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Economic Impact of Values-Based Supply Chain Participation on Small and Midsize Produce Farms

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Abstract

Midsize farms can improve economic viability using alternative marketing channels such as values-based supply chains (VBSCs) that market products differentiated by locality, quality, environmental, social, or health claims. We simulated the economic impact of VBSCs using secondary data and survey data from VBSC-participating farms. Across all simulation scenarios, average net economic impacts from VBSC participation was positive, where 47% of farms showed a net benefit, with wholesale-leaning farms benefiting most. VBSC economic benefits may result from lower marketing costs relative to direct marketing and higher prices than conventional wholesale. While most farms showed small or negative net economic impacts, most also reported noneconomic benefits of VBSC participation.

Keywords: direct marketing, economic impact, farm viability, marketing channels, values-based supply chains, wholesale

Introduction

For decades, the U.S. Department of Agriculture (USDA) and researchers have been concerned about the economic viability of U.S. family farms as the sector trends toward concentration into larger farms alongside many small farms (Burns and Kuhn, 2014; Feenstra and Hardesty, 2016). Meanwhile, the decline of small and midsize commercial farms, collectively called Agriculture of the Middle (AOTM), hollows out the midscale sector that accounts for 36% of all farms, 39% of the value of production, and 50% of all agricultural lands (USDA, 2017b). AOTM farms support rural economies through household income, hired labor, and natural resource management and may contribute to food system resilience in the face of climate change, economic disruptions, and other disturbances (Clancy and Ruhf, 2010; Stevenson et al., 2011; Low et al., 2015; Feenstra and Hardesty, 2016; Duncan et al., 2018).

AOTM farms are positioned to improve their economic viability by participating in midscale supply chains selling products that are differentiated by place or production practices (Lev and Stevenson, 2011; Low et al., 2015; Berti and Mulligan, 2016; Matteson, 2017). While significant research attention has focused on local and regional food marketing in the United States, little research has looked into the tradeoffs that farms face when presented with midscale marketing channels that better match AOTM production and marketing scale and diversify farm marketing portfolios (Low et al., 2015; Angelo, Jablonski, and Thilmany, 2016; Bauman, Thilmany, and Jablonski, 2017; Conner et al., 2017).

We examine marketing channel tradeoffs to assess the economic impact of intermediated midscale marketing through values-based supply chain businesses (VBSCs) on a sample of AOTM farms. VBSCs aggregate, process, market, and distribute food products that are differentiated by locality, quality, environmental, social, or health claims at regional levels while engaging in equitable business relationships with producers (Stevenson et al., 2011; Berti and Mulligan, 2016; Feenstra and Hardesty, 2016; Tanaka et al., 2017). Partnering with 17 VBSCs nationwide, we obtained 182 usable survey responses from diversified vegetable and fruit farms that sold a portion of their crops to the partnering VBSC in 2016. Marketing channel studies have focused on farms selling fresh vegetables, berries, fruits, nuts, and other products because they face comparable options and challenges: year-round production of multiple perishable products, direct marketing competition at retail prices, and high financial performance in direct and intermediated marketing channels despite high labor costs (Hardesty and Leff, 2010; LeRoux et al., 2010; Park, Mishra, and Wozniak, 2014; Matteson, 2017; Bauman, Thilmany, and Jablonski, 2017; Bauman, McFadden, and Jablonski, 2018).

Utilizing the Tradeoff Analysis for Multi-Dimensional Impact Assessment framework (TOA-MD) (Antle, Stoorvogel, and Valdivia, 2014), we assess the potential economic impact of VBSC marketing on these AOTM farms. Averaging results across all simulation scenarios, we found that 47% of farms would see a net revenue benefit from VBSC marketing, with higher-sales, wholesale-leaning farms benefiting the most. Farms with a preference for direct marketing tended to experience less positive economic benefits from VBSC participation but may choose to participate for other reasons, including an inability to sell more volume or imperfect product through direct markets, relationship-building to scale up production, or other marketing risk management goals. Our results can inform decisions by midsize farmers considering new marketing channels, decisions by VBSCs and other supply chain partners, and policy decisions that address the declining AOTM.

Marketing Channel Tradeoffs for AOTM Farms

AOTM farms are neither very small nor large; in our sample, the two middle-income categories report gross income of US$100,000–$499,999 and $500,000–$999,999. AOTM farms tend to be family-owned and operated, generally categorized as "farming occupation farms" and "midsize family farms" by the USDA, and use production and marketing strategies that tend to emphasize differentiation of products and marketing channels (Agriculture of the Middle, n.d.; Feenstra and Hardesty, 2016). AOTM farms have been in steady decline for decades. Recent data show that from 2011 to 2016, the number of farms in the "farming occupation farms" and "midsize family farms" typologies fell by 9%, a decline of almost 69,000 farms in five years, compared to a decline of 6% for all farms. Meanwhile, 17,814 large and very large farms were added over the same period, a 42% increase, resulting in continued growth in average farm size in the United States (Burns and Kuhns, 2016; USDA, 2017).

The decline in AOTM farms is a result of multiple, interrelated structural factors that are linked to a lack of midscale marketing channels that fit AOTM production volume, such as local and regional intermediated supply chains that include retail, restaurants, institutions, food hubs, or distributors (Agriculture of the Middle, n.d.; Lev and Stevenson, 2011; Stevenson et al., 2011; Low et al., 2015; Berti and Mulligan, 2016). AOTM farms (over $75,000 gross cash farm income [GCFI] in Low et al., 2015) reported higher local and regional sales from intermediated channels than direct-alone or a mix of channels, with local and regional sales growing to an estimated $6.1 billion in 2012, 55% of which came from farms exclusively using intermediated channels.

Marketing skills, management of variable expenses, and farm scale are important determinants of sales and financial efficiency for farms using direct or intermediated marketing, suggesting that there are economies of scale at play that AOTM farms are equipped to achieve (Park, Mishra, and Wozniak, 2014; Bauman, Thilmany, and Jablonski, 2017). However, there is significant heterogeneity in financial efficiency, profitability, and other metrics of financial performance for those using direct and intermediated channels; some small and midsize farms outperform the highest grossing farms, indicating that matching farm production and marketing scale is a key to success at all farm scales (Bauman, Thilmany, and Jablonski, 2017; Bauman, McFadden, and Jablonski, 2018).

Values-based supply chains (VBSCs) are one type of intermediated midscale marketing option that (i) aggregates, processes, markets, and distributes a significant volume of food products that are differentiated by locality, quality, environmental, social, or health claims; (ii) operates effectively at regional levels; and (iii) distributes profits equitably among the supply chain participants, including producers (Stevenson et al., 2011; Berti and Mulligan, 2016; Feenstra and Hardesty, 2016; Tanaka et al., 2017). Recent research found 278 VBSCs in the United States that market on clearly articulated values claims such as local and environmentally sustainable practices. VBSCs can take the form of food hubs, producer co-operatives, private business entities that operate as processors and/or distributors, or others (Tanaka et al., 2017).

Past marketing channel case studies compared farm profitability for various direct and wholesale channels (Hardesty and Leff, 2010; King et al., 2010; LeRoux et al., 2010; Pesch and Tuck, 2015), while studies using national-level data compared financial performance of farms using direct and intermediated local marketing channels (Park, Mishra, and Wozniak, 2014; Park, 2015; Bauman, Thilmany, and Jablonski, 2017; Ahearn, Liang, and Geotz, 2018; Bauman, McFadden, and Jablonski, 2018). Our analysis contributes to this research by employing results from a survey instrument that provides more detailed data on farm price and cost tradeoffs in marketing channels than national-level data but less detailed financial data than a small case study. To analyze the survey results, we employ the Tradeoff Analysis for Multi-Dimensional Impact Assessment (TOA-MD) framework, a parsimonious simulation approach that has been used extensively to analyze the impacts of technology adoption on an agricultural sector (Antle and Valdivia, 2006; Antle, 2011; Claessens et al., 2012; AgMIP, 2017; Antle et al., 2018). Because it is difficult to obtain specific income, price, and cost data from farmers in a survey, this simulation approach allows us to estimate the distribution of the net economic impact of VBSC participation by combining secondary data with farm survey responses on the direction of farm price and cost differences between direct marketing, VBSCs, and conventional wholesale channels.

When presented with a new technology, in this case a marketing channel with different economic parameters, farmers are assumed to make a rational choice by allocating sales to different channels based on expected economic returns: revenue minus production and marketing costs. Here we treat production volume and costs as predetermined by the farms and only consider the marketing decision, consistent with previous research (Hardesty and Leff, 2010; LeRoux et al., 2010). Thus, farm net returns in market channel studies depend on the mix of marketing channels selected and the prices received in each channel relative to marketing costs, other constraints such as volume and risk, and farm-level characteristics (Neven et al., 2009; Hardesty and Leff, 2010; King et al., 2010; LeRoux et al., 2010; Park, Mishra, and Wozniak, 2014). Producers assess the tradeoffs in each channel, filling demand in their preferred channel then sending additional product to other channels. Furthermore, diversifying the marketing portfolio can reduce marketing risk and increase overall profitability, where the optimal marketing portfolio depends on farm characteristics and operator management skills and preferences (Hardesty and Leff, 2010; LeRoux et al., 2010; Diamond and Barham, 2011; Park, Mishra, and Wozniak, 2014; Bauman, Thilmany, and Jablonski, 2017; Bauman, McFadden, and Jablonski, 2018).

Assessing price tradeoffs, prices are expected to be highest in direct markets, followed by VBSCs, and lowest in conventional wholesale markets (Hardesty and Leff, 2010; King et al., 2010; LeRoux et al., 2010). To some extent, farmers are price makers in direct markets, although their price setting is constrained by competition with other farm direct marketers and consumer willingness to pay above supermarket prices, resulting in direct marketing pricing that is competitive with retail but where producers retain all of the consumers' dollar (Gunderson and Earl, 2010; Day-Farnsworth and Morales, 2011; Park, Mishra, and Wozniak, 2014; Low et al., 2015; Martinez, 2016; Valpiani et al., 2016; Trant et al., 2018). In conventional wholesale, prices are based on a globalized market, where farms compete on price and lose their product identity (Day-Farnsworth and Morales, 2011; McLaren, 2015). VBSC channels promise to pay producers higher prices than wholesale, in part because they sell differentiated products, but price premiums are also limited by conventional retail competition and consumer willingness to pay (Swinnen and Vandeplas, 2014; McLaren, 2015). VBSCs also often set prices paid to farmers on producer-reported cost of production or negotiation, with the goal of passing on a higher share of the retail price to producers (King et al., 2010; Day-Farnsworth and Morales, 2011; Diamond and Barham, 2011; Hardesty et al., 2014; Feenstra and Hardesty, 2016; Tropp and Moraghan, 2017).

Marketing costs are also highest in direct markets and lowest in conventional wholesale. Marketing costs include post-harvest costs such as washing, packing, storage, food safety, handling and transportation; selling costs such as negotiating with a buyer and promotion (e.g., samples, farm tours); and costs (e.g., record keeping, inspections, and fees) for third-party certification such as USDA-certified organic, animal welfare, or food safety certifications (Hardesty and Leff, 2010; LeRoux et al., 2010; Christiansen, 2017). Direct marketing costs are substantially higher than VBSC or wholesale channels due to high labor requirements (stocking, making transactions) and nonlabor costs (transportation, infrastructure, vendor fees, packaging, scales, signage, product liability insurance, licensing) (Hardesty and Leff, 2010; LeRoux et al., 2010). VBSCs have lower marketing costs than direct marketing but likely have higher marketing costs than conventional wholesale because farmers may have to maintain higher-quality product, preserve farm identity, or obtain food safety or environmental certifications, depending on the marketing strategy of the VBSC (King et al., 2010; Diamond and Barham, 2011; Hardesty et al., 2014; Feenstra and Hardesty, 2016; Matteson, 2017).

Volume constraints and marketing risks also determine suitability of marketing channels (LeRoux et al., 2010; Matteson, 2017). Direct markets have lower sales volumes and higher risk of sort-outs and unpaid product (Hardesty and Leff, 2010; LeRoux et al., 2010), some of which comes from overproduction for direct market demand (Trant et al., 2018). From 2007 to 2012, total sales in direct markets have leveled off, declining nearly 1%, while the number of direct marketing farms increased by 5.5% (Low et al., 2015; O'Hara and Low, 2016). Direct markets are also limited by climate, proximity to population centers, and other factors (Born and Purcell, 2006; Park, Mishra, and Wozniak, 2014; Ahearn Liang, and Geotz, 2018; Bauman, McFadden, and Jablonski, 2018). Conversely, wholesale markets take large volumes that preclude some small and midsize farms, or they face the risk of not meeting volume commitments (LeRoux et al., 2010). VBSCs that are committed to working with small and midsize farms help manage marketing risks through negotiation on volume and price commitments, long-term business relationships, transparency, predictable and timely payments, and shared values. Farmers report that VBSC participation reduces marketing stress when their VBSC aligns with their values and production choices (Diamond and Barham, 2011; Stevenson et al., 2011; Feenstra and Hardesty, 2016).

Methods

Survey

We conducted a survey to assess farmers' reasons for, perceptions of, experiences in, and impacts from participating in VBSC marketing channels. The survey was designed for the target population of small to midscale U.S. commercial farms that marketed through a VBSC in 2016. We reached out to more than 30 VBSC businesses, of which 19 agreed to share their supplier lists. Administered by the Social and Economic Sciences Research Center at Washington State University, 1,954 farms were contacted during February through May 2017 following Dillman's Tailored Design Method (Dillman, Smyth, and Christian, 2014), which entails introductory contact, first and second mailing of the questionnaire, and three reminders. The survey was available in hard copy and online, in both English and Spanish. We received 445 responses (27.4% of those that farmed in 2016). In our analysis, we use responses from diversified vegetable farms that sold to 17 of the partnering VBSCs in 2016. Of 274 qualifying responses, 182 responded to key questions and were usable. Statistical patterns in the data were detected using analysis of variance (ANOVA) and χ_2 tests.

TOA-MD Simulation

Using the TOA-MD framework, we define the impact of VBSC participation on farm net returns for an individual farm as farm net returns with VBSC participation (V_1) minus farm net returns without VBSC participation (V_0) (Roy, 1951):

(1) $$Impact = V_1 - V_0.$$

In our case, farm net returns with VBSC participation (V_1) are observed. This return is equal to revenue minus marketing costs from each of the three main channel types: direct marketing (d), wholesale (w), and VBSC (v), where c_m ($m = d$, w, and v) is the ratio of costs to revenue and R_m is revenue from each marketing channel:

(2) $$V_1 = (1 - c_d)R_d + (1 - c_w)R_w + (1 - c_v)R_v.$$

The unobserved counterfactual is farm net returns without VBSC participation, V_0. We assume that without the VBSC channel, the farm allocates VBSC sales to direct marketing and conventional wholesale channels. As such, approximating V_0 requires assumptions on the proportion of VBSC sales that would be allocated to each channel and the price differences between channels. Then, we calculate V_0, where δ is the proportion of VBSC sales allocated to direct marketing, $1 - \delta$ is the proportion of VBSC sales allocated to wholesale channels, and p_m ($m = d, w,$ and v) is the price received in each channel:

(3) $$V_0 = (1 - c_d)R_d + (1 - c_w)R_w + \delta(1 - c_d)R_v\left(\frac{p_d}{p_v}\right) + (1 - \delta)(1 - c_w)R_v\left(\frac{p_w}{p_v}\right).$$

Equation (3) shows the three pieces of information required to estimate VBSC impact on farm net returns: cost-to-revenue ratios in each marketing channel (c_m), the percentage of allocation between the two alternative marketing channels (δ, $1 - \delta$), and relative prices between the marketing channels (p_m). Model parameters were obtained from secondary data and farm-specific reports obtained from the VBSC farmer survey (see Results).

The impact of VBSC marketing on farm net returns (equation 1) is the difference between the net revenue reported from VBSC participation (equation 2) versus the same product sold through only direct and conventional wholesale channels (equation 3). Thus, equation (4) represents the estimated impact of VBSC participation:

(4) $$Impact = (1 - c_v)R_v - \left[\delta(1 - c_d)R_v\left(\frac{p_d}{p_v}\right) + (1 - \delta)(1 - c_w)R_v\left(\frac{p_w}{p_v}\right)\right]$$

The goal of simulation is to obtain the most plausible estimate of the average impact of VBSCs across farms in our sample and the percentage of these farms that benefit from VBSC participation. Because survey responses did not indicate specific magnitudes of these key parameters, equation (1) is simulated for each farm under five scenarios of how VBSC prices compare with direct and wholesale prices to test the sensitivity of results across a range of plausible economic conditions. Each scenario is simulated for 1,000 iterations per farm, resulting in 182,000 simulated impacts. The scenario-specific mean impact is calculated as the mean of impacts across all farms and iterations. The percentage of farms benefiting from VBSCs is defined as the percentage of positive impact values across all farms and iterations in a given scenario. The simulation is carried out using STATA (Stata Corp, 2017).

Results

VBSC Farm Survey and Secondary Data

Table 1 shows select statistics for our sample of farms. The mean operated area in the sample is 264.6 acres, but many farms have much smaller areas, as indicated by the high standard deviation. While the sample includes farms from across the United States, the most represented regions are the Pacific (36%) and the Northeast (27%), both of which were identified by Bauman, McFadden, and Jablonski (2018) as having better market conditions for direct and intermediated sales.

Table 1. Summary Statistics on Survey Respondents

Survey Respondents' Farm and Marketing Characteristics		
Mean operated farm acres (*N* = 182)	264.6 (808.9)	
Percentage of total sales to VBSC (*N* = 182)	25.1%	
Gross cash farm income (*N* = 182)	Percentage of Farms	Percentage Sales to VBSC
$0–$99,999	28.0%	36.8%
$100,000–$499,999	33.0%	24.2%
$500,000–$999,999	11.0%	16.8%
$1,000,000 or more	28.0%	17.7%
Channel choices (*N* = 182)	Percentage of Farms	
Sells to wholesale	64.8%	
Sells to grower/farmer co-operatives	30.8%	
Sells to food co-operatives	45.1%	
Sells direct to consumers	78.0%	
Sells to retailers	76.9%	
U.S. location (*N* = 178)	Percentage of Farms	
Great Lakes, Heartland, Upper Midwest	14.0%	
Northeast	27.0%	
Northwest	14.0%	
Pacific	36.0%	
Other	9.0%	

To simulate the VBSC impact on each farm, we first construct the value of VBSC sales for each farm by randomly drawing a farm income value from the reported income ranges for each farm in each iteration (1,000 iterations per farm). Small and midscale farms (<$500,000 GCFI) account for 61% of our sample (Table 1). For the 28% of farms that reported income above $1 million (with no upper bound), we assigned a randomly drawn income value between $1 million and $3.6 million, based on the $2.3 million mean farm income for large and very large (>$1 million GCFI) U.S. vegetable farms (USDA, 2015).

Next, we multiply the income value by the reported percentage of sales made to VBSCs, which gives each farm's VBSC revenue (R_v) in each iteration. On average, VBSC sales make up about one-quarter of total farm sales. In addition to the partnering VBSCs, 78% of farms sell direct to consumers, 77% sell direct to retailers, 65% sell to wholesalers, 45% sell to food co-operatives, and 31% sell to grower/farmer co-operatives (Table 1). While our analysis only includes data on the tradeoffs between VBSCs, direct marketing, and conventional wholesale, it is important to recognize that farms have multiple intermediated marketing options.

Survey data were also used to specify each farm's ratio of costs to revenue for each marketing channel (c_m, $m = d$, v, and w) and the price ratios (p_d/p_v and p_w/p_v) used in the simulation. Each farm reported whether prices and costs were higher, the same, or lower between the VBSC and other channels; however, the magnitude of differences was not reported. Table 2 summarizes the comparisons with direct marketing in the left half and with conventional wholesale in the right half. The survey included separate questions for labor and nonlabor cost components of post-harvest, marketing, and certification costs, which are combined in the table to determine whether costs can be classified as strictly higher, the same, or lower. The "undetermined" in Table 2 refers to responses where farms reported that either the labor or nonlabor cost component was higher while the other was lower.

Price Tradeoffs

Consistent with the past case studies in the literature, most farms (69%) reported that VBSC prices (p_v) were lower than direct marketing prices (p_d) at venues such as farmers' markets, farm stands, CSAs, or others (Table 2, left half). Compared to conventional wholesale, 37% of farms reported higher prices in VBSCs than wholesale (p_w), while 39% report that prices were the same in both channels, and 24% reported that prices were lower in VBSCs than in wholesale (Table 2, right half).

Cost Tradeoffs

Regardless of prices differences between VBSC and direct marketing outlets, production costs were the same for the majority of farms while marketing costs associated with direct sales tended to be higher, confirming findings by Hardesty and Leff (2010) and LeRoux et al. (2010). Certification costs were reported to be similar (72%) between the direct and VBSC marketing channels (Table 2, left half), while the 14% that reported that VBSC prices were higher than direct marketing prices were the most likely of any price group to report higher production (28%), certification (24%), post-harvest (48%), and marketing (46%) costs, indicating that some may have sought certifications or engaged in other special practices to participate in the VBSC that pays high prices for their products. It would still be rational for those farms to sell to the VBSC if the price premium compensated the higher costs.

The relative costs between VBSC and conventional wholesale are more ambiguous and vary more widely across farms. In all price and cost categories, the most common response was that VBSC and wholesale costs are the same (Table 2, right half). About half of the farms that reported higher

Table 2. Comparison Respondents' Perception of VBSC Prices (p_v) and Costs (c_v) with Direct Marketing Prices (p_d) and Costs (c_d) and Conventional Wholesale Prices (p_w) and Costs (c_w)

VBSC Compared to Direct Marketing Channels						VBSC Compared to Conventional Wholesale Channels					
Output Prices	**Costs[a]**	**Production**	**Post-Harvest**	**Marketing & Selling**	**Certifications**	**Output Prices**	**Costs***	**Production**	**Post-Harvest**	**Marketing & Selling**	**Certifications**
$p_d < p_v$	$c_d < c_v$	28%	48%	46%	24%	$p_w < p_v$	$c_w < c_v$	35%	33%	27%	45%
14%	$c_d \sim c_v$	64%	48%	31%	64%	37%	$c_w \sim c_v$	58%	53%	41%	47%
	$c_d > c_v$	8%	4%	23%	8%		$c_w > c_v$	8%	14%	32%	6%
	Undet.	0%	0%	0%	4%		Undet.	0%	0%	0%	2%
	N_b	25	25	26	25		N_b	66	66	66	64
$p_d \sim p_v$	$c_d < c_v$	3%	7%	20%	17%	$p_w \sim p_v$	$c_w < c_v$	6%	9%	7%	8%
16%	$c_d \sim c_v$	87%	87%	63%	70%	39%	$c_w \sim c_v$	91%	84%	71%	86%
	$c_d > c_v$	10%	7%	13%	13%		$c_w > c_v$	3%	7%	20%	6%
	Undet.	0%	0%	3%	0%		Undet.	0%	0%	1%	0%
	N	30	30	30	30		N	70	70	70	71
$p_d > p_v$	$c_d < c_v$	6%	15%	17%	19%	$p_w > p_v$	$c_w < c_v$	9%	19%	23%	15%
69%	$c_d \sim c_v$	69%	46%	18%	72%	24%	$c_w \sim c_v$	77%	62%	40%	79%
	$c_d > c_v$	25%	36%	62%	8%		$c_w > c_v$	14%	17%	35%	5%
	Undet.	0%	3%	4%	1%		Undet.	0%	2%	2%	0%
	N	126	126	125	122		N	43	42	43	39

Note: Highlighted boxes indicate >50%, 40%–50%, and 30%–40%, respectively, of respondents that indicated the given price relationship also indicated the given cost relationship.

[a] Cost comparisons are VBSC costs relative to direct market or conventional wholesale costs, combining responses for labor and nonlabor components of each cost subcategory, e.g., strictly higher cost (>) means costs are strictly higher in VBSC than direct market/conventional wholesale channel; undetermined (undet.) means that survey response indicated either labor or nonlabor cost components of the category were higher while the other was lower, so strict total cost comparisons within the category cannot be determined.

[b] N = number of respondents in each price category that provided adequate responses to determine their cost outcomes.

prices in VBSC than wholesale reported that certification costs were higher in VBSCs, while the remaining farms indicated that certification costs were the same between the channels, pointing to certification being a potential avenue for price premiums in VBSCs.

Price and Cost Ratios

Each farm in each iteration is assigned price ratios (p_d/p_v, p_w/p_v) consistent with their survey response to calculate the unobserved counterfactual farm net returns in equation (3), representing what farms would earn if they were not selling to the VBSC. Where farms indicated the expected price relationships ($p_d/p_v \geq 1$, $p_w/p_v \leq 1$), secondary sources indicate that the ratio of direct marketing to VBSC prices ranges between 1.52 and 2.56 (Table 3; see Appendix A), while the ratio of wholesale to VBSC prices ranges between 0.38 and 0.9 (Table 3; see Appendix A). Where farms reported that price relationships are equal or reversed ($p_d/p_v \leq 1$, $p_w/p_v \geq 1$), plausible ranges are specified. These values are used as a base scenario, and we also test a high-price-disparity scenario and a low-price-disparity scenario to test a large range of plausible price differences between marketing channels (Table 3; see Appendix A).

Table 3. Marketing Channel Price Disparity Scenarios

Scenario Description	**Reported Relationship between Output Prices**	**VBSC vs. Direct Marketing Channels: Price Ratio Ranges**	**VBSC vs. Direct Marketing Channels: No. of Obs.**	**VBSC vs. Conventional Wholesale Channels: Price Ratio Ranges**	**VBSC vs. Conventional Wholesale Channels: No. of Obs.**
Base	Higher in VBSC	0.8–1[a]	26	0.38–0.9[b]	68
	Same	0.9–1.1[a]	30	0.9–1.1[a]	71
	Lower in VBSC	1.52–2.56[a]	126	1–1.2[a]	43
Low price disparity between channels	Higher in VBSC	0.9–1[a]	26	0.72–1.08[c]	68
	Same	0.95–1.05[a]	30	0.95–1.05[a]	71
	Lower in VBSC	1.21–1.82[c]	126	1–1.1[a]	43
High price disparity between channels	Higher in VBSC	0.7–1[a]	26	0.36–0.53[d]	68
	Same	0.85–1.15[a]	30	0.85–1.15[a]	71
	Lower in VBSC	1.73–2.56[b]	126	1–1.3[a]	43

[a] Values assumed based on secondary database lines and to conform to reported price relationships in survey data.
[b] Calculated based on secondary data, see Appendix A.
[c] Low/high end of base scenario ranges, +/− 20% to create range.
[d] Low end of range is same as base scenario (0.36) and high end of range is +40%.

Because farms did not report the magnitude of price and cost differences, secondary data are used to construct marketing cost-to-revenue ratio ranges for the simulation (Table 4) (Hardesty and Leff, 2010; LeRoux et al., 2010; King et al., 2010; Christiansen, 2017). The ranges of cost ratios overlap to allow for all reported cost relationships in the survey. We obtain VBSC net returns by multiplying VBSC revenue (R_v) in each iteration by a randomly drawn VBSC marketing cost ratio from the range in Table 4. Then, each farm's cost-to-revenue ratios for direct marketing and conventional wholesale (c_d, c_w) are randomly drawn in each iteration from the ranges in Table 4 to be consistent with the farm's reported cost relationships between channels and assigned VBSC marketing cost ratio.

Table 4. Marketing Channel Ratio of Marketing Costs to Revenue

Channel Type	Marketing Cost to Revenue Ratio Range	Source
All marketing channels	0.30–0.49	Christiansen (2017) and Hardesty and Leff (2010)
Wholesale marketing	0.20–0.50	Christiansen (2017); Hardesty and Leff (2010); King et al. (2010); and LeRoux et al. (2010)
Direct marketing	0.25–0.75	Christiansen (2017); Hardesty and Leff (2010); King et al. (2010); and LeRoux et al. (2010); direct marketing channels have a wider range, chose values between 25th and 75th percentiles from studies and consistent with expected relationship that direct marketing costs are higher than wholesale costs.

Allocation of VBSC Sales

Direct market allocation percentages (δ) are based on farmers' survey responses, in which they ranked the importance of each marketing channel, whether they had sold to each channel in the last year, and whether they planned to increase sales to various channels in future years. The secondary data indicate that the amount of additional product that can be sold through direct markets is bounded because of plateauing direct market sales in recent years (Low et al., 2015; O'Hara and Low, 2016). Table 5 shows the direct market allocation ranges for farms based on income level and revealed preference for direct markets: farms have a lower allocation percentage to direct markets if (i) they ranked direct marketing as less important than wholesale marketing and (ii) they have high income, which implies a limited ability to move additional high product volume through direct markets. Farms are randomly assigned a percentage for direct market allocation in each iteration based on their income and marketing preference responses (δ) from Table 5, then the remaining VBSC sales are allocated to conventional wholesale ($1-\delta$) to calculate the farm's counterfactual net returns without VBSC participation (equation 3) in each iteration.

Table 5. Direct Market Allocation Scenarios

	Sells Direct, Plans to Increase Direct, Prefers Direct to Wholesale		Sells Direct, Plans to Increase Direct		Others	
Income Group	***N***	**Direct Allocation**	***N***	**Direct Allocation**	***N***	**Direct Allocation**
\$0–\$99,999	22	0.20–0.80	8	0.10–0.50	21	0–0.10
\$100,000–\$499,999	29	0.20–0.80	9	0.10–0.50	22	0–0.10
\$500,000–\$999,999	9	0.10–0.50	3	0.05–0.25	8	0–0.05
\$1,000,000 or more	9	0.05–0.20	15	0–0.10	27	0–0.05

TOA-MD Analysis Results for VBSC Impact on Farm Net Returns

Each farm's net return with and without VBSC participation is calculated 1,000 times to find the distribution of possible farm net return outcomes for each farm, which is done for all 182 farms, abiding by their reported income, percentage of sales to VBSCs, price and cost tradeoffs between VBSCs, direct marketing, and conventional wholesale, and their preference and ability to sell more product through direct channels in the absence of their VBSC. This Monte Carlo–style simulation exercise using the TOA-MD framework simulates a distribution of vegetable and fruit farms with the characteristics of those that participated in VBSC marketing, giving us insight into the range of possible net economic benefits conferred by VBSC participation for this or a similar population of farms. Equation (1) is simulated under five combinations of base, low, and high price disparity scenarios (Table 6).

Table 6 summarizes the simulation results across income groups and price scenarios. The upper panel of Table 6 shows the average impact of VBSC participation for each income group and scenario. Comparing different scenarios, average VBSC impacts range from −\$3,992 in Scenario D (high price disparity between direct and VBSC, similar prices between wholesale and VBSC) to \$19,450 in Scenario E (similar prices between direct and VBSC, high price disparity between wholesale and VBSC), with an average net impact of \$7,873 across all scenarios. The farms reporting the lowest income (\$0–\$99,999) have mean impacts between −\$1,006 and \$421, with an average negative impact across all scenarios, while the farms reporting the highest income (\$1,000,000 or more) have mean impacts ranging from −\$5,857 to \$59,723, with an average positive impact across all scenarios.

The lower panel of Table 6 shows the percentage of iterations with 0 or positive impact for each scenario in each income group. The percentage of farms benefiting from VBSCs is lowest for midsize farms with income of \$500,000–\$999,999—only 29%–51% of farms show net benefits—and highest for farms with income of at least \$1,000,000, showing 44%–65% benefiting. For the two middle income groups, results signal that the impact distributions are not symmetric in certain scenarios. In other words, there may be more "losers" than "gainers" from pursuing VBSC sales, but the aggregate gains in net income outweigh the aggregate losses.

For each income group, the lowest mean impact occurs in scenario D, a situation in which direct market prices are considerably higher than VBSC prices and wholesale prices only slightly lower than VBSC prices. About one-third of midscale farms have positive net benefits in this scenario, possibly because they are still allocating a significant percentage of their sales to direct markets (Table 5); without VBSCs, the simulation assumed that they would be able to increase their direct market sales to take advantage of the higher prices. Meanwhile, scenario E, a situation in which direct market prices are only slightly above VBSC prices and wholesale prices are considerably lower than VBSC prices, shows the highest net impact. Here, middle-income farms fare considerably better with VBSCs, likely with little ability to obtain high price premiums in direct markets, the VBSCs outperform a higher wholesale allocation with relatively lower prices. These cases illustrate the importance of the actual magnitude of price differences between channels when evaluating channel benefits and the value of including multiple price scenarios in the simulation.

Table 6. Simulation Results by Farm Gross Income and Price Scenario

Gross Income	*N*	Iterations	Scenario A		Scenario B		Scenario C		Scenario D		Scenario E		All Scenarios	
Mean Impact of VBSC on Farm Net Returns (US$)														
$0–$99,999	51	1000	−408	(17)	−436	(11)	−148	(22)	−1,006	(14)	421	(20)	−315	(8)
$100,000–$499,999	60	1000	−1,050	(82)	−765	(50)	477	(100)	−4,615	(71)	4,328	(89)	−325	(36)
$500,000–$999,999	20	1000	2,829	(255)	−2,050	(147)	7,708	(349)	−4,985	(159)	10,642	(349)	2,829	(121)
$1,000,000 or more	51	1000	30,684	(580)	−3,573	(324)	57,439	(810)	−5,857	(329)	59,723	(803)	27,683	(278)
	182		8,449	(170)	−1,601	(94)	17,058	(240)	−3,992	(97)	19,450	(238)	7,873	(81)
Percentage of Farms Benefiting from VBSC														
$0–$99,999	51	1000	45.7%		44.7%		46.6%		35.8%		55.0%		45.5%	
$100,000–$499,999	60	1000	42.4%		44.6%		44.2%		32.6%		55.6%		43.9%	
$500,000–$999,999	20	1000	41.8%		37.7%		45.3%		28.7%		51.1%		40.9%	
$1,000,000 or more	51	1000	60.4%		47.4%		62.9%		44.2%		64.6%		55.9%	
	182		48.3%		44.6%		50.2%		36.3%		57.4%		47.4%	

Note: Standard errors of mean estimates are reported in parentheses. The percentage of farms benefiting from VBSC is the percentage of positive impact values across all iterations and all farms in each income group. Scenario Definitions: A: Base; B: All low-price disparity; C: All high-price disparity; D: High disparity direct–VBSC, low disparity wholesale–VBSC; E: Low disparity direct–VBSC, high disparity wholesale–VBSC (see Table 3 for ranges).

Table 7 shows how price differentials differ for farms negatively and positively impacted by their VBSC participation. Of negatively impacted farms, 80% receive lower VBSC prices than direct market prices, as expected, but only 36% of those farms reported that their costs were lower in VBSCs than in direct markets. For positively impacted farms, the price and cost differences between direct markets and VBSCs were more uniform, where higher costs in VBSCs correspond to higher prices as well. For positively impacted farms reporting lower VBSC than direct market prices, cost differences were ambiguous. While VBSCs are unlikely to offer prices as high as direct markets, they could focus on lowering costs for farmers to improve net economic benefit to their participating farms.

Table 7. Percentage of Losers and Gainers from VBSC Participation that Reported Price and Cost Relationships between VBSC and Direct Markets and Conventional Wholesale Channels

VBSC vs. Direct Marketing Channels						VBSC vs. Wholesale Marketing Channels					
Compared to Direct, VBSC Prices Are			Compared to Direct, VBSC Costs Are			Compared to Wholesale, VBSC Prices Are			Compared to Wholesale, VBSC Costs Are		
Higher	**Same**	**Lower**	**Higher**	**Ambig.**	**Lower**	**Higher**	**Same**	**Lower**	**Higher**	**Ambig.**	**Lower**
Losers: Mean impact all scenarios < 0 (N = 111)											
6%	14%	80%	20%	44%	36%	14%	52%	34%	19%	68%	14%
Gainers: Mean impact all scenarios ≥ 0 (N = 71)											
27%	21%	52%	27%	41%	32%	75%	18%	7%	39%	30%	31%

Note: Highlighted boxes focus on the highest concentration of price-cost relationships; indicates a high spread between price and costs in the channel associated with the losers and the gainers, while indicates a low spread between price and costs in the channels associated with losers and gainers.

There seems to be a much stronger price effect for conventional wholesale results. VBSC prices are reported to be higher by 75% of the positively impacted farms, while only 39% report that VBSC costs are higher; thus, many benefit from the price premium offered by VBSCs without incurring additional costs. For the negatively impacted farms, only 14% report higher prices in VBSCs than wholesale markets, while their cost differences are ambiguous. Relative to wholesale channels, VBSCs can benefit farms when they are able to maintain higher prices than conventional wholesale markets.

Survey Results for Nonmonetary Impacts of VBSC Participation

Farms consider more than prices and costs when choosing marketing channels. As LeRoux et al. (2010) point out, risk and volume are key considerations. Farmers also have preferences for marketing channels based on values, lifestyle, stress, and marketing experience. Given the inherent risk management benefit of a diverse marketing portfolio, VBSCs are another option with different characteristics to add to the mix.

Survey respondents were asked, "What benefits do you feel that marketing through (VBSC) offers?" and "What challenges do you face from selling through (VBSC)?" for their particular VBSC partner. Large majorities of all farmer respondents (not limited to those used in the simulation exercise) agreed with several benefits (Table 8), including "fits with my values," "access to new and larger markets," "predictable and/or timely payments," and "strengthened identity in the marketplace," each receiving agreement from over two-thirds of respondents. A slim majority reported "receive a premium for my products" as a benefit, which aligns with their responses to the price comparison with conventional wholesale. The only challenge that over 50% of the respondents agreed with was "[VBSC] won't take enough volume," indicating a desire to sell more through the VBSC given the opportunity. Although farmers indicated that certification costs were generally higher in VBSCs, they were not identified as a challenge in the survey, with food safety regulations, required production practices, organic certification, labor standards, and animal welfare standards at the bottom of the challenges list.

Table 8. Survey Reported Benefits and Challenges of VBSC Marketing

Benefit of VBSC	**Percentage Agree**
Fits with my values (*N* = 222)	87.8%
Access to new and larger markets (*N* = 227)	80.6%
Predictable and/or timely payments (*N* = 227)	79.3%
Strengthened identity in the marketplace (*N* = 225)	72.0%
My environmental values are communicated to consumers (*N* = 217)	65.0%
My commitment to the well-being of my community is communicated to consumers (*N* = 213)	63.8%
Marketing services (*N* = 226)	58.4%
Receive a premium for my products (*N* = 227)	53.3%
Strengthened connections with other businesses in the supply chain (*N* = 226)	47.3%
Network with other farmers (*N* = 225)	35.1%
Technical assistance regarding farming practices (*N* = 224)	13.4%
VBSC Challenges	**Percentage Agree**
They won't take enough volume (*N* = 132)	68.9%
Transportation and delivery logistics (*N* = 134)	35.8%
I don't have enough volume (*N* = 131)	26.0%
Variable and/or delayed payments (*N* = 134)	23.9%
Quality standards (*N* = 132)	22.0%
Finding enough, qualified labor (*N* = 134)	21.6%
Food safety regulations (*N* = 134)	18.7%
Required production practices (*N* = 134)	17.2%
Organic certification (*N* = 130)	7.7%
Labor standards (*N* = 134)	6.7%
Animal welfare standards (*N* = 116)	1.7%

Discussion and Conclusion

The simulation results indicate that average total net economic impacts from VBSC participation are positive, but slightly less than half of participants show a net economic benefit from participation. This is a plausible outcome for this sample of farms participating in VBSCs, considering that over half of local and regional marketing farms at the national level reported negative returns and only the top quartile in all farm scale categories reported positive returns on assets (Bauman, McFadden, and Jablonski, 2018). For AOTM farms, the net benefit from VBSC participation averaged across farms and scenarios was positive but suggests that fewer than half of farms gain more than the loss accrued by the remaining half. VBSC gains depend on the relative prices and costs of the marketing channel options, but the nonmonetary aspects of VBSCs are also important to farm participation.

Our results clarify who benefits from VBSC participation. First, as direct marketing prices increase relative to the cost of direct marketing and VBSC prices, VBSC participation is unlikely to provide higher farm net returns in cases where farms have direct marketing options. For the farmers in this survey, VBSCs offer lower prices, as expected, but do not seem to consistently lead to lower marketing costs compared to direct marketing. For some portion of farm output, the price–cost tradeoff in VBSCs does appear to be large enough to offset the revenue losses of choosing VBSCs over direct markets, or the VBSC allows farms to realize some revenue from direct marketing sort-outs and unpaid product. If direct market demand is plateauing in their area, farmers may turn to VBSCs as an outlet for additional sales (Born and Purcell, 2006; Park, Mishra, and Wozniak, 2014; Low et al., 2015; Ahearn, Liang, and Geotz, 2018; Bauman, McFadden, and Jablonski, 2018). While some midscale farms have found benefit from “downscaling” into direct markets to diversify their marketing portfolio, their ability to allocate a significant amount of product to direct markets may be limited, making VBSCs an important alternative (Matteson, 2017). The farms in this study specialize in vegetables and fruits, a mainstay of direct markets, where they have experienced success (Park , Mishra, and Wozniak, 2014; Bauman et al., 2017; Bauman, McFadden, and Jablonski, 2018).

VBSC participation may provide higher net returns when farms’ alternative options fall in the conventional wholesale category: larger farms and those that specialize in products that are not well-suited to direct marketing. As expected, these gains increase when VBSC prices are relatively high compared to wholesale prices. For those who gained, 75% reported that VBSCs offer higher prices than conventional wholesale, while the cost of VBSC participation was similar (Table 7). VBSC product differentiation through farm certifications seems to be a successful strategy for obtaining price premiums, as the majority of farms reporting higher prices in the VBSC report higher certification costs, and certification costs were not rated as a challenge. Thus, it appears that VBSCs can be a beneficial marketing option compared to conventional wholesale if they can offer higher prices, more consistent payments, product differentiation (e.g., certifications), and positive business relationships (as shown in survey responses).

Across all simulations, VBSC participation had very small positive or negative economic impacts relative to farm income, suggesting that VBSC impacts are transitory for some (or all) farms or they adjust their participation and expectations of all marketing options. In this case, average impacts are close to 0, consistent with the economic theory that firms will enter an industry (or choose a particular practice) up to the point that the expected return is 0. Farms may also adjust their VBSC participation over time if they are in the process of scaling up production; indeed, the second-highest reason for choosing VBSCs was "access to new and larger markets," and the only challenge identified by a majority of farms was "won't take enough volume" (Table 8). When small commercial and midsize farmers scale up, increasing participation in direct markets requires high labor costs; successfully growing their operations requires expanding to higher-volume marketing channels and lowering per unit production costs through investments in mechanization and other infrastructure (Hardesty and Leff, 2010; LeRoux et al., 2010; Low et al., 2015; Ahearn, Liang, and Geotz, 2018; Bauman, McFadden, and Jablonski, 2018; Trant et al., 2018). Considering that a majority of respondents reported low product volume as a challenge, it could be that VBSCs are also growing their businesses. VBSCs and participating farms may be in a mutual growth phase, with the VBSCs developing the demand-side of their business or making strategic business decisions to work with as many farmers as possible to diversify their supply portfolio as they also seek to increase the volume of their businesses.

As for the benefits of VBSC participation for the AOTM sector, we first note that average commercial vegetables farms have relatively high gross income compared to all farms, so the benefits to the higher sales categories in the simulations could be consistent with benefits to some AOTM farms—these could be farms that have scaled up due in part to their VBSC participation. The results may also demonstrate the unique marketing challenges of AOTM fresh produce farms, which prefer direct markets more strongly than their larger counterparts (Tables 1 and 5), resulting in a negligible net benefit of VBSCs across all scenarios. It also provides insights on the assistance that could be provided by VBSCs to AOTM produce farms: As they scale up and move away from direct markets, VBSC marketing gives farms advantages over conventional wholesale if they increase prices relative to marketing costs, reduce marketing risks, and negotiate on volume constraints.

Our survey data and simulation results provide us with valuable categorical relationships between prices and costs across marketing channels to help farmers, VBSC managers, and advisors deliver better marketing information to farms. The results indicate a common thread in the economics of marketing channels: Farms incur larger costs to obtain higher prices, which can benefit farm economic viability. In the case of VBSCs relative to direct and wholesale channels, the key difference may be the spread between price and cost differentials between channels—the farms that showed least financial benefit from VBSCs reported that where prices were lower, accompanying costs were not proportionately lower. It is common that the impact (benefit or loss) is ambiguous when we consider a population of farms; that is, some will gain and some will lose. Furthermore, farms may still choose VBSCs for reasons which are not easily observed or modeled. Farms report choosing VBSCs because they "fit with my values," which could mean offering a marketing outlet that is consistent with their preselected production practices (e.g., sustainable practices, organic, local). Farms may also choose VBSCs for risk reduction and business connections as they grow and expand their business. There is no one perfect marketing mix for any type of farm across all time periods; each farm must evaluate the price–cost and other marketing channels tradeoffs for their own situation (Bauman, McFadden, and Jablonski, 2018). The results show us how the interplay of price and cost relationships between channels translates into channel choice impacts in a real-world farm population.

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Appendix A. Price Scenarios

Because our survey data only indicated whether VBSC prices were higher or lower than direct or conventional wholesale channels, the simulation exercise required us to develop plausible assumptions on price ratios between marketing channels consistent with survey responses to simulate the economic impact of VBSC participation. We use two different approaches to develop a range of plausible price relationships between marketing channels.

The first approach to developing an assumption on marketing channel price ratios uses information from secondary sources and USDA reports on wholesale and retail prices. In general, direct-to-consumer prices appear to be competitive with conventional retail prices (Gunderson and Earl, 2010; Martinez, 2016; Valpiani et al., 2016). Considering these findings, we assume that direct market prices are 10% lower than conventional retail prices, on average, for fruits and vegetables:

(A1) $$p_d = 0.90 p_r,$$

where p_r is retail price and p_d is the direct-to-consumer price for fruits and vegetables.

The USDA reports on the relationship between wholesale and conventional retail prices for the whole of the United States According to the USDA (2016, 2017a), wholesale prices for fruit are 38% of conventional retail and wholesale prices for vegetables are 26% of conventional retail, on average. We use the midpoint of these percentages (32%) to represent the relationship between wholesale and retail prices for fruits and vegetables in general:

(A2) $$p_w = 0.32 p_r.$$

These secondary sources do not provide explicit information on VBSC prices. Based on survey responses, roughly 76% of farms reported that VBSC prices are the same (39%) or greater than (37%) wholesale prices. As such, we assume that VBSC prices are 10% higher than wholesale prices (ratio of 1.10). The ratio of direct market prices to VBSC prices can be calculated using equations (A1) and (A2):

(A3) $$\frac{p_d}{p_v} = \frac{0.90 p_r}{1.10\left(0.32 p_r\right)} = \frac{0.90}{0.352} = 2.56,$$

which is used as an upper bound in the direct-to-VBSC price scenarios in Table 3.

A second approach is to utilize observed prices from different channels across the country to calculate price ratios. A handful of case studies have recorded prices and percentages of the retail price retained by producers for different products in different channel settings and locations across the United States. Table A1 reports these price observations and the percentage of retail price retained by the producer, net of marketing and processing cost.

Table A1. Secondary Data on Prices and Percentage of Retail Price Retained by Farm by Marketing Channel

	Wholesale		Direct Marketing		Intermediated	
Product	**Price (US$/lb)**	**Percentage of Retail Price Retained**	**Price (US$/lb)**	**Percentage of Retail Price Retained**	**Price (US$/lb)**	**Percentage of Retail Price Retained**
Apples (NY)[a]	0.26	35%, 47%, 60%	0.40	80%	0.26	36.00%
Berries (OR)[b]	0.86	27.00%	2.43	73%	2.53	46.40%
Spring mix (CA)[c]	0.79	12.00%	5.92	74%	3.00	50.10%
Cabbage (NY)[d]	0.16	26.00%	0.32	56%	0.19	26.60%
Potato (NY)[e]	0.27	45.30%	0.34	56%	0.22	36.90%
Fruit and vegetable average	0.47	36.00%	1.88	67.80%	1.24	39.20%

[a] The study looked at three mainstream retailers, producing this range based on the retail price at each location and the packing and shipping costs estimated. The producer percentage of mainstream price retained is fairly high because producers were also packer-shippers in this case, so the retained both the wholesale price and packing and shipping (which did not get paid to a third party). Intermediated market was average of sales to a retail store through distribution center, bulk and bagged apples, and selling to school districts through a wholesaler (Cuellar-Healey, 2013; King et al., 2010).

[b] Berries were sold to a retail grocery store as the intermediated buyer; the intermediated retail price was above mainstream retail and above direct marketed prices (King et al., 2010).

[c] Spring Mix was sold to a retail co-op grocery store in this case as the intermediated buyer.

[d] Conventional wholesale price averages three states based on USDA data. Direct was estimated from the retail price reported in the case study, subtracting marketing costs estimated based on Hardesty and Leff (2010) estimates of percentage of revenue spent on farmers' market for midsize farms. This case study did not include details on direct marketing supply chains. Intermediated is a regional sale from farm to wholesaler (Park, Gómez, and Clancy, 2017a,b).

[e] Conventional wholesale prices from national grower–shipper. Direct was estimated from the retail price reported in the case study, subtracting marketing costs estimated based on Hardesty and Leff (2010) estimates of percentage of revenue spent on farmers' market for midsize farms. This case study did not include details on direct marketing supply chains. Intermediated is a regional grower–shipper to wholesaler (Park, Gómez, and Clancy, 2017a).

Table A1 reports wholesale and direct market prices, and the intermediated price is used to represent VBSC prices. The observations on prices and percentage of the retail price retained are averaged to create index prices for each channel (last row). In general, the relative magnitudes of each index value are consistent with the relationships reported by most respondents ($p_d > p_v > p_w$). The price ratios between channels from this approach are calculated using the ratios of the price index values. The ratio of wholesale to VBSC prices is 0.38 and the ratio of percentage retail price retained is 0.92 between these channels. For direct marketing and VBSCs, the ratio of prices is 1.52 and the ratio of percentage retail price retained in 1.73. These ratios are also used in the direct to VBSC price disparity scenarios in Table 3.

These two approaches to approximating the price relationships between channels allow us to develop a range of price ratios that account for plausible price relationships that are higher or lower than the secondary data ranges and that appropriately account for each farms' survey report of price comparisons between channels. For instance, the base scenario for the direct market to VBSC prices for fruits and vegetables ranges from 1.52 to 2.56 based on the above calculations. To account for other price possibilities, we simulate a low price disparity scenario by setting the price ratio range closer to 1, with the farms that reported lower prices in VBSCs assigned a value centered on the low end of the base scenario range (1.52) plus or minus 20%, such that the prices assigned to those farms are strictly lower in VBSCs than direct markets in the simulations. High price disparity scenarios are also constructed by extending the price ranges and using secondary data results. We also construct price disparity scenarios for wholesale and VBSC comparisons using the same techniques (Table 3).

We also investigate whether reported price differences between each marketing channel varied by other farm characteristics. We found no statistically significant differences in reported farm gross income or percentage of sales to VBSCs (Table A2). The only statistically significant difference was that farms with smaller land area tended report that VBSC prices were lower relative to direct markets than farms with larger area (ANOVA *t*-test, $p < 0.01$) (Table A2). These differences are accounted for through the price ratio scenarios that are assigned to each farm based on their survey responses; however, the analysis focuses on farm income as a measure of farm size rather than acreage.

Table A2. Relationship between Farm Characteristics and Output Prices, VBSC to Direct Marketing and Wholesale

	VBSC vs. Direct Marketing				**VBSC vs. Conventional Wholesale**			
	Higher Prices in VBSC	**Same Prices in VBSC**	**Lower Prices in VBSC**	***p*-Value**	**Higher Prices in VBSC**	**Same Prices in VBSC**	**Lower Prices in VBSC**	***p*-Value**
Operated acres	239.1 (609)	674.5 (1,708)	172.3 (384)	0.01	339.8 (1,060)	270.3 (751)	136.5 (246)	0.44
Farm gross income								
\$0–\$99,999	23.1%	36.7%	27.0%		26.5%	23.9%	37.2%	
\$100,000–\$499,999	38.5%	13.3%	36.5%		30.9%	36.6%	30.2%	
\$500,000–\$999,999	15.4%	10.0%	10.3%		10.3%	8.5%	16.3%	
\$1,000,000 or more	23.1%	40.0%	26.2%	0.39	32.4%	31.0%	16.3%	0.39
Percentage of total sales to VBSC	33.9%	25.0%	23.3%	0.26	28.9%	23.5%	21.7%	0.40
N	26	30	126		68	71	43	

Note: Operated acres and VBSC sales percentage values are averages. The standard deviation of farm size is shown in parentheses. For farm gross income categories, the percentages represent the percentage of farms in each price category with the corresponding income range (columns add to 100%). For operated acres and VBSC sales percentages, the *p*-values result from ANOVA. For gross income, the *p*-value results from Pearson's χ_2 test using the categorical income variable from the original survey.

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A Hard Nut to Crack: Identifying Factors Relevant to Chestnut Consumption

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Abstract

Chestnuts are popular worldwide, but they are not commonly purchased in the United States. Using a survey of over 1,000 U.S. and over 1,000 Chinese consumers, we use geospatial techniques and explore why over half of U.S. consumers have never eaten a chestnut. We test questions regarding key geographic, social, and cultural characteristics of likely U.S. chestnut consumers. Results suggest that immigration patterns weakly affect chestnut consumption but that age is a more important predictor of consumption frequency. Our empirical analysis suggests that consumers in coastal states consume the most chestnuts and that socioeconomic characteristics significantly influence consumption.

Keywords: chestnut consumption, consumer characteristic, immigration

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Introduction

Despite many cross-country consumer comparisons, little is known about cultural differences in nut consumption (Lusk, Roosen, and Fox, 2003; Loureiro and Umberger, 2007; Labrecque et al., 2006; Rozin et al., 1999). Understanding cultural differences in nut preferences is likely to become increasingly important as climate-conscious policy makers frequently campaign against meat consumption and advocate for alternate sources of protein and healthy fats (Elzerman et al., 2011; De Boer and Aiking, 2011; Aiking, 2011; Schösler, De Boer and Boersema, 2012; Beverland, 2014). Thus, identifying reasons why U.S. consumers might be averse to switching their consumption patterns toward plant-based alternatives is of increasing importance.

We contribute to the literature via data from Chinese and U.S. consumers to test institutional explanations for the disparity of chestnut consumption in the two countries. By comparing the relatively small U.S. market with the largest chestnut market in the world, we investigate the potential for U.S. chestnut producers. In 2017, China produced nearly 1.9 million tons of chestnuts, representing 80% of global production and 23 times the production scale of Bolivia, the second-largest chestnut producer (FAO, 2017). China is also the world's leading consumer of chestnuts, consuming nearly 1,651,000 tons in 2015, 80% of global consumption (IndexBox, 2018). This article highlights an interesting difference between consumption patterns in the two countries. By comparing the relationship between production and consumption regions in the two countries, we can examine the likely effects of localized supply chains on consumer behavior.

By focusing our empirical analysis on chestnuts, we also identify potential marketing paths to increase U.S. domestic chestnut consumption. While U.S. chestnut production has increased significantly over the past decade, few peer-reviewed articles have generated marketing information for the industry. Filling this gap in the literature is especially important as specialty crop producers are increasingly interested in diversification (Lancaster and Torres, 2019). Chestnuts are unique among nuts as they have a sweet, mild flavor profile and contain significant nutritional value. (Aguilar, Cernusca, and Gold, 2009; Ertürk, Mert, and Soylu, 2006; University of Missouri Center for Agroforestry, 2006). Chestnuts contain no cholesterol and only trace fats, and they are the only nut that contains a significant amount of vitamin C. They also have a high concentration of complex carbohydrates, a low glycemic index, and only one-third the calorie content of peanuts and cashews.

To assess this market opportunity, growers would benefit from understanding key characteristics of chestnut consumers. In the prior literature on chestnut demand, a few studies have focused on the influence of institutional and behavioral features. For example, Gold, Cernusca, and Godsey (2004) show that most participants were unaware of two of the most basic chestnut facts (i.e, need for refrigeration and fat content). Gold, Cernusca, and Godsey (2005) also pointed out U.S. consumers' unfamiliarity with chestnuts, including unawareness of their properties and unfamiliarity about where to buy and how to prepare them. However, these studies only revealed consumer familiarity with chestnuts; they did not explore factors likely to influence chestnut consumption. By combining participant familiarity with production location data, we seek to begin a dialogue about this relationship. Similarly, Bodet (2001) suggests that ethnic Asian and European dietary cultures are likely to be correlated with chestnut familiarity and consumption. We empirically test this assertion by focusing on the correlation between chestnut consumption, dietary cultural characteristics such as ethnicity, and each consumer's relationship with agriculture.

Every year, the average European consumer eats 1 lb (0.5 kg) of chestnuts and the average Chinese, Japanese, or Korean consumer eats 5.7 lb (2.5 kg) (Vossen, 2000). Despite this popularity overseas, the average American consumes a mere 0.10 lb (0.05 kg) per year (Vossen, 2000). Where prior studies focused on convenience samples to acquire their survey respondents (Gold, Cernusca, and Godsey, 2004; Aguilar, Cernusca, and Gold, 2009), this study is more representative, as our data for both China and the United States are nationwide and include more than 1,000 participants from each country. Additionally, nothing has been published in peer-reviewed journals that explores chestnut consumption after 2008. Instead, the literature has focused on other important nuts such as pecans (Kim and Dharmasena, 2018), making our data a timely contribution in guiding present-day chestnut marketing strategies.

As such, this article focuses on likely demand-side institutional features inherent to the chestnut market that might influence the geographic relationship between U.S. chestnut supply and demand . We explore the potential influence of ethnicity among chestnut consumption in different states, hypothesizing that states with more immigrants from high-chestnut consumption regions (e.g., Asia) are more likely to consume chestnuts. In addition, we empirically test for relationships between other likely factors such as farming experience and grocery shopping frequency.

Background

There is perhaps a historical explanation for the unusually low chestnut consumption in the United States. U.S. chestnut trees narrowly escaped extinction in the nineteenth century due to the accidental introduction of an Asian chestnut blight fungus, *Cryphonectria parasitica* (Anagnostakis, 1987). Within 50 years, the fungus killed almost all of the 4 billion American chestnut trees in the eastern forests of the United States (Roane, Griffin, and Elkins, 1986). Thanks in large part to exhaustive research efforts that identified improved cultivars of non-American chestnuts (Gold, Cernusca, and Godsey, 2006), the chestnut industry has experienced a rapid resurgence over the past few decades. The production gains for chestnut orchards have also coincided with a growing consumer interest in healthy and alternative foods (Gold, Godsey, and Josiah, 2004), creating conditions to support a growing U.S. chestnut market.

Despite this potential, most chestnuts in the United States are imported from Italy and, to a lesser extent, from Asia (U.S. Department of Agriculture, 1976). This unbalanced trade relationship is poised to change, as U.S. growers now primarily cultivate Chinese and Japanese–European hybrids, which have many superior production qualities, including reduced susceptibility to *C. parasitica* (Anagnostakis, 1987). Additionally, U.S. chestnut growers have a comparative advantage over growers from overseas as they can provide freshly harvested local chestnuts with lower transportation costs.

Prior studies have focused on chestnut demand or market opportunity, although shortcomings remain. Bodet's (2001) summary of existing chestnut literature suggests that domestic ethnic Asian and European markets have a longstanding cultural use of chestnuts; they also find that consumers who have heard about chestnuts via songs such as Nat King Cole's "The Christmas Song" might have a stronger preference for chestnut consumption. Another study on chestnut culture in California also showed that U.S. consumers are likely to be enthusiastic in their acceptance of chestnuts (Vossen, 2000). Smith et al. (2002) and a report from the University of Nebraska-Lincoln Food Processing Center (2002) also identified marketing opportunities for chestnuts by showing that restaurant chefs have substantial interest in chestnut products. Other research illustrates the potential of increasing chestnut demand as chestnuts experienced a surge in popularity in many European countries, Australia, New Zealand and the United States (Kelley and Behe, 2002). From 2007 to 2015, the average annual growth rates of chestnut consumption in many European countries, including Italy, reached over 6.0% per year (IndexBox, 2018).

Other studies of chestnut consumption have found that quality, freshness, production region, and nutrition are important features for consumer demand. The University of Nebraska-Lincoln (2002) study indicates that freshness and quality are extremely important for upscale restaurant chefs in choosing chestnut products. Similarly, chefs prefer peeled to unpeeled chestnuts and use them in a variety of dishes (Kelley and Behe, 2002). Gold, Cernusca, and Godsey (2004) assess consumer preferences among attendees at the Missouri Chestnut Roast and find that nutrition/diet/health, quality, and local production influence purchase and consumption decisions for chestnut consumers. Gold, Cernusca, and Godsey (2004, 2005) also report that U.S. consumers prefer buying chestnuts from grocery stores or farmers' markets and that organic and chestnut cultivar labeling can help capture price premiums. Aguilar, Cernusca, and Gold (2009) reanalyze survey data from Missouri Chestnut Roasts and find that festival participants ranked product quality, local production, and nutritional value as the most important attributes. Size also matters, as festival-goers showed more interest in medium-sized chestnuts. The current study builds on this previous work as we focus on a sample more representative of the U.S. chestnut market. This is especially important as chestnut consumption frequency is likely to be geographically heterogeneous.

Methods

This article explores the potential influence of institutional and behavioral factors likely to increase chestnut consumption. To accomplish this task, we use two survey datasets collected in the summer of 2017 by Survey Sampling International (SSI®), which maintains panels of likely consumers in both China and the United States. Both primary datasets were collected based on a survey written in the Qualtrics software program under the guidance of the Oklahoma State University Food Demand Survey (Lusk, 2017). We analyze the data in two ways. First, we test for correlations between chestnut production and consumption in the U.S. and Chinese markets. These relationships are likely to matter, as the notion of "place" has become increasingly important for consumer decision making (Duram and Oberholtzer, 2010). A product's "localness" has been shown to draw a premium in the United States, so it follows that production regions are likely to have a relationship with demand (Bir et al., 2019; Printezis, Grebitus, and Hirsch, 2019; Zepeda and Li, 2006). Second, we run a series of regression models to identify correlations between demographics and consumption frequency, culminating with zero-inflated negative binomial models. These models are especially helpful when a significant proportion of the sample has no observations at all. Similar zero-inflated methods have been utilized to test for policy effects on the number of craft breweries in each county (Malone and Lusk, 2016), consumer demand for tobacco (Harris and Zhao, 2007), and U.S. mushroom consumption (Jiang et al., 2017).

Data Description

To identify U.S. chestnut consumption, we evaluated responses on the Food Demand Survey (FooDS), an online survey that was conducted monthly to track consumer preferences and sentiments on food safety, quality, and price (Lusk, 2017). The survey also collected consumers' demographic information, including gender, age, education, income, marital status, and ethnicity. The July 2017 survey asked participants to identify the frequency with which they consumed an assortment of nuts, including chestnuts, using a Likert scale. In total, 1,034 U.S. consumers completed the survey. To identify consumption frequency in China, we utilize a survey of 1,000 likely Chinese food consumers collected by the Food Demand Survey team (Lusk, 2017). Table 1 reports descriptive statistics of key variables for this study. The average U.S. consumer eats chestnuts about twice per year, while Chinese consumers eat chestnuts monthly. The average U.S. consumer in our sample is slightly older and slightly more educated than the average Chinese consumer in our sample, while Chinese participants had more children on average. Nearly 77% of Chinese participants were the primary shopper for their family, while only 67% of U.S. participants were the primary shopper for their household.

Empirical Methods

Using Python, we analyzed regional differences in chestnut consumption geometrically and statistically. We then used multiple regression models to analyze the relationship between chestnut consumption and other independent variables such as gender, age, education, and race. Prior research suggests that many U.S. consumers have never consumed a chestnut (Gold, Cernusca, and Godsey, 2004). Thus, we apply the Poisson and negative binomial regression model for analysis. Assuming that chestnut consumption frequency satisfies a Poisson distribution, and so y_i, the chestnut consuming frequency of individual i given $\boldsymbol{X}_i$ is Poisson distributed with density

(1) $$f\left(y_i|\boldsymbol{X}_i\right)=\frac{\lambda_i^{y_i}\cdot\exp\left(-\lambda_i\right)}{y_i!},\ y_i=0,1,2,\ldots,$$

where $\boldsymbol{X_i}=[\boldsymbol{x}_{1i},\boldsymbol{x}_{2i},\ldots,\boldsymbol{x}_{ki}]'$ is the k-dimensional vector of covariates and $\lambda_i=\exp(\boldsymbol{X}_i'\boldsymbol{\beta})$, in which $\boldsymbol{\beta}$ is the vector of parameters (Cameron and Trivedi, 2013).

We estimate the log-linear equation in a Poisson regression model (Frome, 1983; Silverberg and Verspagen, 2003):

(2) $$\ln\left(E\left(y_i|\boldsymbol{X}_i\right)\right)=\sum_{j=1}^{k}\beta_j x_{ji}.$$

Table 1. Descriptive Statistics

Variables	**U.S. Consumers**	**Chinese Consumers**
Chestnut consumption frequency		
Never	62.0%	2.3%
Once per year	14.5%	8.4%
Twice per year	4.6%	8.3%
3–6 times per year	7.1%	18.5%
7–11 times per year	4.6%	19.3%
Monthly	4.5%	22.7%
Weekly or Daily	2.6%	20.5%
Male	44.0%	51.0%
Age		
18–24	11.9%	0.3%
25–34	19.6%	41.5%
35–44	17.5%	34.9%
45–54	15.2%	16.5%
55–64	17.7%	6.0%
65–74	13.5%	0.0%
> 74	4.6%	0.8%
Education		
Less than high school	0.3%	6.3%
High school	20.7%	0.0%
Some college	21.4%	0.1%
2-year college degree	8.4%	2.1%
4-year college degree	27.5%	24.4%
Graduate degree	21.8%	6.8%
Marital status (single or unmarried)	72.0%	
Family size	2.6	3.3
Have child in family	22.0%	73.0%
Prior shopper	67.0%	77.0%
Vegan	4.0%	
Farmer	2.0%	
Hispanic/Latino/Spanish origin	20.5%	
Race		
White	70.1%	
African American/American Indian	12.4%	
Asian	4.5%	
Others	13.0%	
Number of observations	1,033	1,000

Note: Except for family size, numbers in the table represent the ratio of relative populations.

We also applied the most frequently cited alternative to the Poisson regression—the negative binomial (NB) regression model—as the other benchmark model for our analysis of count data.

Since expected value and variance are equal in Poisson distribution, the NB regression might provide a better fit than the Poisson regression in the presence of Poisson overdispersion for count data, in which the variance in the Poisson model is larger than the expected value (Greene, 2003; Gardner, Mulvey, and Shaw, 1995; Land, McCall, and Nagin, 1996). By contrast, the NB model addresses the issue of overdispersion by assuming that unexplained variability exists among individuals who have the same expected value, allowing higher variability among individuals (Coxe, West and Aiken, 2009). The probability mass function (*pmf*) of the negative binomial distribution in the NB model can be specified as

$$\text{(3)} \qquad \mathrm{Prob}(\mathrm{y}) = \frac{\Gamma(\mathrm{y}+\theta)}{\Gamma(\theta)\, y!} \mu^{\theta} (1-\mu)^{\mathrm{y}} \quad \theta > 0, \quad y = 0, 1, \ldots$$

where $\mu = \dfrac{\theta}{\theta+\lambda}$ and (θ, λ) is the parameter vector of the distribution.

We include social characteristics such as gender, age, education, marital status, and income in our model since many studies have shown that these are significant determinants of consumption (Schifferstein and Ophuis, 1998; Verbeke, 2005; Hughner et al., 2007). We also include ethnic variables (such as Latino origin and race) to estimate the possible influence of immigrant food cultures on chestnut consumption.[1] Finally, we include variables for farmers, vegans, and primary shopper designation (the person with the main responsibility of shopping in the family).

For this study, we focus on chestnut consumption frequency. Using a Likert scale, participants identified the frequency with which they consumed chestnut. Since the dependent variable is a count variable, we first estimate the Poisson regression model and the NB regression model (see Table 2). Since nearly 62% of U.S. survey participants had never eaten a chestnut, we also estimate zero-inflated Poisson (ZIP) and zero-inflated negative binomial (ZINB) regressions to mitigate concerns about potentially excessive numbers of zero observations.

Following the assumptions of zero-inflated count data models, the counts can be modeled in two parts: One estimates the probability that the observation is 0 while the second portion is a general count data model for analyzing regular count data. (Wagh and Kamalja, 2018). The two parts of ZIP model contain the logit model for predicting excess zeros and the Poisson count model. The ZIP model assumes that the count variable satisfies the zero-inflated Poisson distribution with *pmf*:

[1] *Latino* is the dummy variable that represents whether the individual identifies as Hispanic, Latino, or Spanish; *race* is a group variable that separates participants into four racial groups: white, African American, Asian, and other.

(4) $$\text{Prob}(y) = \begin{cases} \omega + (1-\omega)e^{-\theta}, & y = 0 \\ (1-\omega)\dfrac{\theta^{y}e^{-\theta}}{y!}, & y > 0 \end{cases},$$

where (θ, ω) is the parameter vector of the distribution (Mullahy, 1986).

The ZINB model is also formed with two parts: the logit model for predicting excess zeros and a negative binomial count model, but the *pmf* is quite different:

(5) $$\text{Prob}(y) = \begin{cases} \omega + (1-\omega)\left(\dfrac{1}{1+\varphi\theta}\right)^{\varphi^{-1}}, & y = 0 \\ (1-\omega)\left(\dfrac{\Gamma(y+\varphi^{-1})}{\Gamma(\varphi^{-1})\Gamma(y+1)}\right)\left(\dfrac{1}{1+\varphi\theta}\right)^{\varphi^{-1}}\left(\dfrac{\varphi\theta}{1+\varphi\theta}\right)^{y}, & y > 0 \end{cases},$$

where (θ, φ, ω) is the parameter vector of the distribution (Cameron and Trivedi, 2013).

Results

Figure 1 displays the frequency distribution of chestnut consumption in the United States and China. While almost every Chinese consumer (97.7%) had eaten a chestnut in the past year, fewer than half of U.S. consumers had ever tried a chestnut.

Differences in U.S. and Chinese consumers are key to this study. Figure 2 illustrates the frequency of chestnut consumption by province in China. On average, consumers in southeastern coastal areas and the provinces around Beijing, the capital of China, consume more chestnuts.[2]

Figure 3 displays chestnut production data for each province from the China Agricultural Database (2014). As the largest country in terms of chestnut production, chestnuts are grown in over 90% of Chinese provinces. Hubei, Shandong, Hebei, Yunnan, and Anhui provinces produce the most chestnuts.[3]

Figure 4 demonstrates the correlation between chestnut production and consumption in the Chinese provinces. Results suggest that, at least in China, chestnut consumption is positively correlated with chestnut production; consumers who live in provinces with higher yearly chestnut outputs consume chestnuts more frequently (correlation coefficient = 0.258).

[2] We also calculated the Moran's I, a statistical measure of spatial correlation developed by Moran (1950). The Moran's I of our province-level Chinese chestnut consumption data is 0.046 (p-value = 0.94), which indicate no statistically significant spatial autocorrelation between provinces.

[3] The Moran's I of province-level Chinese production data is −0.622 (p-value = 0.37), which again indicates that there is no statistically significant spatial autocorrelation at the province level.

Figure 1. Chinese and U.S. Chestnut Consumption Frequency

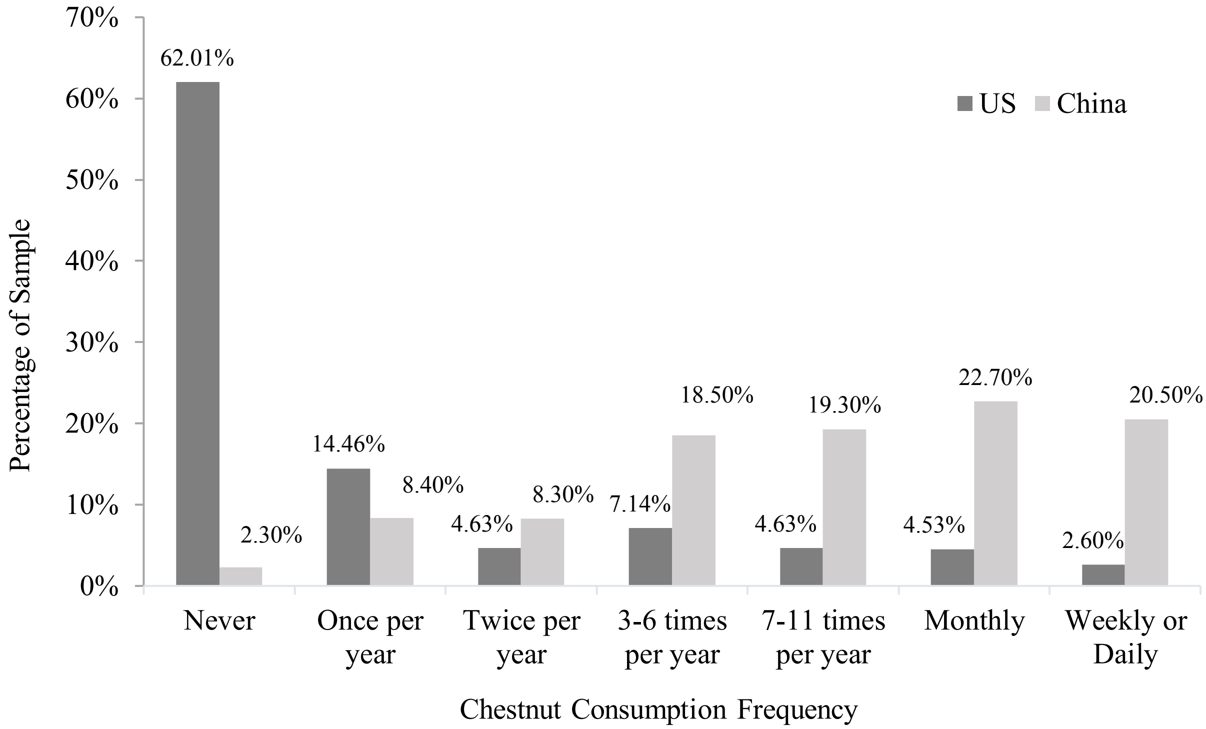
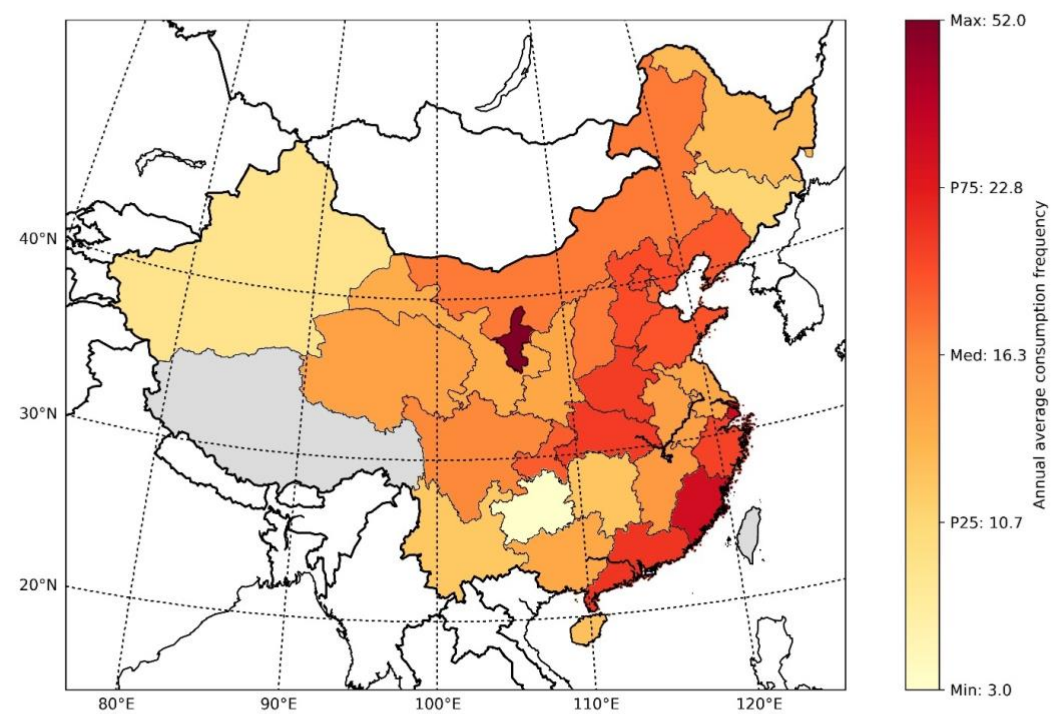
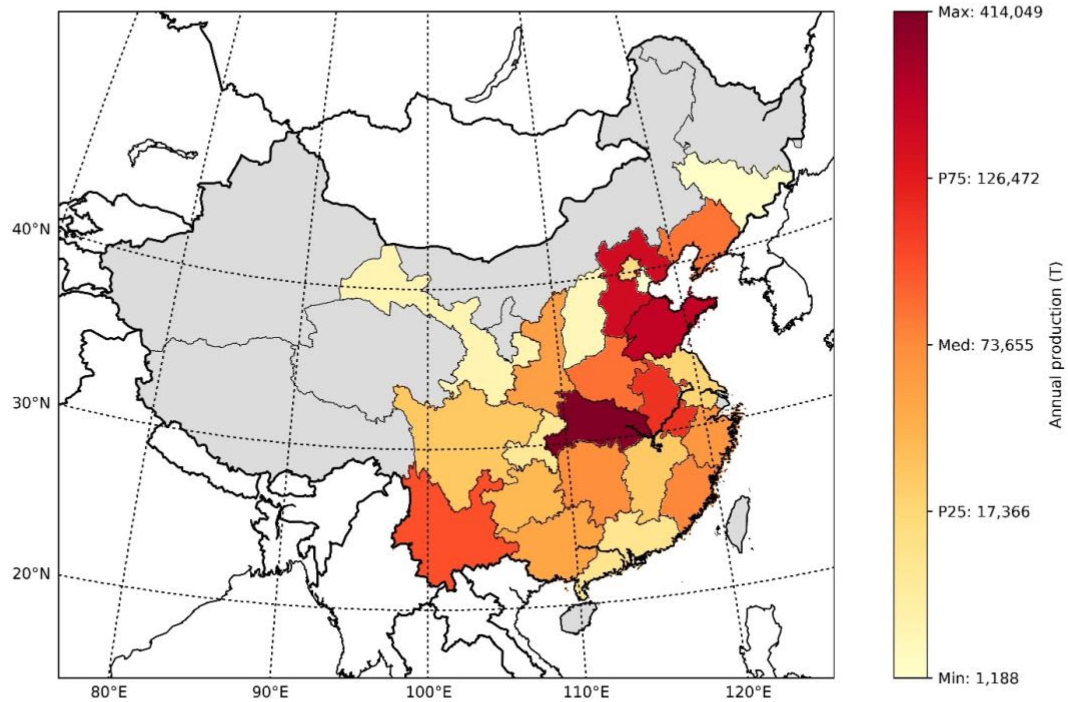


Figure 2. Chinese Chestnut Consumption, 2017



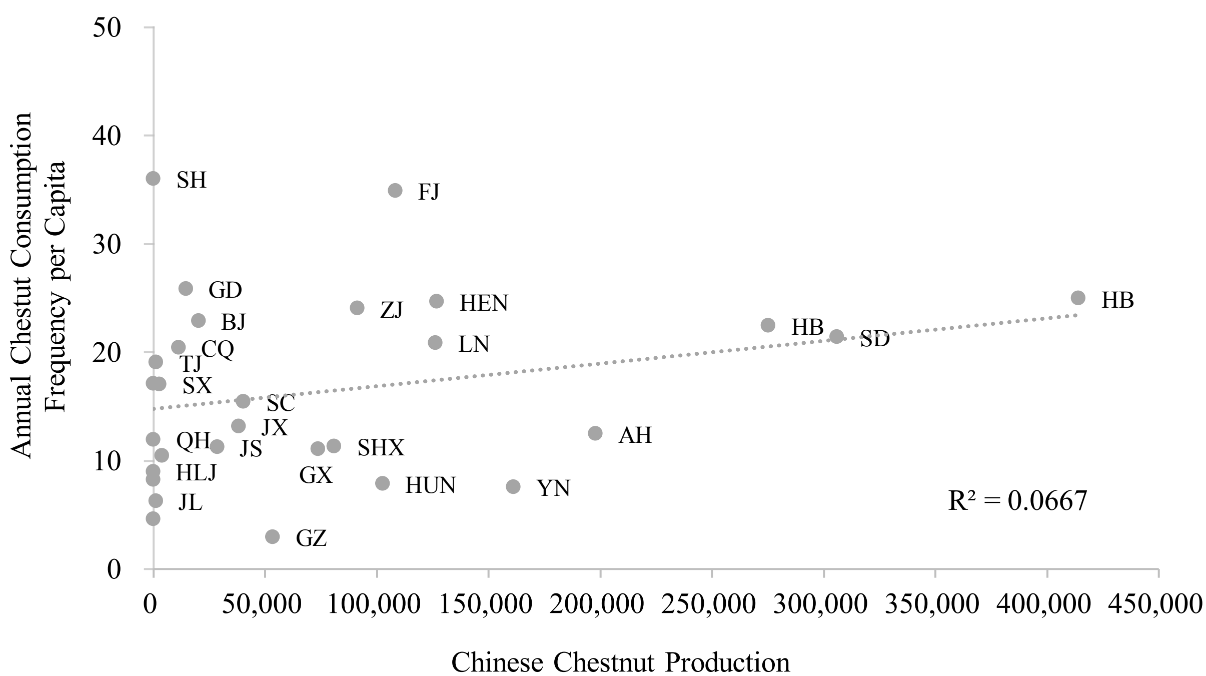
Note: Darker color reflects higher average chestnut consumption. Grey indicates provinces without observations.

Figure 3. Chinese Chestnut Production, 2014



Note: Darker color reflects higher average chestnut production. Grey indicates provinces without production data.

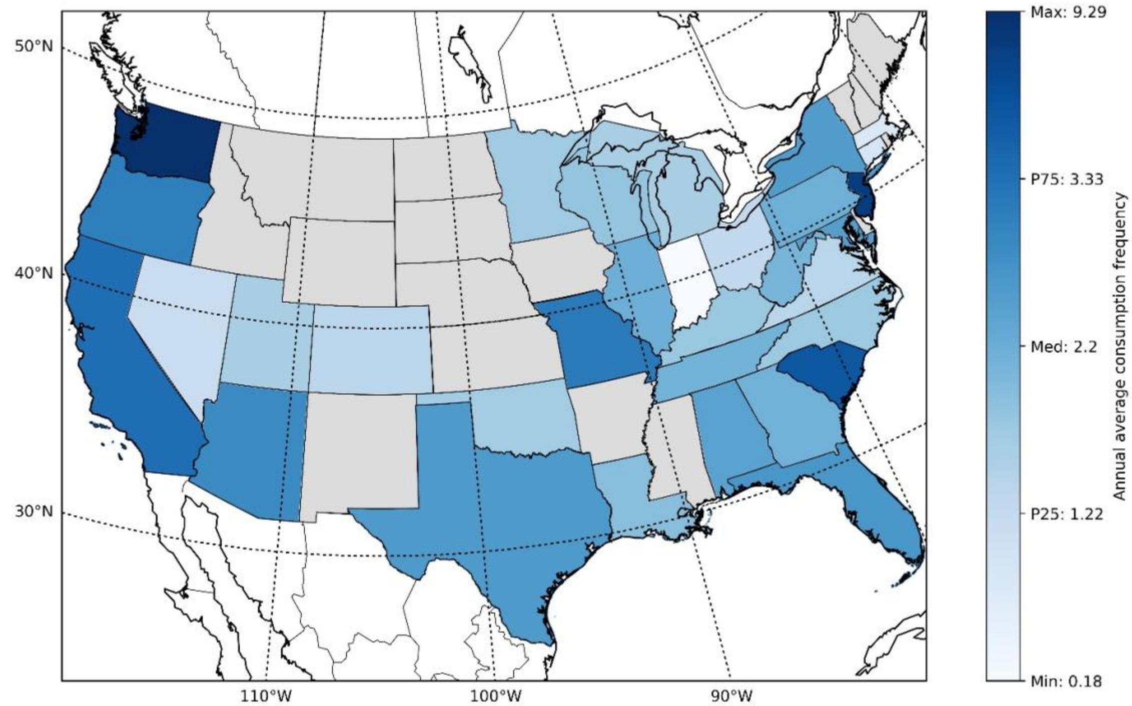
Figure 4. Chinese Chestnut Output and Consumption Frequency by Province, 2014



Note: Each point represents a province. See the appendix for full province names.

Figure 5 displays average state-level per capita U.S. chestnut consumption drawn from FooDS survey data. States near the coast are more likely to consume chestnuts.[4]

Figure 5. U.S. Chestnut Consumption, 2017



Note: Darker color reflects higher average chestnut consumption per capita. Grey indicates states with fewer than 10 observations while white indicates low average chestnut consumption per capita.

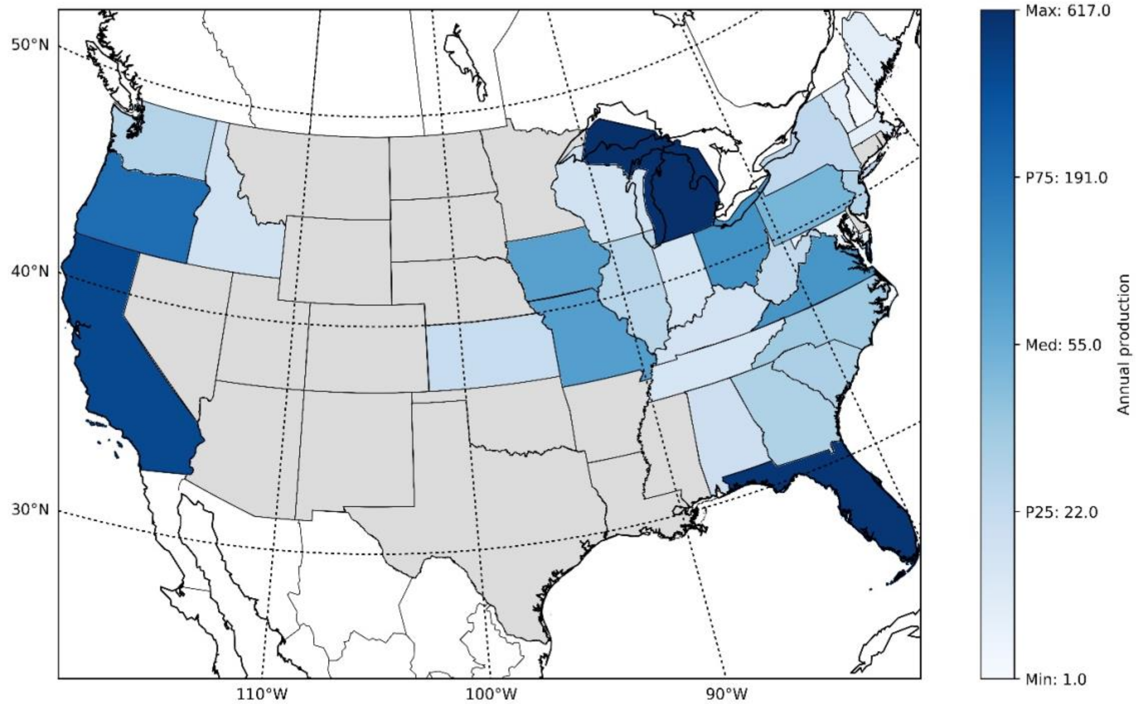
Figure 6 displays U.S. chestnut production in 2012 (U.S. Department of Agriculture, 2012). Few states actually produced chestnuts in 2012, as most chestnuts in the United States are imported.[5]

One key question is whether the positive relationship between production and consumption seen in China also exists in the United States. We find no significant correlation between chestnut consumption and production in the United States (Figure 7). This is interesting, as prior research suggests that local production is a critical component of chestnut demand.

4 The Moran's I is 0.057 (*p*-value = 0.42), which indicates that is no geographic autocorrelation in U.S. chestnut consumption data.

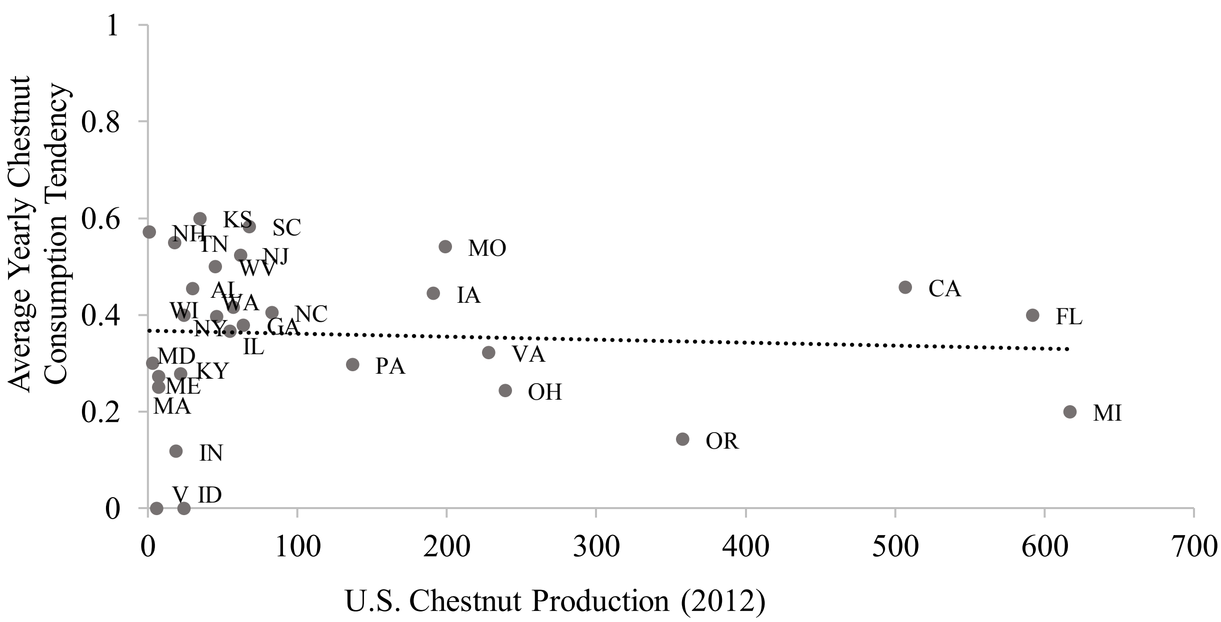
5 Again, the Moran's I between state production is not statistically different from 0 (0.025, *p*-value = 0.62), which did not show significant autocorrelation in U.S. chestnut production.

Figure 6. U.S. Chestnut Production, 2012



Note: Darker color reflects higher average chestnut production. Grey indicates states with no production data.
Source: U.S. Department of Agriculture (2012)

Figure 7. U.S. Chestnut Production and Consumption Frequency by State



Note: Each point represents a state. See the appendix for full state names.

Regression Results

Table 2 reports regression results for U.S. consumers. While the Poisson distribution is not the model of best fit, we include its results for reference. Coefficients from Poisson models can be interpreted as, all other variables held constant, a 1-unit change in the variable will lead the difference in the logs of expected chestnut consumption to change by the respective coefficient. For example, according to the Poisson model in column 1 of Table 2, an increase from the age of "25–34" to "35–44" will lead to an exp(−0.275) = 0.760 − 1 = 24% decrease in the frequency of consuming chestnuts. Simply speaking, all else held constant, younger consumers are more likely to regularly consume chestnuts.

In column 2 of Table 2, the NB regression shows a significant dispersion parameter (alpha), which suggests that our data is over-dispersed, meaning the NB fits the data better than does the Poisson model. However, most of the conclusions generated using the Poisson regression do not change significantly when we use the NB model.

As previously noted, over half of Americans have never tried a chestnut; our data contain an excessive number of zeros, which limits the goodness-of-fit for a Poisson model. To control for this possible issue, we also estimated ZIP and ZINB models (columns 3 and 4 of Table 2). The insignificant log-transformed over-dispersion parameter (Lnalpha) suggests that there is no overdispersion in the zero-inflated model. The similarity between the results of the ZIP and ZINB models also implies that the parameters are robust. Results suggest that several factors that affect chestnut consumption, although some of them only influence the likelihood that a consumer has ever tried chestnuts, while others also affect consumption frequency. The logit link function includes variables for gender, age, education, ethnicity, and dummy variables for being a farmer, a vegetarian/vegan, and the primary household shopper. These variables may affect whether participants have knowledge about or experience with chestnuts, which might decide whether an individual has ever tried them. As such, those parameters can be interpreted as identifying how each variable influences the likelihood that a consumer has ever tried a chestnut.

In these models, being a farmer or having a vegetarian/vegan in the family significantly increases the likelihood the participant had tried a chestnut. For example, the odds of never having tried chestnuts decreases by exp = 2.326 times if the consumer is a vegetarian/vegan. The farmer's odds of not having tried chestnuts is exp(1.926) = 6.862 times lower than nonfarmers. This is likely because farmers and vegetarians/vegans are more aware of chestnuts. However, the Poisson portion of the ZIP model and the NB portion of the ZINB model both indicate that being a farmer or vegetarianism/veganism is not correlated with higher chestnut consumption. In contrast, being a primary shopper affects the likelihood the participant has tried chestnuts but *does* affect consumption frequency. In the ZINB model, the expected log of consumption frequency is 0.478 higher for primary shoppers than for those who are not primary shoppers.

Age and gender influence the likelihood that participants have never tried chestnuts and also the consumption frequency of chestnuts. The results from the ZIP and ZINB models suggest that younger male participants have a higher likelihood of having ever tried chestnuts as well as a

Table 2. Factors Affecting U.S. Chestnut Consumption (*N* = 1,030)

Variables	**Poisson**	**NB**	**ZIP**	**ZINB**
Intercept	−0.489* (0.281)	−0.360 (0.297)	0.356 (0.229)	0.352 (0.232)
Male	0.404*** (0.093)	0.420*** (0.113)	0.234*** (0.083)	0.236*** (0.083)
Age	−0.275*** (0.042)	−0.279*** (0.041)	−0.166*** (0.041)	−0.167*** (0.040)
Education	0.063** (0.031)	0.041 (0.038)	0.014 (0.024)	0.013 (0.025)
Income	0.035 (0.025)	0.014 (0.028)	0.018 (0.021)	0.018 (0.021)
Marital status (unmarried)	0.121 (0.130)	0.069 (0.141)	0.130 (0.117)	0.129 (0.118)
Family size	−0.008 (0.052)	0.024 (0.059)	0.067 (0.049)	0.067 (0.050)
Have child in family	0.354*** (0.135)	0.334** (0.155)	0.129 (0.117)	0.134 (0.121)
Ever farmed	−0.133 (0.149)	−0.104 (0.188)	−0.053 (0.127)	−0.055 (0.129)
Region (South)	–	–	–	–
West	−0.024 (0.112)	−0.080 (0.141)	−0.080 (0.089)	−0.081 (0.090)
Mideast	−0.082 (0.142)	−0.137 (0.162)	−0.013 (0.110)	−0.015 (0.112)
North	−0.075 (0.127)	−0.030 (0.148)	−0.010 (0.100)	−0.011 (0.101)
Latino	0.234* (0.129)	0.293* (0.168)	0.025 (0.109)	0.026 (0.110)
Race (white)	–	–	–	–
African American/Am. Indian	−0.062 (0.137)	−0.079 (0.157)	0.025 (0.104)	0.024 (0.105)
Asian	0.298* (0.170)	0.477** (0.226)	0.060 (0.151)	0.062 (0.154)
Others	−0.002 (0.233)	−0.127 (0.337)	−0.025 (0.186)	−0.024 (0.188)
Primary shopper	0.665*** (0.140)	0.666*** (0.140)	0.473*** (0.150)	0.478*** (0.154)
Vegan or vegetarian	0.428*** (0.143)	0.530** (0.221)	0.182 (0.116)	0.185 (0.119)
Farmer	0.553*** (0.156)	0.565* (0.311)	0.168 (0.140)	0.170 (0.142)
Lnalpha (Log-transformed over-dispersion parameter)		0.437*** (0.107)		−4.182 (3.115)
Logit link function				
Intercept			0.650* (0.338)	0.637* (0.346)
Male			−0.348** (0.168)	−0.346** (0.170)
Age			0.182*** (0.058)	0.181*** (0.058)
Education			−0.094* (0.051)	−0.095* (0.052)
Have child in family			−0.252 (0.181)	−0.247 (0.184)
Hispanic/Latino/Spanish origin			−0.503** (0.246)	−0.506** (0.249)
Asian			−0.897** (0.430)	−0.904** (0.441)
Prior shopper			−0.381 (0.239)	−0.374 (0.244)
Vegan or vegetarian			−0.841** (0.386)	−0.844** (0.391)
Farmer			−1.926** (0.801)	−1.950** (0.827)
Log pseudo-likelihood			−1,256.983	−1,256.918

Note: Robust standard errors are in parentheses. Vuong test of ZINB vs. standard negative binomial: z= 4.13***. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively.

higher consumption frequency. Further, more educated participants are more likely to consume chestnuts frequently, although education levels do not affect the odds of having tried chestnuts. The ZINB and ZIP models suggest that there is no relationship between participants who have children and chestnut consumption.

The variables representing immigration or food culture allow us to conclude that Asian and Latino participants are more likely to frequently consume chestnuts than White consumers. However, the ZIP or ZINB model shows that the influence of the ethnic variable is only significant in the logit model part, which indicates that Asian or Hispanic/Latino/Spanish consumers have higher odds of having tried chestnuts but that their expected consumption frequency is not significantly higher than that of non-Asian or Hispanic/Latino/Spanish consumers. This conclusion could be possibly explained by the fact that chestnuts are popular in Asian and Hispanic/Latino/Spanish food cultures.

Conclusion

This article identified key geographic, cultural, and social characteristics of U.S. chestnut consumers. First, we showed that geography has different effects on chestnut consumption in the United States and in China. This is most likely the result of the relatively low domestic production of chestnuts in the United States since most chestnuts in the U.S. market are imported. These results also provide evidence that chestnut producers might benefit from targeting markets outside their local region. Further, we find that young people, males, those with higher levels of education, primary shoppers, farmers, and vegetarians/vegans are more likely to consume chestnuts. Companies in the chestnut industry could use these social characteristics to target potential consumers.

We find that cultural characteristics have a significant influence on chestnut consumption in our ZIP/ZINB model. From the significant influence of Latino origin and Asian ethnicity in our inflated model, we might infer that food culture as a part of immigration culture affects consumption of plant-based proteins such as including chestnuts. This finding suggests some interesting next steps for research regarding on the role of immigration in food choice. It is likely that food choices have always been influenced by consumers' culture, which often leads to the development of local food identities (Malone and Flores Moreno, 2018). Future studies might consider popular foods with ethnic heritages, including edamame (Wolfe et al., 2018), quinoa (Stevens, 2017), or asiago cheese (Vecchio and Annunziata, 2011). That is, understanding how cultural identity influences food choice is likely to be an important next step for interpreting best practices for marketing strategies for chestnuts as well as other foods with a cultural heritage.

Future research on chestnut consumption might address some of the key shortcomings of this research. First, this study utilized consumption data reported via survey methods. Future work might benefit from considering scanner-level data in its analysis, which might help answer questions about how chestnut consumers classify chestnuts. Chestnuts are generally lower in protein than most nuts but higher in carbohydrates, potassium, and vitamin C. As such, the nutrient content of chestnuts is perhaps more comparable to a banana than to other tree nuts. Future studies might explore whether consumers actually substitute from chestnuts to other nuts or are more likely to substitute from chestnuts to fruits and vegetables with similar nutritional profiles. Relatedly, this study omits prices, which are likely important when consumers make decisions about substituting between chestnuts and other, similar products. Finally, we proxied immigrant food culture with participant ethnicity. Future work might reveal stronger correlations between culture and chestnut consumption if a more refined measure of immigrant food culture were utilized. Despite these shortcomings, this paper has some key implications for chestnut marketing. Rather than chasing immigrant populations as an avenue for real market growth, chestnut marketers might benefit by focusing on younger, more educated consumers.

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Appendix:
Corresponding Table of Abbreviation and Full Province/State Names

China		United States	
Full Name	Abbreviation	Full Name	Abbreviation
Anhui	AH	Alabama	AL
Beijing	BJ	California	CA
Chongqing	CQ	Florida	FL
Fujian	FJ	Georgia	GA
Gansu	GS	Idaho	ID
Guangdong	GD	Illinois	IL
Guangxi	GX	Indiana	IN
Guizhou	GZ	Iowa	IA
Hainan	HN	Kansas	KS
Hebei	HB	Kentucky	KY
Heilongjiang	HLJ	Maine	ME
Henan	HEN	Maryland	MD
Hubei	HB	Massachusetts	MA
Hunan	HUN	Michigan	MI
Jiangsu	JS	Missouri	MO
Jiangxi	JX	New Hampshire	NH
Jilin	JL	New Jersey	NJ
Liaoning	LN	New York	NY
Neimenggu	NMG	North Carolina	NC
Qinghai	QH	Ohio	OH
Shaanxi	SHX	Oregon	OR
Shandong	SD	Pennsylvania	PA
Shanghai	SH	South Carolina	SC
Shanxi	SX	Tennessee	TN
Sichuan	SC	Vermont	VT
Tianjin	TJ	Virginia	VA
Xinjiang	XJ	Washington	WA
Yunnan	YN	West Virginia	WV
Zhejiang	ZJ	Wisconsin	WI

Note: Some provinces/states are not listed in the table due to data limitations.

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Consumer Demand for Organic Food Groups and Implications for Farmers' Revenues under the Organic Land Subsidy Scheme: The Case of Denmark

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Abstract

We fit a family of differential demand systems to Danish organic food data and use the selected model's parameters to calculate conditional expenditure and price elasticities for five organic food groups (cereals, meats, dairy products, fruits and vegetables, and other organic foods) to evaluate the implications of the Danish Organic Land Subsidy Scheme for organic farmers. Simulations indicate that, without conversion subsidies, producers of the five organic food groups would have experienced disproportionate changes in revenues due to higher nonsubsidized organic food prices. Producers of meats and other organic foods would lose most in revenues, followed by fruit and vegetable producers.

Keywords: Organic Land Subsidy Scheme, conditional differential demand systems, organic food

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Introduction

The global organic market grew from US$17.9 billion in 2000 to US$81.6 billion in 2015 (Willer and Lernoud, 2017, p. 23). In Europe, the organic food market expanded from 2000 (€7 billion) to 2015 (€29.8 billion) according to data compiled by the Research Institute of Organic Agriculture and the Agricultural Market Information Company. The highest per capita consumption of organic food in 2015 was in Switzerland (€262), followed by Denmark (€191) (Willer, Schaack, and Lernoud, 2017, p. 229). In 2017, Denmark had the largest share of organic foods to total foods in the world (Kaad-Hansen, 2019).

A major force behind the rapid growth of the organic food industry since 2000 has been consumer demand for organic food (Wier et al., 2003, p. 261; Dimitri and Dettmann, 2012). The response to consumer demand has led to a rapid increase in farmland allocated to organic farming and in government incentives designed to encourage farmers to switch from conventional farming to organic farming. As a result, organic food has turned from a niche product sold in a limited number of retail outlets to one available in a wide variety of venues, including supermarkets, convenience stores, farmers' markets, and pharmacies (Willer and Lernoud, 2017).

Most of the research on demand for organic food has focused on analyzing the demand for single organic food groups, such as dairy products (e.g., Wier et al., 2003, for Denmark; Schröck, 2012, for Germany; Alviola and Capps, 2010; Chen, Saghaian, and Yuqing, 2018; Li, Peterson, and Xia, 2012, for the United States), baby food (e.g., LeBeaux, Epperson, and Huang, 2009, for the United States), disaggregated organic fruits (e.g., Lin et al., 2009, for the United States), or disaggregated vegetable products (e.g., Zhang et al., 2011; Kasterisdis and Yen, 2012, for the United States; Fourmouzi, Genius, and Midmore, 2012, for the United Kingdom). None of these studies, to the best of our knowledge, examines the within-group demand relationships of different organic food aggregates. In this study, we use the systemwide approach to consumer demand to fit a demand system to the data of a variety of organic food groups (Theil, 1980). We use the estimated elasticities for simulations to evaluate the impact of government subsidy programs on different organic food industries.

The organic food industry—in Europe in general and in Denmark in particular—continues to enjoy significant governmental support to help farmers convert from conventional to organic farming. Proper evaluation of governmental or regional support programs requires reliable estimates of organic consumers' responsiveness to changes in prices and expenditures. Elasticity estimates allow us to draw conclusions on the extent to which Danish government efforts to increase the organic food supply leave farmers better off. Accurate estimates of organic food demand elasticities also help farmers, wholesalers, distributors, food processors, and retailers plan for production and sales.

Our objective is to provide a detailed demand system analysis of organic food consumption in Denmark and to use the estimated elasticities to evaluate the impact of the Organic Land Subsidy Scheme on Danish organic producers' revenues.[1] Four competing differential demand systems—the Rotterdam model (Theil, 1965), the Central Bureau Service (CBS) model (Keller and van Driel, 1985), the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980), and the National Bureau of Research (NBER) model (Neves, 1994)—are fit to the data. Additionally, we use a nesting model, first developed by Barten (1993) and extended by Lee, Brown, and Seale (1994), to choose the model that best fits this dataset. Expenditure elasticities and price elasticities are estimated from the parameters of the chosen model. Based on these elasticity estimates, we simulate the effects of the Organic Land Subsidy Scheme on organic food producers.

Overall, our results suggest that, conditional on total organic food expenditures, organic cereals and organic dairy products are expenditure-inelastic, while organic meats, fruits and vegetables, and other organic foods are expenditure-elastic. Conditional on total organic food expenditures, organic cereals and meats are price-inelastic, and organic dairy, organic fruits and vegetables, and other organic food products are price-elastic, holding both real income and nominal income constant. Simulation results indicate that, in the absence of the Organic Land Subsidy Scheme, different organic producers would have experienced disproportionate changes in revenues as a result of the same percentage increase in prices of all organic food groups.

Background

The first organic crop sold in Danish retail stores was carrots in 1982 (Organic Denmark, 2016). The first legislation governing organic food production was passed in 1987, followed by the introduction of the Danish state-controlled organic inspection label (the red Ø-label) in 1989. Denmark was the first country in the world to pass a law on organic farming and to introduce government inspection of the organic production chain. Today, Denmark continues to enjoy strong government support for organic agriculture (Organic Denmark, 2017a,b).

The Danish government implemented both supply-side subsidy programs and demand-side marketing policies to boost organic production and consumption. In 1987, the government introduced direct farm subsidies to ease conversion from conventional to organic farming for the first 3 years of the conversion period. Additional conversion payments for organic livestock production were introduced in 1989. The passage of European Economic Community (EEC) Regulation 2078/92 in 1992 prompted the Danish government to introduce permanent subsidies for organic farming in 1994 (Daugbjerg and Svendsen, 2011).[2] This new scheme provided land-based conversion subsidies for 2 years and permanent organic subsidies. Eligibility required

[1] The Organic Land Subsidy Scheme is part of the Organic Action Plan for Denmark (Ministry of Food, Agriculture and Fisheries of Denmark, 2015).

[2] The full title of this regulation is "Council Regulation (EEC) No. 2078/92 of 30 June 1992 on Agricultural Production Methods Compatible with the Requirements of the Protection of the Environment and the Maintenance of the Countryside."

organic farming for at least 5 years. In 1993, organic food consumption spiked when the retail chain SuperBrugsen joined efforts to boost organic consumption by offering massive reductions in organic prices and increasing the marketing of organic food. Other retail chains followed SuperBrugsen, leading to an overall price reduction of 15%–20% for organic foods (van der Grijp and den Hond, 1999, p. 31).

The relative success of Danish organic farming was interrupted by a period of stagnation and decline between 1992 and 1994. The organic subsidy scheme was changed in 1996 to provide additional support to organic produce farms and to pay a specific subsidy to organic pork producers. The government's efforts, coupled with increased demand-side policies and consumer confidence in the Ø-mark standards, led to a resurgence in organic food sales after the stagnation period (Organic Denmark, 2016).

After many years of overproduction of organic dairy and cereals, selective support schemes for specific commodity groups were abandoned and replaced by the 2004 scheme, which instead paid organic farmers an environmental subsidy for environmentally friendly farming.[3] The only remaining organic-only subsidy in 2004 was the conversion payments, for which dairy farmers were ineligible at the time. In 2007, dairy farmers became eligible for conversion subsidies again due to the low forecast for future organic dairy production (Daugbjerg and Svendsen, 2011).

Currently, Denmark has a simplified subsidy scheme for organic farmers. In 2011, the government paid a permanent subsidy of 750 Danish kroner (DKK) per hectare per year for environmentally friendly farming and a conversion subsidy of 1050 DKK per hectare per year for the first 2 years, followed by 100 DKK per hectare per year for subsequent years in the commitment period (Norfelt, 2011). The Danish government is committed to doubling total organically farmed area by 2020, which would account for approximately 12% of Danish farmland (MFAFD, 2015).[4] According to Statistics Denmark (2014), the official Danish statistical agency, sales of selected major organic foods between 2003 and 2007 showed a persistent increase, peaking at a 33% increase in 2007. Between 2003 and 2013, total sales of the major organic food groups increased from approximately 2 billion DKK to around 5.8 billion DKK. Over the same period, the total quantity sold of the selected products increased from approximately 154,000 tons to around 248,000 tons (Statistics Denmark, 2014). The Danish organic market further expanded by 12% between 2014 and 2015, and retail sales reached €1,079 million (or 8.1 billion DKK) in 2015 (Willer, Schaack, and Lernoud, 2017, pp. 227–229).

Methods

We consider a family of differential demand systems to estimate demand for organic food groups in Denmark. Theil (1965) derived the differential demand equation,

[3] Nonorganic but environmentally friendly farmers were also eligible for these new subsidies; however, organic farmers were prioritized (Daugbjerg and Svendsen, 2011).
[4] The support is partly financed through the European Union's Rural Development Program.

(1) $$w_{it} d\left(\ln q_{it}\right) = \theta_i \, d\left(\ln Q_t\right) + \sum_j \pi_{ij} d\left(\ln p_{jt}\right),$$

where w_{it} is the budget share of good $i = 1, \ldots, n$ at time t; n is the number of goods; θ_i is the marginal share of good i at time t; $d\left(\ln Q_t\right) = \sum_j w_{it} d\left(\ln q_{it}\right)$ is the Divisia volume index, representing the log change of real expenditure; and the π_{ij} are Slutsky (compensated) price parameters. The matrix $\pi = \left[\pi_{ij}\right]$ is negative semidefinite of rank $n - 1$. Note that θ_i and π_{ij} need not be constants.

To make the problem of estimating the demand for five groups of organic foods (i.e., cereals, meats, dairy products, fruits and vegetables, and other organic food products) manageable, we apply a commonly used method of two-stage budgeting (Theil, 1975; Barten, 1977; Rickertsen, 1998; Carpentier and Guyomard, 2001). In this approach, consumers first allocate their total income (expenditure) among broad categories of goods, including organically grown food consumed at home and conventionally grown food consumed at home. In the next stage, consumers allocate total expenditure for organically grown food at home among, in this case, the five groups of organically grown foods.

In its conditional form, the differential demand system may be written as

(2) $$w_{it}^* d\left(\ln q_{it}\right) = \theta_i^* d\left(\ln Q_{gt}\right) + \sum_{j \in S_g} \pi_{ij}^* d\left(\ln p_{jt}\right), \; i, j \in S_g,$$

where $w_{it}^* = \dfrac{w_{it}}{W_{gt}}$ is the conditional budget share of good $i \in S_g$ at time t; W_{gt} is the budget share of group S_g; $\theta_i^* = \dfrac{\theta_i}{\Theta_g}$ is the conditional marginal share of $i \in S_g$ at time t; Θ_g is the marginal share of group S_g; and the π_{ij}^* are conditional Slutsky (compensated) price parameters. The matrix $\pi^* = \left[\pi_{ij}^*\right]$ is negative semidefinite of rank $n - 1$. As in the unconditional differential demand system of equation (1), θ_i^* and π_{ij}^* need not be constants.

By treating θ_i^* and π_{ij}^* in equation (2) as constants to be estimated, Theil (1965) developed the Rotterdam model. The conditional Rotterdam in finite-change form instead of the infinitesimal-change form is

(3) $$\bar{w}_{it}^* Dq_{it} = \theta_i^* DQ_{gt} + \sum_{j \in S_g} \pi_{ij}^* Dp_{jt} + \varepsilon_{it}^*, \; i, j \in S_g,$$

where $\bar{w}_{it}^* = \frac{1}{2}\left(w_{i,t}^* + w_{i,t-1}^*\right)$; $Dq_{it} = \ln q_{i,t} - \ln q_{i,t-1}$; $Dp_{jt} = \ln p_{j,t} - \ln p_{j,t-1}$; $DQ_{gt} = \sum_{j \in S_g} \bar{w}_{jt}^* Dq_{jt}$ is the Divisia volume index for group S_g, representing total real expenditure for all goods in group S_g; and ε_{it}^* is a random error term. The conditional Rotterdam model satisfies the adding-up $\left(\sum_{i \in S_g} \theta_i^* = 1;\ \sum_{i \in S_g} \pi_{ij}^* = 0\right)$, homogeneity $\left(\sum_{j \in S_g} \pi_{ij}^* = 0\right)$, and Slutsky symmetry $\left(\pi_{ij}^* = \pi_{ji}^*,\ i, j \in S_g\right)$ theoretical constraints.

There is no theoretical reason for the parameters of equation (2) to be constant, and Keller and van Driel (1985) developed the CBS model by replacing the constant marginal shares of the Rotterdam model with the marginal shares of Working's (1943) model, $w_{it} = \alpha_i + \beta_i \ln Q_t + \varepsilon_{it}$, where $\theta_i = \beta_i + w_i$, β_i is the income parameter of Working's model and Q represents real income. In the conditional context, $\theta_i^* = \beta_i^* + w_{it}^*$, substituting $\beta_i^* + w_{it}^*$ for θ_i^* in equation (3) and rearranging terms yields the conditional CBS model:

$$\text{(4)} \qquad \bar{w}_{it}^* D\frac{q_{it}}{Q_{gt}} = \beta_i^* DQ_{gt} + \sum_{j \in S_g} \pi_{ij}^* Dp_{jt} + \varepsilon_{it}^*,\ i, j \in S_g.$$

The following constraints of demand theory apply to the CBS model: adding-up $\left(\sum_{i \in S_g} \beta_i^* = 0;\ \sum_{i \in S_g} \pi_{ij}^* = 0\right)$; homogeneity $\left(\sum_{j \in S_g} \pi_{ij}^* = 0\right)$; and Slutsky symmetry $\left(\pi_{ij}^* = \pi_{ji}^*,\ i, j \in S_g\right)$.

Deaton and Muellbauer's (1980) time-series AIDS model can also be written in the conditional differential form (Barten, 1993):

$$\text{(5)} \qquad d\bar{w}_{it}^* = \beta_i^* DQ_{gt} + \sum_{j \in S_g} \gamma_{ij}^* Dp_{jt} + \varepsilon_{it}^*,\ i, j \in S_g.$$

This time-series AIDS model satisfies the adding-up $\left(\sum_{i \in S_g} \beta_i^* = 0;\ \sum_{i \in S_g} \gamma_{ij}^* = 0\right)$, homogeneity $\left(\sum_{j \in S_g} \gamma_{ij}^* = 0\right)$, and Slutsky symmetry $\left(\gamma_{ij}^* = \gamma_{ji}^*,\ i, j \in S_g\right)$ theoretical conditions.

Another variant of the differential demand system, the NBER model proposed by Neves (1994), can be obtained by replacing β_i^* in equation (5) with $\theta_i^* - w_{it}^*$ and rearranging the terms:

$$\text{(6)} \qquad d\bar{w}_{it}^* + \bar{w}_{it}^* DQ_{gt} = \theta_i^* DQ_{gt} + \sum_{j \in S_g} \gamma_{ij}^* Dp_{jt} + \varepsilon_{it}^*.$$

The NBER model satisfies adding-up $\left(\sum_{i\in S_g}\theta_i^* = 1;\ \sum_{i\in S_g}\gamma_{ij}^* = 0\right)$, homogeneity $\left(\sum_{j\in S_g}\gamma_{ij}^* = 0\right)$, and Slutsky symmetry $\left(\gamma_{ij}^* = \gamma_{ji}^*,\ i,j\in S_g\right)$ theoretical conditions.

All four models discussed have the same righthand-side (RHS) parameterization and variables but different left-hand-side (LHS) variables. Also, none of the models is nested with the others. Barten (1993) developed a more general model that nests the above four models with the addition of only two more parameters. Lee, Brown, and Seale (1994) extended Barten's method by rearranging the four models to have the same Rotterdam dependent variables with different RHS parameterizations. Specifically, the four models with Rotterdam dependent variables are, in conditional form,

(7) Rotterdam: $$\bar{w}_{it}^* Dq_{it} = \theta_i^* DQ_{gt} + \sum_{j\in S_g}\pi_{ij}^* Dp_{jt} + \varepsilon_{it}^*,\ i,j\in S_g;$$

(8) CBS: $$\bar{w}_{it}^* Dq_{it} = \left(\beta_i^* + \bar{w}_{it}^*\right) DQ_{gt} + \sum_{j\in S_g}\pi_{ij}^* Dp_{jt} + \varepsilon_{it}^*,\ i,j\in S_g;$$

(9) AIDS: $$\bar{w}_{it}^* Dq_{it} = \left(\beta_i^* + \bar{w}_{it}^*\right) DQ_{gt} + \sum_{j\in S_g}\left(\gamma_{ij}^* - \bar{w}_{it}^*\left(\delta_{ij} - \bar{w}_{jt}^*\right)\right) Dp_{jt},\ i,j\in S_g;$$

where δ_{ij} is the Kronecker delta, which equals 1 for $i = j$ and 0 otherwise, and

(10) NBER: $$\bar{w}_{it}^* Dq_{it} = \theta_i^* DQ_{gt} + \sum_{j\in S_g}\left(\gamma_{ij}^* - \bar{w}_{it}^*\left(\delta_{ij} - \bar{w}_{jt}^*\right)\right) Dp_{jt},\ i,j\in S_g.$$

Next, Lee, Brown, and Seale (1994) developed the nesting model:

(11) $$\bar{w}_{it}^* Dq_{it} = \left(d_i^* + \delta_1\bar{w}_{it}^*\right) DQ_{gt} + \sum_{j\in S_g}\left(e_{ij}^* - \delta_2\bar{w}_{it}^*\left(\delta_{ij} - \bar{w}_{jt}^*\right)\right) Dp_{jt},\ i,j\in S_g,$$

where $d_i^* = \delta_1\beta_i^* + \left(1-\delta_1\right)\theta_i^*,\ i\in S_g$, and $e_{ij}^* = \delta_2\gamma_{ij}^* + \left(1-\delta_2\right)\pi_{ij}^*,\ i,j\in S_g$, with δ_1 and δ_2 the two additional parameters to be estimated. When $\delta_1 = 0$ and $\delta_2 = 0$, the nesting model is the Rotterdam model; when $\delta_1 = 1$ and $\delta_2 = 0$, the nesting model is the CBS model; when $\delta_1 = 1$ and $\delta_2 = 1$, it is the AIDS model; and when $\delta_1 = 0$ and $\delta_2 = 1$, it is the NBER model. The nesting model obeys the adding-up $\left(\sum_{i\in S_g} d_i^* = 1-\delta_1;\ \sum_{i\in S_g} e_{ij}^* = 0\right)$, homogeneity $\left(\sum_{j\in S_g}\gamma_{ij}^* = 0\right)$, and Slutsky symmetry $\left(e_{ij}^* = e_{ji}^*,\ i,j\in S_g\right)$ conditions.

The four differential demand systems and the nesting system can be estimated using the maximum likelihood (ML) method. Due to the adding-up condition, the contemporaneous covariance matrix Ω is singular. Barten (1969) showed that ML estimates of the parameters of the complete n-equation system can be obtained using estimates from $n - 1$ equations. Further, the procedure yields ML estimates that are invariant to the equation deleted. Therefore, we estimate the conditional differential demand systems considered in the previous section with ML using iterative seemingly unrelated regressions (SUR). The cross-equation restrictions of symmetry necessitate the use of iterative SUR to obtain efficient point estimates (Barten, 1969). This SUR procedure iterates over Ω and converges to the ML estimator if the normality of the error terms holds (Berndt and Savin, 1975; Rickertsen, 1998).

Results and Discussion

Data on organic food expenditures and quantities are constructed using surveys conducted by Statistics Denmark (2015) of Danish supermarket chains, department stores, and wholesale chains between 2003 and 2015. The detailed commodities surveyed by Statistics Denmark are aggregated into five major Danish organic food groups for estimation purposes: cereals, meats, dairy products, fruits and vegetables, and other organic food products. The cereals group consists of rice, bread, pasta, flour, groats, cornflakes, muesli, crispbread, rice cakes, and other flour and groats products. The meats group is made up of beef, pork, chicken, cold cuts of meat and poultry, meat spreads, and offal. The dairy group consists of milk; cream; sour cream; other mild, fermented products; and cheeses. The fruits and vegetables group consists of fruits (fresh citrus, fresh bananas, fresh apples, fresh stone fruits and berries, pineapple, kiwi, melon, other fruits, dried fruit, nuts, and almonds) and vegetables (fresh lettuce, fresh Chinese cabbage, fresh spinach, fresh cabbage, fresh tomatoes, fresh cucumbers, fresh sweet peppers, fresh capsicum, fresh carrots, fresh potatoes, fresh onions, frozen vegetables, potato products, and canned vegetables). The other organic food products group consists of eggs, fats and oils including butter and cooking oils, fish, sugar, jams, syrup, honey, chocolate, candy, ice cream, spices and stocks, ketchup, dressing, mayonnaise, processed baby food, coffee, tea, cocoa, juices and fruit juices, wine, cider, and beer. [5]

Total sales and quantities of the organic commodities in the data are converted to per capita measures using annual population data obtained from Statistics Denmark (2019) for the same period. Computed unit prices (per capita expenditures divided by per capita consumption) are used for the analysis due to lack of explicit retail price information. Table 1 reports summary statistics of data. From 2003 to 2015, the budget share of organic cereals increased by about 7%, while the share of meats increased by 44%, the share of dairy products decreased by 37%, the share of fruits and vegetables increased by 79%, and the share of other organic food products increased by approximately 22%. In the same period, the unit prices per ton of cereals, meats, dairy products, fruits and vegetables, and other organic food products increased by 46%, 42%,

[5] Organic fish quantities and expenditures are reported as 0 for most cases. As such, leaving "fish" in the "meats" category would have caused meat expenditures to be independent of meat prices. We included "fish" in "other organic foods" category to circumvent this issue.

50%, 65%, and 33%, respectively. The highest mean budget share in the sample period was for dairy products (40%), followed by fruits and vegetables (21%), other organic food products (20%), cereals (13%), and meats (7%). There was substantially more variation in the budget share of organic dairy products than in the budget share for the other four organic food products (Table 1).

Table 1. Summary Statistics of Danish Organic Food Data, 2003–2015 (*N* = 280)

Organic Food Groups	Cereals	Meats	Dairy	Fruits–Veg.	Other
Per capita consumption (kilograms per capita)					
Minimum	2.70	0.33	19.38	3.68	1.53
Mean	4.56	0.63	23.98	7.62	2.81
Maximum	6.18	1.03	27.21	12.47	4.36
Std. dev.	1.30	0.19	2.62	2.66	0.90
Unit prices (Danish kroner per kilogram)					
Minimum	15.20	65.54	9.87	15.19	45.76
Mean	21.90	89.87	12.32	21.52	54.75
Maximum	26.16	103.53	15.54	27.31	65.82
Std. dev.	4.38	11.79	2.06	4.32	7.18
Expenditures (Danish kroner per kilogram)					
Minimum	41.14	21.52	191.30	58.15	70.21
Mean	104.61	58.33	298.59	172.73	159.08
Maximum	144.99	96.00	386.95	324.39	265.42
Std. dev.	43.99	21.45	71.53	83.18	66.42
Budget shares (percentage of total organic food expenditures)					
Minimum	0.10	0.06	0.32	0.15	0.18
Mean	0.13	0.07	0.40	0.21	0.20
Maximum	0.15	0.09	0.51	0.27	0.22
Std. dev.	0.02	0.01	0.06	0.04	0.02

Note: Cereals includes rice, bread, pasta, flour, groats, cornflakes, muesli, crispbread, rice and cakes, and other flour and groats products. Meats includes beef, pork, chicken, cold cuts of meat and poultry, meat spreads, and offal. Dairy includes milk, cream, sour cream, other mild, fermented products, and cheeses. Fruits and vegetables includes fruits (fresh citrus, fresh bananas, fresh apples, fresh stone fruits and berries, pineapple, kiwi, melon, other fruits, dried fruit, nuts, and almonds) and vegetables (fresh lettuce, Chinese cabbage, spinach, cabbage, tomatoes, cucumbers, sweet peppers, capsicum, carrots, potatoes, and onions; frozen vegetables; potato products; and canned vegetables). Other organic food products includes eggs, fats and oils (including butter and cooking oils), fish, sugar, jams, syrup, honey, chocolate, candy, ice cream, spices and stocks, ketchup, dressing, mayonnaise, processed baby food, coffee, tea, cocoa, juices and fruit juices, wine, cider, and beer. Unit prices are computed as per capita expenditures divided by per capita consumption.

Estimated Differential Demand Systems and Elasticities

We first estimate unconstrained forms of the models given in equations (7)–(10) along with the nesting model in equation (11). The theoretical restrictions of homogeneity are tested using a small sample Hotelling's T^2 test developed by Laitinen (1978). The test statistics for homogeneity restrictions for all five models are all smaller than the 5% critical value of 46.39 (Table 2). Therefore, the null of homogeneity cannot be rejected for any of the five functional forms and should be imposed on all five demand systems. We test symmetry relative to the homogeneity-restricted models for all five demand systems using log-likelihood-ratio (LR) tests. All models have LR test statistics lower than the 5% critical value of 12.59; therefore, symmetry is not rejected for any of the five models at the 5% significance level (Table 2).

Table 2. Homogeneity, Symmetry, and Autocorrelation Tests for the Five Demand Systems

	Test Statistic					**Critical Value**
Restriction/Test	**Rotterdam**	**CBS**	**AIDS**	**NBER**	**Nesting**	**(α = 0.05)**
Homogeneity	22.93	16.30	23.08	23.89	16.88	46.39
Symmetry	8.65	4.28	3.02	3.43	4.81	12.59
Autocorrelation	2.35	1.32	3.61	0.18	1.81	3.84

Notes: Homogeneity is tested using Hotelling's T^2 test, as recommended by Laitinen (1978). Symmetry restrictions and AR(1) autocorrelation are tested using log-likelihood-ratio tests.

We also test for first-order autocorrelation, AR(1), in the error terms of each demand system by testing the AR(1)-imposed demand systems with ML using the Hildreth–Lu (1960) method with the LR test. We reject AR(1) autocorrelation in all of the demand systems considered (Table 2). For all five systems, the test statistics are smaller than the critical value at the 5% level. This is not surprising, because the log-difference transformations of the data in the conditional differential demand systems tend to wipe out the autocorrelation in the data (Barten, 1969, 1977).[6]

Next, based on the homogeneity and symmetry-imposed demand systems, we use LR tests to select the model that best fits the dataset compared to the nesting model. Table 3 reports the LR test statistics and critical value of 5.99 at the 5% level for model selection tests. When tested against the nesting model, none of the four competing models (i.e., Rotterdam, CBS, AIDS, and NBER) are rejected. In other words, the LR tests indicate that, from a statistical point of view, all models fit the data as well as the nesting model does. However, from an economics viewpoint, the four models do not perform well. In the case of the four competing models, the required negativity condition of the Slutsky price matrix is violated; the own-price parameter of organic cereals is statistically 0 but positive. Because the nesting model is more flexible than the other

[6] Unit-root tests have also been implemented to confirm the stationarity of the variables used in the model. The null of unit roots has been rejected in all cases. Results are available upon request.

four models, its added flexibility is able to handle the negativity condition of the Slutsky price matrix, that is, the negativity condition is not violated, and all own-price Slutsky parameters are negative, as dictated by economic theory. Based on its added flexibility, its adherence to the negativity condition, and that it is considered a complete demand system in its own right, we use its parameters to calculate and report conditional expenditure elasticities, conditional Slutsky price elasticities, and conditional Cournot price elasticities (Barten, 1993; Lee, Brown, and Seale, 1994; Asci et al., 2016).

Table 3. Functional Form Tests of Four Alternative Models against the Nesting Model

Model	H_0	Likelihood Ratio Test	Critical Value ($\alpha = 0.05$)
Rotterdam	$\delta_1 = 0,\ \delta_2 = 0$	5.90	5.99
CBS	$\delta_1 = 1,\ \delta_2 = 0$	4.68	5.99
AIDS	$\delta_1 = 1,\ \delta_2 = 1$	3.21	5.99
NBER	$\delta_1 = 0,\ \delta_2 = 1$	4.03	5.99

Table 4 reports the conditional demand elasticity estimates.[7] The top panel reports the conditional expenditure and Slutsky (compensated) price elasticities. The bottom panel reports the conditional Cournot (uncompensated) price elasticities. The conditional expenditure elasticities, η_i^*, are positive and significantly different from 0 at the 5% significance level. Those of the organic groups of meats, fruits and vegetables, and other organic food products are conditionally elastic with point estimates greater than unitary. Conditional expenditure elasticities of meats and fruits and vegetables are 1.5, while that of other products is 1.1.

As total expenditures for organic foods in Denmark increase, quantities demanded of meats and fruits and vegetables are expected to grow the fastest for a given percentage change in total organic food expenditure. Demand for organic cereals and dairy products are conditionally expenditure-inelastic, with point estimates less than unitary. The smallest is that of dairy (0.6). For a 1% increase in total organic food expenditure, the quantity demanded by Danish consumers of the organic groups of meats, fruits and vegetables, and other organic food products would increase by more than 1% and those of organic cereals and dairy products by less than 1%; the quantities demanded by Danish consumers of organic groups meats, fruits and vegetables, and other organic food products are more sensitive to a change in total organic food expenditure than those of organic cereals and dairy products.

[7] The complete set of formulae to calculate conditional demand elasticities for the nesting model is given in Lee, Brown, and Seale (1994).

Table 4. Conditional Demand Elasticities of Five Organic Food Groups, Denmark, 2004–2015

Commodity	**Conditional Expenditure Elasticity**	**Cereals**	**Meats**	**Dairy**	**Fruit–Veg.**	**Other**
Conditional Slutsky (compensated) price elasticities (S^*_{ij})						
Cereals	0.90**	−0.06	−0.20	0.76	−0.16	−0.34**
	(0.36)	(0.42)	(0.21)	(0.50)	(0.41)	(0.13)
Meats	1.51**	−0.35	−0.73**	0.14	0.49	0.45**
	(0.35)	(0.36)	(0.33)	(0.55)	(0.47)	(0.20)
Dairy	0.59**	0.25	0.03	−1.15**	0.38	0.48**
	(0.20)	(0.17)	(0.11)	(0.36)	(0.29)	(0.09)
Fruit–veg.	1.53**	−0.10	0.17	0.70	−1.05**	0.28**
	(0.31)	(0.25)	(0.17)	(0.53)	(0.48)	(0.14)
Other	1.10**	−0.22**	0.17**	0.94**	0.30**	−1.19**
	(0.10)	(0.09)	(0.07)	(0.18)	(0.15)	(0.10)
Conditional Cournot (uncompensated) price elasticities (C^*_{ij})						
Cereals		−0.18	−0.27	0.41	−0.35	−0.52**
		(0.44)	(0.20)	(0.48)	(0.42)	(0.16)
Meats		−0.54	−0.85**	−0.44	0.17	0.15
		(0.38)	(0.32)	(0.53)	(0.48)	(0.22)
Dairy		0.18	−0.02	−1.38**	0.26	0.36**
		(0.18)	(0.10)	(0.35)	(0.30)	(0.11)
Fruit–veg.		−0.29	0.06	0.11	−1.38**	−0.02
		(0.26)	(0.16)	(0.52)	(0.49)	(0.16)
Other		−0.37**	0.09	0.52**	0.07	−1.41**
		(0.09)	(0.07)	(0.18)	(0.15)	(0.10)

Notes: Elasticities are calculated from the nesting model, homogeneity and symmetry imposed. Numbers in parentheses are asymptotic standard errors. Double and single asterisks (**, *) indicate significance at the 5% and 10% levels, respectively.

The conditional Slutsky own-price elasticities (S_{ii}^{*}) are compensated and measure the percentage change in quantity demanded when own-price changes by 1%, keeping the real total organic food expenditure constant. The conditional own-price elasticities (both S_{ii}^{*} and C_{ii}^{*}) are all negative as expected, with four of the five significantly different from 0 at the 5% significance level. Demand for two organic groups (cereals and meats) is conditionally inelastic, with S_{ii}^{*} less than 1 in absolute value, fruits and vegetables is essentially unitary-elastic, and dairy and other organic foods are own-price elastic with elasticities greater than 1 in absolute values. This indicates that the quantities demanded of other organic food products and dairy products are the most sensitive to changes in their own prices, followed by organic fruits and vegetables and then meats. The quantity demanded of organic cereals is least sensitive to an own-price change among the five organic food groups. This is likely because Danes consider cereals (including bread and pastries) to be staples in their habitual diet (Engeset et al., 2015).

The conditional Cournot own-price elasticities (C_{ii}^{*}) are uncompensated and measure the percentage change in quantity demanded when own-price changes by 1%, keeping the nominal total organic food expenditure constant. The conditional Cournot (C_{ii}^{*}) own-price elasticities are larger in absolute values than the corresponding Slutsky (S_{ii}^{*}) ones. The conditional own-price elasticities of cereals (−0.18) and meats (−0.85) continue to be inelastic, with that of cereals still the smallest. The other three conditional Cournot own-price elasticities (dairy, fruits and vegetables, and other organic foods) are still larger than 1 in absolute values, with other organic foods having the largest elasticity (−1.41) and dairy and fruits and vegetables both having a Cournot own-price elasticity of −1.38. Note that Cournot price elasticities include both the substitution effect and the income effect of a price change on quantity demanded, while Slutsky price elasticities only measure the substitution effect of a price change.

A conditional cross-price elasticity measures the percentage change in quantity demanded of good *i* when the price of good *j* changes by 1%. A positive conditional Slutsky cross-price elasticity indicates that goods *i* and *j* are substitutes. As such, the quantity demanded of good *i* increases when the price of good *j* increases. A negative sign indicates that goods *i* and *j* are complements. Of the 20 conditional Slutsky cross-price elasticities (S_{ij}^{*}, for $i \neq j$), 14 are positive. The pairs for meats–other, dairy–other, and fruits and vegetables–other are positive and significantly different from 0, indicating that these goods are substitutes. Only the cereals–other pair has negative and significant Slutsky cross-price elasticities, indicating that cereals and other products are complements. The remaining conditional Slutsky cross-price elasticities are not significantly different from 0. For example, the quantity demand of organic meats is not sensitive to a change in the price of organic cereals and vice versa. Other pairs like these are meats–dairy, meats–fruits and vegetables, dairy–fruits and vegetables, and cereals–fruits and vegetables.

Because conditional Cournot cross-price elasticities are equal to the corresponding Slutsky ones minus a positive income effect of price changes, they do not indicate whether a good is a complement or a substitute. They are, however, better indicators of the market response of a price change than the Slutsky cross-price elasticities. For instance, a Cournot cross-price elasticity may be negative while the corresponding Slutsky one is positive if the income effect of a price change is larger in absolute value than the substitution effect of the same price change. The conditional Cournot cross-price elasticities of dairy and other organic foods continue to be positive and significantly different from 0 while those of cereals and other organic foods continue to be negative and significantly different from 0. Note that magnitudes of Cournot cross-price elasticities may be asymmetric between goods A–B and goods B–A.

Simulated Effects of the Danish Organic Land Subsidy Scheme

In this section, the estimated Cournot price elasticities are used to simulate the impact of the Organic Land Subsidy Scheme on Danish organic food demand.[8] In general, demand for organic products is high in Denmark and is expected to continue to grow (Organic Denmark, 2017b). The Organic Land Subsidy Scheme essentially removes barriers associated with large sunk costs of entering into the organic agricultural industry. Without the Organic Land Subsidy Scheme, prices would have to be higher to attract new farmers to enter the market and to compensate conventional farmers for the cost of changing over to organic food production.

The subsidies provided to organic farmers by the Danish government to convert conventional agricultural land to organic agriculture decrease the current or observed prices relative to what prices would be without those subsidies. In this section, we simulate the effects of higher nonsubsidized prices on production and revenues for the five categories of organically produced products (i.e., cereals, meats, dairy products, fruits and vegetables, and other organic food products). Specifically, the simulations are based on 2015 quantities, expenditures, and prices under four price scenarios, which are that prices without the Organic Land Subsidy Scheme would be 10%, 20%, 30%, or 40% higher than the observed (conversion subsidized) prices.

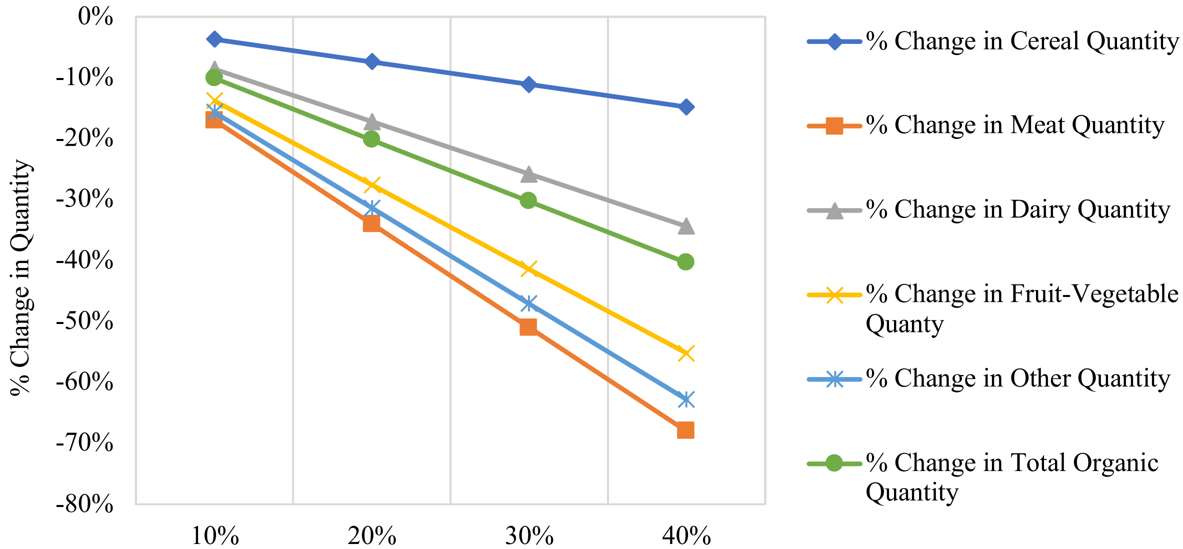
In the four simulation scenarios of higher prices without conversion subsidies, the quantities demanded of all five organic food groups decrease relative to the corresponding 2015 base quantities (Table 5 and Figure 1). The quantity responses to the price changes vary, with the quantity demanded of cereals the least sensitive to its own-price change or to price changes in the other four organic food groups. Quantities demanded of dairy are moderately sensitive to price changes, with its quantities demanded decreasing less percentage-wise than the percentage increases in all prices. For example, when all prices increase by 40%, the quantity of dairy demanded decreases by 34%. The quantities demanded of the other three groups—meats, fruits and vegetables, and other organic foods—decrease more in percentages than the percentage increases in all prices. Of these three groups, the quantities demanded of meats fall the most, followed by quantities demanded of other organic foods and then quantities demanded of fruits and vegetables. The percentage change in demand for total organic food range from −10% for a 10% higher (hypothesized) nonsubsidized price to −40% for a 40% higher nonsubsidized price. The same pattern exists for the 20% and 30% price-increase scenarios, indicating that the effect of a percentage change in all prices of the five organic food groups due to hypothesized absence of the Organic Land Subsidy Scheme on the total organic food quantity is unitary.

[8] Statistically insignificant Cournot elasticities are treated as no changes in quantities due to the price changes.

Table 5. Cumulative Simulated Effects of Four Price Scenarios on Five Organic Food Groups Based on Cournot Price Elasticities

Organic Food Category	2015 Quantity (tons)	2015 Expenditure (million DKK)	2015 Prices (DKK/ton)	Hypothesized Nonsubsidized Prices (DKK/ton)	Change from 2015 Quantity (tons)	Change in Quantity (%)	Expenditure Based on Nonsubsidized Prices (million DKK)	Change in Expenditure (million DKK)	Change in Expenditure (%)
10% increase in without-conversion-subsidy prices									
Cereals	35,004	812.2	23,203.1	25,523.4	−1,295.1	−3.7	860.4	48.2	5.9
Meat	5,851	543.4	92,870.8	102,157.9	−994.7	−17.0	496.1	−47.3	−8.7
Dairy	146,091	2,190.1	14,991.7	16,490.8	−12,563.8	−8.6	2,202.0	11.8	0.5
Fruits–veg.	70,569	1,836.0	26,017.5	28,619.2	−9,738.5	−13.8	1,740.9	−95.1	−5.2
Others	24,690	1,502.3	60,846.5	66,931.2	−3,876.3	−15.7	1,393.1	−109.2	−7.3
Total	282,205	6,884.1			−28,468.5	−10.1	6,692.5	−191.6	−2.8
20% increase in without-conversion-subsidy prices									
Cereals	35,004	812.2	23,203.1	27,843.7	−2,590.3	−7.4	902.5	90.3	11.1
Meat	5,851	543.4	92,870.8	111,444.9	−1,989.3	−34.0	430.4	−113.0	−20.8
Dairy	146,091	2,190.1	14,991.7	17,990.0	−25,127.7	−17.2	2,176.1	−14.0	−0.6
Fruits–veg.	70,569	1,836.0	26,017.5	31,221.0	−19,477.0	−27.6	1,595.1	−240.9	−13.1
Others	24,690	1,502.3	60,846.5	73,015.8	−7,752.7	−31.4	1,236.7	−265.6	−17.7
Total	282,205	6,884.1			−56,937.0	−20.2	6,340.8	−543.2	−7.9
30% increase in without-conversion-subsidy prices									
Cereals	35,004	812.2	23,203.1	30,164.0	−3,885.4	−11.1	938.7	126.5	15.6
Meat	5,851	543.4	92,870.8	120,732.0	−2,984.0	−51.0	346.1	−197.2	−36.3
Dairy	146,091	2,190.1	14,991.7	19,489.2	−37,691.5	−25.8	2,112.6	−77.5	−3.5
Fruits–veg.	70,569	1,836.0	26,017.5	33,822.7	−29,215.6	−41.4	1,398.7	−437.3	−23.8
Others	24,690	1,502.3	60,846.5	79,100.5	−11,629.0	−47.1	1,033.1	−469.2	−31.2
Total	282,205	6,884.1			−85,405.5	−30.3	5,829.2	−1,054.8	−15.3
40% increase in without-conversion-subsidy prices									
Cereals	35,004	812.2	23,203.1	32,484.3	−5,180.6	−14.8	968.8	156.6	19.3
Meat	5,851	543.4	92,870.8	130,019.1	−3,978.7	−68.0	243.4	−299.9	−55.2
Dairy	146,091	2,190.1	14,991.7	20,988.3	−50,255.3	−34.4	2,011.4	−178.7	−8.2
Fruits–veg.	70,569	1,836.0	26,017.5	36,424.5	−38,954.1	−55.2	1,151.6	−684.5	−37.3
Others	24,690	1,502.3	60,846.5	85,185.2	−15,505.3	−62.8	782.4	−719.9	−47.9
Total	282,205	6,884.1			−113,874.0	−40.4	5,157.6	−1,726.4	−25.1

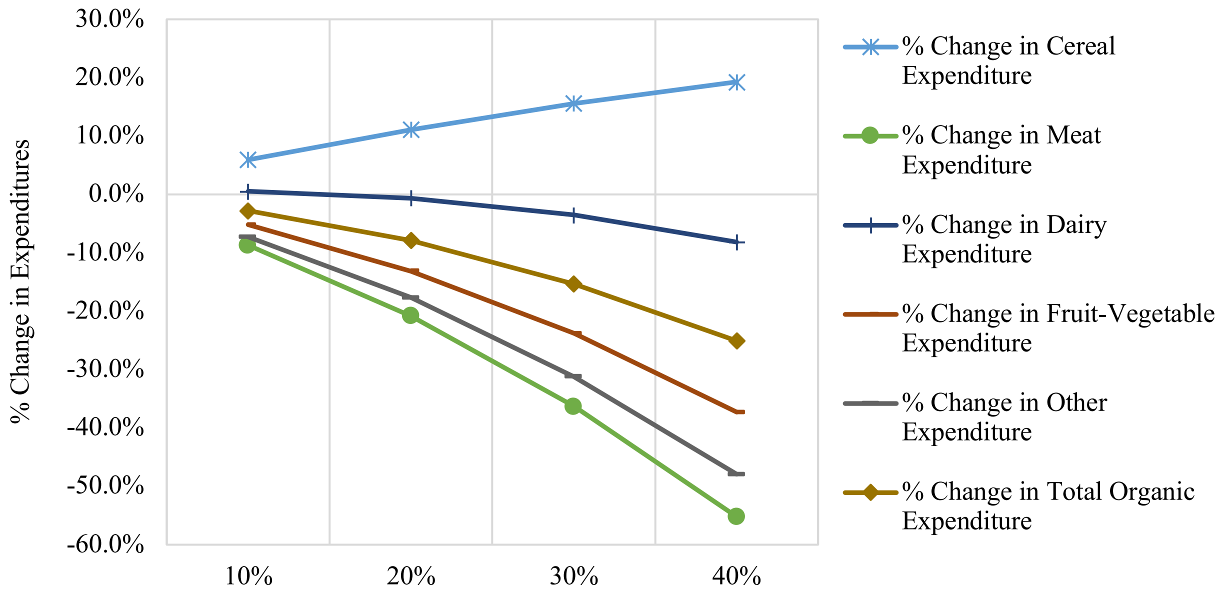
Figure 1. Simulation Results: Percentage Changes in Five Organic Food Group Quantities as a Result of Hypothesized 10%, 20%, 30%, and 40% Increases in Without-Conversion-Subsidy Prices



Source: Authors' computations.

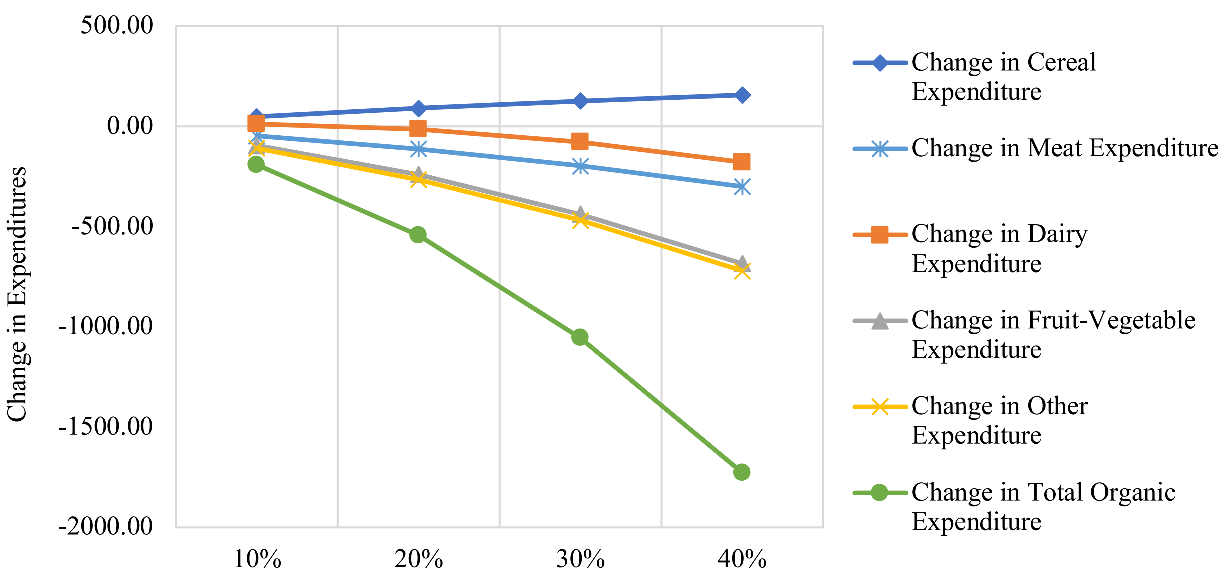
Differences in the effects on expenditures of the five organic food groups of having higher without-conversion-subsidy prices are striking. For the first scenario of 10% increases in without-conversion-subsidy prices, two groups—organic cereals and organic dairy—would have realized 5.9% and 0.5% higher total expenditures, respectively, without the Organic Land Subsidy Scheme and with the higher resulting (hypothesized) nonsubsidized prices. The other three groups—meats, fruits and vegetables, and other organic foods—would have realized lower total expenditures without the Organic Land Subsidy Scheme (Table 5, Figures 2 and 3). For the other three price scenarios of 20%, 30%, and 40% increases in without-conversion-subsidy prices, only organic cereals would have received higher expenditures without the Organic Land Subsidy Scheme, with gains of 11%, 16%, and 19%, respectively. Expenditures for dairy products increase with a 10% higher hypothesized price but decrease at all other, higher hypothesized prices (20%, 30%, and 40%). The losses in terms of lower expenditures (i.e., revenues) due to (hypothesized) nonsubsidized prices are lowest for dairy products (ranging from −0.6% to −8.2%), next for fruits and vegetables (ranging from −5.2% to −37.3%), next for other organic foods (ranging from −7.3% to −47.9%), and highest for organic meats (ranging from −8.7% to −55.2%). For the whole organic food sector, the percentage changes in total revenue (expenditure) for the four price-change scenarios range from −2.8% to −25.1%. The absolute-value changes in expenditures for the five organic food categories under the four price-change scenarios follow similar patterns as those with respect to the percentage changes in expenditures (Figure 3). Overall, removing the Organic Land Subsidy Scheme and the resulting (hypothesized) increases in prices of organic foods would most affect producers of meats and other organic foods in terms of a reduction in revenues. In other words, the Organic Land Subsidy Scheme helps the organic food industry disproportionately, with producers of organic meats and other organic foods likely realizing the highest revenue gains due to subsidies.

Figure 2. Simulation Results: Percentage Changes in Five Organic Food Group Expenditures as a Result of Hypothesized 10%, 20%, 30%, and 40% Increases to Without-Conversion-Subsidy Prices



Source: Authors' computations.

Figure 3. Simulation Results: Changes in Five Organic Food Group Expenditures (millions DKK) as a Result of Hypothesized 10%, 20%, 30%, and 40% Increases to Without-Conversion-Subsidy Prices



Source: Authors' computations.

Conclusions

In this study, we estimate Danish consumers' demand for five organic food groups. We accomplish this by first fitting four differential demand systems and a nesting model to Danish data on five organic food groups. While the four models statistically fit the data as well as does the nesting model, all four violate the negativity condition, while the more flexible nesting model does not. Accordingly, we use the parameters of the more flexible nesting model, a valid demand system in its own right, to estimate conditional demand elasticities for the five organic food groups.

Our results indicate that the organic food groups of meats, fruits and vegetables, and other respond more than proportionately to a proportionate change in Danish total expenditure allocated to organic food consumption; these groups are conditionally expenditure-elastic. Dairy consumption will grow slowest among the five groups, while consumption of meats and fruits and vegetables will grow fastest for a given percentage increase in total organic food expenditure. Evidence from the nesting model indicates that the own-price elasticities are negative and consistent with economic theory. Quantities demanded of organic cereals are found to respond the least to own-price changes. The organic meats group is also own-price inelastic, while organic dairy, fruits and vegetables, and other organic foods are own-price elastic. Conditional Slutsky cross-price elasticities reveal that, in general, most organic food groups are economically "unrelated" to each other for Danish consumers; in other words, quantity demanded of one organic group is typically not responsive to changes in the prices of remaining organic food groups. The exception to this is the other organic foods group; the pairs other–meats, other–dairy, and other–fruits and vegetables are substitutes, while other–cereals are complements. The complementarity of cereals (including breads) and other organic foods is likely driven by the inclusion of butter, fats, oils, jams, and other sweets in the other organic foods group.

In all simulated cases, the percentage changes in quantities demanded of the five organic food groups due to the hypothesized absence of the Organic Land Subsidy Scheme with accompanying increases in prices (relative to observed lower subsidized prices) are all negative, as expected, but of different magnitudes. The percentage decrease in quantity demanded due to price increases is smallest for organic cereals, moderate for dairy and fruits and vegetables, and higher for meats and other organic foods. The changes in expenditures among the five organic food groups (thus, revenues for organic producers) resulting from higher without-conversion-subsidy prices are also asymmetric across the five organic food groups. Organic cereals would have observed higher total expenditures in the absence of the Organic Land Subsidy Scheme that would have resulted in price increases of 10%, 20%, 30%, or 40%. Organic dairy would have realized a slight increase in expenditures with a 10% hypothesized price increase; however, the gains in expenditures would disappear at higher hypothesized price increases. Under four scenarios, the remaining three organic food groups—meats, fruits and vegetables, and other organic foods—would have had decreases in total expenditures due to the absence of the Organic Land Subsidy Scheme and resulting increases in their prices relative to lower observed subsidized prices. For the organic food industry as a whole, removing the Organic Land Subsidy

Scheme, which increases prices by 10%, 20%, 30%, or 40%, would lead to negative percentage changes in total expenditures (i.e., total revenues) in the organic industry.

Our findings have interesting implications for the Danish organic food sector. We find that the Danish Organic Land Subsidy Scheme induces higher revenues for the organic food sector as a whole under all four simulation scenarios. In other words, removing the current Organic Land Subsidy Scheme would result in revenue losses for the organic food industry as a whole. Moreover, our simulation exercises show that the same percentage increase in prices due to the hypothesized absence of the Organic Land Subsidy Scheme would result in disproportionate changes in revenues for different organic sectors. In all the hypothesized price-increase scenarios (i.e., the absence of the Organic Land Subsidy Scheme), producers of organic cereals gain in terms of increased expenditures, while those of organic meats, fruits and vegetables, and other organic foods lose revenues relative to the case in which conversion subsidies are present. Organic dairy would have experienced a slight benefit in the case of no land conversion subsidies and accompanying differences of 10% between subsidized and nonsubsidized prices; however, this gain would disappear if differences between subsidized and nonsubsidized were higher. The organic food industry as a whole always benefits from higher revenues due to the Organic Land Subsidy Scheme. Overall, the Organic Land Subsidy Scheme results in higher quantities demanded of organic food for consumers and higher revenues for producers, except for organic cereals producers. Revenue gains (losses) in the presence (absence) of the Organic Land Subsidy Scheme are highest for producers of meats and other organic foods, followed by producers of fruits and vegetables.

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Factors Influencing Consumers Familiarity with State Branded Programs: A Case Study for South Carolina

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Abstract

Previous studies often highlight that consumers are willing to pay price premiums for products with state brands. However, limited research exists regarding the factors influencing consumers' level of familiarity with state-branded logos. This study evaluates the impact of South Carolinians' demographic characteristics and food shopping behaviors on their degree of familiarity with the "Certified South Carolina Product" logo. Data were obtained from an online survey. Results reveal that respondents who purchase fresh products from direct marketing outlets and have lived longer in South Carolina are more likely to be familiar with the logo. Marketing recommendations are also discussed.

Keywords: familiarity with local labels, local foods, South Carolina Certified Product, state-branding campaigns

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Introduction

Growing consumer concerns about the viability of local farms, food safety, carbon footprint, food origins, and agricultural production practices has stimulated a resurgence of interest for local food products in the United States after the second half of the twentieth century (Hinrichs, 2000; Giovannucci, Barham, and Pirog, 2010; Feldmann and Hamm, 2015). Subsequently, the popularity of local food products has steadily increased (Meas et al., 2014; Printezis and Grebitus, 2018; Aprile, Caputo, and Nayga, 2016). The substantial growth in the number of direct marketing outlets and the supply of local foods in major grocery stores over the last two decades are often cited as indicators of increased consumer interest in local food products (Ahearn, Liang, and Goetz, 2018; Printezis and Grebitus, 2018). This trend has attracted considerable attention from scholars, who have identified numerous reasons that can potentially explain consumers' preferences for local foods (Onozaka and McFadden, 2011). Feldmann and Hamm (2015) and Bogomolova et al. (2016) review related contemporary research endeavors.

Concurrently, government agencies across the European Union (EU), United States, and Canada actively support the local food movement through different programs (Ahearn, Liang, and Goetz, 2018; Printezis and Grebitus, 2018; Hughes and Massa, 2015; O'Hara and Coleman, 2017; Knight, 2013; Campbell, Lesschave, and Bowen, 2010). Among the most prominent of these policies are regional and state promotion campaigns (Hughes and Massa, 2015; Onken and Bernard, 2010; Campbell, Lesschave, and Bowen, 2010). State-based branding campaigns were initially introduced in the United States during the 1980s with the "Vermont Seal of Quality" (1980) and the "Jersey Fresh" (1983) logos (Onken and Bernard, 2010; Campbell and Bickle, 2017). At some point over the last four decades, every state had a similar promotion program (Hughes and Massa, 2015; Onken and Bernard, 2010; Katz, Campbell, and Liu, 2019; Naasz, Jablonski, and Thilmany, 2018).

Potential positive contributions to the local economy, through income and employment growth, are commonly used to justify the popularity and widespread adoption of state branding programs (Hughes and Massa, 2015; O'Hara and Coleman, 2017; Feldmann and Hamm, 2015; Mugera, Burton, and Downsborough, 2017). Although a number of studies have evaluated the multiplier effect of those campaigns on local economies, divergences exist (McCaffrey and Kurland, 2015; Knight, 2013; Hughes and Massa, 2015; Tootelian, Liebich, and Thompson, 2007). For instance, Govindasamy et al. (2004), Otto and Varner (2005), and Rossi, Johnson, and Hendrickson (2017) estimate positive economic effects, but Hughes and Massa (2015) indicate that the Certified South Carolina (SC) campaign did not have a substantial impact on the South Carolina economy.

State branding programs also aim to (i) increase the opportunities for local farmers to benefit from the premium consumers are potentially willing to pay (WTP) for local foods, (ii) disseminate information about the origins of a product to consumers, and (iii) support and promote the marketing of locally grown and processed food products (Naasz, Jablonski, and Thilmany, 2018; Mugera, Burton, and Downsborough, 2017; Knight, 2013; Feldmann and Hamm, 2015; Aborisade et al., 2016; Aprile, Caputo, and Nayga, 2016). Consumer familiarity with regional promotion campaigns is a crucial element that can substantially influence campaigns' effectiveness and whether they can achieve the aforementioned objectives (Khachatryan et al., 2017; Knight, 2013). Specifically, if a program successfully makes buyers aware of the state brand campaign, then it is more likely that consumers will consider buying the product rather than a nonbranded one (Porral and Mangin, 2016; Carpio and Massa, 2010; Nganje, Hughner, and Lee, 2011; Tootelian, Liebich, and Thompson, 2007).

Similarly, variations in consumers' awareness of local labels have been documented in the literature. For example, Onken and Bernard (2010) utilize a mail survey to evaluate consumer familiarity with regional promotion programs in five Mid-Atlantic States. The results highlight a range of familiarity from approximately 48% (Pennsylvania) to 84% (New Jersey). Low familiarity rates were also reported for the Certified South Carolina (30%), Kentucky Proud (25%), Arizona Grown programs (44%), and across southern Missouri for the Agrimissouri logo (36%) (Carpio and Massa, 2010; Zarebanadkoki and Woods, 2015; Brown, 2003; Nganje, Hughner, and Lee, 2011).[1] Conversely, Naasz, Jablonski, and Thilmany (2018) determine that more than 86% of Colorado residents are familiar with the "Colorado Proud" program, Aborisade et al. (2016) indicate that more than 60% of their sample had seen and used the Appalachian Grown label, and Tootelian, Liebich, and Thompson (2007), indicated a high familiarity with the California Grown campaign. Mixed results regarding familiarity with regional branding campaigns are also obtained from Canadian surveys: For example, levels of familiarity with Foodland Ontario were found to be 97%, while only 33% of survey respondents were aware of Select Nova Scotia (Ontario Ministry of Agriculture, Food and Rural Affairs, 2016; Knight, 2013).

To improve (or build) consumer awareness of state branding campaigns, some programs spend a high percentage of their budget for advertising purposes (Patterson et al., 1999; Hughes and Massa, 2015). Considering these expenses, understanding the factors that influence consumers' familiarity with the state/regional promotion programs is of paramount importance. Moreover, illustrating program effectiveness is critical for determining whether these programs should be continued (Onken, Bernard, and Pesek, 2011). Nevertheless, relevant literature is scarce and, in some cases, rather dated (i.e., Patterson et al., 1999; Jekanowski, Williams, and Schiek, 2000; Knight, 2013; Zarebanadkoki and Woods, 2015).

The present study is an effort to cover this gap in the literature by investigating the role of demographic variables and consumers' food shopping preferences on the probability that South Carolina residents will be familiar with the Certified SC program. The campaign was introduced in 2007 and includes four logos: (i) Certified SC Product, (ii) Certified SC Grown, (iii) Certified SC Seafood, and (iv) Fresh on the Menu. Over the last decade, the average annual budget for the program exceeded $1 million, with more than 70% of the budget allocated to advertising. Further, the "Certified SC" is one of the programs that advertises outside the state (Crenwelge, 2016; Hughes and Massa, 2015; Niblock, 2017). Membership in the Certified SC program has consistently increased since its inception and today includes more than 2,000 members and 120

[1] Zarebanadkoki and Woods (2015) evaluate familiarity using a 4-point Likert scale question. The 25% refers to the "very familiar" category. Other studies evaluate familiarity using a binary option (i.e., "familiar," "not familiar").

products (Niblock, 2017). This study focuses on the Certified SC Product logo (Figure 1).[2] The results of the study can provide guidance for policy makers, producers, and marketing agencies on how to more effectively promote local/state logos given campaigns' limited budgets.

Figure 1. Certified SC Product Logo

Data

We used an online survey to address the study objective. The questionnaire was distributed to adult (18 years or older) South Carolina residents who were the primary grocery shoppers for their households. To evaluate whether household location influenced participants' familiarity with the Certified SC program, we utilized the National Center for Health Statistics (NCHS) urban–rural classification scheme to define and differentiate rural and urban counties (Ingram and Franco, 2013). For the purposes of this study, we designated a county as urban if the NCHS classifies it as a large or medium metro. Suburban counties are those classified by the NCHS as fringe metro, and small urban counties are those classified as small metro. Rural counties are those that do not belong in any of the previous categories.

Survey respondents were recruited through Qualtrics, an online survey software provider commonly used for applied economics research, from January 18 to January 23, 2018. Prior to the completion of the survey, we organized two focus groups of approximately 10 members each to test the survey wording and content. The final survey sample included 512 respondents.

[2] According to the South Carolina Department of Agriculture (2019), products that are eligible for inclusion in the Certified SC Product include

> agricultural products and food products that are manufactured or processed in the state that may or may not always include ingredients grown exclusively in South Carolina. This includes value added products, manufactured food products, and other agricultural products that may be further sorted, graded, blended, processed and packaged, in South Carolina. In addition, Specialty agricultural food businesses located in South Carolina may have an exclusive recipe manufactured in another state, under the South Carolina address and company label, and be eligible for membership in the program.

Survey participants were provided a picture of the Certified SC brand logo (Figure 1) to trigger brand recall before being asked to rate their familiarity with the label. Respondents' level of brand awareness was measured on a 3-point Likert scale question (1 = "The label is completely unknown to me," 2 = "I am somewhat familiar with this label," and 3 = "I am very familiar with this label"). Approximately one-third (31.25%) of survey participants indicated that the label was completely unknown to them, and 44% mentioned indicated that they were very familiar with the label. Compared to the findings of Carpio and Massa (2010), our results indicate a higher percentage of respondents who are familiar with the label.

Table 1 reports summary statistics for respondents' demographic characteristics. Compared to the South Carolina population, the study sample overrepresented females as well as participants who had obtained associates, bachelor's, or other higher education degrees. The gender overrepresentation can be easily explained by the role of females in U.S. households as the primary grocery shoppers and cooks for their family. With the exception of households reporting annual income below \$14,999 or greater than \$150,000, the sample is comparable to the South Carolina population.

Methods

We used a Tukey–Kramer test to facilitate comparisons across the three groups (completely unknown, somewhat familiar, and very familiar with the Certified SC Product label). Based on the Tukey–Kramer test, a statistically significant difference between two means exists when

$$\frac{|\overline{Y_i} - \overline{Y_j}|}{S\sqrt{\frac{\left(\frac{1}{n_i}+\frac{1}{n_j}\right)}{2}}} \geq q\left(\alpha;k,v\right), \tag{1}$$

where, $\overline{Y_i}$ and $\overline{Y_j}$ are the means for groups i and j, respectively, s is the root mean square error (pooled standard deviation), n_i and n_j are the number of observations and $q(\alpha;k,v)$ is the critical value for the studentized distribution of k normally distributed variables with degrees of freedom equal to v and a significance level of α (Katchova, 2006).

Considering the nominal and unordered nature of the dependent variable, we used a multinomial logit model to estimate the impact of selected explanatory variables on the probability that a respondent would be familiar with the Certified SC Product label. Following Cameron and Trivedi (2010), the probability of the jth familiarity category for respondent i is given by

$$P_{ij} = \frac{\exp\left(\beta_j x_i\right)}{\sum_{j=1}^{J}\exp(\beta_l x_i)} \qquad j = 1,2,3, \tag{2}$$

Table 1. Demographic Characteristics for the Sample and South Carolina

	Sample	State
Gender (%)		
Female	84.57	51.5
Age (%)		
18–25 years	10.55	9.7[a]
26–34 years	23.63	13.1
35–54 years	33.79	25.6
55–64 years	17.77	13.1
> 65 years	14.26	16.3
Education (%)		
Not a high school graduate	1.95	13.5
High school or equivalent	19.14	29.4
Some college/associates degree	39.65	30.1
Bachelor's degree	25.59	17.2
Graduate degree	13.67	9.8
Annual household income (%)		
< $14,999	9.38	15.5
$15,000–$24,999	12.50	12.7
$25,000–$49,999	28.52	26.4
$50,000–$74,999	23.05	18.0
$75,000–$99,999	13.09	11.2
$100,000–$149,000	2.15	10.4
> $150,000	1.76	6.0
SC residency (%)[b]		
Urban county	70.90	66.33
Suburban county	6.05	
Small urban county	9.70	
Rural county	13.28	33.67

Note: State-level statistics are based on the 2017 American Community Survey (https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/).

[a]At the state level, population is based on individuals at least 25 years of age.

[b]At the state level, values are based on the 2010 census. For the sample, the classification of counties is based on the National Center for Health Statistics (Ingram and Franco, 2013).

where x_j are the characteristics of the respondents and P_{ij} is the probability of outcome *j* given consumer *i*. Considering that the probabilities of all choices sum to 1, a convenient normalization is to set β_j for one of the categories equal to 0. For this study, we designate "I am very familiar with the logo" as the base category.

To gain further insights into the impact of the explanatory variables on respondents' familiarity with the label, the marginal effects are calculated as follows (Cameron and Trivedi, 2010):

$$\frac{\partial p_{ij}}{\partial x_i} = p_{ij}\left(\beta_j - \overline{\beta_i}\right). \tag{3}$$

Results

Table 2 reports descriptions of and summary statistics for the explanatory variables used in the model estimation. Our *a priori* hypothesis is that consumers who (i) have lived longer in South Carolina, (ii) cook, (iii) care about the nutrients in their food products, and (iv) shop at direct marketing outlets are more likely to be familiar with the Certified SC Product logo.

Table 3 reports summary statistics by respondents' level of familiarity with the label and indicates whether the pairwise comparisons between degrees of familiarity are statistically significant based on the Tukey–Kramer procedure. The findings indicate that consumers who are very familiar with the label tend to be younger, have lived longer in South Carolina, and shop at direct marketing outlets more often than those who are less familiar with the label. Compared to respondents who are very familiar or somewhat familiar with the logo, survey participants who are unfamiliar with the campaign tend to live in suburban areas. These results are consistent with previous studies highlighting that very few of the demographic characteristics examined had an impact on consumers' awareness of labels (Knight, 2013; Patterson et al., 1999).

Table 4 reports the estimates of the multinomial logit regression model. Consistent with previous studies (Knight, 2013; Zarebanadkoki and Woods, 2015; Patterson et al., 1999), the findings indicate that most of the demographic characteristics did not have a statistically significant impact on the probability that a survey respondent will be familiar with the Certified South Carolina Product logo. Nevertheless, age has a statistically significant negative impact on the probability that a survey participant was familiar with the label. It is plausible that marketing campaigns are processed differently by different age groups (Campbell and Bickle, 2017). In addition, it may be more difficult for older consumers to understand the labels (Cowburn and Stockley, 2004).

Similarly, the results indicate that length of residency has a significant impact on the probability that a survey participant is familiar with the Certified South Carolina Product logo: Respondents who have lived less than 10 years in South Carolina are more likely to be less familiar with the label. A possible explanation for this finding: Individuals who reside longer in an area have, potentially, more opportunities to see the labels (Naasz, Jablonski, and Thilmany, 2018).

Table 2. Summary Statistics and Description of Variables

Variables	Description	Mean	Std. Dev.
Demographics			
Female	Dummy variable; 1 = female, 0 otherwise.	0.845	0.361
Income	Estimated average annual household income; original question included intervals.	59.424	41.163
Age	Age in years; original question included intervals, so medians were taken when coding the data.	44.950	15.441
Less than high school education	Dummy variable; 1 = does not have a high school degree, 0 otherwise.	0.019	0.138
High school graduate or equivalent	Dummy variable; 1 = graduated high school or received an equivalent degree (e.g., GED), 0 otherwise.	0.191	0.393
Associates degree	Dummy variable; 1 = graduated from a 2-year university or college, 0 otherwise.	0.396	0.489
Bachelor's degree	Dummy variable; 1 = graduated from a 4-year university or college, 0 otherwise.	0.256	0.437
Graduate degree	Dummy variable; 1 = graduate, professional, or other advanced degree, 0 otherwise.	0.137	0.343
Caucasian	Dummy variable; 1 = Caucasian, 0 otherwise.	0.832	0.374
Children in the household	Dummy variable; 1 = yes, 0 otherwise.	0.422	0.494
Household size	Number of individuals in the household.	2.757	1.464
Nutrition and cooking			
Hours cooking per week	Average number of hours spent cooking weekly; original question included intervals, so medians were taken when coding the data.	4.739	1.800
Nutrients never	Dummy variable; 1 = respondent answered "never" to the "I need to know what nutrients the food product contains" question, 0 otherwise.	0.084	0.278
Nutrients rarely	Dummy variable; 1 = respondent answered "rarely" to the "I need to know what nutrients the food product contains" question, 0 otherwise.	0.137	0.344
Nutrients some	Dummy variable; 1 = respondent answered "sometimes" to the "I need to know what nutrients the food product contains" question, 0 otherwise.	0.334	0.472

Table 2. Summary Statistics and Description of Variables (continued)

Variables	Description	Mean	Std. Dev.
Nutrition and cooking (continued)			
Nutrients most	Dummy variable; 1 = respondent answered “most of the time” to the “I need to know what nutrients the food product contains” question, 0 otherwise.	0.298	0.458
Nutrients always	Dummy variable; 1 = respondent answered “always” to the “I need to know what nutrients the food product contains” question, 0 otherwise.	0.146	0.354
SC residency (counties are classified based on the National Center for Health Statistics (2013) urban–rural classification)			
Urban county	Dummy variable; 1 = Aiken, Anderson, Berkeley, Calhoun, Charleston, Dorchester, Edgefield, Fairfield, Greenville, Howry, Kershaw, Laurens, Lexington, Pickens, Richland, Saluda, Spartanburg, Union; 0 otherwise.	0.709	0.455
Suburban county	Dummy variable; 1 = Chester, Lancaster, York; 0 otherwise.	0.060	0.238
Small urban county	Dummy variable; 1 = Beauford, Darlington, Florence, Sumter; 0 otherwise.	0.097	0.297
Rural county	Dummy variable; 1 = Abbeville, Allendale, Bamberg, Barnwell, Cherokee, Chesterfield, Claredon, Colleton, Dillon, Georgetown, Greenwood, Hampton, Lee, Marion, Marlboro, McCormick, Newberry, Oconee, Orangeburg; 0 otherwise.	0.133	0.339
Lived in SC < 10 years	Dummy variable; 1 = < 10 years, 0 otherwise.	0.298	0.458
Purchasing outlets			
Direct market (e.g., farmers’ market or CSA)	Dummy variable; 1 = direct marketing outlets are the most frequently preferred purchasing outlet for fruits and vegetables, 0 otherwise.	0.072	0.259
Specialty store (e.g. Whole Foods, Ingles, Trader Joe’s, etc.)	Dummy variable; 1 = Specialty stores are the most frequently preferred purchasing outlet for fruits and vegetables, 0 otherwise.	0.045	0.207
Box store (e.g. Sam’s Club or Costco)	Dummy variable; 1 = box store are the most frequently preferred purchasing outlet for fruits and vegetables, 0 otherwise.	0.012	0.107
Grocery store (e.g. Bi-Lo, Publix, Aldi)	Dummy variable; 1 = grocery stores are the most frequently preferred purchasing outlet for fruits and vegetables, 0 otherwise.	0.654	0.476
Wal-Mart	Dummy variable; 1 = Wal-Mart is the most frequently preferred purchasing outlet for fruits and vegetables, 0 otherwise.	0.216	0.412

Further, respondents living in suburban counties (based on the NCHS classification) are more likely to be completely unfamiliar with the label relative to residents of rural counties. A potential explanation for this finding is that suburban residents tend to purchase local food less often compared to rural residents and could potentially be less interested in supporting local farms (Brown, 2003; Racine et al., 2013). However, there is no statistically significant difference between rural and urban areas. This finding is consistent with Chambers et al. (2007), who did not identify differences between urban and rural residents.

A preference for point-of-sale purchases of produce is also an important determinant of the probability that a survey participant will be familiar with the logo. Specifically, compared to respondents whose preferred point of sale is Wal-Mart, consumers who purchase fruit and vegetables mainly from direct marketing outlets are more likely to be very familiar with the label. Moreover, the probability of being somewhat familiar with the label is lower for grocery store customers relative to respondents who purchase produce at Wal-Mart. This result is not surprising considering previous studies indicating that consumers prefer to purchase local food products from grocery stores (i.e., Printezis and Grebitus, 2018; Lim, Vassalos, and Reed, 2018).

We estimate marginal effects to quantify the impact of the explanatory variables on the probability that a consumer is familiar with the local label (Table 5). A 1-year increase in consumer age reduces the probability of being very familiar with the label by 0.6 percentage points. This provides further support for the need for specific marketing strategies targeted at specific age groups. This finding is consistent with Campbell and Bickle (2017), who indicated that younger generational cohorts of South Carolina consumers (i.e., millennials) are more likely to be familiar with the label, so marketers should focus on improving brand awareness among older consumers. Further, respondents who have moved to the state recently (less than 10 years ago) are, on average, 13.9 percentage points less likely to be familiar with the label. Respondents who shop at direct marketing outlets are 39.2 percentage points more likely to be familiar with the labels, and respondents who live in suburban counties are 22.5 percentage points less likely to be very familiar with the label.

Conclusions

At some point over the last four decades, every state in the United States has introduced a state-branded food campaign program. The potential economic benefit to the local economy, the opportunity for producers to differentiate their products, and a desire to define “local” to consumers are among the most commonly used arguments to explain this trend (Nganje, Hughner, and Lee, 2011; Naasz, Jablonski, and Thilmany, 2018; O’Hara and Coleman, 2017). To increase the visibility of the state-branded programs, these campaigns commonly use logos to showcase where a product was produced (Naasz, Jablonski, and Thilmany, 2018).

Previous research indicates that consumers are willing to pay a price premium for products that include a state-brand logo (i.e., Nganje, Hughner, and Lee, 2011, Carpio and Massa, 2009; Merritt et al., 2018; Bosworth, Bailey, and Curtis, 2015; Hu et al., 2012). However, overall, little is known regarding the factors that may influence consumers’ familiarity with state-branded

Table 3. Descriptive Statistics by Familiarity Group

	Completely Unknown		Somewhat Familiar		Very Familiar	
Variables	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Demographics						
Female	0.856	0.352	0.835	0.373	0.844	0.363
Average income	56.727	38.437	55.244	38.120	63.701	44.338
Average age	46.981	15.920	47.736	15.549	41.931[bc]	14.545
High school diploma or equiv.	0.194	0.396	0.213	0.411	0.177	0.383
Associates degree	0.419	0.494	0.433	0.497	0.360	0.481
Bachelor's degree	0.256	0.438	0.220	0.416	0.275	0.448
Graduate degree	0.119	0.325	0.102	0.304	0.168	0.375
Caucasian	0.850	0.358	0.819	0.386	0.826	0.379
Household has children	0.418	0.495	0.362	0.482	0.457	0.499
Household size	2.762	1.600	2.685	1.473	2.795	1.360
Nutrients and cooking						
Nutrients never	0.119	0.324	0.087	0.282	0.057	0.233
Nutrients rarely	0.131	0.339	0.189	0.393	0.111	0.315
Nutrients sometimes	0.375	0.486	0.307	0.463	0.320	0.467
Nutrients most	0.212	0.410	0.315	0.466	0.351[b]	0.478
Nutrients always	0.162	0.370	0.102	0.304	0.160	0.367
Average hours spent cooking per week	4.578	1.864	4.830	1.833	4.802	1.735
SC residency[d]						
Lived in SC < 10 years	0.400	0.491	0.291	0.456	0.231[b]	0.422
Urban county	0.656	0.476	0.779	0.416	0.707	0.455
Suburban county	0.125	0.332	0.023	0.152	0.035[ab]	0.186
Small urban county	0.113	0.317	0.071	0.257	0.102	0.304
Rural county	0.106	0.309	0.125	0.333	0.155	0.363
Purchasing outlet						
Direct market	0.012	0.111	0.047	0.213	0.128[bc]	0.335
Specialty store	0.043	0.205	0.039	0.195	0.048	0.216
Box stores	0.006	0.079	0.024	0.152	0.009	0.094
Grocery stores	0.675	0.469	0.614	0.489	0.662	0.474
Wal-Mart	0.262	0.441	0.275	0.448	0.151[bc]	0.359

Note: Superscript a indicates statistically significant difference between the completely unfamiliar and somewhat familiar groups. Superscript b indicates statistically significant difference between the completely unfamiliar and very familiar groups. Superscript c indicates statistically significant difference between the somewhat familiar and very familiar groups, at the 5% level.
[d]Counties are classified based on the National Center for Health Statistics (NCHS) 2013 urban-rural classification.

Table 4. Multinomial Logit Model's Estimation Results (n = 512)

	This Label Is Completely Unknown to Me		Somewhat Familiar with the Label	
Variables	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**
Demographics				
Female	0.137	0.328	0.058	0.333
Income	−0.005	0.003	−0.004	0.003
Age	0.030***	0.008	0.026***	0.008
Caucasian	0.185	0.329	−0.180	0.324
High school graduate[a]	0.446	1.019	−0.330	0.807
Associates degree[a]	0.771	1.005	−0.232	0.787
Bachelor's degree[a]	0.768	1.024	−0.404	0.813
Graduate degree[a]	0.530	1.044	−0.704	0.813
Children in the household	0.019	0.362	−0.353	0.379
No. of individuals in the household	0.110	0.121	0.093	0.127
Nutrition and cooking				
Hours cooking per week	−0.038	0.653	0.056	0.070
Nutrients rarely[b]	−0.504	0.501	0.173	0.525
Nutrients some[b]	−0.435	0.436	−0.387	0.480
Nutrients most[b]	−1.133**	0.454	−0.405	0.482
Nutrients always[b]	−0.405	0.498	−0.588	0.561
SC residency				
Urban county[c]	0.341	0.349	0.386	0.352
Suburban county[c]	1.775***	0.570	−0.155	0.776
Small urban count[c]	0.743	0.477	−0.008	0.528
Lived in SC < 10 years	0.861***	0.248	0.413	0.267
Purchasing outlets				
Direct market[d]	−2.758***	0.792	−1.383**	0.541
Specialty stores[d]	−0.369	0.606	−0.629	0.635
Box stores[d]	−0.581	1.304	0.632	1.003
Grocery stores[d]	−0.475	0.293	−0.573*	0.301
Constant	−2.116		−1.013	
Model fit statistics				
McFadden R^2	0.099			
Log-likelihood	−493.846			
Log-likelihood ratio test (46)	108.629***			
Count R^2	0.520			

Note: Base outcome is "I Am Very Familiar with This Label. Base categories are [a]less than a high school degree, [b]"I never care about the nutrient label when making a purchase decision," [c]rural county, [d]Wal-Mart. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Multinomial Logit Marginal Effects

	Completely Unfamiliar		Somewhat Familiar		Very Familiar	
Variables	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**	**Coeff.**	**Std. Error**
Demographics						
Female	0.021	0.055	0.000	0.053	−0.021	0.060
Income	0.000	0.001	0.000	0.000	0.001	0.001
Age	0.004***	0.001	0.002*	0.001	−0.006***	0.001
High school[a]	0.111	0.185	−0.085	0.106	−0.025	0.171
Associates degree[a]	0.161	0.166	−0.094	0.112	−0.067	0.162
Bachelor's degree[a]	0.177	0.177	−0.119	0.105	−0.057	0.164
Graduate degree[a]	0.151	0.193	−0.138	0.091	−0.013	0.180
Caucasian	0.047	0.053	−0.047	0.055	−0.001	0.059
Children	0.030	0.063	−0.062	0.060	0.032	0.066
Household size	0.014	0.020	0.008	0.020	−0.022	0.022
Nutrients and cooking						
Nutrients rarely[b]	−0.101	0.069	0.068	0.089	0.032	0.097
Nutrients some[b]	−0.052	0.067	−0.035	0.070	0.087	0.082
Nutrients most[b]	−0.172***	0.063	0.005	0.073	0.166*	0.086
Nutrients always[b]	−0.036	0.078	−0.069	0.075	0.105	0.096
Hours cooking	−0.011	0.011	0.013	0.011	−0.001	0.012
SC residency						
Lived in SC < 10 years	0.137***	0.044	0.003	0.041	−0.139***	0.044
Urban county[d]	0.036	0.058	0.042	0.054	−0.077	0.061
Suburban county[d]	0.382***	0.096	−0.158**	0.064	−0.225***	0.082
Small urban county[d]	0.150	0.092	−0.060	0.074	−0.090	0.081
Purchasing outlets						
Direct market[c]	−0.280***	0.043	−0.112*	0.064	0.392***	0.072
Specialty stores[c]	−0.028	0.099	−0.076	0.080	0.104	0.111
Box stores[c]	−0.140	0.152	0.171	0.200	−0.031	0.202
Grocery[c]	−0.044	0.049	−0.065	0.048	0.110**	0.052

Note: Base categories are [a]less than a high school degree, [b]"I never care about the nutrient label when making a purchase decision," [c]Wal-Mart, [d]rural county. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% levels, respectively.

logos, a critical factor for campaign effectiveness and success. Further, considering that a substantial amount of the campaigns' budgets is devoted to promotion and advertising, it is crucial to identify appropriate target groups.

This study is an effort to cover this gap in the literature. Using a sample of South Carolina residents (n = 512), we examined factors influencing their degree of familiarity with the "Certified South Carolina Product" logo. The campaign was originally introduced in 2007, and approximately 70% of the budget is for advertising and promotional endeavors. We evaluated consumers' familiarity with the label using a 3-point Likert-scale ("completely unknown," "somewhat familiar," "very familiar").

Our findings indicate that consumers' demographic characteristics, except for respondent age, do not have a statistically significant effect on their degree of familiarity with the label. Consumers who prefer direct marketing outlets to purchase fresh produce are more likely to be familiar with the logo compared to respondents whose preferred outlet is Wal-Mart. People who have resided in the state for more than 10 years are also more likely to be familiar with the logo. Last, the results suggest that consumers living in suburban counties (based on the NCHS urban–rural continuum) are more likely to be unfamiliar with the Certified SC Product logo.

Considering that more than one-third of survey participants (31.2%) are not familiar with the Certified SC Product logo, the aforementioned findings can be helpful to producers, restaurants, and policy makers who want to increase residents' familiarity with the logo. According to a recent survey, the primary target group for the Certified SC Product marketing campaign includes females 25–54 years old (Crenwelge, 2016). However, based on our findings, a preferred course of action could be to focus on residents who purchase groceries primarily at Wal-Mart, and on new residents instead of focusing on demographic characteristics. New residents are crucial, considering that South Carolina has added more than 310,000 residents from domestic migration since 2010 (Slade, 2018).

A potential shortcoming of the study is that it focuses only on South Carolina. However, program success varies based on state residents' preferences and state regulations (Naasz, Jablonski, and Thilmany, 2018). Potential future work should include similar research from different states to evaluate potential similarities and differences across states. Further, future research is needed to investigate the effectiveness of different outlets (e.g., farmers' markets, grocery stores, restaurants) for promoting states' certified products as well as comparing factors influencing degree of familiarity across labels.

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