweries positions them as potential cornerstones for economic development. For example, according to the Brewer's Association (2022), small and independent breweries were responsible for 460,000 jobs and more than $72 billion of economic impact.

The increased consumer appeal of craft beer has several motivations. First, many consumers appreciate products and brands that connect them with their locality via geographically specific ingredients, character, aesthetics, style, and variety (Long et al., 2018; Patterson and Hoalst-Pullen, 2020; Sanchez et al., 2022). Sensory attributes, such as flavor/taste, aroma, and alcohol content, are also mentioned as a reason for higher consumption (Gabrielyan et al., 2014; Malone and Lusk, 2018; Betancur et al., 2020; Staples, Malone, and Sirrine, 2020; Steinbach, Burgardt, and Machado-Lunkes, 2023). Third, the context of beer consumption (i.e., food pairing, beer tourism) has also been identified as influencing craft beer consumption (Betancur et al., 2020; Capitello and Todirica, 2021).

Furthermore, although in previous generations, bars and other alcohol-serving establishments were associated with negative impacts on communities, today craft breweries are part of a broader cultural shift that sees local businesses and products as social goods. Craft breweries are now associated with revitalizing "Main Street," downtowns, and abandoned industrial areas, supporting other local businesses and providing character to and promoting unique aspects of local places (Feeney, 2017; Nilsson and Reid, 2019). At the industry level, many craft brewers have cooperative—rather than competitive—relationships with other brewers within and between regions (Kraus et al., 2018). Many craft breweries are "content to improve their own practices behind the scenes, helping out fellow brewers whenever asked" (Jones, 2017, p. 19). Overall, craft beer, as both a phenomenon and industry, seemingly serves as a counterpoint to the perceived homogenizing impulses of mass-produced consumer culture.[1]

In some cases, breweries actively support local food businesses by offering space for start-up restaurants, food trucks, small-scale farmers' markets, and CSA drop-offs (Rossi and Hyden, 2015). These collaborations create opportunities to cross-promote farm brands, food businesses, and locally unique products. Further, establishing breweries can lead other businesses, such as

[1] We say "seemingly" because we do observe large, highly commercial beer companies rapidly buying up craft brands. We also see larger craft beer companies actively competing with much smaller breweries through litigation related to beer names and other aspects of branding.

farm-to-table restaurants, to locate nearby, sometimes revitalizing unused commercial or industrial spaces.

Consumers' positive perception of local breweries' performance is critical for the craft beer industry to continue being successful and, consequently, helping the local economies (Murray and Kline, 2015; Li et al., 2023). Nevertheless, the literature regarding customer satisfaction from local breweries is somewhat limited (Malone and Lusk, 2018; Tong, 2022). This research extends the literature by evaluating potential characteristics that can lead to higher customer satisfaction. Specifically, using survey data collected from 13 localities in the southeastern United States, we assess how demographic factors and other food system aspects affect consumer/residents' perceptions of the performance of local craft breweries.

The Role of Craft Breweries in the Local Food System

Research endeavors related to craft breweries have advanced because of the continued growth of the industry, its expansive prevalence, and its relationship to the local economy and other local businesses (Baiano, 2021; Nave et al., 2021). Part of this literature examines the sociodemographic characteristics of craft beer consumers across different countries. For example, previous research has often indicated that millennials are the most likely group to drink craft beer (Long et al., 2018; Malone and Lusk, 2018; Lerro, Marotta, and Nazzaro, 2020), although exceptions exist (Aqualini et al., 2015). Furthermore, although an increasing number of females purchase draft beer, the primary consumers are male (Chapman et al., 2018; Long et al., 2018; Baiano, 2021; Read, 2022). Lastly, craft beer consumers have higher incomes (Long et al., 2018; Baiano, 2021).

A limited strand of this literature examines consumers' willingness to pay for beer produced by local breweries. Results of these studies indicate that consumers are willing to pay a premium for local beer (Hart, 2018; Atallah et al., 2021). Other research endeavors evaluate the relationship between craft breweries and "neolocalism" (Taylor and Pietro, 2020; Nelson, 2021) and the function of breweries as "third places" (Reid, Gripshover, and Bell, 2020; Perry and Woolard, 2023), which refers to social gathering spaces outside of the home (first place) and work (second place). Furthermore, there is a growing literature that examines the role of craft breweries in a wide array of community, economic, and regional development contexts (Moore, Reid, and McLaughlin, 2016; Gatrell, Reid, and Steiger, 2018; Reid, 2018; Nilsson and Reid, 2019; Apardian and Reid, 2020; Reid, 2021; Reid and Gatrell, 2023).

Survey Design and Data Collection

The data for this study were obtained from a comprehensive survey instrument administered to residents from 13 communities of various sizes (see Table 1) in six southern states (Kentucky, South Carolina, North Carolina, Tennessee, Alabama, and Louisiana). These regions were selected in consultation with extension agents, university faculty, and local food experts who recommended different communities with observed, diversified local food activity. The southern states have been slower to join the craft beer movement (McLaughlin, Reid, and Moore, 2014; Zook and Poorthuis, 2014). However, following modifications in alcohol-related policies, these states also share the common growth trend in the craft brewery industry (Elzinga, Tremblay, and Tremblay, 2015; Murray and Kline, 2015; Whitham and Leite, 2023). Consequently, learning more about consumers' perceptions is crucial as the industry expands.

Table 1. Demographics of Communities Surveyed

	N	HH Income (Median)		Other Survey Demographics		
		Survey	**Census**	**Age**	**Sex (% Male)**	**% Med or High Interest**
Upstate SC	408	$50–$75K	$50K	50.3	33%	65%
Columbia, SC	263	$50–$75K	$54K	50.5	36%	64%
York County, SC	146	$50–$75K	$62K	52.4	43%	55%
Louisville, KY	541	$50–$75K	$55K	48.0	32%	62%
Edgecombe County, NC	152	$25–$49K	$43K	55.3	33%	60%
Little Rock, AR	234	$25–$49K	$52K	46.3	31%	68%
Baton Rouge, LA	212	$50–$75K	$57K	45.5	36%	58%
Nashville, TN	542	$50–$75K	$63K	44.9	34%	58%
Knox County, TN	245	$50–$75K	$55K	46.3	27%	71%
Montgomery, AL	164	$50–$75K	$49K	42.1	25%	65%
Raleigh/Durham, NC	567	$50–$75K	$67K	46.9	28%	64%
Boyd County, KY	121	$50–$75K	$45K	50.8	38%	66%
Clark County, KY	69	$50–$75K	$52K	44.0	37%	68%

The survey instrument was iteratively developed using a combination of focus groups with residents in the South, discussions with local food researchers across the United States, a pilot survey, and a smaller working group of extension-oriented researchers from four universities. Participants in the focus groups were asked to identify which aspects of their communities were critical to supporting a vibrant, active, and broadly inclusive food system (i.e., a system with high vitality). The survey designers workshopped these questions with various stakeholders and researchers to identify local food system (LFS) aspects important to supporting systemwide vitality.

Survey participants were recruited using: i) mailed surveys (1,500 per community), ii) online recruitment using Dynata (an online survey service), and iii) in-person events where surveys were distributed (limited to regions with poor broadband access and/or a high percentage of low-income residents). Paper surveys were distributed via mail using addresses purchased from PostcardMania, a commercial marketing service. For paper and online surveys, both services were asked to select addresses/respondents that accurately reflected income diversity (i.e., property values/household income) and population levels of the communities of selected Zip codes. The final sample includes 3,638 usable responses.

In the questionnaire, survey participants are asked to evaluate the performance of 29 aspects of their Local Food Systems using a 5-point Likert scale question ("Very Poor" to "Excellent").[2] Performance measures how well different components of the food system meet the needs and expectations of community residents. The general question text for measuring performance for each aspect was "How would you rate the performance of the following aspects of your community's local food environment?"

Each participant's perception of performance may vary due to different experiences within and outside the food system. Consequently, the survey provides guidance for what is considered high performance among different LFS aspects. In this analysis, we only consider residents' performance evaluations of craft breweries. A previous publication evaluates a larger set of LFS aspects using the same dataset (Rossi and Woods, 2023).

While there are several definitions of "craft beer" and "craft breweries" worldwide, we rely on a broad definition where craft brewers must be small, independent, cooperative, and locally based. This approach expands the Brewer's Association's definition by incorporating cultural and geographical elements alongside their numerical qualifications. According to the Association, a brewer must i) be "small," producing at most 6 million barrels of beer per year,[3] ii) be "independent," meaning that "less than 25% of the craft brewery is owned or controlled (or equivalent economic interest) by a beverage alcohol industry member that is not itself a craft brewer (2021)," and iii) brew most of its total beverage alcohol volume from traditional or innovative brewing ingredients. In addition to being small, independent, and following traditional brewing practices, other definitions emphasize that cooperation amongst brewers is a critical element of the definition of a "craft brewery" (Baiano, 2021).

Approach

Our analysis involves two separate estimations. First, a probit model was utilized to understand which individuals in our sample are more likely to be aware of craft breweries in their area. To do this, we recoded the brewery performance score, our dependent variable, into a binary variable.[4] We consider respondents to be aware of craft breweries if they provided a performance score other than "Don't Know." The independent variables included in the model are i) self-reported level of interest in local food systems, ii) standard demographic characteristics (gender, age, and income), iii) the number of years the person had been a resident of their community, and iv) the size of the respondent's community. "Small" communities were defined as having a population under 100,000, "medium" communities were defined as having populations between 100,000 and

[2] All respondents also had an opportunity to answer "Don't Know." When we measure the overall performance scores for each LFS aspect of a community, we remove "Don't Know" responses from the analysis since respondents were not aware of or not engaged with these particular aspects of their LFS.

[3] This 6-million-barrel figure is somewhat controversial in the brewing community. It was created by the Brewer's Association as a sort of "protection" against companies like Anheuser-Busch claiming to be a "craft" brand. Some brewers do not agree with this definition, but it is useful in drawing a line between "beer" and "craft beer" and will be used as such in this research. See Fisco (2019) for more details on the controversy.

[4] All performance scores are originally on a 1–5 Likert scale, with "Don't Know" responses considered a non-response. For the probit analysis, we re-coded "Don't know" = 0, and any 1–5 performance score = 1.

500,000, and "large" communities had more than 500,000 residents. See Table 2 for definitions and codes for these variables.

Table 2. Definitions and Descriptions of Demographic Variables

Variable	Abbreviation	Description
Years of residence	Yrs resident	Number of years respondent has been a resident of their community
Sex	Sex	Binary: 0 = female, 1 = male
Age	Age	Age of consumer
Income	Income	Consumer income level: 12.5 = \$0–\$24,999 37.5 = \$25,000–\$49,999 62.5 = \$50,000–\$74,999 87.5 = \$75,000–\$99,999 112.5 = \$100,000–\$124,999 137.5 = \$125,000–\$149,999 162.5 = \$150,000–\$174,999 187.5 = \$175,000–\$199,999 250 = \$200,000 and up
Interest in local food	Lfs_interest	Interest in local food system: 0 = Not interested: low 1 = Somewhat interested: medium 2 = Very interested: high
Size	Size	Size of community: 0 = Urban, less than 500,000 residents: medium 1 = Rural, non-urban: small 2 = Urban, more than 500,000 residents: large

The probit equation is described below:

We assume the latent variable y^*_{ij} is a function of observed and unobserved variables behind the respondent i decision (i.e., j) to provide a performance score for craft breweries and can be described as:

$$y^*_{ij} = x'_i\beta + \varepsilon_{ij}, \tag{1}$$

where xi is a vector of observable variables that could be correlated with the decision to provide a performance score for breweries, such as respondent demographics and interest in local food systems; β is a vector of coefficients capturing the correlation between the various observable variables and the respondent decisions; and ε_{ij} is the random disturbance term. We do not observe y^*_{ij}, but we only observe whether the respondent provides a performance score for breweries such that:

$$y_{ij} = \begin{cases} 1 \text{ if } y^*_{ij} \geq 0; \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

where y^*_{ij} is the dependent variable to be used in the probit regressions identifying which factors influence the likelihood of a respondent providing a performance score for breweries. The probability of respondent *i* providing breweries with a performance score (i.e., decision *j*) is defined as (Greene, 2008),

$$\begin{aligned} P(y_{ij} = 1 \mid x_i) &= P(y^*_{ij} \geq 0 \mid x_i) = P(x'_i\beta + \varepsilon_{ij} \geq 0 \mid x_i) \\ &= P(\varepsilon_{ij} \geq - x_i\beta \mid x_i) = P(\varepsilon_{ij} \leq x_i\beta \mid x_i) \\ &= F(x'_i\beta) = \Phi\,(x'_i\beta), \end{aligned} \tag{3}$$

where $F(.)$ is the cumulative distribution function for the random variable ε_{ij}. We assume ε_{ij} is normally distributed; therefore, $\Phi(.)$ is the cumulative normal distribution.

Once we evaluated who is more likely to be aware of craft breweries, we then utilized an ordered logistic regression to understand how demographic and geographic variables impact a respondent's likelihood of evaluating breweries more or less positively. We maintained the same independent variables as in our probit model but allow the brewery performance score to retain its original coding on a 1–5 Likert scale. "Don't know" responses are coded and removed from this analysis to include only the subset of our initial sample that is aware of breweries. The total number of usable observations in the ordered logit of performance is 2,514.

Summary statistics of the variables included in this analysis are reported in Table 3. We compare the values (% of categorical variables, mean for continuous variables) between the two models to show any differences among the respondents who provided performance scores for craft breweries (i.e., the subset of respondents in the ordered logit) and all respondents sampled (i.e., the respondents included in the probit model). Those who provided performance scores for breweries were slightly younger, had higher household incomes, were more interested in local food, and were more likely to be male.

Table 3. Summary Statistics Performance Model Awareness Model

	Performance Model	Awareness Model
	%	**%**
Sex		
Male	35.1	32.5
Female	64.9	67.5
Interest in Local Foods		
Low	32.7	37.3
Medium	31.8	30.3
High	35.5	32.4
Community Size		
Small	15.0	17.2
Medium	29.4	30.0
Large	55.6	52.8
	Mean	**Mean**
Years of Residence	16.4	16.6
Age	45.6	47.3
Income	80.2	75.1

Note: N = 2514 for all variables in the performance model; N = 3,638 for all awareness variables. The average brewery performance score is 3.6 out of 5.0. The average awareness of breweries is 69.1%.

Results

Household income for survey participants[5] generally matched the 2020 census data (see Table 1). The majority of the survey respondents, between 55% and 71%, indicated that they are either "somewhat interested" or "very interested" in one aspect of Local Food Systems. Thus, this sample provides insights into the perceptions of individuals who have some awareness of and experience with local food in their communities.

The results of the probit model are shown in Table 4. These results indicate which variables are associated with an increased likelihood that a respondent will provide a performance score other than "Don't Know" for craft breweries. We consider these individuals to be "aware" of breweries. Regarding demographics, if a respondent is male, younger, and has a higher income, they are more likely to be aware of breweries. Those more interested in local food are also more likely to know about breweries. Additionally, individuals from smaller communities are less likely to be aware of breweries. Each rural community surveyed had at least one craft brewery. The marginal effects indicate that males are 10 percentage points more likely to be aware of craft breweries, compared to females. On the other hand, being a resident of a small rural community reduces the probability of awareness by 7.3 percentage points.

[5] Participants chose a household income range.

Table 4. Probit Estimation for Awareness of Craft Breweries Coefficient Standard Error Marginal Effects

	Coefficient	Standard Error	Marginal Effects	
Years of residence	0.002	0.002		
Male	0.305	0.051	0.100	***
Age	-0.014	0.001	-0.004	***
Income	0.003	0.000	0. 001	***
Community size				
Small	-0.212	0.066	-0.073	***
Large	0.048	0.052		
Interest in local				
Medium	0.356	0.054	0.122	***
High	0.129	0.054	0.160	***

Notes: ***, **, * represent significance at the 99%, 95%, and 90% levels.
N = 3,638; Pseudo R2 = 0.063; Pearson GOF *p*-score = 0.074; model correctly classifies 70.4% of observations based on independent variables

The results of the ordered logistic regression of performance are included in Table 5. The first main observation is that fewer demographic variables were statistically significant, compared to the probit estimation. Higher income individuals were more likely to rate the performance of breweries higher. Newer residents were also likelier to give breweries a more positive performance score. Respondents in smaller communities were more likely to score local craft breweries lower than their larger community counterparts. They were also less likely to know about breweries. Respondents from the largest communities generally had a more positive perception of brewery performance than those from other community sizes. Finally, respondents who answered that they were somewhat or very interested in local foods were more likely to score breweries higher.

Table 5. Ordered Logistic Estimation for Performance of Craft Breweries

	Coefficient	Standard Error	
Years of Residence	-0.004	0.002	**
Male	-0.030	0.046	
Age	0.001	0.001	
Income	0.001	0.000	*
Community Size			
Small	-0.538	0.066	***
Large	0.126	0.048	***
Interest in Local			
Medium	0.291	0.053	***
High	0.503	0.052	***

Note: ***, **, * represent significance at the 99%, 95%, and 90% levels. N = 2514; Pseudo R2 = 0.028

Table 6 presents a demographic breakdown of individuals who rate brewery performance differently. For sex, community size, and interest in local, we present the percentage of individuals within each category to provide a particular brewery performance score.[6] Residents providing lower performance scores often have lower incomes. Respondents in smaller communities have a higher percentage of lower performance scores than those in the two other size classes. Women have a larger share of high-performance scores than men, even though they are less likely to be aware of brewery performance. Individuals with a high interest in local food systems have a larger percentage of high-performance scores. This pattern is similar to what was observed in the awareness analysis, where higher interest in local foods is associated with a more heightened awareness of breweries.

Table 6. Demographic Breakdown of Brewery Performance Scores

	Low Performance	Medium Performance	High Performance
Years of Residence	16.5	16.8	15.7
Age (yrs)	44.8	47.7	44.0
Income ($1,000s)	76.9	82.1	83.5
Sex			
Male (%)	42.3	38.1	19.6
Female (%)	39.6	38.2	22.2
Community size (%)			
Small	57.7	31.0	11.3
Medium	39.5	39.5	21.1
Large	36.4	39.5	24.1
Interest in local			
Low	51.8	35.6	12.5
Medium	37.9	44.3	17.8
High	32.4	35.1	32.5
N	1,019	960	535

Discussion and Conclusion

Craft breweries have become increasingly popular over the last 30 years, in parallel to consumers' rising preferences for different aspects of local food markets over the same period. The literature regarding consumers' willingness to pay for products at craft breweries and the characteristics of craft breweries' patrons is evolving. However, limited research has evaluated residents' perceptions of the performance of craft breweries. This study is an effort to expand this literature by utilizing survey data from 13 localities in the southern United States. This region is selected because of the substantial growth in the number of craft breweries that followed fairly recent regulatory changes related to alcohol consumption.

[6] Low performance = 1–3; medium performance = 4; and high performance = 5

The results of this analysis indicate a relationship between consumers' perceptions of craft breweries and interest in local food systems across the American South. Those interested in local food systems are more likely to know about and give more positive performance scores to their local craft breweries. These results seem intuitive. For example, food trucks and nearby local restaurants might support breweries without food service. Breweries and these dining establishments often promote each other and hold collaborative events. Patrons of these institutions are likely interested in quality, local products, and, perhaps, unique experiences.

Breweries can also serve as spaces to promote and support unique, local agricultural (heritage) crops, and other community-supported agriculture endeavors. Similarly, breweries might host or sell at farmers' markets or services such as a CSA pickup station (Spence, 2017; Eat Local First, 2022; Graham, 2023; Jones, 2023).

According to this analysis, demographic aspects, such age, sex, and income, were statistically significant in terms of residents' awareness of breweries but less predictive of their perceptions of performance. In terms of both performance and awareness, it appears that consumers' perceptions of and interactions with other LFS aspects are worth considering when evaluating craft breweries. Perhaps as local breweries mature in product development and engage in more competitions that bestow indications of quality, consumers will become more sensitized to brewery performance. Our findings are consistent with previous studies indicating that male and higher income individuals are more likely to visit craft breweries.

Although demographics, including years of residence in a community, were significant to understanding who might be aware of breweries, they had less impact on the perceptions among the subset of those who were aware of breweries. This finding indicates that breweries could improve awareness by marketing their products and non-beer-related activities (e.g., providing community gathering spaces, CSA dropoffs, craft markets) to audiences beyond younger males (who have a higher household income and are newer to the community). Cross-promotion of craft and local enterprises—especially if included in a broad local marketing campaign—will likely generate awareness of these activities. In short, there are opportunities to pair local food marketing with other connected products and experiences, such as those offered by craft breweries. Once this is accomplished, then the next logical step might be to engage in broader regional culinary or agritourism trails projects.

These results also illustrate that more rural communities view their local craft breweries as performing below their counterparts in more urban communities. This finding may indicate an opportunity for growth for these rural craft breweries. Each smaller community in this analysis has at least one craft brewery nearby. The lower scores could be explained by the limited number of breweries or the variety of what each brewery offers. Perhaps residents view these establishments as too expensive, elitist, or catering toward out-of-town visitors, or the local breweries in smaller communities are indeed of lower quality. This warrants further study, as it would be interesting to understand how the craft brewery experience can be tailored to locales with less dense populations.

Additionally, it would be interesting to determine whether tourists have different perceptions of craft breweries than residents. Potentially, a survey distributed to tourists or visitors might offer an interesting perspective on the differences in perceptions among those who live in a place and those who visit. Another potentially interesting area of study would be to evaluate consumer perceptions of these local food system elements in a post-COVID-19 world. Because this survey was completed before the onset of widespread COVID-19 restrictions in 2020, it would be interesting to know whether respondents' perceptions were changed by their pandemic experience. The survey developers are collecting post-COVID results in some of these communities, and future work will show how local food systems responded.

Since this is a case study of the American Southeast, we expect the results would differ in other parts of the United States because of cultural differences and because the brewery industry is more mature in some of those regions. The Local Food Vitality Survey shows great promise in evaluating consumer perceptions and would be useful in evaluating interest and perceptions of communities beyond U.S. borders. In conclusion, this study offers insights into how people in the American South perceive their local craft breweries. First, the results indicate that residents are engaged with the local food system and, thus, perceive many of its elements positively, and second, this analysis also suggests a relationship between local food systems and craft brewing. One crucial policy suggestion from this study is that closer collaboration among the various components of the food system could yield significant benefits. Knowing this creates a host of opportunities for facilitating collaboration across these domains.

Acknowledgement

This work was supported by the USDA National Institute of Food and Agriculture.

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Journal of Food Distribution Research
Volume 54, Issue 3, pp. 117–139

A Profile of Tennessee Farmstead Milk Consumers

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Abstract

An online survey of 817 Tennessee consumers identified those more likely to be familiar with and purchase bottled milk produced and processed at the same farm (i.e., farmstead milk [FSM]). Three logistic regression models were analyzed for variables, including heard of, previously purchased, and future interest in purchasing FSM. Few variables impacted each model, with only respondents' age and local food purchase frequency impacting all models. Findings suggested that some consumer demographics may impact knowledge and purchase likelihood of FSM, but they changed based on region. Producers may benefit from specialized marketing strategies targeting younger, married individuals with children who are local-oriented consumers.

Keywords: farmstead, milk, consumer preference

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Introduction

Tennessee (TN) has 18 farmstead dairy (FSD) operations with growth potential. However, little is known about the consumer of dairy products produced and processed at the same farm, or farmstead dairy products. A key success factor for these operations is a better understanding of their target market; without this understanding, these enterprises are unlikely to succeed. A target market is a group of homogenous customers who can be reached with tailored marketing strategies. Consumer preference studies are used to determine traits consumers deem desirable in food products and marketing and to determine what leads to consumers purchasing various food products. These studies are often surveys conducted in person, over the phone, by mail, or online.

This study aimed to provide TN FSD with marketing and product data of TN residents who consumed dairy products by determining how demographics impact a consumer's likelihood of hearing about and purchasing local farmstead milk (FSM). Demographics have not been seen as a reliable way of predicting a potential consumer when evaluating FSM due to the variation among respondents. In other products and industries, demographics have impacted consumer preferences and tastes (Patterson et al., 1999; Brown, 2003; Keeling Bond, Thilmany, and Bond, 2009; Khachatryan et al., 2018), which implies they may have an impact on FSM purchasing behavior.

Background

Outside sources may sway consumer preferences toward a product. A 2020 study of Tennessee milk consumers found that 65% trusted doctors to learn about milk, followed by other family members (23%) and community educators (20%) (Eckelkamp et al., 2021). However, while 46% did consult doctors to receive information on milk, 43% sought information from online articles, 27% went to registered dieticians/nutritionists, and 4% sought out industry peer-reviewed journals (Eckelkamp et al., 2021). This study showed a discrepancy between where consumers place their trust and where consumers seek information about milk. If consumers receive information from misinformed sources, their willingness to purchase a farmstead milk product might be hindered.

Several surveys focused on consumers' perceptions of and their willingness to pay for local products in the 1990s (Adelaja, Brumfield, and Lininger, 1990; Gallons et al., 1997; Patterson et al., 1999) and 2000s (Brown, 2003; Maynard, Burdine, and Meyer, 2003; Keeling Bond, Thilmany, and Bond, 2009).

One possible driving factor for these surges of interest could have been the early 1990s and 2000s recessions and the Great Recession of 2007. An interest in local agricultural products re-emerged in 2018 and remained a hot topic due to the COVID-19 pandemic and the resulting COVID-19 recession (de Paulo Farias and dos Santos Gomes, 2020; Google, 2021). The pandemic severely impacted processing plants, partly due to the close quarters that many food processing workers experienced (Waltenburg et al., 2020). Infections of COVID-19 linked to these plants, of both employees and their associates, equated to 6% to 8% of all U.S. cases as of July 21, 2020 (Taylor, Boulos, and Almond, 2020). The high number of COVID-19 cases led to temporary shutdowns of processing facilities, impacting meat availability for consumers. There was an increase in Google searches for “farmers market,” “butcher,” “pick your own,” and “farm fresh” around the time food chain issues as a result of COVID-19 were becoming prominent. The most notable spike for the terms “farmers market,” “pick your own,” and “farm fresh” occurred between March and May of 2020 (Google, 2021). This spike coincided with COVID-19 reaching the United States, and stay-at-home orders were issued (Moreland et al., 2020). The term “butchers” had a smaller spike around this time, with the most significant spike around November and December 2020. The term “farmers market” increased between July and September, coinciding with the previous 5 years’ trend in search history (Google, 2021).

These trends showed that consumers sought localized products and sources for those products and persisted through the pandemic, benefiting programs like “Pick TN,” which advertises local producers-processors in Tennessee who sell meat, dairy, fresh produce, and other crops. The COVID-19 pandemic, followed by other global wars and catastrophes, allowed consumers to witness the global food system’s fragility, which led to an elevated and sustained interest in local and farmstead agricultural products. To take full advantage of the increased interest in locally sourced food items, FSDs need a clearer understanding of who their current consumers are and what demographics they should target to maximize profit.

This study aimed to identify customer attributes that impact Tennessee FSM customer awareness and purchasing behaviors. Based on a review of the available literature, we hypothesized that some potential consumer attributes may impact whether a respondent has heard of, purchased, or is interested in purchasing FSM in the future. A complete list of hypotheses can be seen in Table 1. Results showed that younger, married individuals with a farm background and children in the home who lived in East or Middle TN and frequently purchased local foods were likely to be aware of and intend to purchase products produced on the same farm that milk was produced. These results, along with others, can inform future marketing strategies of FSM businesses.

Table 1. Expected Impacts of Variables on Consumers' Familiarity with and Purchase Likelihood of Farmstead Milk Based on the Current Literature

Variable	Heard of FSM	Sources	Purchase likelihood of FSM	Sources
TN region	+		+	
Age	·	Patterson et al., 1999	·	Patterson et al., 1999 Zepeda and Li, 2006 DeLong et al., 2020
Current local purchase habits	+		+	
Farm background	+	Brown, 2003	+	Brown, 2003
Area of residence	+	Brown, 2003 Keeling Bond, Thilmany, and Bond, 2009	+	Brown, 2003 Keeling Bond, Thilmany, and Bond, 2009
Children	·	Patterson et al., 1999	+	Patterson et al., 1999 Best and Wolfe, 2009 Ortez et al., 2020
College education	+	Patterson et al., 1999	·	Patterson et al., 1999 Brown, 2003 DeLong et al., 2020
Male	·	Patterson et al., 1999	·	Patterson et al., 1999 Zepeda and Li, 2006 DeLong et al., 2020
Weekly food budget	+	Zepeda and Li, 2006 Best and Wolfe, 2009	·	Zepeda and Li, 2006 Best and Wolfe, 2009
Weekly dairy expenditure	+	Regmi et al., 2020	+	Regmi et al., 2020
Household size	?		+	Zepeda and Li, 2006 Khachatryan et al., 2018
Income	·	Patterson et al., 1999	·	Patterson et al., 1999 Keeling Bond, Thilmany, and Bond, 2009 DeLong et al., 2020
Married	?		+	Keeling Bond, Thilmany, and Bond, 2009

Note: + indicates positive association; - indicates negative association; · indicates no association; ? indicates uncertain effects

Material and Methods

An online survey was used to evaluate the research hypotheses. This analysis was based on a subset of questions from a more extensive study that included a choice set experiment and survey instrument, which categorized Tennessee consumer desires, created an ideal consumer profile, and determined willingness to pay based on specific fluid milk attributes (for more details on the experimental design, see Jensen et al., 2021). The survey was distributed through QualtricsXM (Provo, UT) from March 2021 to May 2021. It targeted 840 respondents who were TN residents, 18 years of age or older, and the primary food shopper of a household that consumed milk or dairy products.

The survey required a sample representative of the TN population, so a stipulation of similar percentage breakdowns per region (East, Middle, West) was given to QualtricsXM. The survey remained open for another two weeks to obtain a similar percentage to the West TN population density and concluded in May 2021.

The survey consisted of 90 questions about participants' familiarity with locally produced and processed milk, prior and future purchases, purchase likelihood both on and off-farm, desires when participating in a dairy farm visit, perceptions of local milk products, general demographics, purchase behaviors, and likelihood of purchasing milk with various attributes. Because some survey questions asked respondents how much they thought they would spend on FSM, we reiterated that spending the chosen amount would mean less money to spend elsewhere to remind respondents of their household budget constraints and reduce hypothetical bias. Multiple choice and open-ended questions captured age, gender, children, marital status, education, income, and farm background. Likert scale questions (1 = a great deal, …, 5 = not at all; 1 = extremely important, …, 5 = not important at all; 1 = strongly agree, … 7 = strongly disagree) were used to determine respondents' purchase behaviors and perceptions of local dairy products.

Each respondent was asked three questions on which study's models were built: "Have you heard of milk that is both produced, processed, and packaged on a Tennessee dairy farm (Tennessee farmstead milk)?" "Have you purchased fluid milk that was produced, processed, and packaged on a Tennessee farm (Tennessee farmstead milk)?" and "In the future, would you be interested in purchasing milk that is produced, processed, and packaged on a Tennessee dairy farm (Tennessee farmstead milk)? (Keep in mind the farmstead milk could be purchased at a variety of retail outlets including directly from the farm)." The University of Tennessee Institutional Review Board reviewed the survey for appropriate human subject protocols and approved it under UTK IRB-21-06261-XM; a copy of the survey is available upon request from the corresponding author.

Survey Respondent Demographics

The survey had 817 usable responses with distributions similar to the state population distribution by region (East: 36.7% sample vs. 36.5% population; Middle: 42% vs. 41.2%; West: 21.3% vs. 22.3%, respectively [U.S. Census Bureau, 2022]), thus resulting in a representative sample of Tennessee's population by distribution.

Approximately 62% of the respondents were female, and 38% were male (Table 4). This makeup was expected because research asserts that females are the primary food shoppers in most households (Schafer and Schafer, 1989; DeLong et al., 2020), which was a criterion for participating in the survey. Respondents were 49 ± 17 years old (see Table 5), slightly higher than the state mean of 39 years old (U.S. Census Bureau, 2022), which was expected because the survey only considers individuals 18 and older.

More of our respondents had a bachelor's degree or higher than the state mean (40% for the sample and 29% for the state, respectively [see Table 4]). A contributing factor could be that the age range was 18 years or older, and the state's education age range only considered those 25 years old and younger, which may help explain why the sample's educational attainment was 11% higher than the state mean (U.S. Census Bureau, 2022). Within the respondent group, 83% were white; 23% had children less than 12 years old in the house; and approximately 26% had a farm background. The average household size was 2.7 ± 1.5 people; 53% of respondents were married; and 25% lived in rural areas.

Table 2. Comparison of Survey Respondent Demographics to the Distribution of Tennessee Residents in 2021

Demographic	Percentage	State Estimate 18+[1]	State Percent 18+[1]
Region			
East (n = 300)	36.72%	1,959,391	36.54%
Central (n = 343)	41.98%	2,209,503	41.21%
West (n = 174)	21.30%	1,193,164	22.25%
College education (n = 326)	39.90%		28.70%
Female (n = 504)	61.99%	3,500,059	51.30%
Male (n = 309)	38.01%	3,329,115	48.70%
Children (n = 190)	23.26%		
Farm background (n = 212)	25.95%		
Race–Caucasian (n = 680)	83.23%	5,272,910	77.20%
Race–Other (n = 137)	16.77%		22.80%
Married (n = 430)	52.63%	2,740,130	49.20%

Note: [1] Numbers retrieved from U.S. Census Bureau (2022) population estimates.

Table 3. Comparison of Survey Respondent Demographics to the Mean Tennessee Population in 2021

Demographic	Number of Respondents	Mean ± Standard Deviation[1]	State Mean[1]
Age (year)	817	49.02 ± 16.52	39 ± 0.2
Weekly dairy expenditure ($ per week)	805	10.62 ± 9.51	
Weekly food budget ($ per week)	801	124.82 ± 90.12	
Household number (#)	816	2.70 ± 1.47	2.51 ± 0.01
Income ($ per year)	765	59,228.76 ± 41,030.49	78,035 ± 785

Note: [1] Numbers retrieved from U.S. Census Bureau (2022) population estimates.

Respondents made an annual income of $59,229 ± 41,030. Finally, respondents spent $10.62 ± 9.51 on dairy products per week and had a weekly food budget of $124.82 ± 90.12, meaning they spent 8.5 ± 10.6% of their weekly food budget on dairy products.[1] Results are comparable to national spending on dairy products, which was $10.44 per trip in 2022 (Progressive Grocer, 2022).

There were 366 respondents indicated they had heard of FSM in the past (44.80%), while 451 indicated they had not heard or were unsure if they had heard of it. When asked if they had purchased FSM that "was produced, processed, and packaged on a Tennessee farm (Tennessee farmstead milk)," 267 (32.68% of total respondents and 72.95% of respondents who had heard of FSM) responded "yes" they had purchased either on the farm, at another location, or both. Finally, when asked if they would be interested in purchasing FSM in the future, 781 (95.59%) respondents said "maybe," "probably yes," or "definitely yes."

Demographic Impact Analyses

Analyses were done in Stata 16.1 (StataCorp LLC, College Station, TX). Respondent demographics were described using tabulate and summarize commands. Logit models (using the *logit* commands in Stata) were used to determine the variables associated with respondents that 1) had heard of local farmstead milk (FSM1), 2) had previously purchased local farmstead milk (**FSM2**), and 3) had an interest in purchasing local farmstead milk in the future (**FSM3**). Each model used the same respondents, and respondents were excluded from the model if they did not have answers to questions corresponding to each variable (61 excluded; n = 756). Each model's dependent variable was analyzed for correlation using the *corr* command. Have heard of (FSM1) had a strong correlation to have purchased (r = 0.773) and a weak correlation to interested in purchasing FSM in the future (FSM3; r = -0.011). Have purchased (FSM2) had a weak correlation to interested in purchasing FSM in the future (FSM3; r = 0.073). *Margins dydx(*)*, *estat classification*, and *estat summarize* commands were used to analyze the results further. Collinearities and confounding effects were checked with *regression* commands and *estat VIF*

[1] Respondent descriptors can be compared to Tennessee's census data in Tables 4 and 5.

commands. The model was further validated using a multivariate probit analysis (*mvprobit* command); results of this analysis are located in Table 9.

Table 2. Multivariate probit analysis of the impacts of Tennessee consumer demographics on whether or not they had heard of farmstead milk prior to the study, purchased farmstead milk in the past, and their interest in purchasing farmstead milk in the future

	FSM1: Have heard of farmstead milk		**FSM2: Have purchased farmstead milk in the past**		**FSM3: Interested in purchasing farmstead milk in the future**	
Variable Name[1]	**Estimated Coefficient**	**Standard Error**	**Estimated Coefficient**	**Standard Error**	**Estimated Coefficient**	**Standard Error**
West Tennessee	-0.498***	0.138	-0.373***	0.144	-0.049	0.250
Middle Tennessee	-0.173	0.111	-0.204*	0.108	-0.113	0.210
Age (yr)	-0.017***	0.003	-0.020***	0.003	-0.010	0.006
Current local purchase habits	0.357***	0.054	0.404***	0.056	0.241	0.105
Farm background	0.297**	0.118	0.501***	0.115	0.391	0.265
Rural location	0.001	0.121	-0.061	0.121	0.335	0.254
Children < 12 yr	0.280**	0.142	0.258*	0.138	0.264	0.306
College education (≥ bachelor's)	0.204*	0.115	0.235**	0.115	0.105	0.216
Male	0.123	0.104	0.264**	0.103	-0.143	0.187
Weekly food budget ($/wk)	0.001	0.001	0.001	0.001	0.003	0.002
Weekly dairy expenditure ($/wk)	0.001	0.006	0.007	0.006	-0.003	0.011
Household (count)	-0.010	0.043	-0.025	0.043	-0.155	0.078
Income ($/yr)	7.98e-07	1.56e-06	-7.84e-08	1.56e-06	-3.31e-06	2.96e-06
Married	0.112	0.114	0.287**	0.113	0.646	0.226

…
N = 756
Wald chi2(42) = 225.89
Log likelihood ratio = -735.50829
Prob > chi2 = 0.0000

Notes: * indicates $P < 0.10$, ** indicates $P < 0.05$, and *** indicates $P < 0.01$
[1]reference Table 2 for full list of variables, variable definitions, and the explanation of base variables (ex. East TN)

Model 1 (FSM1) and model 2 (FSM2) had the same independent variables, while model 3 (FSM3) included all independent variables seen in both prior models and two additional independent variables: have heard of and have purchased.

$$FSM_1 = \beta_0 + \beta_1 TNregion + \beta_2 age + \beta_3 local + \beta_4 farm + \beta_5 rural + \beta_6 children + \beta_7 college + \beta_8 gender + \beta_9 weekly\ food\ budget + \beta_{10} weekly\ dairy\ expenditure + \beta_{11} household\ number + \beta_{12} income + \beta_{13} married \quad (1)$$

$$\mathrm{FSM}_2 = \beta_0 + \beta_1 \mathrm{TNregion} + \beta_2 \mathrm{age} + \beta_3 \mathrm{local} + \beta_4 \mathrm{farm} + \beta_5 \mathrm{rural} + \beta_6 \mathrm{children} + \beta_7 \mathrm{college} + \beta_8 \mathrm{gender} + \beta_9 \text{weekly food budget} + \beta_{10} \text{weekly dairy expenditure} + \beta_{11} \text{household number} + \beta_{12} \mathrm{income} + \beta_{13} \mathrm{married} \quad (2)$$

$$\mathrm{FSM}_3 = \beta_0 + \beta_1 \mathrm{TNregion} + \beta_2 \mathrm{age} + \beta_3 \mathrm{local} + \beta_4 \mathrm{farm} + \beta_5 \mathrm{rural} + \beta_6 \mathrm{children} + \beta_7 \mathrm{college} + \beta_8 \mathrm{gender} + \beta_9 \text{weekly food budget} + \beta_{10} \text{weekly dairy expenditure} + \beta_{11} \text{household number} + \beta_{12} \mathrm{income} + \beta_{13} \mathrm{married} + \beta_{14} \text{have purchased} + \beta_{15} \text{have heard of} \quad (3)$$

Sample sociodemographic descriptors are defined and described in Table 2. Briefly, respondents were grouped by education level (college-educated: yes or no), family status (children: yes or no), annual household income level ($5,000 to $150,000), and farm background (yes or no). Respondents' age was reported in years. Annual household income level was asked in categories (options were in increments of $10,000 except for $100,000 to $149,000 and $150,000 or more) to control for and minimize "prefer not to answer" selections as disclosure of annual household income may be considered a sensitive topic.

A local index, called "local," was created to determine the respondent's willingness to purchase local foods based on a series of four Likert-scale questions (1 = not at all, …, 5 = a great deal) about local food purchase desires and actions. The following questions were used to generate the local variable because the series of local statement questions were highly correlated (Cronbach's alpha: 0.8496; see Table 3 for a complete list of pairwise correlations between variables): "I purchase local foods on a regular basis" (2.79 ± 1.11), "I shop at local farmers markets on a regular basis" (3.50 ± 1.20), "I am willing to pay price premiums for local foods" (3.07 ± 1.16), and "I choose my grocer on whether they offer local foods" (3.49 ± 1.32). Responses for each question were averaged together to create our local variable, and the higher the number, the more inclined respondents were to purchase local foods (1 = not at all likely to purchase local foods, …, 5 = purchase local foods a great deal).

Table 5. Lists of Variables with Coding Used in Logit Models for Familiarity with and Purchase Likelihood of Farmstead Milk

Variable Name	**Coding**
TN region (location)	1 = East Tennessee[2]
	2 = Central Tennessee
	3 = West Tennessee
Age	Years
Current local purchase habits (local)	1 = not at all
	2 = a little
	3 = a moderate amount
	4 = a lot
	5 = a great deal
Farm background (farm)	0 = otherwise[2]
	1 = yes
Area of residence (rural)	0 = otherwise[2]
	1 = rural
Children < 12 yr	0 = no/no answer[2]
	1 = children < 12 years
College education (college)	0 = no/no answer[2]
	1 = Bachelor's or Higher
Gender (male)	0 = otherwise[2]
	1 = yes
Weekly food budget (WFB)	$ per week
Weekly dairy expenditure (WDE)	$ per week
Household	Total
Income	$ per year
Marital Status (married)	0 = otherwise[2]
	1 = married
Have heard of farmstead milk[1]	0 = otherwise[2]
	1 = yes
Have purchased farmstead milk in the past[1]	0 = otherwise[2]
	1 = yes
Interested in purchasing farmstead milk in the future	0 = otherwise[2]
	1 = yes

Notes: [1] indicates these variables were not used in only the third model (FSM3; interested in purchasing farmstead milk in the future); [2] indicates the omitted variable level that was the base category for the corresponding variables for each model.

Table 6. Pairwise Correlations between Four Statements Housed within the Local Variable

Variable	"I purchase local foods on a regular basis"	"I purchase local foods on a regular basis"	"I am willing to pay price premiums for local foods"	"I choose my grocer on whether they offer local food"
"I purchase local foods on a regular basis"	1.000	0.623[1]	0.551[1]	0.578[1]
"I purchase local foods on a regular basis"	0.623[1]	1.000	0.599[1]	0.587
"I am willing to pay price premiums for local foods"	0.551[1]	0.599[1]	1.000	0.592[1]
"I choose my grocer on whether they offer local food"	0.578[1]	0.587[1]	0.592[1]	1.000

Note: [1]Pairwise correlation was significant at $P < 0.05$.

Results and Discussion

Farmstead Milk Budget

Respondents who purchased FSM in the past purchased it an average of 30 times per year (n = 817, or 2.5 times per month) and indicated they purchased 6.6 L at each purchase (n = 741; those who selected "prefer not to answer" were not included). When asked how much respondents would spend on FSM per purchase, they indicated they would spend $1.41/L (n = 735; those who selected "prefer not to answer" were not included). Using these numbers, we concluded that TN consumers would be willing to spend $178.00 ± $190.94 annually on FSM. Given that respondents spent $552.24 ± 494.52 on dairy products, TN consumers would spend approximately 32% of their yearly dairy products budget on FSM.

Demographic Impacts across Familiarity with and Purchase Likelihood of Farmstead Milk

The impacts of the variables on each dependent variable can be viewed in Tables 6, 7, and 8. Only two variables were significant in all three models; the first was age. As respondents aged one year, the probability of hearing of FSM decreased by 0.54% ($P < 0.001$, see Table 6). As age increased by one year, respondents were 0.55% less likely to have purchased FSM ($P < 0.01$, see Table 7), and 0.09% less likely to be interested in purchasing FSM in the future ($P < 0.10$, see Table 8). Our results confirmed research by Keeling Bond, Thilmany, and Bond (2009) that found older, single consumers were less likely to purchase local products than younger, married respondents ($P < 0.05$). Another study of in-state produced ornamental plants found that older individuals were less likely to purchase in-state grown plants ($P < 0.01$) (Khachatryan et al., 2018). However, results from this study differed from Best and Wolfe (2009), who found that consumers between 25 and 64 years of age had a higher purchase likelihood of local products. Despite our findings and prior discussed literature, most literature reports that age does not impact consumers' knowledge of, purchase likelihood for, and willingness to pay for local produce and dairy products (Patterson et al., 1999; Zepeda and Li, 2006; DeLong et al., 2020).

Table 7. Logistic Regression That Determined the Impact of Tennessee Consumer Demographics on Whether or Not They Had Heard of Farmstead Milk Prior to the Study

Variable Name[1]	**Estimated Coefficient**	**Standard Error**	**Marginal Effect**	**Standard Error**
West Tennessee	-0.822***	0.228	-0.164***	0.044
Middle Tennessee	-0.273	0.184	-0.055	0.037
Age (yr)	-0.027***	0.006	-0.005***	0.001
Current local purchase habits	0.575***	0.090	0.115***	0.016
Farm background	0.504***	0.194	0.101***	0.038
Rural location	-0.021	0.200	-0.004	0.040
Children < 12 yr	0.460*	0.243	0.092*	0.048
College education (≥ bachelor's)	0.312*	0.190	0.062*	0.038
Male	0.180	0.173	0.036	0.034
Weekly food budget ($/wk)	0.001	0.001	2.64e-04	2.28e-04
Weekly dairy expenditure ($/wk)	0.002	0.010	3.60e-04	0.002
Household (count)	0.010	0.073	0.002	0.015
Income ($/yr)	7.96e-07	2.57e-06	1.59e-07	5.14e-07
Married	0.175	0.188	0.035	0.037
…				
N = 756				
LRchi2(14) = 158.55				
Log likelihood ratio = -442.032				
Pseudo R2 = 0.152				
Correctly classified 67.72%				

Notes: * indicates $P < 0.10$, ** indicates $P < 0.05$, and *** indicates $P < 0.01$
[1]Reference Table 2 for full list of variables, variable definitions, and the explanation of base variables (e.g., East TN)

A possible reason for the decreased awareness and purchase behaviors of FSM as a person ages could be that most FSD enterprises advertise their products through digital media, including, but not limited to, social media channels, farm websites, or online listings (Zaring, 2022). Research shows older individuals use social media less (Hruska and Maresova, 2020). This finding supports the idea that the older the individual, the less likely they are to encounter advertisements for FSM and the operations producing FSM. Further, there may be a confounding effect of digital media advertising not targeting older individuals, which could account for the decreased awareness of and purchase behaviors of FSM. More research should be conducted to assess the impact of social media on advertising on an individual's likelihood to be aware of and purchase FSM products; results could further inform marketing tactics of these operations and increase FSM sales.

The second and final variable to impact all three models was current local purchase habits. As respondents' frequency of purchasing local products increased (1 = not at all willing to purchase,

…, 5 = willing to purchase a great deal), respondents were 11.51% more likely to have heard of ($P < 0.01$; Table 6), 11.56% more likely to have purchased ($P < 0.01$; Table 7), and 1.84% more likely to be interested in purchasing FSM in the future ($P < 0.05$; Table 8). These results were expected because purchasing local foods often requires visiting websites such as PickTN (https://www.picktnproducts.org/) or farmers markets, which expose patrons to different FSM products. The findings suggest that targeting markets that currently purchase local agricultural products may lead to a higher success rate for FSM operations.

Table 8. Logistic Regression That Determined the Impact of Tennessee Consumer Demographics on Whether or Not They Had Purchased Farmstead Milk in the Past

Variable Name[1]	**Estimated Coefficient**	**Standard Error**	**Marginal Effect**	**Standard Error**
West Tennessee	-0.676***	0.253	-0.112***	0.041
Middle Tennessee	-0.361*	0.201	-0.060*	0.033
Age (yr)	-0.033***	0.006	-0.005***	0.001
Current local purchase habits	0.701***	0.098	0.116***	0.014
Farm background	0.845***	0.207	0.140***	0.033
Rural location	0.008	0.223	0.001	0.037
Children < 12 yr	0.481*	0.254	0.079*	0.041
College education (≥ bachelor's)	0.326	0.208	0.054	0.034
Male	0.419**	0.187	0.069**	0.030
Weekly food budget ($/wk)	0.001	0.001	1.78e-04	1.95e-04
Weekly dairy expenditure ($/wk)	0.013	0.010	0.002	0.002
Household (count)	-0.034	0.078	-0.006	0.013
Income ($/yr)	1.75e-07	2.78e-06	2.89e-08	4.58e-07
Married	0.442**	0.208	0.073**	0.034
…				
N = 756				
LRchi2(14) = 209.59				
Log likelihood ratio = -379.14				
Pseudo R2 = 0.217				
Correctly classified 77.12%				

Notes: * indicates $P < 0.10$, ** indicates $P < 0.05$, and *** indicates $P < 0.01$

[1]Reference Table 2 for full list of variables, variable definitions, and the explanation of base variables (ex., East TN)

Table 9. Logistic Regression That Determined the Impact of Tennessee Consumer Demographics on Whether or Not They Had Interest in Purchasing Farmstead Milk in the Future

Variable Name[1]	Estimated Coefficient	Standard Error	Marginal Effect	Standard Error
West Tennessee	-0.158	0.567	-0.006	0.021
Middle Tennessee	-0.292	0.451	-0.011	0.017
Age (yr)	-0.025*	0.013	-0.001*	4.90e-04
Current local purchase habits	0.504**	0.241	0.018**	0.009
Farm background	0.707	0.572	0.026	0.021
Rural location	0.660	0.536	0.024	0.020
Children < 12 yr	0.515	0.671	0.019	0.025
College education (≥ bachelor's)	0.340	0.466	0.012	0.017
Male	-0.367	0.400	-0.013	0.015
Weekly food budget ($/wk)	0.008*	0.004	2.79e-04*	1.51e-04
Weekly dairy expenditure ($/wk)	-0.009	0.024	-3.43e-04	8.94e-04
Household (count)	-0.306*	0.164	-0.112*	0.006
Income ($/yr)	-7.42e-06	6.33e-06	-2.71e-07	2.33e-07
Married	1.308***	0.494	0.048***	0.020
Have purchased	1.184*	0.611	0.043*	0.023
Have heard of	-1.129**	0.465	-0.041**	0.018
…				
N = 756				
LRchi2(16) = 37.85				
Log likelihood ratio = -110.45				
Pseudo R2 = 0.146				
Correctly classified 95.90%				

Notes: * indicates $P < 0.10$, ** indicates $P < 0.05$, and *** indicates $P < 0.01$
[1]Reference Table 2 for full list of variables, variable definitions, and the explanation of base variables (ex., East TN)

Four variables were significant in two of the three FSM models; the first was farm background. Respondents with a farm background were 10.09% more likely to have heard of FSM ($P < 0.01$; Table 6) and 13.95% more likely to have purchased FSM in the past ($P < 0.01$; Table 7). However, a farm background did not significantly impact future interest in purchasing FSM (see Table 8). Prior literature varies on how farm background impacts consumers' familiarity with and purchase likelihood of local products. A survey of southeast Missouri residents reported that those with a farm background who lived in rural locations were more likely to search out locally grown foods and pay a higher premium for local foods versus conventional food products (Brown, 2003). Similar research found that TN consumers were more willing to pay for local dairy products labeled with a "Made with Tennessee Milk" logo but were not likely to pay a higher price for the logo (Regmi et al., 2020). Converse to our second model (past purchases), but like our third model (interest in purchasing FSM in the future), DeLong et al. (2020) reported that a farm background did not influence a consumer's decision to purchase milk with a "Tennessee Milk" logo.

Possible reasons for why respondents were more likely to have heard of FSM and purchased it in the past if they had a farm background might be because they understand the work local farmers have devoted to their products and want to support those farms local to them, or possibly even those operations and individuals they know. However, those with a farm background were no more or less likely to be interested in purchasing FSM in the future than those without a farm background. Thus, consumers without farm backgrounds could have similar motives of supporting farms close to their community than those with farm backgrounds. More studies should be done to understand the motivations behind consumer purchase intentions of local dairy products to understand how one's background and experiences could impact them.

Marital status was another variable that impacted two of the three FSM models. Married respondents were no more likely than unmarried respondents to have heard of FSM (see Table 6), but they were 7.29% more likely to have purchased FSM in the past ($P < 0.05$; Table 7) and 4.78% more likely to be interested in purchasing FSM in the future than unmarried individuals ($P < 0.01$; Table 8). Little research has explored how marital status impacts FSM or local food purchasing habits, but what research exists differs from our results. Keeling Bond, Thilmany, and Bond (2009) found that younger and single individuals were less likely to purchase locally grown produce than older married individuals. Another study determined that unmarried customers had a higher willingness to pay for locally produced and processed steaks (Maynard, Burdine, and Meyer, 2003). Possible reasons for these differences might be attributed to the fact that our study focused on dairy products, while these studies focused on locally produced meats and produce. Differences could also be attributed to the fact that the previous studies were conducted more than 12 years before this study.

Another significant variable in two of the three models was the presence of children in the home. If children under 12 years of age were present in the house, respondents were 9.20% more likely to have heard of FSM ($P < 0.10$; Table 6) and 7.93% more likely to have purchased FSM in the past ($P < 0.10$; Table 7). However, the presence of children did not alter an individual's likelihood of purchasing FSM in the future (see Table 8). This result was consistent with studies conducted by Regmi et al. (2020) and Khanal, Lopez, and Azzam (2020), who found that the presence of children did not impact purchase intentions of local dairy products. On the other hand, Best and Wolfe (2009) and Patterson et al. (1999) found a greater likelihood of purchasing local products when children were present in the home. Additionally, research stated that households with children under 19 years of age had an overall higher willingness to pay for locally produced and processed meats (Maynard, Burdine, and Meyer, 2003) and would pay \$0.038/L premium for milk advertised with added health properties and \$0.429/kg premium for butter with the same advertisements (Maynard and Franklin, 2003).

These results suggest that while households with children may not be more likely than households without children to purchase FSM in the future, they were more likely to have heard of and purchased FSM in the past, but that local products, such as milk, sold to households with children may command a higher price. This finding suggests that households with children are more often marketing targets than households without, and that operations should consider marketing channels carefully to ensure they are reaching a wide range of individuals, including those without children present in the household. More research should be done to understand where households with children are becoming familiar with FSM and other local products, as this information can be used to discover untapped marketing channels and refine targeted marketing tactics further.

During data collection, respondents were enlisted from West, Middle, and East TN. The West TN and Middle TN regions were independently compared to East TN in each model to determine how region impacted whether respondents had heard of, purchased FSM in the past, or intended to purchase FSM in the future. West TN was the final variable to impact two of the three models, while Middle TN impacted only one model. West TN was 16.44% less likely to have heard of FSM ($P < 0.01$; Table 6) and 11.16% less likely to have purchased FSM ($P < 0.01$; Table 7) than those in East TN. Individuals in Middle TN were 5.96% less likely to have purchased FSM in the future ($P < 0.10$; Table 7) when compared to those in East TN. These results show that individuals in East and Middle TN were both equally and most likely to have heard of FSM, but those in Middle TN were most likely to have purchased FSM in the past. However, individuals in each region were equally likely to be interested in purchasing FSM in the future.

In 2022, 54% of dairy operations in TN were located in East TN, 38% were in Middle TN, and 8% were in West TN (J. Strasser, Tennessee Department of Agriculture, Nashville, TN, personal communication). As of 2021, 56% of the current and prospective FSD enterprises were in East TN, 38% were in Middle TN, and 6% were in West TN (Zaring, 2022). Additionally, approximately 37% of the TN population lives in East TN, 42% in Middle TN, and 22% in West TN (U.S. Census Bureau, 2022). Understandably, East and Middle TN respondents are most likely to have heard of FSM, as most FSD and TN residents are in these regions. Despite Middle TN having a smaller concentration of FSD than East TN, the majority of these operations are located near densely populated areas within Middle TN, unlike those in East TN, which are far enough away from densely populated areas that the advertising and sale of products is more difficult. This factor contributes to why those from Middle TN were most likely to have purchased FSM in the past and why those in West TN were least likely. Interestingly, all regions' respondents were equally likely to be interested in purchasing FSM in the future. This information can help to inform marketing analyses for dairies considering opening a FSD operation in West TN.

In addition to the Middle TN region, six other variables impacted a single model. The first was college education. Respondents with a bachelor's degree or higher were 6.24% more likely to have heard of FSM ($P < 0.10$; Table 6), but college education did not impact past or future purchase intentions. Similar to this study's findings, an Arizona study found that respondents who had a bachelor's degree or higher were more likely to be aware of the local promotional program known as "Arizona Grown" (Patterson et al., 1999). Other research reported that college education did not impact purchase likelihood or willingness to pay for local produce and dairy products (Brown, 2003; Khachatryan et al., 2015; DeLong et al., 2020).

As household size increased by 1, respondents were 1.12% less likely to be interested in purchasing FSM ($P < 0.10$; Table 8). Of the literature reviewed, only one study found similar results. Khanal, Lopez, and Azzam (2020) found that respondents were 0.4% less likely to prefer local milk as household size increased by 1. Farmstead milk is a specialty product that can command a higher price than conventional milk bought in a grocery store or supermarket. It may be less feasible to purchase a higher-priced specialty product, especially when it is a household staple, as household size increases.

Contrary to this study's findings, other studies have found a positive relationship between household size and the purchase likelihood of local produce and locally produced ornamental plants (Zepeda and Li, 2006; Khachatryan et al., 2015). Finally, a study found that household size did not impact a respondent's purchase likelihood for locally produced milk labeled with a state promotional label (DeLong et al., 2020). The DeLong et al. (2020) study and this study were administered to a similar population (TN milk consumers) using the same platform. However, DeLong et al. (2020) focused on the purchase intention of locally produced milk with a state promotional logo attached and did not consider FSM as our study did. Thus, this subject matter distinction is large enough to justify the difference in results.

Our study revealed that males were 6.92% more likely to have purchased FSM ($P < 0.05$; Table 7) than females. This result was notable because the primary household food shopper has been consistently identified as female (Schafer and Schafer, 1989; DeLong et al., 2020). However, these results are consistent with Best and Wolfe (2009), who state that males had a higher purchase likelihood for locally produced dairy products. This finding indicated a narrower pool of consumers than initially anticipated, and further studies may be warranted to understand why men were more likely to purchase FSM than women. One likely reason males have purchased more in TN FSM might be due to promotional milk campaigns, such as the "Fuel up to play 60" campaign, between the Dairy Alliance and the Tennessee Titans professional football team promoting whole chocolate milk as a pre- and post-workout recovery drink. Such advertising campaigns targeted to men could have impacted respondents' purchase likelihood because of the exposure to whole milk campaigns as a health and fitness component.

However, men were no more likely to have heard of or be interested in purchasing FSM in the future than females (see Tables 6 and 8). Another study found that females were likely to pay more for local products (Brown, 2003), while Regmi et al. (2020) and DeLong et al. (2020) found that gender did not impact whether TN consumers would be more likely to purchase or pay more for milk products with a "Made with Tennessee Milk" logo and milk with a "Tennessee Milk" logo, respectively. Further, an Iranian study found that females were more likely to purchase full-fat yogurt and cream cheese than males (Ahmadi Kaliji et al., 2019). However, males were more likely to purchase butter (Ahmadi Kaliji et al., 2019). Future work could examine drivers of preference differences for FSM by gender.

The variables "have purchased FSM in the past" and "have heard of FSM" were included in the "interested in purchasing" model. Those who had purchased FSM in the past were 4.33% more likely to be interested in purchasing in the future ($P < 0.10$; Table 8), indicating that those who have purchased before have had good experiences and would be willing to purchase again. Additionally, FSM is not a novel product, so there is less hesitation than there could be for a new purchaser who wants to avoid different products. Respondents who had heard of FSM were 4.13% less likely to be interested in purchasing it in the future ($P < 0.05$; Table 8), possibly because, as discussed earlier, they are comfortable with the milk they usually purchase and thus are less inclined to purchase something novel to them. Another possible reason could be that respondents who had heard of FSM may not have been informed sufficiently; the information they were given was not enough to entice them; or they were not satisfied with the information provided and possibly did not trust FSM products. They may have been unwilling to pay a price premium for FSM, or they did not know where to purchase FSM.

Respondents were 0.03% more likely to be interested in purchasing FSM as their weekly food budget increased ($P < 0.10$; Table 8), possibly because of the greater amount that could be spent on specialty food products, such as FSM. However, weekly food budget had no significant effects on whether a respondent had previously heard of or purchased FSM. The impact weekly food budget has on intent to purchase FSM is significant but minute, suggesting that those with a larger food budget are more likely to be interested in purchasing; however, respondents with a lower weekly food budget should not be excluded as potential FSM consumers.

Another financial variable considered in each model was weekly dairy expenditure, which did not significantly impact a respondent's awareness or purchase decisions of FSM. This result differed from many other published research. A prior "Tennessee Milk" logo study found that as consumers spent more on milk per month, the more likely they were to purchase milk with a TN milk logo and that as their weekly budget for milk increased by \$10, consumers were 7% more likely to purchase logoed milk (DeLong et al., 2020). Another TN survey found that spending more on dairy products improved the likelihood of consumers purchasing locally produced and processed milk (Regmi et al., 2020). This study found that TN consumers with higher weekly dairy expenditures were willing to pay \$0.115 premiums for milk products labeled with a "Made with Tennessee Milk" logo. Results of this study may differ from other studies because they did not ask about a weekly food budget in addition to weekly dairy budget. Weekly dairy expenditure may not have been relevant because the impact was seen with weekly food budget. Perhaps respondents place more weight on an overall food budget than a budget grouped by food types.

Like weekly dairy expenditure, income did not impact awareness or purchase decisions of FSM. Studies by Patterson et al. (1999), Brown (2003), and DeLong et al. (2020) reported that income had no significant impacts on awareness of or purchase likelihood for local produce and dairy products. Regmi et al. (2020) reported that annual income did not impact consumers' willingness to pay for dairy products labeled with a "Made with Tennessee Milk" logo.

However, a study of local produce in the southeast United States found that consumers with an annual income greater than \$30,000 were more likely to purchase local produce (Best and Wolfe, 2009), while another survey found that consumers with an annual income of greater than \$66,000 were 1.5% more likely to purchase local fluid milk than non-local milk (Khanal, Lopez, and Azzam, 2020). Other studies of local foods, local ornamental plants, and local dairy products found that the higher their annual income, the less likely consumers were to purchase these products (Zepeda and Li, 2006; Khachatryan et al., 2015; Ahmadi Kaliji et al., 2019). Brown (2003) found that household income greater than $50,000 equated to a higher willingness to pay for local produce.

The differing result could be partly due to the location and time of the study or similar to weekly food budget and weekly dairy expenditures, many studies only factored in one financial variable. Specifically, studies by DeLong et al. (2020) and Regmi et al. (2020) factored in both weekly dairy expenditure and income, and the effect of financials may have been captured with weekly dairy expenditure rather than income. In contrast, other studies such as Khachatryan et al. (2015) and Brown (2003) factored the financial impact of income alone and found a significant effect on willingness to pay.

Finally, the respondent's area of residence (rural versus urban) had no significant impact on whether or not they had heard of, had purchased, or would be likely to purchase FSM in the future (see Tables 6–8). Findings from our study confirm prior research in TN, which found that area of residence did not impact whether a person would purchase "Made with Tennessee Milk" dairy products (Regmi et al., 2020). However, our research counters other studies from different locations. One found that consumers in rural locations were less likely to prefer "Arizona Grown" local produce (Patterson et al., 1999), while another study of local produce found urban consumers were less likely to purchase locally produced items (Keeling Bond, Thilmany, and Bond, 2009). Regional differences in preference and perceptions of these programs may account for some discrepancies.

Closing Remarks

This study provided insight into what type of consumer an FSD business could target with the greatest likelihood of purchasing FSM products. Younger, married individuals with a farm background and children present in the home who lived in East or Middle TN and frequently purchased local foods were more likely to have heard of or purchased FSM. Results show that while a narrower group of people have purchased FSM before, the type of person who could be interested in purchasing FSM varies greatly.

One limitation of this study was that the survey was representative of a snapshot in time, specifically during COVID-19. As consumers and markets constantly evolve, some results would likely change if this study were conducted today. While these results are specific to a particular time in TN, they can and should still be used to guide marketing strategies for FSD operators across the state. Additional research, such as marketing analyses, should be done on the target marketing area to provide a complete and up-to-date view of the consumers within the market area. This is especially true for rural areas and those with limited computer access, as this survey was administered online and did not include those without internet access, which could exclude 18% of the population (National Center for Education Statistics, 2019).

This survey targeted TN consumers and only analyzed FSM. More studies should be done for other farmstead dairy products, such as cheese and ice cream, and should be expanded to surrounding states to determine why customers choose certain products. Understanding these concepts could aid extension personnel in providing FSD with likely customers, increase visits and sales, and create targeted marketing materials.

While these results should not be used alone, they can be used in addition to supplementary research to guide marketing strategies for other farmstead agricultural industries and FSD across the United States. This study revealed that a person's background, former experiences, lifestyle, and demographics may influence their purchase intentions. Further studies should be conducted to understand why these factors affect purchase intentions. Understanding these influences can further inform business owners and their marketing strategies. Using this information, FSD owners and managers can alter where they market their products and to whom they market. For example, older individuals are less likely to have heard of, purchased, or be interested in purchasing FSM. If researchers can understand why older individuals are less likely to purchase, solutions can be created to encourage those individuals to purchase. Businesses can tailor their marketing tactics, possibly by providing more print advertisements or targeting older demographics with online ads.

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