Title

Effects of Information Provision for Food Products: Applications to Transitional Organic Certification, Food-Safety Advisories, and Locally Produced Products

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Effects of Information Provision for Food Products:
Applications to Transitional Organic Certification, Food-Safety Advisories, and Locally Produced Products

By

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DISSERTATION

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Abstract

This dissertation draws on theories of product differentiation from industrial organization and on agricultural economics, more broadly, to study the effect of information on consumer and producer behavior as it relates to agricultural commodities and food products. Agricultural markets are rife with information asymmetries, as complex production practices and modern supply chains and retail systems can obfuscate information about how and where products are produced and the health implications from consuming them. As a result, downstream actors rarely have perfect information about the food they are purchasing, and regulators often face difficulties tracing foodborne illnesses back to the source.

The first essay examines the impact of introducing a government certification and labeling program for transitional organic crops on organic and conventional markets. Premiums garnered by transitional labels may reduce conversion costs and increase conversion, but some existing organic producers worry it may dilute the value of the existing organic label. I construct static and dynamic models of vertical product differentiation to explore how transitional certification and commensurate labeling impacts prices and market shares for conventional and organic versions of a generic commodity, and, in turn, organic conversion rates. I index consumers' valuation of the high-quality commodity (i.e., organic) using a flexible Kumaraswarmy distribution instead of the uniform distribution typically used in these types of models, as consumers valuation of quality may vary by commodity and over time. I then estimate outcomes for the domestic strawberry market by assigning values to the model parameters using data obtained from a survey developed in collaboration with a

major berry producer and relevant prior research. Results from the static model indicate that, in the short run, transitional certification and labeling slightly decrease prices for organic strawberries, do not alter conventional prices, and improve or hold constant welfare for all consumers. In the long run, transitional labeling significantly increases the share of acreage devoted to organic strawberries, holding total strawberry acreage constant, and subsequently increases prices for both organic and conventional strawberries. The price increase is because the yield gap between conventional and organic strawberries leads to a reduction in total strawberry output as more acres convert. The increased prices benefit strawberry producers but come at the expense of strawberry consumers. These results suggest that a national transitional certification policy may be a useful tool in increasing domestic commodity production.

Essay 2 analyzes the economic losses resulting from the November, 2018 food safety advisory that warned consumers, retailers, and restaurants not to eat, sell, or serve any romaine lettuce or mixed salads containing romaine due to an outbreak of E. coli infections linked to romaine. Detected outbreaks including the one studied here are usually characterized by uncertainty and lack of information as to the scope of implicated products and regions, which often results in broad advisories and widespread damages. I separately estimate losses to growers, processor/shippers, retailers, and food-service operators, in addition losses to society, during and after the advisory period using wholesale data from a cooperating processor that supplies both food-service and retail outlets combined that with public data on spot-market prices and movement provided by the USDA-Agricultural Marketing Service and retail scanner data from the Nielsen Company. I then use regression analysis to predict what prices and sales would have been in the "but for" world absent the E. coli advisory, compare these values to the real-world prices and quantities during the advisory period and aftermath for romaine and its substitutes, and compute economic impacts from price changes and lost sales. Due to the structure of grower contracts, growers were minimally impacted by the advisory, while processors and shippers lost approximately $52.7 million from price and quantity impacts. Retailers amassed $25.7 million in losses mostly due to pulling product from their distribution channels and shelves in response to the advisory. Conversely, food-service operators were little impacted. I further estimate that societal losses from the Fall 2018 incident were in the range of $280 to $350 million.

The third essay evaluates consumers' stated and revealed preference for locally produced food products using both a survey and a market-level labeling experiment. The survey, distributed by two Sacramento-area food co-ops, assessed differences in willingness-to-pay (WTP) and intensity of preference for local produce and processed foods and examined which characteristics consumers associate with a "Local" label. For the labeling experiment, I introduced "Local" shelf labels to products in five processed-food categories in one of these stores for four weeks. Both stores provided weekly sales data by UPC for four weeks prior to, during, and after the experiment, and I further collected detailed information on product claims, product placement, and promotions for each product. The vast majority of shoppers at both stores expressed a preference for locally produced produce and processed foods and indicated they would be willing to pay a premium for them. These preferences, however, did not carry forward to increased sales for products affixed with a "Local" label in the retail experiment. An analysis of the sales data in a triple-triple difference framework fails to detect significant average treatment effects. Significant heterogeneous treatment effects suggest that the experimental labels primarily draw attention to or highlight products at the point of purchase, and might be more effective for products that do not already capture consumers' attention through manufacturer's claims, retailer discounts, or prime shelf-positioning.

Taken together, the research in this dissertation provides valuable insights on when the provision of information might help advance policy goals and when it might fall short in that regard. Further, it illustrates how imprecise and overly broad information, like that provided many initial food safety advisories, can generate far-reaching economic losses.

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Introduction

As policy is increasingly geared toward getting information into consumers' hands, the agricultural economics profession has come to recognize the important role of information and information asymmetries. Agricultural markets are rife with information asymmetries, as complex production practices and modern supply chains and retail systems can obfuscate information about how and where products are produced and the health implications from consuming them. As a result, downstream actors rarely have perfect information about the food they are purchasing, and regulators often face difficulties tracing foodborne illnesses back to the source.

Information is the common thread connecting the three essays comprising this dissertation. I draw on theories of product differentiation from industrial organization and on agricultural economics, more broadly, to study the effect of information on consumer and producer behavior as it relates to agricultural commodities and food products. I focus on information about both credence attributes, specifically organic food and local production, and food safety. With regard to the former, this research considers the provision of information on credence attributes by way of government certification and labels and by informal labels designed by retailers. On the latter topic, it evaluates how the imprecise and broad information provided in a specific food safety advisory has far-reaching effects on players across the agricultural supply chain.

The first chapter examines the effect of introducing a government certification and labeling program for transitional organic crops on organic and conventional markets. The market for organic commodities is one of the fastest growing in the U.S., with sales of organic products increasing by double digits every year since the National Organic Program was established in 2000. The U.S. government supports and promotes conversion of agricultural land to organic production through a variety of programs in an effort to provide economic opportunities to producers and reduce the incidence of fraudulent imports. Nonetheless, organically farmed land comprises less than 1% of total U.S. cropland, and the U.S. remains a net importer of organic commodities.

Domestic farmers often cite the transition period, the three-year window during which farmers must adopt more costly organic production practices but cannot yet access organic premiums, as a major impediment to organic conversion. In an effort to create a market for crops in years 2 and 3 of the transition period and help producers earn a premium to alleviate the financial burden of transitioning, a number of agencies have implemented transitional certification guidelines and labels in recent years, and some have introduced certified transitional labels. The U.S. Department of Agriculture (USDA) drafted plans for a National Certified Transitional Program in early 2017, but the effort was put on hold after opposition by some organic industry groups over concerns that such a label would dilute the value of the existing organic label.

I construct static and dynamic models of vertical product differentiation to explore how transitional certification and commensurate labeling impacts prices and market shares for conventional and organic versions of a generic commodity, and, in turn, organic conversion rates. In the static model, production levels for the conventional, transitional, and organic commodities are fixed, whereas the dynamic model allows producers to convert from conventional to organic over time. The models compare the organic price premium and organic market share under a baseline scenario of no transitional certification and labeling to the equilibrium where a certified transitional product is introduced, labeled, and operates as a good of "intermediate" quality between conventional and certified organic. Further, I index consumers' valuation of the high-quality commodity (i.e., organic) using a flexible

Kumaraswarmy distribution instead of the uniform distribution typically used in these types of models, as consumers valuation of quality may vary by commodity and over time. I then estimate outcomes for the domestic strawberry market by assigning values to the model parameters using data obtained from a survey developed in collaboration with a major berry producer and relevant prior research.

Results from the static model indicate that, in the short run, transitional certification and labeling slightly decrease prices for organic strawberries, do not alter conventional prices, and improve or hold constant welfare for all consumers. In the long run, transitional labeling significantly increases the share of acreage devoted to organic strawberries, holding total strawberry acreage constant, and subsequently increases prices for both organic and conventional strawberries. The price increase is because the yield gap between conventional and organic strawberries leads to a reduction in total strawberry output as more acres convert. The increased prices benefit strawberry producers but come at the expense of strawberry consumers. Other policies that induce the same level of conversion (e.g., direct cash payments for conversion) will have similar long-run effects on conventional and organic prices, consumer welfare, and surplus for organic producers. Relative to policies that do not create a market for the transitional commodity, however, a transitional certification and labeling policy will further benefit producers in the midst of transition while also partially blunting the increase in organic commodity prices during all periods in which there exists transitional cropland and output. This is because competition with the transitional commodity puts downward pressure on the price of the organic commodity. These results suggest that a national transitional certification policy may be a useful tool in increasing domestic commodity production.

The second essay analyzes the economic losses resulting from the November, 2018 food safety advisory that warned consumers, retailers, and restaurants not to eat, sell, or serve any romaine lettuce or mixed salads containing romaine due to an outbreak of E. coli infections linked to romaine. Damages from food-safety advisories can be widespread. Detected outbreaks including the one studied here are usually characterized by uncertainty and lack of information for regulators and market participants as to the scope of implicated products and regions. This results in broad advisories that impact production that is later determined not to have been implicated in the incident.

I am able to separately estimate losses to growers, processor/shippers, retailers, and food-service operators, in addition to losses to consumers and providers of inputs during and after the advisory period. The broad scope of this analysis is facilitated by access to proprietary data on prices and sales within the leafy-greens supply chain. I obtained wholesale data from a cooperating processor that supplies both food-service and retail outlets and combined that with public data on spot-market prices and movement provided by the USDA-Agricultural Marketing Service (AMS) and retail scanner data from the Nielsen Company. I then use regression analysis to predict what prices and sales would have been in the "but for" world absent the E. coli advisory. I compare these but-for prices and quantities to the prices and quantities that actually did occur during the advisory period and aftermath for romaine and its substitutes and compute economic impacts from price changes and lost sales.

Results suggest that growers were minimally impacted by the advisory, even though the incident originated at the grower level. The structure of grower contracts largely insulates them from loss in a food-safety event, as processors typically bear responsibility for product that cannot be sold. As such, processors and shippers were hit hardest by the incident, losing approximately \$52.7 million from price and quantity impacts. Retailers were also impacted significantly, amassing \$25.7 million in losses mostly due to pulling product from their distribution channels and shelves in response to the advisory. Conversely, food-service operators were little impacted because the loss associated with destroying affected product was was offset by lower acquisition costs for romaine on net during the advisory and its aftermath. Only spot-market sellers were exposed to the full impact of the incident, losing several hundred thousand dollars from lost sales and adverse price movements. I further estimate that societal losses from the Fall 2018 incident were in the range of \$280 to \$350 million.

The third essay returns to the topic of providing consumers with information about credence attributes, with a focus on local production. The USDA lists regional food systems as one of the four pillars of a new rural American economy, along with bio-based manufacturing, conservation markets, and agricultural production. The extent to which the local food movement can support policy goals will depend largely on how consumers respond to marketing strategies available to local producers. I evaluate, consumers' stated and revealed preference for locally produced food products using both a survey and a market-level labeling experiment. The survey, distributed by two Sacramento-area food co-ops, assessed differences in willingness-to-pay (WTP) and intensity of preference for local produce and processed foods and examined which characteristics consumers associate with a "Local" label. For the labeling experiment, I introduced "Local" shelf labels to products in five processed-food categories in one of these stores for four weeks. Both stores provided weekly sales data by UPC for four weeks prior to, during, and after the experiment, and I further collected detailed information on product claims, product placement, and promotions for each product.

The vast majority of shoppers at both stores expressed a preference for locally produced produce and processed foods. Respondents valued both local ingredients and local production for processed foods but placed a larger emphasis on local ingredients. Over half of the respondents were able to name specific local brands and were aware of existing promotional efforts to highlight local foods at their store. Their knowledge and perceptions of what local means differed greatly, however. Few (10%) could correctly state their store's definition of local production, and when asked to pick the statement most likely to be associated with a "Local" label displayed by either store, the storeâs definition of local was not ranked as the most likely association. Rather, respondents ranked a conjunction of traits such as organic production, small or artisan production, and an overall higher quality as more likely to be associated with the "Local" label. This suggests consumers' preferences for local foods are driven by a complex array of perceived quality attributes.

The preferences expressed in the survey do not carry forward to increased sales for products affixed with a "Local" label in the retail experiment. An analysis of the sales data in a triple-triple difference framework fails to detect significant average treatment effects. I do, however, detect significant heterogeneous treatment effects for select products. For instance, across all products and relative to products with no manufacturer claims, "Local" labels have a smaller effect on sales of organic products. Similarly "Local" shelf labels have a smaller effect on sales for products with packaging that highlights their geographic origin relative to products without a specified geographic origin. The results are consistent with the idea that the experimental labels primarily draw attention to or highlight products at the point of purchase, and might be more effective for products that do not already capture consumers' attention through manufacturer's claims, retailer discounts, or prime shelf-positioning.

Taken together, the research in this dissertation provides valuable insights on when the provision of information might help advance policy goals and when it might fall short in that regard. Further, it illustrates how imprecise and overly broad information, like that provided many initial food safety advisories, can generate far-reaching economic losses.

Essay 1

Transitional Organic Certification: Diluting the Value of Organic?

1.1 Introduction

The market for organic agriculture is one of the fastest growing in the U.S., with sales increasing 6.5% in 2018 and comprising 5% of all food sales (U.S. Department of Agriculture, Agricultural Marketing Service, 2020). While not as specific as the European Union's target of at least 25% organic farmland by 2025, the United States Department of Agriculture (USDA) currently has a general goal to increase the number of certified organic farming operations in the U.S. It believes organic certification will provide economic opportunities to producers and handlers in the form of accessing new and rapidly expanding markets, garnering premiums, more easily marketing their products to consumers, and supporting local economies (U.S. Department of Agriculture, Agricultural Marketing Service, 2021; U.S. Department of Agriculture, Economic Research Service, 2021). It further views organic farming as contributing to a more sustainable agricultural system and yielding environmental benefits (e.g. improved water quality, increased biodiversity, etc.). In service of this goal, the USDA funds research on organic production practices and markets and invests in programs to assist farmers with the cost and process of conversion.

Despite this, fewer than 1% of U.S. cropland is organically farmed, and the U.S. remains a net importer of organic goods amidst concerns of fraudulent organic imports. The low penetration of organic farmland even though a growing body of research that indicates organic farms have a profitability advantage over their conventional counterparts (Chavas, Posner, and Hedtcke, 2009; Delbridge et al., 2011, 2013) suggests there remain significant barriers to transition. These barriers include insufficient crop insurance coverage (Morris, Belasco, and Schahczenski, 2019), lack of physical infrastructure to store, transport, and market organic commodities, scarcity of information on organic production methods, price uncertainty, and the three-year transition period, during which farmers incur costs associated with organic production but cannot yet access organic premiums.

Private entities looking to ensure consistent and reliable supply chains to meet growing demand for their organic food products and to maintain the integrity of organic certifications have put forth their own efforts to reduce these barriers and support domestic organic production. Citing grain shortages, Nature's Path Foods Inc., the largest independent organic breakfast and snack food brand, purchased thousands of acres of organic farms in Montana (Strom, 2016). Some are going further and helping promote and finance additional conversion. In 2016, General Mills announced plans to more than double the domestic organic acreage from which it sources ingredients from by 2019 (Moos, 2016). Two years later, it announced a sourcing agreement with a farm in South Dakota to convert 34,000 acres of conventional cropland to organic by 2020. Under the agreement, the company will help farm operators adopt regenerative practices and commit to purchasing organic wheat from the farm for the company's Annie's brand (General Mills, 2016).

In an effort to create a market for crops in the midst of the three-year transition period and help producers earn a premium to help cover transition costs, a number of agencies have proposed or implemented transitional certification guidelines in recent years, and some have introduced certified transitional labels. In 2016, the first food products marketed as Certified

Transitional hit the market. Products with this label are made with certified transitional inputs, which are commodities in the second and third years of the three-year transition period from conventional to organic.

The Organic Trade Association (OTA) stopped short of endorsing such labels, noting that transitional labels could dilute the value of the existing organic label and specifically expressing concern about "an 'organic-lite' label out there competing for shelf space with organic farmers" (Fassler, 2017). To avoid this, they worked with the United States Department of Agriculture (USDA) in 2016 to draft plans for the National Certified Transitional Program (NCTP) that stops at the farm level and does not include a consumer-facing label. Instead, it includes stipulations about the composition and location of third-party labels, e.g. the label must be distinct from the certifying agency's organic label and not use the word organic. The program is currently on hold, however, due to objections from the Western Organic Dairy Producers (WODPA) because they believe that a transitional label will "compromise the integrity of the NOP standards and denigrate the organic label" (Mathews, 2016). Others, such as the president of one of the largest vineyard management companies in Napa Valley, contend that the label should not be used because it will confuse consumers (Cave, 2017).

This paper studies the impacts of the introduction of certified transitional products and commensurate labeling on the organic price premium, the return on investment of converting from conventional to organic and, thus, organic conversion rates. To that end, I construct static and dynamic models of vertical product differentiation to explore how introducing products with a certified transitional label impacts prices and market shares for conventional, organic, and certified transitional products and, in turn, conversion rates from conventional to organic. In the model, a certified transitional label may dilute the organic premium due to impacting consumers' self-selection constraints by introducing certified transitional products as a relatively close substitute for certified organic products. Thus, farmers contemplating organic conversion may earn higher returns during the conversion period but lower returns post conversion due to competition from transitional organic products produced by farmers who convert later in time and organic products produced by farmers who have completed the conversion process.

The models compare the organic price premium and organic market share under a baseline scenario of no transitional certification and labeling to the equilibrium where a certified transitional product is introduced, labeled, and operates as a good of "intermediate" quality between conventional and certified organic. In the latter environment, organic and transitional products compete directly for sales to consumers who place a high value on goods embodying organic or transitional characteristics.

While the static model holds the share of conventional, transitional, and organic cropland for a given commodity fixed, the dynamic model allows producers to convert from conventional to organic over time. Specifically, the dynamic model shows that the impact of introducing transitional certification and labeling on organic conversion depends on consumers' perceived quality of transitional relative to organic and the distribution of consumer preferences for quality attributes embodied in organic or transitional products. Comparative statics from the model yield insights as to how the introduction of a certified transitional label into the retail space will impact organic conversion for different commodities. Key variables include (i) consumers' perceived quality of the transitional product relative to organic, (ii) distribution of consumer preferences for quality attributes contained in organic and transitional organic products, and (iii) farmers' discount rates.

The effects of the introduction of certified transitional products, both labeled and unlabeled, on commodity prices and organic conversion rates have, to my knowledge, not yet been studied. Prior to the introduction of goods labeled transitional into the retail space, Williams (2013) estimated willingness to pay for hypothetical transitional produce using a stated preference methodology and found a positive willingness to pay for transitional goods. Regarding the decision to convert to organic, Delbridge and King (2016) seek to explain low organic conversion rates by modeling the organic adoption probabilities using net present value (NPV) and options value frameworks. They find that the adoption probabilities for large farms are especially sensitive to the size of organic premiums. Kuminoff and Wossink (2010) explore how financial compensation can be used to induce conventional farmers to convert their operations to organic. They estimate that the amount of money required to induce a risk-neutral soybean farmer with a 10 percent discount rate is $311 per acre for ten years. This would cover conversion costs and compensate farmers for higher production costs and increased market risk associated with organic production, perhaps indicating that TO premiums of sufficient size would be successful in inducing organic conversion.

Mussa-Rosen models of vertical differentiation, used here to model consumption, are applied to a variety of industries and products, including organic food products. Empirical research has established consumers view goods produced organically as higher quality (Yiridoe, Bonti-Ankomah, and Martin, 2005) and have a higher willingness to pay for them relative to their conventional counterparts (Kiesel and Villas-Boas, 2010; Willis et al., 2013). Survey results presented in Section 5 of this essay corroborate these findings, showing not only that, on average, consumers are willing to pay a premium for organic goods but that they also perceive them to be of higher quality.

Other examples of use of Mussa-Rosen models to study related problems include Giannakas (2002) and Giannakas (2016). They model, respectively, the effect of mislabeling organic products and the coexistence of genetically modified (GM), conventional, and organic food products. Merel and Carter (2005) employ a modified Mussa-Rosen model to analyze the impacts of GM technologies on conventional and organic production.

The framework used here, however, differs from the conventional Mussa-Rosen framework and applications of it in three important ways. First, producers are not choosing whether or not to introduce a new, intermediate-quality good. Ex ante, the intermediate (TO) good exists and is “hiding” in a quasi-pooling equilibrium in absence of TO certification and labeling. Second, low-quality (conventional) producers cannot choose to produce the high-quality (organic) good without first producing the intermediate-quality good. That is, the intermediate-quality is a necessary step in the process of converting a crop from low to high quality.

Finally, I model heterogeneity in consumers' intensity of preference for organic goods using the Kumarawamy distribution, rather than the uniform distribution typically used by those adopting the Mussa-Rosen framework. The Kumaraswamy (K) distribution is similar to the Beta distribution employed by Mérel and Sexton (2012) to model consumers' taste for products with geographic indicators (GI) but provides added simplicity over the Beta because its probability density (PDF) and cumulative distribution (CDF) functions can be expressed in closed form. Both distributions are more flexible than the uniform distribution because their PDFs can take on a wide array of shapes, including that of the uniform distribution, depending on the distribution parameter values. This allows the model to conform to a number of different commodities.

I first solve the model for a generic commodity and then estimate outcomes in the domestic strawberry market. I assign values to all but the distribution parameters using both data obtained from a survey developed in collaboration with and conducted by a major berry producer and from prior research. The survey asks customers to rate the quality of USDA organic, certified transitional, and conventional strawberries, providing values for the quality parameters. I rely on existing research on strawberry production for the remaining parameter values. I select values for the K-distribution parameters to calibrate the model to fit real-world prices for organic and conventional strawberries. Results indicate the transitional certification and labeling significantly increases the share of acreage devoted to organic strawberries, holding total strawberry acreage constant, and subsequently increases prices for both organic and conventional strawberries.

1.2 Industry Background

The roots of modern organic agriculture in the U.S. can be traced back to the 1970s. Though organic farming practices and consumer interest in organic produce predate this period, it was then that third-party certifications emerged to set standards and ensure customers got products that met those standards. California Certified Organic Farmers (CCOF) was the first organization to create an official certification program in 1973. By the end of the following decade, many other agencies developed their own certification standards. The standards adopted by each agency had substantial overlap but differed on details pertaining to such things as pesticide residue testing, field buffer zones, and nitrate use. The lack of consistency across certifying agencies complicated matters for producers of products containing multiple ingredients, all of which may have been certified according to different standards, and highlighted the need for one uniform standard.

The Organic Foods Production Act of 1990 (OFPA), part of the 1990 Farm Bill, authorized the USDA's Agricultural Marketing Service (AMS) to create a National Organic Program (NOP) and established a National Organic Standards Board (NOSB). The NOP is responsible for creating, interpreting, and enforcing the National Organic Standard (NOS). The NOSB is comprised of 15 individuals from the organic industry who are appointed by the USDA and advise the NOP on interpretation of the Organic Standard. The NOP did not release its initial draft of the NOS until 1997. It immediately drew ire among organic proponents for allowing the use of genetically engineered crops and genetically modified organisms (GMOs), among other things. The NOP took these complaints into account and released a revised draft in 2000 that was finalized that same year but did not go into effect until late 2002.

The NOS is extensive and covers every facet of crop and livestock production and processing. Certified crop producers must have clear boundaries and buffer zones to prevent contamination from neighboring fields; improve and conserve soil quality by using cover crops, mulches, conservation tillage, strip cropping, adding compost and green and animal manures, among other practices; use organic seeds and planting stocks;[1] practice crop rotation; and manage pests, weeds, and diseases manually or with approved natural or synthetic substances. Natural materials are typically allowed unless explicitly prohibited on the National List of Allowed and Prohibited Substances (NL), whereas synthetic substances are prohibited unless specifically allowed on the NL. Producers must refrain from using prohibited substances for three years prior to being certified as organic.

The NOS requires all organic producers and handlers with over $5,000 in sales to be certified by accredited certifying agents (ACAs). Operations with sales under $5,000 are free to label their products as organic if following organic practices but cannot use the USDA Organic label. Firms wishing to be certified must submit an Organic System Plan (OSP) as part of their application that describes how they will comply with the NOS. Further, firms must keep detailed records of all inputs, yields, and sales that align with what was proposed in the OSP.

1.2.1 Organic Production and Imports

U.S. demand for organic food products has long eclipsed domestic production of organic commodities and supply of certified organic cropland. Sales of organic products have grown over 700% since the NOP was finalized in 2000, averaging 12.3% growth per year (Delbridge et al. 2017; Silva et al. 2012). During the same period, the amount of domestic certified organic acreage increased by only 200% (Delbridge et al., 2017). In more recent years, the number of certified organic acres in the U.S. has surged, growing 17.4% per year on average between 2014 and 2017. Even so, the U.S. remains a net importer of organic commodities, with value of organic imports reaching $1.7 billion in 2016, an increase of over 20% from the prior year (Demko et al., 2017). Over half of some organic commodities such as corn, soybeans and coffee are imported to the U.S., some from as many as 100 countries.

[1] conventional seeds may be used when organic seeds are not available, but they may not be genetically engineered or modified

Imported organic products must be certified by a USDA-authorized organization abroad or be certified according to an authorized international standard. Such standards are established by equivalency agreements, under which two countries agree that their organic programs are equivalent. The U.S. has established agreements with the E.U., Canada, Japan, Korea, and Switzerland.

Despite this, there are concerns and evidence of fraudulent organic imports. A 2017 investigation by the Washington Post found evidence of three large corn and soybean shipments from Turkey presented as organic but not produced organically. In one instance, 36 million pounds of soybeans originating in Ukraine were shipped to California by way of Turkey and sold as organic, despite being grown with pesticides prohibited by the NL and originally marketed and priced as conventional (Whoriskey, 2017). The shipments analyzed were large enough to make up a substantial share of the U.S. supply of those commodities in the year in which they were imported.

Other groups like the Organic Farmers Agency for Relationship Marketing (OFARM) and the Cornucopia Institute have similarly found evidence of fraud when tracking massive shipments of grain routed through Turkey, now the largest importer of organic crops into the U.S. They estimate the number of cropland acres certified as organic in the origin countries is not sufficient to have produced the quantity of organic grain reported to have been imported from those countries. In 2018, OFARM's executive director noted that "serious questions as to whether some countries, like Kazakhstan, even have organic production acreage are alarming, considering reports that imports from these regions have filled the U.S. organic supply chain" (Held, 2020).

To curb organic fraud both abroad and domestically, the NOP released the Strengthening Organic Enforcement Proposed Rule in 2020. The proposed ruled, hailed by OTA as the "largest single piece of rule making since the organic regulations were implemented in 2002," would, among other things, require electronic certificates to trace and track imported organic foods and expand the type of operations that must obtain USDA-NOP certification to include importers, brokers, traders of organic products (Held, 2020).

1.2.2 Barriers to and Assistance with Organic Conversion

While organic commodities command a higher price at the farmgate and a premium at retail relative to their conventional counterparts, potentially providing farmers with higher variable profits per hectare compared to conventional crops (Chase et al., 2008), farmers face a number of obstacles when converting from conventional to organic production. One key obstacle often cited by farmers as an impediment to conversion is the transition process. Transitioning to organic is a costly and time-intensive process. Farmers must produce using organic methods for three years before being certified. During this three-year period, referred to as the transition period, farmers often make significant capital investments, experience lower yields, and usually fail to garner price premiums on output.

A variety of federal programs exist to assist with organic production and certification. Under the USDA's Organic Cost Share program, certified organic farmers receive up to $750 per year to cover the cost of organic certification. The USDA further provides financial and technical assistance via the Agriculture Management Assistance (AMA) program in 16 states to farmers who invest in conservation measures to address water management, water quality, erosion control, and other issues. Eligible conservation practices include transitioning to organic farming. Despite this support, the National Sustainable Agriculture Coalition and the Organic Farming Research Foundation say these and other programs could be expanded to better support farmers in the transition process by, for instance, making cost-share funds available to farmers in transition and expanding the number of states eligible for AMA (Charney, 2017).

A relatively new approach to easing the financial strain of the transition period is to create a new product category to generate higher returns for farmers in transition. Quality Assurance International (QAI), California Certified Organic Farmers (CCOF), Organic Certifiers (OC), and Ecocert, all accredited certifying agencies (ACAs), have implemented transitional organic certification guidelines and introduced certified transitional labels in recent years for farms in years two and three of the organic conversion process. The most high profile of these efforts is spearheaded by Kashi, who, in 2016, partnered with QIA to set certification standards for transitioning farms and establish a "certified transitional" label.[2] Kashi was the first company to market a product as "certified transitional" at the retail level.

Figure 1.1: Certified Transitional Labels

Such transitional certification programs aim to generate price premiums for transitional crops, thereby motivating a greater number of conventional farmers to convert to organic. Additionally, proponents claim certification will improve access to USDA support services like farm loan products during the transition, facilitate better supply chain management, and establish a market for transitional crops. Despite the purported benefits, the Organic Trade Association (OTA) and other incumbents in the organic industry worry that certification and accompanying labels will weaken the value of organic certification.

To alleviate these concerns and establish uniform certification guidelines, the USDA proposed the National Certified Transitional Program (NCTP) in early 2017. The proposed program utilized standards developed by the OTA, allowed ACAs to certify transitional producers, and established strict labeling guidelines to limit the possibility that consumers would confuse or closely associate transitional and organic products. Goods certified under

[2]Kashi is an U.S.-based producer of cereals and other plant-based foods that are sold in the U.S. and Canada.

the program cannot use the word "organic" on any labels and must refrain from including a label on the product's primary panel. Even so, the program was put on hold in 2017 after WODPA threatened legal action against the USDA if the program came to fruition and currently remains on hold.

The rationale behind these concerns is twofold: First, some consumers may encounter transitional and organic versions of the same product and feel that the transitional product is sufficiently close to organic in quality not to warrant paying the full organic premium. Second, if a label informs consumers of the existence of this transitional period and enables transitional products to capture a premium in the market place, a portion of this premium would then flow to farmers in the form of higher prices paid by processors. Thus, over the long run, a transitional premium could induce conversion of more cropland to certified organic and dilute organic premiums through this supply response.

That is, in the short run, organic premiums may decrease by way of competition with transitional products, and in the long run, they may decrease due to competition with both transitional products and increased organic production. This analysis seeks to evaluate these short- and long-run effects. I address the former using a static model of vertical differentiation and the latter using a dynamic model of vertical differentiation and organic conversion.

1.3 Static Model

Utilizing the framework developed by Mussa and Rosen (1978), I construct a static vertical differentiation model to explore the change in equilibrium price in the markets for conventional and organic products when certified transitional products are introduced into the quality space.

1.3.1 Production

I normalize the magnitude of cropland to 1. Each unit of land, sometimes referred to as acres for convenience, farmed using conventional methods produces one unit of output. To account for yield loss associated with organic production, each unit farmed using organic practices produces γ units of output, where $0 < \gamma < 1$. I assume supply is inelastic in this short-run model. The shares of conventional and transitional cropland are denoted as ρ_c and ρ_{to}, respectively, where $0 < \rho_{to} < \rho_c < 1$. The share of organic cropland, ρ_o, is $(1 - \rho_c - \rho_{to})$. In the absence of transitional certification and labeling, consumers do not distinguish between conventional and transitional production, so the share of production marketed as conventional is $(\rho_c + \rho_{to})$. It follows that total output is equal to $\gamma + \rho_c(1 - \gamma)$.

1.3.2 Utility and Demand

Depending on the policy scenario, the market may consist of conventional (c), transitional organic (to), and organic (o) goods. These goods have homogeneous product attributes (e.g. size, sugar content, etc.) but heterogeneous process attributes that map to quality. Consumers agree on the quality ranking of the conventional, transitional, and organic goods and would purchase the organic good if all goods were sold at the same price. Despite this, consumers differ in their valuation of and willingness to pay for the different quality levels. Consumers are indexed by a valuation parameter $\theta \in [0, 1]$, where higher values of θ are associated with a more intense preference for organic goods. This parameter follows the Kumaraswamy distribution which has a PDF of

$$f(\theta)_{a,b} = ab\theta^{a-1}(1 - \theta^a)^{b-1} \tag{1.1}$$

and CDF of

$$F(\theta)_{a,b} = 1 - (1 - \theta^a)^b \tag{1.2}$$

where pairs $(a, b) \in \mathbb{R}_{>0}$.

Varying the distribution parameters to alter the proportion of consumers with a high willingness to pay for organic goods, effectively allows the model to exhibit an infinite number of consumer-valuation scenarios, some of which are shown in Figure 1.2. I hypothesize that, broadly, the true distribution is generally right skewing with the the majority of customers having a low willingness to pay for organic goods. Such a distribution may explain the small share of retail grocery sales organic goods currently comprise. However, the K distribution will likely differ for a given population across crops. Price premiums for organic commodities are as little as 9% for asparagus and as much as 227% for spinach (U.S. Department of Agriculture, Market News Service, 2021). Thus, by changing the K parameters, one can estimate the effect of introducing TO labeling for different commodities. In section 6, I choose a distribution to fit the model to real-world strawberry prices.

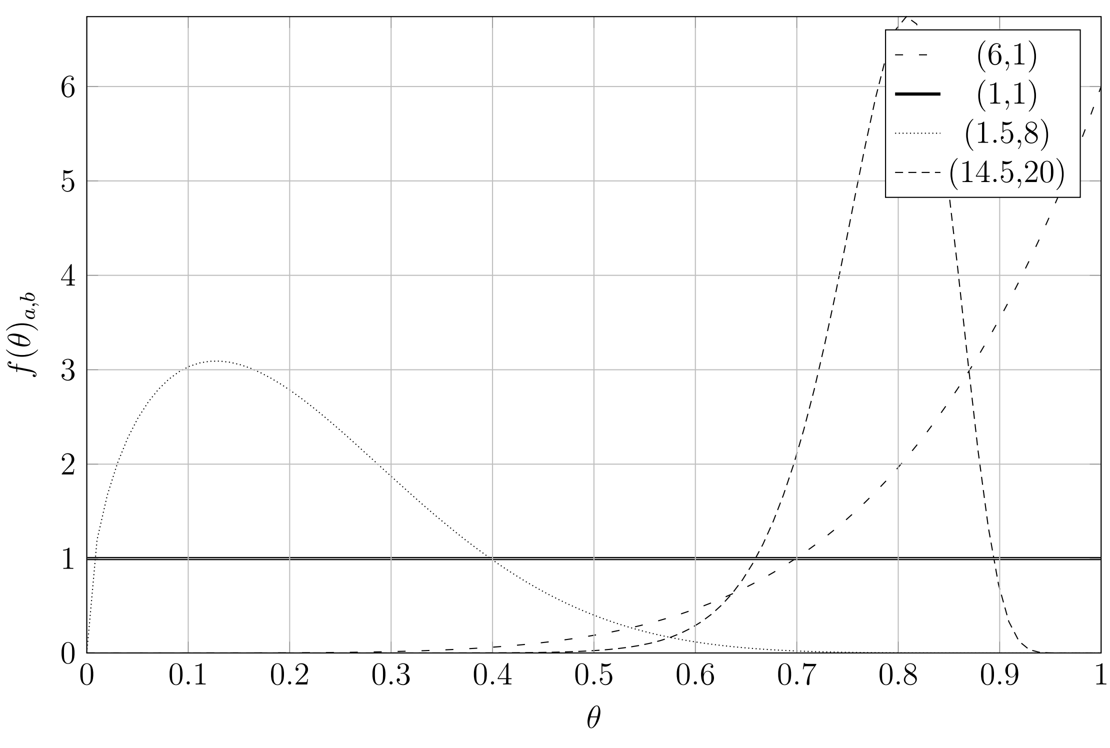


Figure 1.2: Kumaraswamy Probability Density Function for Pairs (a,b)

I assume consumers purchase no more than one unit of one good in the market (i.e., discrete choice and unit demand), and the purchasing decision is a small portion of budget (i.e. there is no income effect). Direct utility for individual i associated with one unit of good j is

$$U_i(q_j, x, \theta) = \theta q_i + x,\ \ j = c, to, o, \tag{1.3}$$

where q_j is the exogenous quality of conventional, transitional organic, and organic goods, respectively, and x is expenditure on other outside goods. I normalize the quality of organic goods to 1, so that q_c and q_{to} represent the relative qualities of conventional and transitional goods. Consumers face an exogenous budget constraint. $I = x + p_j$, with $p_j, j = c, to, o$ being the price of conventional, transitional, and organic commodities, respectively.

Indirect utility is represented as

$$v_i(q_j, x, p_j, \theta) = \begin{cases} \theta q_j + I - p_j, & q_j > 0 \\ I, & q_j = 0, \end{cases} \tag{1.4}$$

where θq_j is the reservation price for a consumer with valuation θ for a good with quality q_j.

1.3.3 Policy 1: No Transitional Certification

All three types of products exist. If, however, in the absence of a transitional certification and labeling, consumers are unaware transitional goods exist in the conventional market, they apply quality q_c to all goods sold in the conventional market. I make this assumption because it is plausible that many consumers are unaware of the three-year transition period and, thus, the possibility of transitional goods existing in the market.[3] Further, the share of transitional cropland for a given commodity may be sufficiently small so as not to impact consumers' perception of goods in the conventional market. The 2019 USDA Organic Survey

[3] Yiridoe, Bonti-Ankomah, and Martin (2005) find that consumers generally have broad awareness of the issues associated with organic farming but lack specific information on and understanding of the the specifics of organic farming practices. For instance, only 56% of U.S. consumers know that certified organic foods do not contain genetically modified ingredients (Campbell et al., 2014).

reports 263,423 acres of transitional cropland and 3,517,051 acres of organic cropland (U.S. Department of Agriculture, National Agricultural Statistics Service, 2019a).[4] In 2017, there were 396,433,817 acres of cropland in the U.S. (U.S. Department of Agriculture, National Agricultural Statistics Service, 2017).[5] This results in $\rho_{to} = 0.00066$. The proportion of unlabeled transitional goods on the market is sufficiently small that the affect on the average quality of conventional goods is negligible.

The consumer indifferent between consuming an organic or conventional good is located at the point where the indirect utility derived from consuming the two types of goods is equal. Likewise, the consumer indifferent between consuming conventional goods and the outside option is located at the point where indirect utility associated with these two consumption choices are equal.

$$v_o = v_c \implies \theta + I - p_o = \theta q_c + I - p_c \implies \theta^1_{oc} = \frac{p_o - p_c}{1 - q_c} \tag{1.5}$$

$$v_c = v_x \implies \theta q_c + I - p_c = I \implies \underline{\theta} < \theta^1_{cx} = \frac{p_c}{q_c} \tag{1.6}$$

The former location is determined by the self-selection constraint as the indifferent consumer between the two product types derives a positive consumer surplus from consuming either type. That is, $v_i(q_o, p_o, \theta^1_{oc}) = v_i(q_c, p_c, \theta^1_{oc}) > v_x$. The latter location is determined by a participation constraint because the indifferent consumer derives zero net utility from participating in the market for this commodity.

Demands for conventional and organic goods are $F(\theta^1_{oc}, a, b) - F(\theta^1_{cx}, a, b)$ and $1 - F(\theta^1_{oc}, a, b)$, respectively. Substituting the location of the indifferent consumers into the PDF of the K-

[4] Transitional acreage is comprised of 39,649 from non-organic farms and 223,774 from certified and exempt farms.

[5] 2017 is the most recent Census of Agriculture.

distribution obtains the following demand functions:

$$Q_o^1(\mathbf{p}|\mathbf{x}) = \left(1 - \left(\frac{p_o - p_c}{1 - q_c}\right)^a\right)^b \text{ and} \tag{1.7}$$

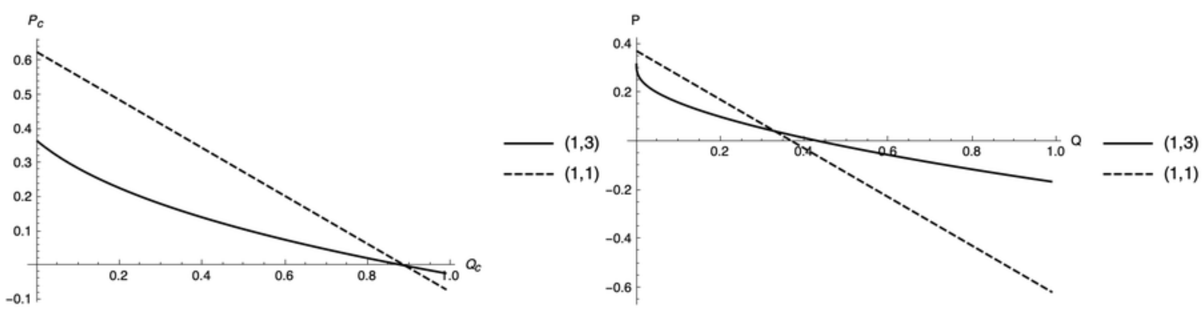
$$Q_c^1(\mathbf{p}|\mathbf{x}) = \left(1 - \left(\frac{p_c}{q_c}\right)^a\right)^b - \left(1 - \left(\frac{p_o - p_c}{1 - q_c}\right)^a\right)^b. \tag{1.8}$$

Inverse demand functions for organic and conventional crops are

$$p_o^1(\mathbf{Q}|\mathbf{x}) = q_c\left(1 - (Q_c + Q_o)^{1/b}\right)^{1/a} - (q_c - 1)\left(1 - Q_o^{1/b}\right)^{1/a} \text{ and} \tag{1.9}$$

$$p_c^1(\mathbf{Q}|\mathbf{x}) = q_c\left(1 - (Q_c + Q_o)^{1/b}\right)^{1/a}. \tag{1.10}$$

Figure 1.3 displays inverse demand for organic goods under right-skewed and uniform K-distributions. The demand curve is highest under the left-skewed distribution, which represents a large share of consumers having a high willingness to pay for organic goods.



(a) Conventional (b) Organic

Figure 1.3: Inverse Demand Curves Under Different K-Distributions

Market Equilibrium Prices

The available production quantities of conventional and organic crops, respectively, are

$$Q_o^1 = (1 - \rho_c - \rho_{to})\gamma \text{ and} \tag{1.11}$$

$$Q_c^1 = (\rho_c + \gamma\rho_{to}). \tag{1.12}$$

Market equilibrium prices are found where inverse demand is equal to supply. Substituting the available production quantities into the inverse demand functions results in equilibrium prices for conventional and organic crops of

$$p_o^{*1} = q_c \left(1 - ((\gamma + (1-\gamma)\rho_c))^{1/b}\right)^{1/a} + (1-q_c)\left(1 - (\gamma\,(1-\rho_c-\rho_{to}))^{1/b}\right)^{1/a} \text{ and} \tag{1.13}$$

$$p_c^{*1} = q_c \left(1 - ((\gamma + (1-\gamma)\rho_c))^{1/b}\right)^{1/a}. \tag{1.14}$$

The resulting market-equilibrium organic price premium relative to conventional is

$$p_o^{*1} - p_c^{*1} = (1-q_c)\left(1 - (\gamma(1-\rho_c-\rho_{to}))^{1/b}\right)^{1/a}. \tag{1.15}$$

The equilibrium premium is decreasing in the ex-ante quantity of organic production, the relative quality of conventional goods, and the relative yield of land produced using organic methods. The distribution of consumers along the valuation space, as determined by the distribution parameters, also affects the premium. By using the K-distribution, I can alter the distribution parameters and quantify how changes in consumers' valuation of organic goods impacts equilibrium prices and premiums, a feat not possible if using the more common uniform distribution. For example, holding b fixed at 5 and increasing a simulates increasing preference for organic products, which increases the equilibrium organic premium.

1.3.4 Policy 2: Transitional Certification and Labeling

Under policy 2, certified transitional goods are labeled and introduced into the market, resulting in the existence of an intermediate-quality product in the quality space. Transitional goods have a quality q_{to}, where $q_c < q_{to} < 1 = q_o$. The quality of transitional crops can be denoted as a linear combination of q_o and q_c such that $q_{to} = \alpha + (1-\alpha)q_c$ and $\alpha \in (0,1)$. Here, α can be interpreted as the substitutability of transitional and organic goods, where α approaching one indicates consumers view transitional and organic goods as having similar quality and, thus, as near-perfect substitutes, and α approaching zero indicates transitional and conventional are near-perfect substitutes.

Consumers who are indifferent between conventional and transitional goods and those who are indifferent between transitional and organic goods are located as follows:

$$v_o = v_{to} \implies \theta^2_{ot} = \frac{p_o - p_{to}}{(q_c - 1)(\alpha - 1)}, \tag{1.16}$$

$$v_{to} = v_c \implies \theta^2_{tc} = \frac{p_{to} - p_c}{\alpha(1 - q_c)}, \text{ and} \tag{1.17}$$

$$v_c = v_x \implies \theta^2_{cx} = \frac{p_c}{q_c}. \tag{1.18}$$

Demands for the conventional, transitional organic, and organic commodity, respectively, are $1 - F(\theta^2_{ot}, a, b)$, $F(\theta_{ot}, a, b) - F(\theta^2_{tc}, a, b)$, and $F(\theta^2_{tc}, a, b) - F(\theta^2_{cx}, a, b)$. Equivalent demand functions are

$$Q^2_o(\mathbf{p}|\mathbf{x}) = \left(1 - \left(\frac{p_o - p_{to}}{(q_c - 1)(\alpha - 1)}\right)^a\right)^b, \tag{1.19}$$

$$Q^2_{to}(\mathbf{p}|\mathbf{x}) = \left(1 - \left(\frac{p_c - p_{to}}{\alpha(q_c - 1)}\right)^a\right)^b - \left(1 - \left(\frac{p_o - p_{to}}{(q_c - 1)(\alpha - 1)}\right)^a\right)^b, \text{ and} \tag{1.20}$$

$$Q^2_c(\mathbf{p}|\mathbf{x}) = \left(1 - \left(\frac{p_c}{q_c}\right)^a\right)^b - \left(1 - \left(\frac{p_c - p_{to}}{q_c - q_{to}}\right)^a\right)^b. \tag{1.21}$$

Inverse demand for the three commodity types are

$$\begin{aligned} p^2_o(\mathbf{Q}|\mathbf{x}) = q_c \left(1 - (Q_c + Q_o + Q_{to})^{1/b}\right)^{1/a} + (q_c - 1) \Big((\alpha - 1) \left(1 - Q_o^{1/b}\right)^{1/a} - \\ \alpha \left(1 - (Q_o + Q_{to})^{1/b}\right)^{1/a}, \end{aligned} \tag{1.22}$$

$$p^2_{to}(\mathbf{Q}|\mathbf{x}) = q_c \left(1 - (Q_c + Q_o + Q_{to})^{1/b}\right)^{1/a} - \alpha(q_c - 1) \left(1 - (Q_o + Q_{to})^{1/b}\right)^{1/a}, \text{ and} \tag{1.23}$$

$$p^2_c(\mathbf{Q}|\mathbf{x}) = q_c \left(1 - (Q_c + Q_o + Q_{to})^{1/b}\right)^{1/a}. \tag{1.24}$$

The price of the organic commodity is dependent on the relative quality of the conventional commodity even though those two products no longer directly compete.

Market Equilibrium Prices

The available production quantities of organic, transitional, and conventional products, respectively, are

$$Q_o^2 = (1 - \rho_c - \rho_{to})\gamma, \tag{1.25}$$

$$Q_{to}^2 = \rho_{to}\gamma, \text{ and} \tag{1.26}$$

$$Q_c^2 = \rho_c. \tag{1.27}$$

Equilibrium prices as a function of production shares, yield loss, and taste and quality parameters are

$$\begin{aligned} p_o^{*2} &= (q_c - 1)\left((\alpha - 1)\left(1 - (-\gamma(\rho_c + \rho_t - 1))^{1/b}\right)^{1/a} - \alpha\left(1 - (\gamma - \gamma\rho_c)^{1/b}\right)^{1/a}\right) + \\ &\quad q_c\left(1 - (\rho_c + \gamma - \gamma\rho_c)^{1/b}\right)^{1/a}, \end{aligned} \tag{1.28}$$

$$p_{to}^{*2} = q_c\left(1 - (\gamma + \rho_c - \gamma\rho_c)^{1/b}\right)^{1/a} - \alpha(q_c - 1)\left(1 - (\gamma - \gamma\rho_c)^{1/b}\right)^{1/a}, \text{ and} \tag{1.29}$$

$$p_c^{*2} = q_c\left(1 - (\gamma + \rho_c - \gamma\rho_c))^{1/b}\right)^{1/a}. \tag{1.30}$$

At these prices, markets clear for all three commodities.

The resulting market-equilibrium organic premium relative to conventional is

$$(q_c - 1)\left((\alpha - 1)\left(1 - (-\gamma(\rho_c + \rho_t - 1))^{1/b}\right)^{1/a} - \alpha\left(1 - (\gamma - \gamma\rho_c)^{1/b}\right)^{1/a}\right). \tag{1.31}$$

Proposition 1. *The introduction of transitional certification and labeling decreases the price of organic goods, and the absolute price decrease is greater for organic commodities with higher demand.*

All else constant, the introduction of certified transitional crops causes market demand for the organic commodity to shift inward, while the available production quantity of organic output remains constant. This leads to a decrease in the price of organic goods, as is depicted in Figure 1.4.

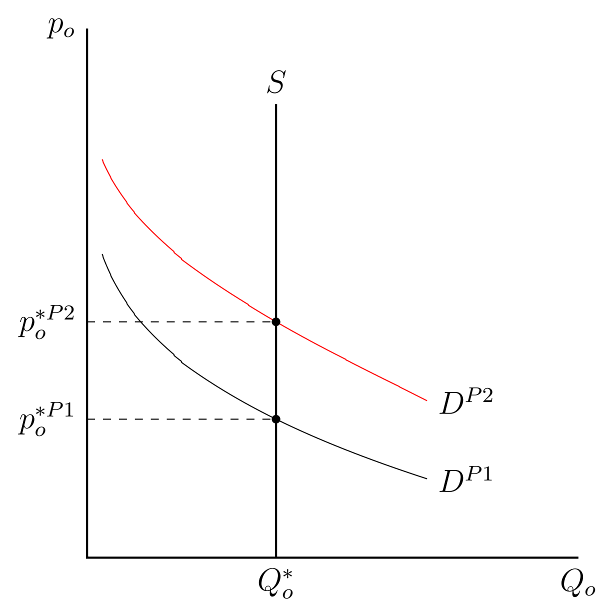


Figure 1.4: Organic Price Under Policies 1 and 2

This change in the price of the organic commodity induced by the introduction of transitional organic certification and labeling (Δp_o) is

$$\alpha(q_c - 1)\left(\left(1 - (\gamma(1 - \rho_c - \rho_t))^{1/b}\right)^{1/a} - \left(1 - (\gamma(1 - \rho_c))^{1/b}\right)^{1/a}\right). \tag{1.32}$$

The sign of Δp_o is negative. The absolute magnitude is increasing in ρ_{to}, γ, and α and decreasing in the quantity of organic output, the quantity of combined transitional and organic output, and q_c. The absolute magnitude of the price change is larger for organic commodities with higher demands based on the K-distribution parameters. For example the price reduction is larger when the K-distribution is left skewed than when it is right skewed.

Proposition 2. *The introduction of transitional certification and labeling does not alter the price of the conventional commodity.*

Under both policies, the prices of conventional commodity, shown in equation 1.14, are equal and are not dependent on the share and substitutability of transitional goods. TO certification and labeling shifts demand for the conventional commodity inward, just as it does for the organic commodity. TO certification simultaneously shifts supply to the left because transitional acres were considered conventional under policy 1, such that the supply and demand effects perfectly counterbalance.

Proposition 3. *It follows from propositions 1 and 2 that the introduction of transitional certification and labeling reduces the organic premium by the same amount as the reduction in the price of organic.*

The change in equilibrium price premiums, $(p_o^{*2} - p_c^{*2}) - (p_o^{*1} - p_c^{*1})$, is equal to

$$\alpha(q_c - 1)\left(\left(1 - (\gamma(1 - \rho_c - \rho_t))^{1/b}\right)^{1/a} - \left(1 - (\gamma(1 - \rho_c))^{1/b}\right)^{1/a}\right). \tag{1.33}$$

Proposition 4. *The price of transitional goods is increasing in the degree to which consumers believe transitional and organic goods are substitutes.*

The derivative of p_{to}^{*2} with respect to α is

$$\frac{\partial p_{to}^{*2}}{\partial \alpha} = (1 - q_c)\left(1 - (\gamma - \gamma\rho_c)^{1/b}\right)^{1/a}. \tag{1.34}$$

As γ are ρ_c, are less than or equal to one, the sign of the derivative is positive.

Proposition 5. *Transitional goods are sold at a premium relative to conventional goods.*

The difference between the equilibrium prices of the transitional and conventional commodities is

$$p_{to}^{*2} - p_c^{*2} = \alpha(1 - q_c)\left(1 - (\gamma - \gamma\rho_c)^{1/b}\right)^{1/a} \tag{1.35}$$

This is positive for all $\alpha > 0$, which indicates transitional certification will allow farmers to obtain higher prices during the transition period than they would in the absence of transitional certification and labeling.

1.3.5 Economic Welfare

Under policy 1, both conventional and transitional producers sell into the conventional market. Organic and transitional producers incur marginal production costs of c_o, and conventional producers have a marginal cost of c_c. Aggregate producer surplus is measured as $(p_j^{*1} - c_j)Q_j^2$ for $j = o, c$.[6] Policy 2 eliminates the presence of the transitional commodity in the conventional market. Aggregate surpluses for producers in the three markets are measured as $(p_j^{*2} - c_j) * Q_j^2$ for $j = o, to, c$.

The aforementioned price changes brought about by TO labeling also affect consumer welfare. To compare consumer surplus before and after TO certification and labeling, consumers can be split into three groups – those who consume the organic commodity under both policies, those who switch from conventional to transitional, and those who consume conventional under both policies. They are located on the following segments along the theta continuum, respectively: $[\theta_{oc}, 1]$, $[\theta_{tc}, \theta_{oc}]$, and $[\theta_{cx}, \theta_{tc}]$.[7]

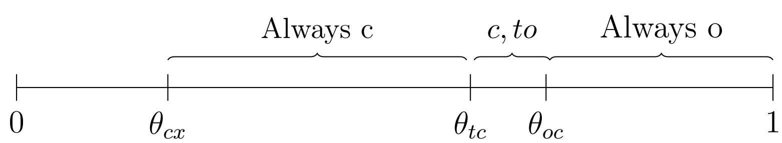


Figure 1.5: Segments of Consumers along the θ Continuum

The difference in indirect utility under policy 2 relative to policy 1 for a given individual in the first group is $p_o^{*1} - p_o^{*2}$. It is $\theta(q_{to} - q_c) - (p_{to}^{*2} - p_c^{*1})$ for an individual in the second

[6]Production quantities under policy 1 reflect the quantities sold into each market. As the market for transitional does not exist, Q_c^1 is the sum of conventional and transitional output. Production quantities under policy 2 reflect both the quantity sold into each market and output by each type of producer, so they are used when computing producer surplus for each type of producer under both policies 1 and 2.

[7]θ_{oc} and θ_{ot} are equivalent. In other words there are no consumers switching from O to TO because O production is unchanged, and the market clears.

group and $p_c^{*1} - p_c^{*2}$ for an individual in the third group.

The aggregate change in surplus for each group is found by integrating the change in individual indirect utility over the group's segment on the theta continuum. The changes in aggregate consumer surplus associated with the introduction of TO certification and labeling for each group are

$$\Delta CS_{o,o} = \int_{\theta_{ot}}^{1} p_o^{*1} - p_o^{*2}\delta\theta = \Delta p_o^*(\theta_{ot} - 1), \tag{1.36}$$

$$\Delta CS_{c,t} = \int_{\theta_{tc}}^{\theta_{oc}} \theta(q_{to} - q_c) - (p_{to}^{*2} - p_c^{*1})\delta\theta = (p_{to}^{*2} - p_c^{*1})(\theta_{tc} - \theta_{oc}) - \frac{1}{2}(q_{to} - q_c)(\theta_{tc}^2 - \theta_{oc}^2), \text{ and} \tag{1.37}$$

$$\Delta CS_{c,c} = \int_{\theta_{xc}}^{\theta_{tc}} p_c^{*1} - p_c^{*2}\delta\theta = \Delta p_c^*(\theta_{cx} - \theta_{tc}). \tag{1.38}$$

Proposition 6. *The introduction of transitional certification and labeling is a Pareto improvement for consumers.*

It follows from proposition 1 that indirect utility is higher under policy 2 for those who always consume organic. It follows from proposition 2 that the change in indirect utility for individuals in group 3 is equal to zero. Those switching from C to TO must be at least weakly better off because they could have continued to consume C at the same price but chose not to. The sign of each aggregate surplus change is equal to the sign of the change for each individual in that group. Therefore, the introduction of TO certification and labeling increases surplus for consumers in groups 1 and 2 and does not alter the surplus of those in group 3. The surplus of those who do not consume the product is unchanged.

Proposition 7. *The introduction of transitional certification and labeling improves welfare for transitional producers, decreases welfare for organic producers, and has no effect on welfare for conventional producers.*

Changes in producer surplus are

$$\Delta PS_o = \Delta p_o^*((1 - \rho_c - \rho_t)\gamma < 0, \tag{1.39}$$

$$\Delta PS_{to} = (p_{to}^{*2} - p)c^{*1})(\rho_t)\gamma > 0, \text{ and} \tag{1.40}$$

$$\Delta PS_c = 0. \tag{1.41}$$

This is a direct result of production quantities remaining constant, while prices received for conventional, transitional, and organic production are unchanged, increase, and decrease, respectively.

In sum, the introduction of transitional certification and labeling causes a decrease in organic price premium in the short run. This effect, however, may be small in magnitude given the limited amount of production that will be certified transitional at an given time. Consumers are strictly better off after TO certification because organic consumers receive a lower price and transitional organic consumers are better able to match their preferences to goods available in the marketplace. Transitional products garner a positive premium over conventional goods, so labeling them increases surplus for producers and may encourage producers to convert more acres from conventional to organic. Over time, this may further reduce the organic premium due to competition with increased organic production. Total welfare rises if I weight consumer and producer welfare equally. In that case, the change in the equilibrium price for the organic commodity nets out because it is a gain for consumer but loss for producers, TO producers and consumers gain, and conventional consumers and producers are unaffected.

1.4 Consumer Survey

I designed a survey in collaboration with a prominent berry seller to utilize their existing consumer panel to estimate values for the α and q_c parameters and explore the distribution of intensity of preference for organic goods. The company invited 8,982 individuals to participate in the survey and received 2,422 responses, split between 2,006 complete and 416 partial responses.[8]

1.4.1 Product Quality

On a scale of 1 to 10, the survey asks respondents to assign values to their perceived qualities for packages of strawberries. One package is conventionally grown and unlabeled, and the others are adorned with a specific label or claims including, but not limited to, USDA Organic and Certified Transitional. The packages are otherwise identical. The additional labels or claims represent credence attributes that, like certified transitional, consumers may perceive as being of intermediate quality between conventional and organic. While I only use the quality values for the conventional, organic, and TO strawberries in this paper, their inclusion provides interesting insights into how consumers view other intermediate labels. Further, the quality values assigned to a full suite of claims that encompass many of the attributes consumers regularly encounter and choose amongst may elicit more true-to-life quality assessments than if presented with our three products of interest in a vacuum.

The survey asks respondents to assign quality ratings to each of the 9 packages of strawberries first with no additional information as to the meaning of each claim and then again after the definition of each claim and information on whether or not the claim is regulated and/or certified and by whom is presented. Respondents are asked to rate how confident they are that they know the exact definition of each label after the initial ratings but before this information is presented. Taken together, this allows me to assess how knowledge of certified transitional claims affects perceived quality. The results of the initial quality ranking are shown in Table 1.1. The average quality for USDA organic strawberries is 7.826, whereas the average quality ratings for conventional and certified transitional strawberries are 5.785 and 4.897, respectively. These values correspond to $q_c = .737$ and $\alpha = -0.421$ and indicate that, on average, respondents do not view certified transitional goods as being of intermediate quality.

Table 1.2 displays consumers' responses to the statement "I feel confident I know the

[8]Because demographics questions were not included and the survey was sent as an anonymous link, I cannot determine whether it is a representative sample when compared to census statistics for the general population. Based on past studies, the panel has a slightly higher representation of retirement age households and female participants.

Table 1.1: Initial Quality Rankings

Variable	Mean	Std. Dev.	Min	Max	P50	Obs
Conventionally grown (unlabeled)	5.765	2.512	1	10	6	2377
USDA Organic	7.826	2.414	1	10	8	2377
Certified Transitional	4.897	2.564	1	10	5	2377
Zero Pesticides	7.451	2.304	1	10	8	2377
Certified Pesticide Residue Free	7.322	2.369	1	10	8	2377
All Natural	6.189	2.661	1	10	7	2377
Certified Naturally Grown	6.608	2.456	1	10	7	2377
Certified Regenerative	4.977	2.616	1	10	5	2377
Local	7.254	2.396	1	10	8	2377

exact definition of this label" for each of the 8 labels included in the survey. Of the 2,351 respondents only 14.8% at are at least somewhat confident that they know the definition of the certified transitional label. This is significantly less than all other labels with the exception of certified regenerative.

Table 1.2: Response to "I feel confident that I know the exact definition of this label"

	USDA Organic	Certified Transitional	Zero Pesticides	Certified Pesticide Residue Free	All Natural	Certified Naturally Grown	Certified Regenerative	Local
Strongly agree	27.2%	2.0%	21.9%	15.0%	11.1%	8.7%	1.9%	29.5%
Agree	32.5%	4.8%	29.8%	22.8%	19.3%	18.5%	4.6%	33.7%
Somewhat agree	22.3%	8.0%	24.3%	27.6%	20.7%	22.7%	7.7%	19.4%
Neither agree nor disagree	9.4%	17.1%	10.5%	12.3%	17.8%	16.2%	17.3%	9.3%
Somewhat disagree	3.8%	8.3%	5.4%	9.2%	10.5%	12.5%	9.1%	3.4%
Disagree	2.4%	16.1%	4.5%	6.6%	10.2%	10.9%	16.2%	2.1%
Strongly disagree	2.3%	43.7%	3.6%	6.5%	10.4%	10.6%	43.2%	2.6%

To determine whether perceived knowledge of the definition of the certified transitional label affects one's quality rating, I first compute the mean quality rating for those who strongly agree, agree, somewhat agree, at least somewhat agree with the statement, and are at most neutral. Those who are most confident that they know the definition on average rate the quality of certified transitional strawberries higher than those with less confidence in the definition. They have a mean quality rating of 6.809, 40% higher than the mean rating over the entire sample population. Similar but slightly smaller increases can be seen for those who are agree or somewhat agree with the question's statement. Compared to those who at least somewhat agree with the statement, those who are at most neutral rate the quality of certified transitional strawberries 2 points less on average. A two-sided t-test confirms that the difference in means of the quality rankings between the two groups is statistically significant. Table 1.3 further displays the corresponding q_c and α for each set of ratings. For all groups who at least somewhat agree with the survey statement, $\alpha \in (0, 1)$, indicating those respondents view it as a good of intermediate quality.

Table 1.3: Initial Quality Rankings and Corresponding Model Parameters by Knowledge of the Definition of the Certified Transitional Label

	Quality Ratings			Parameters	
	Conventional	Certified Transitional	USDA Organic	q_c	α
Somewhat Agree	5.775	6.417	8.139	0.710	0.271
Agree	6.127	6.787	8.384	0.731	0.293
Strongly Agree	5.404	6.809	8.298	0.651	0.485
At Least Somewhat Agree	5.841	6.591	8.241	0.709	0.313
At Most Neutral	5.794	4.525	7.731	0.705	-0.656

The survey then asks consumers to once again rate the quality of all 9 products after being presented with detailed information about the label. The survey defined each label and noted which credence attributes on the labels were certified and by whom. After receiving this information, the mean rating of the certified transitional strawberries increased by 1.85 points. The difference in means for the certified transitional rating before and after the information is given is statistically significant at the 1% level. Further, the mean quality rating is between the mean ratings for conventionally grown and USDA organic strawberries. This suggests that while there is a significant information barrier to overcome in order for products with a certified transitional label to be seen as an intermediate good between conventional goods and USDA organic goods, consumers do view the product as being of intermediate quality.

The mean ratings for conventional, transitional, and organic strawberries post information treatment correspond to $q_c = .705$ and $\alpha = 0.439$. I use these values in simulations later in the paper.

1.4.2 Valuation of Organic Goods

The theoretical model in this paper eschews the standard uniform distribution in favor of the more flexible Kumaraswamy distribution. Its PDF can take a variety of shapes, including

Table 1.4: Quality Rankings - Post Label Definitions

Variable	Mean	Std. Dev.	Min	Max	P50	Obs
Conventionally grown (unlabeled)	5.7	2.54	1	10	6	2109
USDA Organic	8.08	2.324	1	10	9	2109
Certified Transitional	6.745	2.302	1	10	7	2109
Zero Pesticides	6.983	2.464	1	10	8	2109
Certified Pesticide Residue Free	7.26	2.294	1	10	8	2109
All Natural	6.264	2.653	1	10	7	2109
Certified Naturally Grown	7.216	2.28	1	10	8	2109
Certified Regenerative	6.692	2.348	1	10	7	2109
Local	7.001	2.396	1	10	8	2109

uniform, allowing me to model outcomes under different distributions of consumers along the taste parameter for organic goods. These include, but are not limited to, a large share of consumers placing a low premium on organic goods with a few highly valuing organic goods, a mass of consumers value organic somewhat more than conventional with a smaller segment with an intense preference, and so on.

The survey uses willingness to pay a premium for organic goods relative to conventional goods as a proxy for consumers' taste for quality. The survey asks respondents to state the maximum value they would be willing to pay for a pack of strawberries with a USDA organic label if an otherwise identical but conventionally produced pack of strawberries is available for $3.00. Responses are limited to values at $0.25 increments starting at $3.00 and going up to $7.00. That is, possible premiums range from $0.00 through $4.00 for strawberries bearing the USDA organic label.[9]

Figure 1.6 shows the distribution of responses before and after viewing the label definitions. After viewing the label definitions, consumers are willing to pay 3.89, on average, for organic strawberries, a premium of nearly 30%. Nearly 19% of consumers are unwilling to pay a premium compared to 2.5% who are willing to pay double for organic strawberries. Figure 1.7 displays a histogram of the non-zero organic premiums as computed from the responses along with the kernel density estimate. Consumers are not uniformly dis-

[9]These values were chosen based on price premiums observed in retail.

tributed across the willingness-to-pay spectrum. Instead, the distribution of customers is right skewed, with only a small number willing to pay a large premium. This conforms with my ex-ante assumptions and supports the use of a flexible distribution.

Figure 1.6: Willingness to Pay for Organic Strawberries

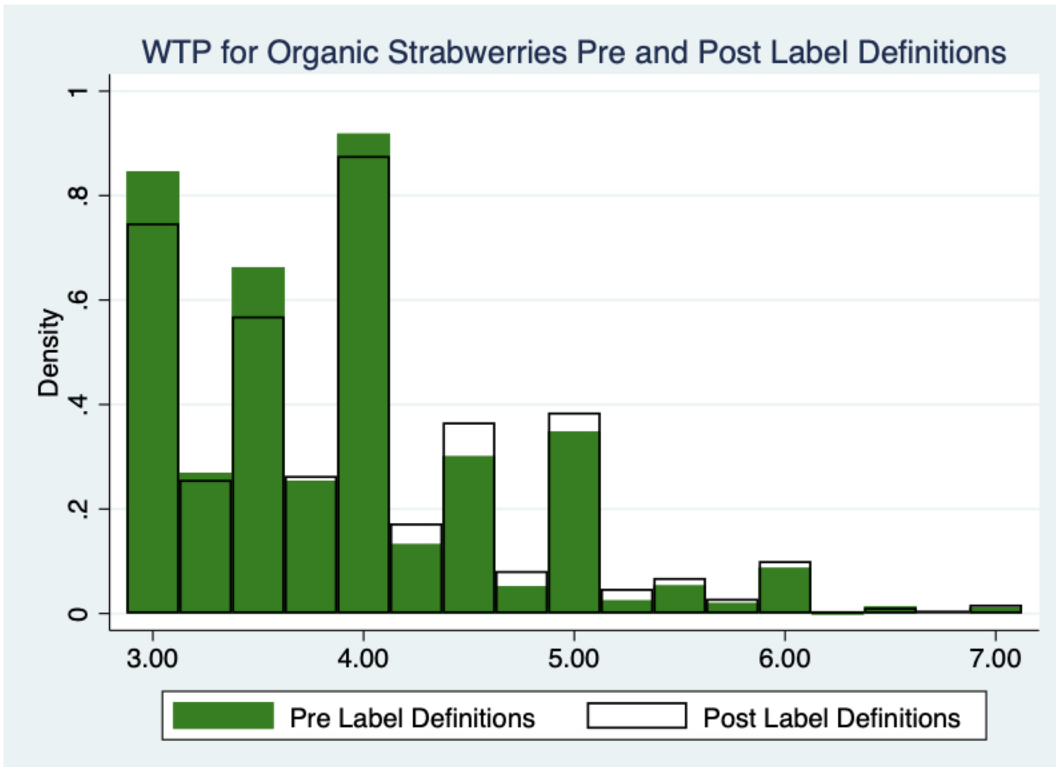
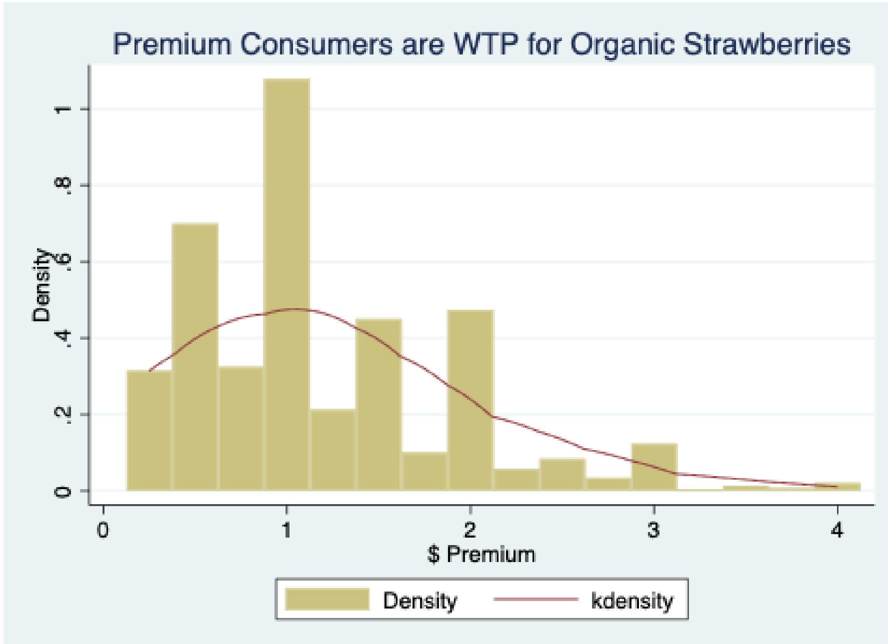


Figure 1.7: Willingness to Pay for Organic Strawberries



1.5 Static-Model Simulation Analysis with an Application to U.S. Strawberries

What follows is a simulation of short-run changes in prices and welfare in the U.S. strawberry market following the introduction of TO labeling. I fix relative quality values at $q_c = .705$ and $\alpha = 0.439$, as derived from the survey. The 2019 UCCE cost and return study for organic strawberries reports strawberry yields are 4,250 and 7,000 trays per acre for organic and conventional operations, respectively, which corresponds to $\gamma = 0.61$ (Smith and Tumber, 2015).[10]

USDA data indicate that there were 43,500 harvested acres of strawberries in the U.S. in 2019, 5,158 of which were certified organic (U.S. Department of Agriculture, National Agricultural Statistics Service, 2019b, 2021). This translates to $\rho_c = 0.881$ and $\rho_o = 0.119$.

[10] Across three meta-analyses synthesized in Meemken and Qaim (2018), mean yield gaps for fruits are estimated to be between -3% and -28%., but these estimates are mostly from test plots, and the data show the gap is larger in the real world.

In contrast, across all U.S. cropland, ρ_c is equal to 0.9905. I allow ρ_t to vary from 0.00066 to 0.02, where the lower bound on ρ_t is as indicated by the USDA data for total U.S. cropland and the upper bound is capped arbitrarily at 2% of cropland converting in the period at hand.[11] Carroll, Charlton, and Tjernström (2012) estimate that between 2007 and 2012, the average prices of organic and conventional strawberries at the farmgate were \$1.72 and \$1.11 per pound, respectively. While they do not provide average variable costs for those years, they report 2010 average variable costs of \$1.12 and \$0.99 per pound for organic and conventional production.

These variable costs are 64% and 82.5% of the 2010 organic and conventional farmgate prices, respectively. Applying those proportions to the 2007 through 2012 average prices results in estimated variable costs of \$1.10 and \$0.92 per pound for organic and conventional strawberries, respectively.

Finally, I alter a and b to calibrate the model to fit the aforementioned 2007-2012 average strawberry prices. Specifically, I locate pairs of a and b such that the output of the static equilibrium price functions under policy 1 correspond to the observed ratio of organic and conventional prices, i.e. 1.55.[12] A number of pairs produce estimates with the proper organic-to-conventional price ratio, and this analysis uses (14.5,20). The PDF for this particular K-distribution is shown in Figure 1.2.[13] The calibrated model produces ex ante conventional and organic strawberry prices of \$0.46 and \$0.72, which correspond to variable costs of \$0.38/lb and \$0.46/lb for conventional and organic strawberries, respectively.[14] Where appropriate, I

[11] The 2014 USDA Organic Survey reports 137,561 acres of transitional cropland and 2,409,869 acres of organic cropland. Transitional acreage is comprised of 24,550 from non-organic farms and 113,011 from certified and exempt farms. In 2012, there were 389,690,414 acres of cropland in the U.S. (U.S. Department of Agriculture, National Agricultural Statistics Service, 2012).

[12] The model does not output prices above 1, which is why I locate (a,b) pairs that output organic prices that are 55% higher than conventional prices instead of (a,b) pairs that output \$1.72 and \$1.11 for equilibrium organic and conventional prices, respectively.

[13] The PDF of this particular K-distribution does not match the shapes of histogram and kernal density shown in figure 1.7. It is, however, locally right, so it can approximate what happens to equilibrium prices when TO certification and labeling are introduced.

[14] The real-world prices and costs presented in the Carroll, Charlton, and Tjernström (2012) can be found by applying a scalar of 2.39 to the calibrated model output; however, I estimate percentage changes in prices, surplus, and conversion, rendering the scalar unnecessary. For these purposes, it is only important that organic and conventional prices be appropriately scaled relative to one another ex ante.

compare output of the calibrated model to that of a uniform-distribution model to examine the extent to which there are discrepancies in predicted outcomes between the two models.

Transitional Strawberry Prices

Under policy 2 the model predicts transitional strawberries will garner a 24% premium over conventional strawberries. This compares to a roughly 55% premium for organic strawberries relative to conventional strawberries under policy 2.

Change in the Price Premium for Organic Strawberries

The percentage change in the premium for organic strawberries associated with the introduction of TO labeling and as a function of ρ_t is shown in Figure 1.8. The percentage change in premium is decreasing in ρ_t. The absolute magnitude of the percentage decrease in the premium is relatively small, ranging from -0.0036% when $\rho_t = 0.00066$ to -0.11% when $\rho_t = .02$. The same model using a uniform distribution overestimates the absolute size the change by an order of magnitude, relative to the calibrated model. Under a uniform distribution, the model predicts that the organic premium decreases by between -0.038% and -1.13%.[15]

Change in Surplus for Strawberry Producers

The percentage change in surplus for organic strawberry producers for varying levels of ρ_t is shown in Figure 1.9. The estimated change for organic producers ranges from -0.006% to -0.19% for the minimum and maximum ρ_t, respectively, and is decreasing in ρ_t.

[15] An alternative version of the model in which consumers assign an average quality to the conventional commodity under policy 1 does not produce qualitatively different simulation results.

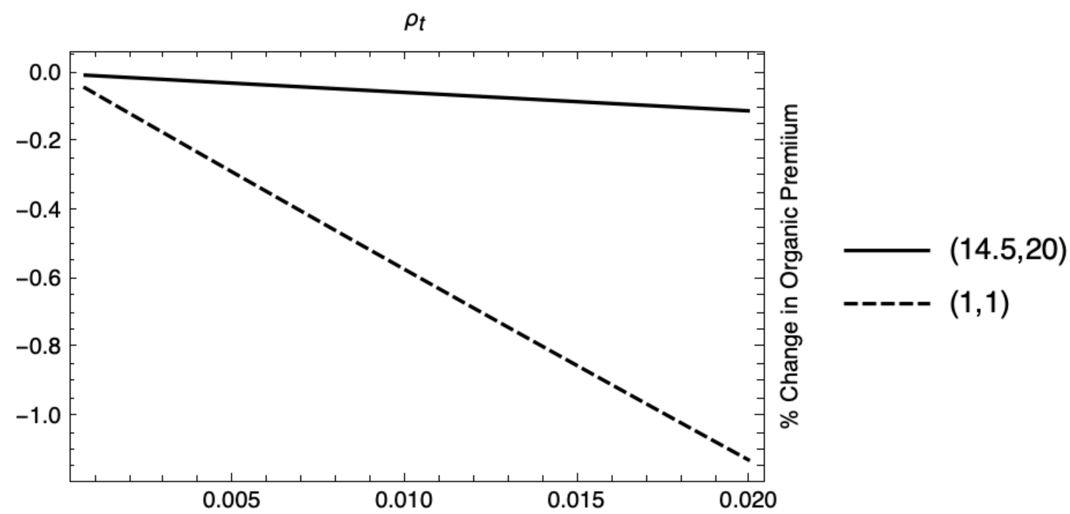


Figure 1.8: % Change in the Premium for Organic Strawberries Resulting from the Introduction of TO Labeling (Static Model)

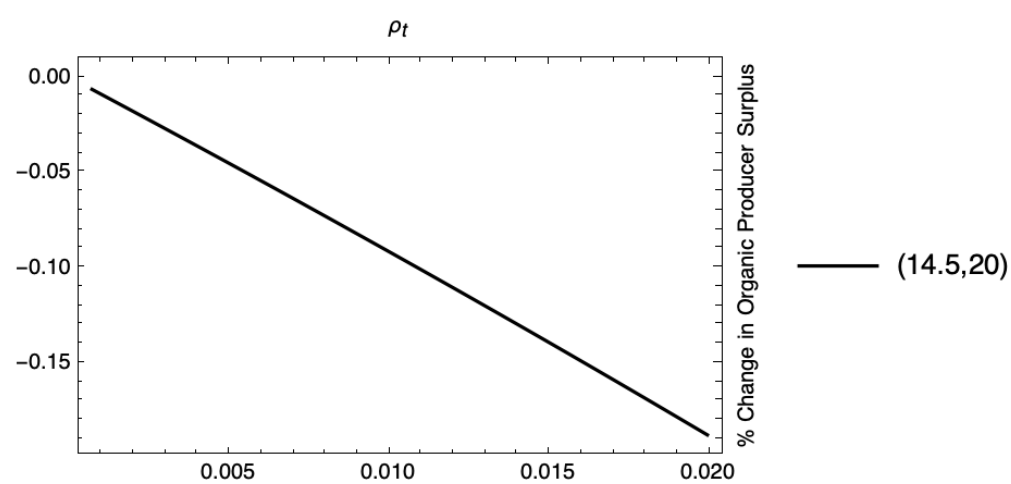
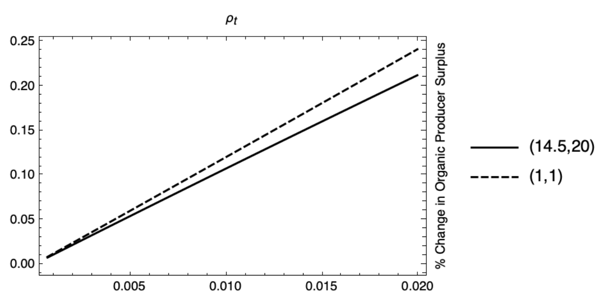


Figure 1.9: % Change in Surplus for Organic Strawberry Producers Resulting from the Introduction of TO Labeling (Static Model)

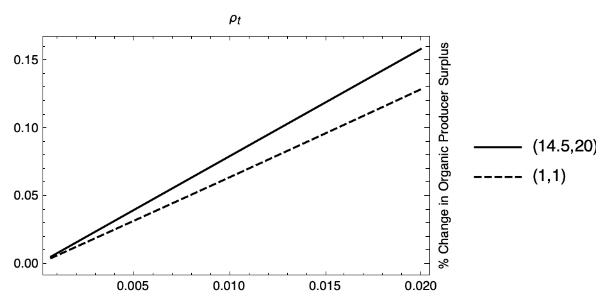
In contrast, transitional producers experience a large increase in surplus, over 2,400% due to TO certification and labeling. The large change is the result of there being nearly no surplus for transitional producers selling in conventional markets where prices exceed costs by a fraction of a cent. Recall that policy 2 does not alter the surplus for conventional strawberry growers.

Change in Surplus for Strawberry Consumers

Consistent with estimated effects from the general model, the introduction of TO labeling is a Pareto improvement for customers. Figure 1.10 shows the percentage change in surplus for consumers of organic strawberries under both policies and those who switch from conventional to transitional strawberries (recall, those who always consume conventional strawberries experience no change in welfare). For all stawberry consumer types, the percentage change in welfare is increasing in ρ_t. The uniform-distribution model overestimates the change for the change in welfare for the first group of consumers and underestimates for the second group.



(a) Always Organic



(b) C to TO

Figure 1.10: % Change in Surplus for Strawberry Consumers Resulting from the Introduction of TO Labeling (Static Model)

1.6 Dynamic Model

To determine long-run price impacts and how the change in price caused by the introduction of transitional certification affects organic conversion rates, I develop a dynamic vertical differentiation model. I adapt the vertical differentiation framework constructed by Saitone and Sexton (2010) to model quality improvement decisions by allowing quality improvements to occur over multiple periods. The underlying assumptions about consumption are the same as in the static model, but production differs.

Production

I, again, set the total land in production to 1 and set output from one conventional unit to 1 and one organic or transitional production unit equal to $\gamma < 1$. Here, $(1 - \rho_c - \rho_t)$, ρ_t, and ρ_c are the ex-ante shares of organic, transitional, and conventional output, respectively, in period 0. Producers are homogeneous. Conventional producers may now choose to adopt organic production practices and convert output from conventional to organic. I assume that once a producer converts, there is no reversion to conventional production. While organic reversion does occur in the real world, the net number of organic operations in the U.S. is increasing to keep up with increasing demand for organic products. Between 2016 and 2019, the number of certified organic operations increased 17%. Further, only 2% of organic farmers in the USDA's 2019 organic survey indicated that they planned to discontinue organic production in the next 5 years U.S. Department of Agriculture, National Agricultural Statistics Service (2019c). As such, I ignore this relatively rare phenomenon to simplify the model. Producers undergo conversion at fixed upfront cost $\beta \in (0, \infty)$, to transition from conventional to organic. Producers incur annual variable costs of c_o and c_c for organic and conventional production, respectively.

I specify time such that the transition to organic production takes one period. Let τ_t be the number of units that are transitioning in period t and, thus, eligible for transitional certification in that period. $T_t \in [0, 1]$ denotes the cumulative number of conventional units of land that have transitioned or are in the process of transitioning to organic in period t. Ex ante, the number of units that have completed or are in the midst of the transition process is $T_0 = 1 - \rho_c$. In period $t \geq 1$ the total number of units that are in the midst of or have completed the transition process is

$$T_t = \underbrace{(1 - \rho_c)}_{\text{ex-ante o + to}} + \overbrace{\sum_{n=1}^{t} \tau_n}^{\text{ex-post to}} ,$$

and the cumulative number of organic land units in T_{t-1}.

1.6.1 Policy 1: No Transitional Certification

All three types of products exist, but transitional goods are marketed and sold as conventional. The locations of indifferent consumers are equal to those presented in the static model in equations 1.5 and 1.6 but with time (t) subscripts on prices to denote the fact that prices may vary from period to period depending on the quantities of organic and conventional production in those periods. Demand functions for conventional and organic commodities in period t are

$$Q^1_{o,t}(\mathbf{p}|\mathbf{x}) = \left(1 - \left(\frac{p_{c,t} - p_{o,t}}{q_c - 1}\right)^{a_t}\right)^{b_t} \text{ and} \tag{1.42}$$

$$Q^1_{c,t}(\mathbf{p}|\mathbf{x}) = \left(1 - \left(\frac{p_{c,t}}{q_c}\right)^{a_t}\right)^{b_t} - \left(1 - \left(\frac{p_{c,t} - p_{o,t}}{q_c - 1}\right)^{a_t}\right)^{b_t}. \tag{1.43}$$

These are the same as the demand functions in equations 1.7 and 1.8 of the static model but with time subscripts on price and time subscripts on K-distribution parameters a and b to demonstrate that the distribution of consumers' valuation of organic may change over time. It follows that the inverse demand functions match those in the static model under policy one (equations 1.9 and 1.10) but with the addition of time subscripts on the production quantities and a and b.

Market Equilibrium Prices

The available production quantities of conventional and organic products, respectively, in period $t \geq 1$ are

$$Q^1_{c,t} = 1 - T_t + \gamma \tau_t \text{ and} \tag{1.44}$$

$$Q^1_{o,t} = \gamma T_{t-1} \tag{1.45}$$

Inserting these values into the inverse demand functions results in the market equilibrium prices of

$$p^{*1}_{o,t} = q_c \left(1 - (1 + \gamma T_t - T_t)^{1/b_t}\right)^{1/a_t} + (1 - q_c)\left(1 - (\gamma T_{t-1})^{1/b_t}\right)^{1/a_t} \text{ and} \tag{1.46}$$

$$p^{*1}_{c,t} = q_c \left(1 - (1 + \gamma T_t - T_t)^{1/b_t}\right)^{1/a_t}. \tag{1.47}$$

Equilibrium Conversion and Prices

Producers in period t choose between converting in that period or remaining conventional. They do so by comparing the net present value (NPV) of the stream of organic profits ($\pi^1_{o,t}$) against the NPV of of the conventional profit stream ($\pi^1_{c,t}$). The cost associated with transitioning to organic in period t is $\beta + \frac{(1+r)c_o}{r}$, where β equals the one-time conversion costs (e.g., inspection and certification fees), and c_o is the variable cost of organic production incurred each period during and after conversion (e.g., fertilizer and labor costs).[16] Producers transitioning in period t earn $p^{*1}_{c,t}$ in period t and $p^{*1}_{o,t+1}$ in every future period.[17] Those remaining in conventional conventional production earn $p^{*1}_{c,t}$ and incur variable production cost c_c in perpetuity.

Holding a and b constant, the net present values (NPV) of the profit streams earned by producers who choose to convert (but are required to sell as conventional in period t) and those who remain conventional, respectively, are $p^{*1}_{c,t} - \beta + \frac{p^{*1}_{o,t+1} - (1+r)c_o}{r}$ and $p^{*1}_{c,t} + \frac{(p^{*1}_{c,t+1} - (1+r)c_c)}{r}$. At the equilibrium level of conversion, a farmer will have the same NPV of profit stream as both an organic and conventional producer. That is, producers convert until the organic premium is just sufficient to cover one-time cost of conversion and the ongoing costs of producing organic relative to the cost of producing conventional.

The equilibrium level of conversion is found by equating the two profit streams. I assume

[16] The net present value of a constant perpetuity is $\frac{a}{r}$ when the first payment occurs at the end of the first year. Here, c_o is incurred in the period in which conversion begins, which is not discounted, and every period thereafter. As such, the NPV of the cost stream is $c_o + \frac{c_o}{r}$, which simplifies to $frac(1+r)c_o r$.

[17] I choose an infinite horizon because the value of organic conversion will be reflected in the property value if and when operators sell.

that production is in equilibrium in period 0. This implies that $\pi^1_{c,0} = \pi^1_{o,0}$, which is equivalent to

$$p^{*1}_{c,0} - \beta + \frac{p^{*1}_{o,1} - (1+r)c_o}{r} = p^{*1}_{c,t} + \frac{(p^{*1}_{c,t+1} - (1+r)c_c)}{r}. \tag{1.48}$$

Because the set of homogeneous producers are not making decisions about conversion beyond period 0, they set $T_t = T_0 \ \forall t \geq 0$ in the above equality. Therefore, $p^{*1}_{c,0} = p^{*1}_{c,1}$, and the organic and conventional prices in equation 1.48 are, respectively, equal to

$$q_c\left(1 - (1 + \gamma T_0 - T_0)^{1/b}\right)^{1/a} + (1 - q_c)\left(1 - (\gamma T_0)^{1/b}\right)^{1/a} \text{ and} \tag{1.49}$$

$$q_c\left(1 - (1 + \gamma T_0 - T_0)^{1/b}\right)^{1/a}. \tag{1.50}$$

$T_0 = (1 - \rho_c)$ is an initial condition of the model and, therefore, is known even without solving the above equality. The equality, however, combined with T_0 allows me to solve for β. This results in

$$\beta = \frac{(1+r)(c_c - c_o) + (1 - q_c)\left(1 - (\gamma - \gamma\rho_c)^{1/b}\right)^{1/a}}{r}. \tag{1.51}$$

Since the profit functions do not change from their period 0 levels, and I hold a and b constant, it follows that producers do not convert additional acres to organic in periods $t \geq 1$, i.e. $\tau_1, ..., \tau_n = 0$, and the equilibrium number of acres converted through period 1 under policy 1 is $T^{*1}_1 = T_0$. So, under policy 1, the equilibrium organic and conventional prices at the equilibrium level of conversion in period one and beyond are equal to equilibrium prices derived in the static model and shown in equations 1.13 and 1.14. The resulting premium is equal to the static-model premium presented in equation 1.15.

1.6.2 Policy 2: Transitional Certification and Labeling

Upon the introduction of transitional certification and labeling in period $t = 1$, there exist consumers who are indifferent between organic and transitional goods, indifferent between transitional and conventional goods, and indifferent between conventional goods and the outside good in period t. Their locations are as they were in the static model with the addition of time subscripts on prices. The sets of demand and inverse demand functions for the three commodity types add time subscripts to both prices, production quantities, and the K-distribution parameters to those presented under policy 2 of the static model (equations 1.19, 1.21, 1.22, and 1.24) but are otherwise equal.

Market Equilibrium Prices

In period $t \geq 1$, the available production quantities of organic, transitional, and conventional products, respectively, are

$$Q_{o,t} = \gamma T_{t-1}, \tag{1.52}$$

$$Q_{to,t} = \gamma \tau_t, \text{ and} \tag{1.53}$$

$$Q_{c,t} = 1 - T_t. \tag{1.54}$$

Equilibrium prices are, thus,

$$p^{*2}_{o,t} = (q_c - 1)\left((\alpha - 1)\left(1 - (\gamma T_{t-1})^{1/b_t}\right)^{1/a_t} - \alpha\left(1 - (\gamma T_t)^{1/b_t}\right)^{1/a_t}\right) + q_c\left(1 - ((\gamma - 1)T_t + 1)^{1/b_t}\right)^{1/a_t}, \tag{1.55}$$

$$p^{*2}_{to,t} = q_c\left(1 - ((\gamma - 1)T_t + 1)^{1/b_t}\right)^{1/a_t} - \alpha(q_c - 1)\left(1 - (\gamma T_t)^{1/b_t}\right)^{1/a_t}, \text{ and} \tag{1.56}$$

$$p^{*2}_{c,t} = q_c\left(1 - (1 + \gamma T_t - T_t)^{1/b_t}\right)^{1/a_t}. \tag{1.57}$$

Equilibrium Conversion and Prices

As under policy 1, the equilibrium level of conversion is such that the NPV of the profit stream associated with converting is equal to the NPV of the profit stream associated with remaining conventional, holding a and b constant. Policy 2, however, alters the profit streams relative to policy 1. The costs of converting or remaining conventional are unchanged from their policy 1 values, but prices differ. Now, conventional producers earn $p^{*2}_{c,t}$ each year, and converting producers earn $p^{*2}_{to,t}$ in period t and $p^{*2}_{o,t}$ in every period thereafter. The NPV of the profit streams in period t for converting and conventional producers, respectively, are $\pi^2_{o,t} = p^{*2}_{to,t} - \beta + \frac{p^{*2}_{o,t+1}-(1+r)c_o}{r}$ and $\pi^2_{c,t} = p^{*2}_{c,t} + \frac{p^{*2}_{c,t+1}-(1+r)c_c}{r}$.

In equilibrium in period 1, it is true that

$$p^{*2}_{to,1} - \beta + \frac{p^{*2}_{o,2} - (1+r)c_o}{r} = p^{*2}_{c,1} + \frac{p^{*2}_{c,2} - (1+r)c_c}{r} \tag{1.58}$$

The homogeneous producers use the above equality to determine present conversion (i.e., T_1) only, so they set $T_t = T_1 \; \forall t \geq 1$. As such, organic, TO, and conventional prices in equation 1.58 are, respectively, equal to

$$\begin{aligned}
&(q_c - 1)\left((\alpha - 1)\left(1 - (\gamma T_0)^{1/b}\right)^{1/a} - \alpha\left(1 - (\gamma T_1)^{1/b}\right)^{1/a}\right) + \\
&q_c\left(1 - ((\gamma - 1)T_1 + 1)^{1/b}\right)^{1/a}, && (1.59)\\
&q_c\left(1 - ((\gamma - 1)T_1 + 1)^{1/b}\right)^{1/a} - \alpha(q_c - 1)\left(1 - (\gamma T_1)^{1/b}\right)^{1/a}, \text{ and} && (1.60)\\
&q_c\left(1 - (1 + \gamma T_1 - T_1)^{1/b}\right)^{1/a}. && (1.61)
\end{aligned}$$

The equilibrium level of conversion, found by equating $\pi^2_{c,1}$ and $\pi^2_{o,1}$ and solving for T_1, is

$$T^{*2}_1 = \frac{\left(1 - \left(\frac{(1+r)(c_c - c_o) - r\beta)}{(q_c - 1)(\alpha r + 1)}\right)^a\right)^b}{\gamma}. \tag{1.62}$$

Substituting β from 1.51 into equation 1.62 results in

$$T_1^{*2} = \frac{\left(1 - \left(\frac{\left(1-(\gamma-\gamma\rho_c)^{1/b}\right)^{1/a}}{\alpha r+1}\right)^{a}\right)^{b}}{\gamma}. \tag{1.63}$$

The introduction of transitional certification and labeling in period 1, thus, causes conversion levels to increase from T_0 to T_1^{*2} as shown in Figure 1.11.

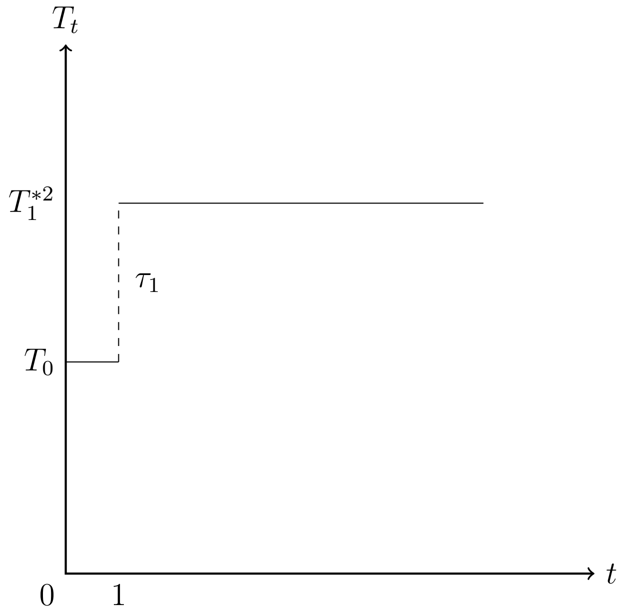


Figure 1.11: Effect of Transitional Certification on Conversion Levels

In period 1, organic and transitional goods coexist and compete against one another, and in period 2, there are no longer transitional organic goods on the market. The equilibrium price of organic goods in period 1 is

$$\begin{aligned} p_{o,1}^{*2} = (1-q_c)&\left((1-\alpha)\left(1-(\gamma T_0)^{1/b}\right)^{1/a} - \alpha\left(1-\left(\gamma T_1^{*2}\right)^{1/b}\right)^{1/a}\right) + \\ &q_c\left(1-\left((\gamma-1)T_1^{*2}+1\right)^{1/b_1}\right)^{1/a}. \end{aligned} \tag{1.64}$$

The price of organic goods in period 2 is

$$p_{o,2}^{*2} = (1-q_c)\left((1-\alpha)\left(1-\left(\gamma T_1^{*2}\right)^{1/b}\right)^{1/a} - \alpha\left(1-\left(\gamma T_1^{*2}\right)^{1/b}\right)^{1/a}\right) +$$
$$q_c\left(1-\left((\gamma-1)T_1^{*2}+1\right)^{1/b}\right)^{1/a}. \tag{1.65}$$

The price of conventional goods at the equilibrium level of conversion is

$$p_{c,1}^{*2} = q_c\left(1-\left(1+\gamma T_1^{*2} - T_1^{*2}\right)^{1/b}\right)^{1/a}, \tag{1.66}$$

and the organic price premiums in periods 1 and 2 are

$$p_{o,1}^{*2} - p_{c,1}^{*2} = (q_c-1)\left((\alpha-1)\left(1-(\gamma T_0)^{1/b}\right)^{1/a} - \alpha\left(1-(\gamma T_1^{*2*2})^{1/b}\right)^{1/a}\right) \text{ and} \tag{1.67}$$
$$p_{o,2}^{*2} - p_{c,1}^{*2} = -(q_c-1)\left(1-(\gamma T_1^{*2})^{1/b}\right)^{1/a}. \tag{1.68}$$

Proposition 8. *The introduction of transitional certification and labeling increases the numbers of acres converted to organic.*

$$\Delta T^* = \frac{\left(1-\left(\frac{\left(1-(\gamma(1-\rho_c))^{1/b}\right)^{1/a}}{\alpha r+1}\right)^a\right)^b}{\gamma} - (1-\rho_c) \tag{1.69}$$
$$> 0$$

The equilibrium level of T is greater under policy two than under policy one. The difference between the two is increasing in r and α and α and decreasing in the ex ante level of organic and transitional output.[18] Since the equilibrium value of T under policy one is independent of r, α, and γ, it follows that the directional effects of these variables

[18]Recall, $(1-\rho_c)\gamma$ is ex ante organic and transitional output.

apply to T_1^{*2}, as well. Further, the shape of the K-distribution's PDF affects how much the introduction of TO certification and labeling increases organic conversion. The greater the share of customers valuing organic goods highly, the more the policy will increase conversion.

Proposition 9. *The introduction of transitional certification and labeling may increase or decrease the price of organic relative to the no-certification scenario depending on the percentage yield loss associated with organic production.*

Price changes for organic in periods 1 and 2 are

$$\Delta p_{o,1} = \alpha(q_c - 1)\left(\left(1 - (\gamma T_0)^{1/b}\right)^{1/a} - \left(1 - (\gamma T_1)^{1/b}\right)^{1/a}\right) \text{ and} \tag{1.70}$$

$$\Delta p_{o,2} = (q_c - 1)\left(\left(1 - (\gamma T_0)^{1/b}\right)^{1/a} - \left(1 - (\gamma T_1)^{1/b}\right)^{1/a}\right). \tag{1.71}$$

Policy 2 may increase prices depending on the magnitude of the yield loss and the relative qualities of conventional and transitional goods. If the yield loss factor is sufficiently high, the increased conversion brought about by the policy reduces total output by enough to offset the decrease in organic prices associated with increased competition with TO or organic goods and cause organic prices to increase.

Proposition 10. *Increased organic production decreases the price of the organic commodity more than the presence of the transitional commodity.*

Under policy two, the equilibrium price of organic goods is less than the equilibrium price of organic goods in period one.

$$\begin{aligned} p_{o,2}^{*2} - p_{o,1}^{*2} &= (\alpha - 1)(1 - q_c)\left(\left(1 - (\gamma t_0)^{1/b}\right)^{1/a} - \left(1 - (\gamma T_1^{*2})^{1/b}\right)^{1/a}\right) \\ &< 0 \end{aligned} \tag{1.72}$$

That is, competition with τ_1 acres of organic output reduces the price of organic more than competition with τ_1 acres of transitional output decreases the price of organic, which is intuitive because transitional products are of lower quality than organic.

Proposition 11. *Increased organic conversion and production increases the price of conventional goods.*

The difference in the price of conventional goods in the presence transitional certification and labeling relative to policy 1 is

$$\Delta p_c^* = q_c \left(\left(1 - (1 + (\gamma - 1)T_1^{*2})^{1/b}\right)^{1/a} - \left(1 - (1 + (\gamma - 1)T_0)^{1/b}\right)^{1/a} \right) \tag{1.73}$$

The price increases because increased conversion associated with the policy decreases total output.

Economic Welfare

Here, I examine the long-run impacts of TO certification and labeling on consumer and producer surplus, where long run refers to the period in which additional conversion spurred by policy 2 has successfully converted to organic. That is, I compare welfare in period 2 under both policies.Going forward, I refer to period 2 as both the long run or long term. The static model sufficiently illustrates the immediate effects on welfare of the three product types coexisting, so my primary focus here is the impact of the increased organic output resulting from the policy change on welfare.

Under policy 1, surpluses for individual conventional and organic producers in period 2 are $(p_{c,2}^{*1} - c_c)$ and $(p_{o,2}^{*1} - c_o) * \gamma$. Producers who remain conventional after the policy change have a surplus of $(p_{c,2}^{*2} - c_c)$, and those already certified as organic prior to the policy change have surpluses of $(p_{o,2}^{*2} - c_o)\gamma$. Producers who convert as a result of the policy change each have a surplus $(p_{o,2}^{*2} - c_o)\gamma$.

In period 2, consumers can be split into the following groups – those who consume organic under both policies, those who consumed conventional under policy 1 and organic under policy 2, those who consume conventional under both policies, and those who consumed conventional under policy 1 and now do not consume the commodity because total output decreased under policy 2.

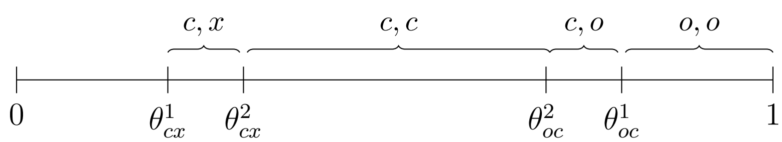


Figure 1.12: Segments of Consumers along the θ Continuum - Dynamic Model

The difference in indirect utility in period 2 under policy 2 relative to policy 1 for a given individual in the first group is $p^{*1}_{o,2} - p^{*2}_{o,2}$. It is $(q_c\theta - p^{*1}_{c,2}) - (\theta - p^{*2}_{o,2})$ for an individual in the second group, $p^{*1}_{c,2} - p^{*2}_{c,2}$ for an individual in the third group, and $p^{*1}_{c,2} - q_c\theta$ for an individual in the fourth group.

Proposition 12. *In the long-run, transitional certification and labeling has an ambiguous effect on surplus for existing organic producers and increases surplus for conventional producers.*

The difference in surplus for individual organic producers under policy 2 relative to policy 1 is $\gamma(p^{*2}_{o,2} - p^{*1}_{o,2})$ in period 2. Because $p^{*2}_{o,2}$ may be greater or less than $p^{*1}_{o,2}$ depending on the level of yield loss, the change in individual surplus for existing organic producers is similarly ambiguous. Producers using conventional practices under both policies are now better off because they receive a higher price for the conventional commodity under policy 2. Producers switching from conventional to organic production under policy 2 now have a surplus of $(p^{*2}_{o,2} - c_o)\gamma$ in period 2 compared to $(p^{*1}_{c,2} - c_c)$ in the same period under policy 1. They must be at least weakly better off because they could continue producing the conventional commodity at a higher price but switched to organic.

Proposition 13. *In the long run, transitional certification and labeling has an ambiguous effect on surplus for those consuming organic under both policies and those consuming conventional under policy 1 and organic under policy 2, decreases surplus for those consuming conventional under both policies, and decreases surplus for those who switch from consuming conventional to organic because of the policy and those who no longer consume the commodity after policy 2 is introduced.*

It follows from proposition 9 that indirect utility is may be higher or lower under policy 2 for those who always consume organic. The sign of the change in utility for individuals in group 2 is similarly ambiguous. It follows from proposition 11 that the change in indirect utility for individuals in group 3 is negative. Consumers in group 4 experience a decrease in indirect utility equal to the utility they received from consuming the conventional commodity under policy 1.

The aggregate change in surplus for each group is found by integrating the change in individual indirect utility over the group's segment on the theta continuum. The changes in consumer surplus associated with the introduction of TO certification and labeling for each group in period 2 are

$$\Delta CS_{o,o} = \int_{\theta_{oc}^1}^{1} (v(p_{o,2}^{*2}, 1) - v(p_{o,2}^{*1}, 1))\delta\theta = (p_{o,2}^{*2} - p_{o,2}^{*1})(\theta_{oc}^1 - 1), \tag{1.74}$$

$$\Delta CS_{c,o} = \int_{\theta_{oc}^2}^{\theta_{oc}^1} (v(p_{o,2}^{*2}, 1) - v(p_{c,2}^{*1}, q_c))\delta\theta = \frac{1}{2}(\theta_{oc}^1 - \theta_{oc}^2)(2p_{o,2}^{*2} - 2p_{c,2}^{*1)} + (q_c - 1)\theta_{oc}^1 + (q_c - 1)\theta_{oc}^2), \tag{1.75}$$

$$\Delta CS_{c,c} = \int_{\theta_{cx}^2}^{\theta_{oc}^2} (v(p_{c,2}^{*2}, q_c) - v(p_{c,2}^{*1}, q_c))\delta\theta = (p_{c,1}^{*1} - p_{c,2}^{*2})(\theta_{oc}^2 - \theta_{cx}^2), \text{ and} \tag{1.76}$$

$$\Delta CS_{c,x} = \int_{\theta_{cx}^1}^{\theta_{cx}^2} -v(p_{c,2}^{*1}, q_c)\delta\theta = -\frac{1}{2}(\theta_{cx}^1 - \theta_{cx}^2)(q_c(\theta_{cx}^1 + \theta_{cx}^2) - 2p_{c,2}^{*1}. \tag{1.77}$$

The sign of each aggregate surplus change is equal to the sign of the change for each individual in that group. Therefore, the introduction of TO certification and labeling increases period-

2 surplus for consumers in group 3, has an ambiguous effect on consumers in group 1, and decreases surplus for consumers in groups 2 and 4. The surplus of those who do not consume the product is unchanged.

In sum, the introduction of transitional certification and labeling causes a increase in organic conversion relative to conversion under policy 1. Competition with increased organic output puts downward pressure on prices for the organic commodity, but a reduction in overall output puts upward pressure on prices of both the organic and conventional commodities. As a result, the sign of the price change for the generic organic commodity is unknown, and the conventional price increases. The change in welfare for organic producers and consumers is similarly ambiguous. Conventional consumers experience a loss in welfare offset by gains to conventional producers.

1.7 Dynamic-Model Simulation Analysis with an Application to U.S. Strawberries

Using results from the dynamic model, I simulate long-run changes in prices, welfare, and organic conversion in the U.S. strawberry market following the introduction of TO labeling. Consistent with the 2019 UCCE cost and return study for organic strawberries, the simulation uses a discount rate of 6.75% (Smith and Tumber, 2015). The remaining parameters are assigned the same values used for the static simulations.

Change in Organic Land Units

TO certification and labeling is predicted to greatly increase the land units devoted to organic strawberry production, as shown in Figure 1.13. The percentage change in organic land units is decreasing in ρ_t and ranges from an increase of 157% to 143% at the minimum and maximum values for ρ_t, respectively. Such increases translate to land shares for organic strawberries of 31% and 33%. This particular result, however, is highly sensitive to the shape of the K-distribution. Even though I fit the distribution to real-world strawberry prices, simulations with other K-distributions provide much more realistic expansion. For example, simulations using a uniform K-distribution result in percentage changes approaching only 40%, and the predicted change is even smaller for a right-skewed distribution such as (3,1).

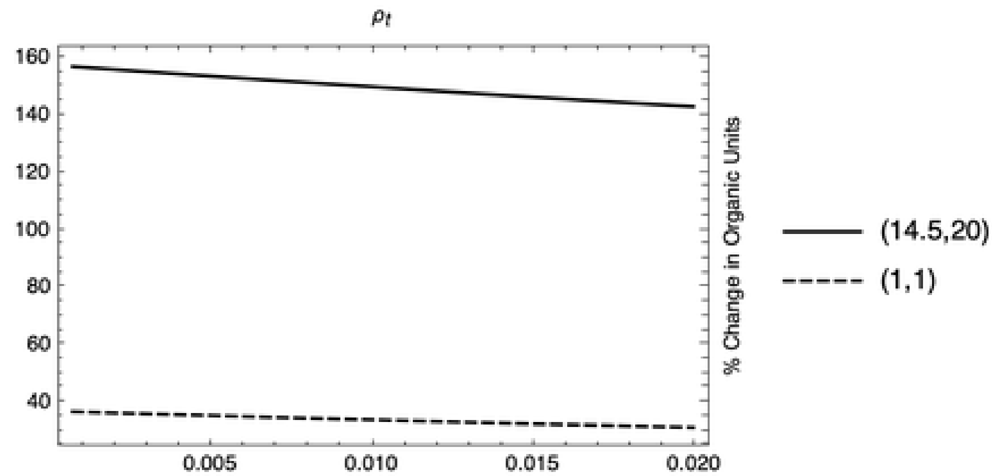
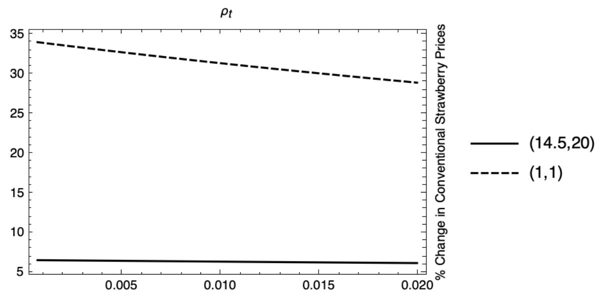


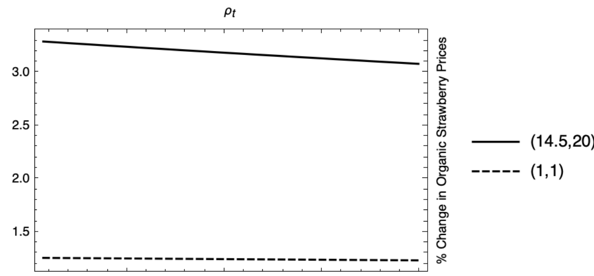
Figure 1.13: Percentage Change in the Share of Organic Land Units Resulting from the Introduction of TO Labeling

Difference in Organic and Conventional Strawberry Prices

Figure 1.15 illustrates the percentage difference in strawberry prices period 2 under policy 2 relative to policy 1. The model indicates that prices for a generic organic commodity may increase or decrease in response to increased conversion resulting from TO labeling. In the case of strawberries, the model predicts organic prices are higher under policy 2 than under policy 1. That is, price decrease associated with the increased organic production noted above is dominated by price increase associated with decreased total output of strawberries. Price increases for conventional and organic strawberries are relatively small, never exceeding 7% and 4%, respectively, along the range of ρ_t. As a result of these price changes, the premium for organic strawberries relative to conventional strawberries is 2.67% in the long run under policy 2. Note that the uniform-distribution model overestimates the increase in conventional prices and underestimates the increase in organic strawberry prices.



(a) Conventional

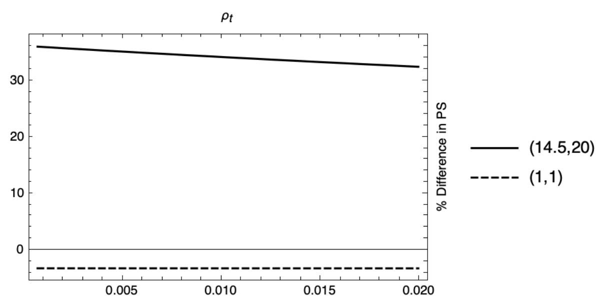


(b) Organic

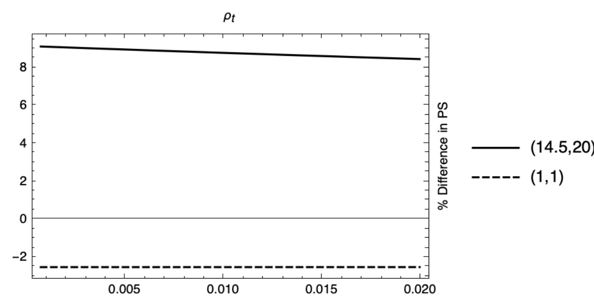
Figure 1.14: % Difference in Prices for Conventional and Organic Strawberries Under Policy 2 Relative to Policy 1

Change in Surplus for Strawberry Producers

In the long run, surpluses for individual conventional and organic strawberry producers are higher under policy 2 than under policy 1. This is a result of increases in organic and conventional strawberry prices resulting from the policy change.



(a) Conventional

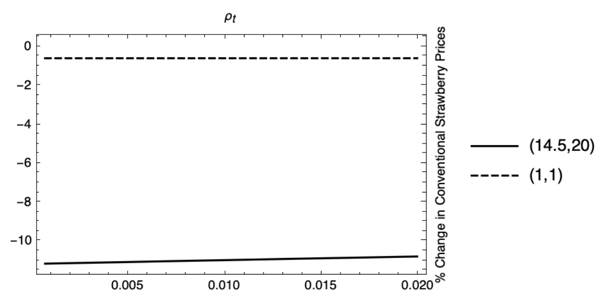


(b) Organic

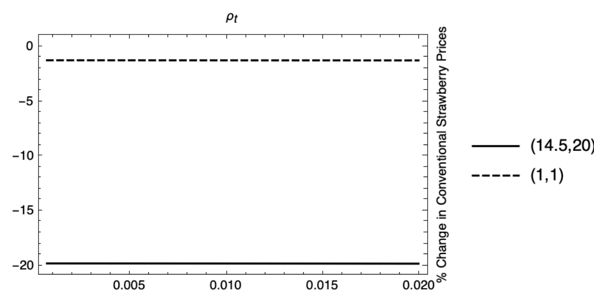
Figure 1.15: % Difference in Surplus for Individual Conventional and Organic Strawberries Producers Under Policy 2 Relative to Policy 1

Change in Surplus for Strawberry Consumers

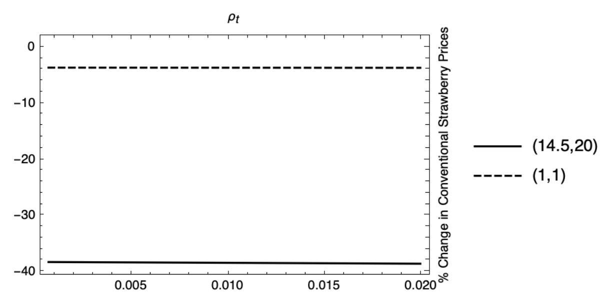
As illustrated in Figure 1.16, surpluses for all strawberry consumers are lower in the long run as a result of policy 2. Note that consumers pushed out of the strawberry market lose the entirety of the surplus they once obtained by consuming conventional strawberries. The loss in surplus for strawberry consumers is a result of higher prices for both conventional and organic strawberries and reduced total strawberries output, which makes it impossible for a portion of consumers once consuming conventional strawberries to continue consuming strawberries altogether.



(a) O Under Both Policies



(b) C under Policy 1, O under Policy 2



(c) C Under Both Policies

Figure 1.16: % Difference in Surplus for Strawberry Consumers Under Policy 2 Relative to Policy 1

1.8 Conclusion

In this analysis, I construct static and dynamic vertical differentiation models to illustrate the immediate and long-term impacts of the introduction of transitional certification and labeling on the market for a generic commodity. In the static model, production levels for conventional, transitional, and organic commodities are fixed. The dynamic model, on the other hand, allows producers to convert from conventional to organic over time. In both models, I index consumers' valuation of the organic commodity using a flexible

Kumaraswarmy distribution instead of the uniform distribution typically used in these types of models. The static model predicts TO certification and labeling will decrease prices for the organic commodity in the immediate term (i.e. the effects prior to changes in ex ante production practices) and be a Pareto improvement for all consumers of the commodity.

The long-term impacts are less clear. Transitional certification and labeling will increase the quantity of organic cropland for a given commodity, thereby decreasing total output for the commodity, increase prices for the conventional commodity, and decrease surpluses for conventional producers and consumers. The effects on the price of the organic commodity and surpluses for organic and conventional producers are ambiguous and may be either positive or negative depending on the values assigned to the model parameters.

I then estimate outcomes for the domestic strawberry market using data obtained from a survey developed in collaboration with a major berry producer and relevant research to assign values to the model parameters. The survey asks customers to rate the quality of USDA organic, certified transitional, and conventional strawberries on a scale of 1 to 10. After being provided the definition of the label claims, responses indicate that consumers view transitional strawberries as an intermediate good and allow me to estimate quality values to input into the model. I rely on existing research on strawberry production for the remaining parameter values, save for the K-distribution parameters. I alter the distribution parameters to calibrate the model to fit real-world prices for organic and conventional strawberries.

The immediate effects of certifying and labeling TO strawberries are that organic strawberry prices decrease due to competition from transitional strawberries, while conventional strawberry prices remain stable, leading to a decrease in the premium for organic strawberries equal to the change in organic prices. The organic price reduction is small, less than two-tenths of a percent, because the shares of transitional cropland modeled are small relative to the large share of cropland for organic strawberries. As a result of the price change, existing organic producers incur a modest reduction in surplus, and surpluses for conventional strawberry producers are unchanged. Transitional strawberry producers go from selling their products in the conventional market at conventional prices that barely cover their variable production costs to garnering a price premium of 55% relative to conventional strawberries. This drastically increases surplus for transitional producers. Similarly, the policy is a Pareto improvement for all strawberry consumers, no matter the quality of strawberry they consume.

In a dynamic setting, the premium for transitional strawberries causes the share of cropland devoted to organic strawberries to increase from nearly 12% to over 30%, holding total strawberry acreage constant. Because there exists a yield gap between conventional and organic strawberries, total strawberry output decreases as a result of the increased conversion. In the long-run (i.e. when conversion spurred by the policy is complete), price increases associated with a reduction in the overall strawberry output dominate price decreases associated with increased supply of organic strawberries, causing price increases for both organic and conventional strawberries. Consequently, TO certification and labeling increases surpluses for both organic and conventional strawberry producers. These same price increases coupled with reduced total output output of strawberries lead to decreases in consumer surplus for all strawberry consumers relative to the no-TO labeling scenario.

These results suggest that a national transitional certification policy may be a useful tool in increasing domestic commodity production, particularly for strawberries. The additional organic strawberry production benefits strawberry producers but comes at the expense of surpluses for strawberry consumers. It is worth noting, however, that any policy that increases organic cropland devoted to and, by extension, organic output of strawberries (e.g. direct payments to cover conversion costs) by the amount estimated here will have similar effects on strawberry prices and the welfare of strawberry consumers and producers in the long-run. Relative to those policies, a policy such as this that reveals an existing intermediate-quality strawberry will further benefit producers in the midst of transition while also partially blunting the increase in organic strawberry prices during all periods in which there exists transitional cropland and output. This is because competition with transitional strawberries puts downward pressure on the price of organic strawberries.

Additionally, this analysis highlights the importance of using a flexible distribution to parameterize consumers' valuation of the organic commodity (or any generic high quality good). Given the parameters derived from the survey and existing research, it is not possible to calibrate the uniform-distribution model to real-world strawberry prices. As a result, the uniform-distribution model greatly underestimates the increase in organic strawberry acreage brought about by TO labeling, underestimates long-term changes in organic strawberries, and overstates long-term increases in conventional prices. The use of the K-distribution allows the model to be calibrated, not only to strawberries, but to an array of different crops that may be desired for future applications of the model.

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Essay 2

Economic Impacts from the November 2018 Romaine Lettuce E. Coli Outbreak

2.1 Introduction

On November 20, 2018, health agencies in the U.S. and Canada issued a food safety advisory, warning consumers, retailers, and restaurants not to eat, sell, or serve any romaine lettuce or mixed salads containing romaine due to an outbreak of E. coli infections linked to romaine. This outbreak, others before it, and subsequent to it have significantly disrupted the leafy green industry and engendered significant economic losses. This report seeks to quantify losses due to the incident in the Fall of 2018 and its aftermath. I identify losses to supply-chain participants in both the food service and retail marketing channels. I also estimate the total social losses from the incident, including losses to consumers and providers of inputs.

Damages from a food-safety advisory can be widespread. Detected outbreaks including the one studied here are usually characterized by uncertainty and lack of information for regulators and market participants as to the scope of products and production regions that are implicated and to be avoided. The result is broad-based advisories that impact production that is determined ultimately to have not been implicated in the incident.

Despite public health agencies' and industry groups' best efforts to provide accurate information, consumers may adopt broad-based avoidance strategies, such as not eating any lettuce or leafy-green products during an advisory period and even after an all clear is issued. Similarly retailers and food service establishments may simply clear their shelves and menus of leafy greens, given consumer avoidance and liability concerns, until they obtain clarity as to the scope of an outbreak.

Impacts on participants in the leafy-greens supply chains are very strongly influenced by the nature of contracting between growers and processors and between processors and their downstream buyers in retail and food service. Nearly all product is procured through contracts. Traditional spot exchanges today account for only about 10% of product movement. Contracts, of course, vary in their provisions, but it is common for contracts in the retail channel to involve fixed prices, while contracts for food service have more flexibility based upon price "triggers." Grower-processor contracts generally attach responsibility for the product to the processor, who, thus, bears most of the loss when product cannot be sold due to a food-safety incident.

My analytical framework involves using econometric methods to forecast prices and sales for romaine and its close substitutes that would have prevailed in the "but-for world" of no outbreak and comparing those predicted prices and volumes to what in fact occurred during the advisory period and its aftermath. Armed with these estimated impacts, I am able to then calculate economic losses from the incident to growers, processors/shippers, grocery retailers, and food-service operators. For reasons noted, this analysis indicates that the processor/shipper group was most impacted by the incident and its aftermath, losing approximately $52.7 million from price and quantity impacts. Retailers were also impacted significantly, with the lion's share of the impact due to having to pull product from their distribution channels and shelves in response to the advisory. I estimate that on net retailers lost $25.7 million due to the incident.

Conversely, food-service operators were little impacted. These firms would have had to destroy product in their possession at the time of the incident, but much of this loss was offset by lower acquisition costs for romaine on net over the life of the advisory and aftermath period. Growers, too, were little impacted, even though the incident originated at the grower level. Contracts provide growers with either fixed prices or prices that only fluctuate when certain triggers are met. Further, as noted, processors bear responsibility in most cases if product is unable to be sold due to a food-safety incident or reduced demand. I estimate, in fact, that contract growers actually gained several hundred thousand dollars due to the incident based on price movements that were favorable on net. Only spot-market sellers were exposed to the full impact of the incident, losing several hundred thousand dollars from lost sales and adverse price movements.

Social losses also include consumers who were unable to consume romaine products due to the advisory or their fears regarding food safety even after the all clear was issued, and input suppliers to the leafy-greens industries who lost employment and sales due to the incident. I estimate that societal losses from the Fall 2018 incident were in the range of $280 to $350 million.

In what follows, I first provide a brief literature review on the economic treatment of food safety incidents, and remind readers of the chronology of the Fall 2018 E. coli incident. I then discuss the key characteristics of the modern leafy greens industry and supply chain that are essential for understanding how a food-safety incident impacts participants. I present the analytical framework for identifying and developing a means to quantify the various damage components. This study is benefited greatly by outstanding data access, which is described in the following section. Next I present the econometric analysis intended to estimate prices and quantities that would have prevailed for romaine and its close substitutes but-for the E. coli incident. I am then in position to present estimates of economic impacts to the various supply-chain participants, and to society as a whole. Finally, I offer concluding comments.

2.2 Literature Review

A number of studies have analysed ex-post economic impacts of food-safety incidents on the agro-food industry; however, much of the prior literature lacks sufficient data to estimate and apportion costs to all stakeholders along the supply chain as I do in this study. Several studies focus exclusively on retail sales using retail scanner data and methodologies of varying complexity. Using weekly sales reported by Nielsen, Kinsey et al. (2011) estimate that dollar sales of fresh spinach fell by over $10.5 million in the five weeks following the 2006 E. coli recall by simply computing the difference in sales at the beginning and end of that period and noting that sales increased over the same period a year prior. Arnade, Calvin, and Kuchler (2009) also analyze the impacts of the FDA's 2006 E. coli spinach warning on retail sales. They use an LA-AIDS system to model expenditures for spinach and a variety of leafy greens that might serve as substitutes, controlling for seasonal expenditure changes and analyzing the transitory nature of the effects using a series of shock and decay variables. The model indicates retail expenditures for bagged spinach decreased by 20% over a 68-week period following the announcement.

Shang and Tonsor (2017) use IRI scanner data containing aggregated monthly sales to estimate the percentage change in unit sales associated with Food Safety Inspection Services (FSIS) for meat by product, recall type, and region. They use an absolute price version of the Rotterdam model, specifying the demand system in eight different U.S. regions, controlling for seasonality of sales using quarterly dummies, and using lags to capture residual effects. Results indicate E. coli recalls reduce demand for ground beef in nearly all regions.

Other studies examine both short- and long-term impacts on commodity prices and financial markets. Analyzing beef recalls over a 20-year period, Houser and Dorfman (2019) estimate long-term effects of recalls on weekly cattle prices. They use an autoregressive model of weekly cattle futures prices with a severity- and time-weighted rolling index of all recalls in the prior two years as the primary exogenous variable and month and year fixed effects to control for inflation and changes in preferences. Combining the estimated price changes with meat yields per cattle and the number of pounds recalled per incident, they find that farm revenue decreases as the number of recalls increases. For instance, in 1998, the year with the largest increase in the recall index over the study period, they estimate cattle farmers lost over $450 million due to increased recalls. McKenzie and Thomsen (2001) use an event-study framework to estimate the impact of E.coli recalls from 1994 through 2000 on Texas-Oklahoma live cattle prices (farm-level) and Chicago Mercantile Exchange (CME) beef price indices (wholesale). Analyzing 18 days around the event, they find no impact on farm-level prices and a drop in wholesale prices for boneless beef on the day of the event. Moghadam, Schmidt, and Grier (2013) similarly use an event-study to measure the effect of E.coli recalls on cattle prices, specifically CME live cattle futures. They assume that, absent a recall, futures prices move in tandem with returns of the stock market index and define abnormal returns as those that deviate from what is predicted by stock market returns. Results indicate prices effects are short lived, less than a week, and translate to an average loss per E. Coli recall to cattle farmers of over $13 million.

In absence of firm-level cost and revenue data, some studies use changes in stock prices to estimate damages to firms (e.g. processors and retailers) associated with recall events. Pozo and Schroeder (2015) posit that stock price reactions are representative of the costs incurred by firms implicated in meat and poultry recalls. They construct a measure of cumulative average abnormal returns for the 20 days following a recall using actual stock prices and predicted prices in absence of the recall for 31 publicly-traded firms implicated in meat and poultry recalls from 1994 to 2013 (e.g. Sanderson Farms Inc., Costco, Nestle, etc.). They estimate the average firm in their sample incurs $109 million in damages 5 days after a recall. Thomsen and McKenzie (2001) use an event-study to measure reductions in the valuation of publicly-traded meat and poultry companies in the 30 days following food-safety incidents and find that while less-severe outbreaks do not decrease shareholder returns, severe outbreaks (class 1) reduce shareholder returns by 1.5-3% on average.

The aforementioned studies contribute collectively to our understanding of economic losses due to food-safety incidents, but they are limited in their ability to generate broad conclusions due to lack of complete data on the supply chain. For example, focusing only on data at retail precludes learning how losses are apportioned across supply-chain actors, such as farmers, processors, and retailers. Focusing only on prices or sales fails to reveal how impacts are apportioned across price and quantity effects. Use of aggregate data, such as monthly sales, can obscure the dynamic pattern of impacts on prices and quantities during a recall period and its aftermath. Whereas stock price impacts can be useful indicator of losses incurred by specific firms, such an approach is only useful for publicly traded traded firms, thereby excluding nearly all farms and several large food processor/shippers.

I expand on the existing literature by directly estimating cost and revenue changes for leafy greens firms, referred to here as processor/shippers, associated with the November 2018 advisory and its aftermath. I do so while simultaneously estimating damages for growers, retailers, and food-service operators, as well as the overall societal loss from the incident. The broad scope of this analysis is facilitated by access to detailed data on prices, costs, and sales within the leafy-greens supply chain. In addition to public data on spot-market prices and movement provided by the USDA-Agricultural Marketing Service (AMS), I acquired wholesale data from a cooperating processor that supplies both food-service and retail outlets, and retail scanner data from the Nielsen Company. Such high-quality industry data allows us to estimate price and demand effects along the supply chain and determine to what extent damages differ for various supply-chain actors.

2.3 The October 2018 E. coli Incident and Food-Safety Advisory

The November 20, 2018 food safety advisory issued by government agencies in the U.S. and Canada followed a multi-state outbreak of E. coli infections reported from October 8 to

October 31. The advisory cautioned everyone not to buy, serve, sell, or eat romaine lettuce. In response, the Leafy Greens Marketing Agreement (LGMA) and other industry produce associations urged an voluntary industry withdrawal of all romaine lettuce in marketing channels and inventory. On November 26, the U.S. Centers for Disease Control (CDC) and Food and Drug Administration (FDA) updated their advisories to specify avoidance of only romaine lettuce harvested from growing regions on California's Central Coast. In a second update issued on December 6, the CDC continued to advise avoidance of romaine lettuce from Monterey, San Benito, San Luis Obispo, Santa Barbara, Santa Cruz, and Ventura counties.

On December 13, the source of the outbreak was identified and produce from Adam Bros. Farming Inc. in Santa Barbara County was recalled. The CDC and FDA further restricted the advisory to encompass only the Salinas-Watsonville and Santa Maria growing regions. On January 9, 2019, the CDC and FDA lifted the advisory for the final two regions, thus marking its official end. As a result of the outbreak, 62 people in 16 states and the District of Columbia reported illnesses traced to E.coli infections, with the last incident reported on December 4.[1]

Notably, the scope and timing of the government-issued advisory in response to the outbreak influenced the size and incidence of losses. The initial advisory was issued for romaine from all U.S. production regions, and was not narrowed for six days. This decision exposed all production regions to economic losses. Significantly, lettuce production was in the middle of its seasonal transition from producing on the Central Coast to producing in the Yuma region on the California-Arizona border. The source of the contamination was in California, where production was winding down, while market supplies during the incident were increasingly sourced from Yuma. Thus, losses sustained by the industry were potentially disproportionately borne by those outside the source region.

[1] Those made ill by E. coli likely incurred damages due to lost income and medical expenses. I have no way to measure such impacts, and they play no role in my analysis of damages.

2.4 Industry Background

Leafy greens have distinct, seasonal growing regions in the U.S., with most lettuces harvested across different regions in California and Arizona. From April to November, production is concentrated in the Central Cost region of California. Operations then move to the Yuma region in Arizona and along the Southern California border. In February, production returns to California and is concentrated in the San Joaquin Valley region until April. The planting, growing, and harvesting cycle for leafy greens ranges from 60-90 days in spring and up to 120 days in fall.

The structure of the produce industry has changed significantly in recent decades. Today only about 10% of production of leafy greens is transacted through spot or cash markets, with the remainder being transacted through various forms of vertical coordination, including contracts and vertical integration by processors and shippers into the production of the leafy greens they market. Even most independent growers operate with contracts that coordinate their activities with their downstream buyers. Similarly, the wholesale terminal markets in major U.S. cities that served as key distribution centers for fresh produce have largely been supplanted by contract exchange between shippers and processors and downstream buyers in both the retail and food-service market channels. Most product that is moved through the terminal markets or other spot transactions is production in excess of what is needed for contract sales due to unplanned demand or supply shocks.

The leafy greens industry maintains two relatively distinct marketing channels—food service and retail. The retail channel is the far more important of the two. I estimate based on the data gathered for this project that retail accounts for 78% of product movement for romaine, with food service comprising the remaining 22%. Growers tend to specialize in producing for one channel or the other. Processors may specialize in one channel or serve both. Romaine is grown and harvested either as hearts or heads, although substitution between the two can be made at time of harvest if market conditions warrant. Harvesting of hearts is more expensive than heads because harvest workers remove the outer leaves on romaine harvested for hearts and pack them differently than heads going to processing plants. Food service utilizes only romaine heads, while retail utilizes both hearts and heads.

Contracts between growers and processor/shippers vary in terms of their duration and pricing arrangements. Contracts may specify prices that are fixed over a given time period or that are subject to change only if a reference price, such as a government-reported spot-market price, changes by a given (trigger) amount. Trigger prices are more commonly observed in contracts associated with the food service marketing channel, while growers producing for the retail channel typically are paid a fixed price per pound or acre of production. Responsibility for the payment of harvest costs also varies across contracts and influences pricing. In the typical case, the processor/shipper pays for harvesting, although in some cases harvesting is the grower's responsibility, or the cost is shared between the grower and shipper.

Financial impacts from a market shock such as the November 2018 E. coli advisory depend importantly on the nature of the grower-shipper contract. For example, contracts that specify a fixed per acre return to growers for romaine production during a particular harvest window result in the shipper or processor bearing the loss in the event some romaine cannot be sold and is plowed under due to a food-safety advisory.

Processor-retailer contracts generally also involve a fixed price and may have a duration of up to two years, precluding transmission of market shocks between processors and retailers. Contracts between processors and food-service distributors tend to have more price flexibility than retail contracts, and in some cases may allow product substitutions when prices spike as a result of severe market shocks.

Thus, although shocks such as the November 2018 E. coli incident roil the market, causing supplies to be removed from the supply chain and consumer confidence in product safety to be shaken, participants operating with fixed-price contracts may have been largely insulated from the disruption at the time. My industry contacts indicated, however, that market disruptions that adversely affected one party to a contract might be addressed when the contract is renegotiated. Thus, even with fixed price contracts, some transmission of gains or losses may eventually occur but be largely invisible to the outside analyst. The wide range of contracts in use in the leafy greens sector between growers and processors and between processors and their downstream customers in retail and food service, combined with the fact that contract provisions are not public information, creates an unavoidable element of uncertainty in my imputation of impacts from the November 2018 E. coli incident across supply-chain participants.

A second significant change in the leafy greens industry that complicates analysis of damages from an external shock like an E. coli outbreak is the proliferation of value-added products offered by the industry. Bulk or random-weight sales have largely been supplanted by value-added packaged products of different sizes and ingredient mixes. The leafy greens processor that contributed data to this study maintains nearly 1,000 different products identified by stock-keeping unit (SKU) across four categories of leafy greens included in this study—romaine, iceberg, spinach, and spring mix. My source for retail sales data, the Nielsen Corporation, reports nearly 2,000 product codes in the pre-packaged salads category.

Packaged leafy greens have a marketable shelf life of 16 days on average once the product is harvested. Products are stored in warehouses for 4-8 of these days, and delivered frequently to retailers to ensure freshness (often twice a week). In the food service sector, large distributors serve a variety of operations and any given restaurant might only have 2-3 days of product on hand at any given time.

Ownership and thus financial responsibility for recalled product varies and creates another element of uncertainty in this analysis. Products that arrive at retailers' stores and warehouses are the responsibility of the retailer. Responsibility for products in transit depends on the delivery methods specified in contracts, such as who owns the truck making the delivery.

Ownership is less uncertain in the food-service channel. Once product leaves the processor's cooler and loading dock, the distributor has ownership of it. Any produce in transit, stored at distributor warehouses, or already delivered that has to be discarded due to a food-safety incident is the responsibility of the distributor or food-service provider.

2.5 Methodology for Damage Calculations

In order to estimate the magnitude of damages caused by the November 2018 - January 2019 advisory to avoid romaine, it is necessary to consider the direct impact for all products containing romaine while an advisory was in effect, and also during the aftermath. Even after an advisory has been lifted, some consumers may remain wary of consuming products with romaine. Further, it is important to consider whether, and the extent to which, the romaine incident spilled over to impact sales of related leafy-green products.

Food-safety incidents and associated advisories will have impacts on both prices and sales for impacted products and, possibly, for related products that incur demand shifts due to consumers' avoidance behaviors. An immediate and direct impact is that products included under the government-issued advisory might be removed from the supply chain. Because these products are perishable, they are destroyed and cannot re-enter the supply chain even if they are later found to be safe.

The loss of supplies from impacted production regions will affect prices received by sellers of romaine producing outside of the impacted regions because total supply of the product to the market is reduced. However, consumer demands are also impacted because, as noted, consumers may adopt simple avoidance strategies such as "eat no leafy greens" because they either don't understand the scope of the advisory or they don't trust that the risk is confined to the indicated producing regions. Reductions in both supply and demand have offsetting effects on prices, making the net effect an empirical question that can be resolved with the appropriate data.

My goal is to project the path of the market for romaine products and close substitutes in terms of prices and volumes in the “but-for world” that would have unfolded had the incident not occurred and compare it to what in fact did happen due to the incident. The difference in the two scenarios for growers, handlers, and retailers or food-service establishments will reveal who benefited and who lost as a consequence of the incident and provide estimates of the gains and losses.

I decompose the damages due to the November 2018 romaine food-safety advisory into three components consistent with this overview. Damage Component 1 (DC1) measures impacts from changes in market prices that occurred due to the E. coli incident. Damage Components 2 and 3 (DC2, DC3) pertain to economic losses for romaine products that were in various stages of the supply chain but could not be sold due to the product recalls.

I separate quantity effects into two damage components because the cost associated with unsold product varies with a product’s location within the supply chain when the recall was announced. DC3 refers to product that had been harvested and processed and was on route to retail or food service or was on retail shelves or in food-service refrigerators. Thus it had incurred all or nearly all costs of production, processing, and transportation before it had to be pulled from the supply chain. The economic loss for this product is the sales revenue it would have earned in the but-for world of no incident.

DC2 pertains to product that was planted but not harvested due to the recall. DC2 may be due both to product that was simply unsalable because it was located within an area subject to the advisory or because of reduced demand caused by the incident. Inability to harvest and sell such product also results in economic losses, but to a lesser extent per unit volume than the product considered in DC3 due to avoided costs of harvesting, processing, transportation, etc.

In addition to quantifying the magnitude of these three damage components to produce-industry participants, this analysis seeks to apportion the gains and losses across the different stages of the supply chain, specifically to growers, processors, and retailers or food-service sellers. As noted, apportionment is an especially challenging aspect of this analysis, given the widespread use of contracts in the industry, lack of information on specific contract provisions, and uncertainty in some cases as to who bore financial responsibility for product that was destroyed due to the advisory. In section 7, I provide a rough apportionment of gains and losses to operators at different stages of the supply chain based on guidance provided by industry sources.

2.5.1 Damage Component 1

DC1 measures damages associated with changes in prices for product that was sold during the outbreak and its aftermath. Such product may have sold at a different price and, thus, generated a different amount of revenue or cost than would have occurred in absence of the outbreak. I was able to observe actual prices at three stages of the supply chain: grower, wholesale (i.e., processor), and retail. Growers experience DC1 only as sellers and then only to the extent that they sell in the spot market or through contracts with price flexibility. Processors incur price impacts as both buyers and sellers, but, once again, the impact depends on the extent, if any, of price flexibility in the processor's contracts with growers and downstream buyers. Retailers incur price impacts as both buyers and sellers. I assumed that food-service operators' prices would have been unaffected by the E. coli incident, and, thus, food-service operators experienced price impacts only as buyers.

Because the E. coli incident caused offsetting impacts on demand and supply of leafy greens, the impact on prices at the various stages of the supply chain is uncertain ex ante and is an empirical question I seek to answer in section 6. Higher prices of course, benefit supply-chain participants as sellers and harm buyers, with the outcome reversed for price decreases. A food-safety incident by its very nature creates market volatility as additional information becomes available and consumers' perceptions change, and as the geographic area of the recall is refined. Thus, it is important to estimate estimate price impacts on a weekly basis in order to capture the effects of shifting market conditions.

I illustrate computation of DC1 for growers selling via contract for food-service sales. These contracts typically have some price flexibility based on trigger-price provisions. Let $t = 1, ..., m$ denote the m weeks between the first FDA alert and the issuance of the all clear—roughly eight weeks in total. Then let weeks $t = m+1, ..., m+n$ denote the aftermath period following the recall when the romaine market was still roiled by consumer concerns about the safety of romaine. The duration of the aftermath period may vary by commodity and is an empirical question addressed in this study. I find significant impacts extending for up to 12 weeks after the all clear for some romaine-based products, i.e., $n = 12$, whereas others appear to have returned to normal conditions more quickly.

Let Q_t and P_t denote the actual food-service sales volume and grower food-service contract price for period $t = 1, ..., m, m+1, ..., m+n$. I use statistical (econometric) methods to estimate what the price would have been in the but-for world of no outbreak (see section 6). Let this predicted price for period t be $\hat{P}_t$. Then estimated damages for DC1 for food-service contract growers in week t are

$$DC1_t = Q_t(P_t - \hat{P}_t), t = 1, ..., m, m+1, ..., m+n_i. \tag{2.1}$$

DC1 can be negative (a loss) or positive (a gain) in any week t depending on how the outbreak affected prices.

Total grower damages in the food-service channel are the weekly damages summed over the incident period and the relevant aftermath period:

$$DC1 = \sum_{t=1}^{m+n} DC1_t. \tag{2.2}$$

2.5.2 Damage Components 2 and 3

DC2 and DC3 measure damages associated with romaine that could not be harvested, processed, and sold due to the advisory and its aftermath. Based on information provided by industry sources, DC2 applies to weeks 3 through 8 of the outbreak in the retail channel, and weeks 2 through 8 for food service. Product moves more quickly from harvest to consumer in the food-service channel than in the retail channel, and the data available varies slightly across channels, resulting in this slight difference in my calculations. DC2 may also extend into the outbreak aftermath if romaine product that was planted cannot be harvested and sold due to reduced consumer demand caused by the outbreak. The initial weeks of the outbreak must be treated separately because they involve romaine that had already been harvested, and was in the supply chain when it had to be pulled and destroyed upon issuance of the advisory.

I first estimated separately the change, $\Delta Q_{i,t}$ in sales for romaine product i for each week t during the advisory and post-advisory periods for the retail and food-service channels:

$$\Delta Q_{i,t} = \hat{Q}_{i,t} - Q_{i,t}, t = 1, ..., m, m+1, ..., m+n_i, \tag{2.3}$$

where $Q_{i,t}$ is the actual pounds sold of product i in week t, and $\hat{Q}_{i,t}$ is the predicted pounds sold but-for the outbreak. In the but-for world of no outbreak and advisory issued, these sales would have earned the predicted but-for price, $\hat{P}_{i,t}$ as described for DC1. Some cost savings would also have been realized depending upon where product was in the supply chain when it was pulled from the market. Romaine that was not harvested from the field due to reduced demand, i.e., category DC2, saves harvest costs and variable costs of processing.

Romaine is grown and harvested in two forms—hearts and heads, and harvest costs differ depending on the harvested form.[2] Harvesting hearts is a more labor intensive process than harvesting heads because field workers remove outer leaves of product harvested as hearts and package hearts differently than heads intended for additional processing. Let these combined harvest and processing cost savings be denoted as c_i, where i denotes romaine hearts or romaine heads on a per pound basis. These per-unit cost savings for unharvested

[2]Planting methods differ for romaine intended to be harvested as hearts vs. heads as well. For example, spacing in the field will be less for romaine planted for hearts. However, product intended for heads can be harvested as hearts and vice versa if market conditions warrant the change.

product are assumed to be constant over the damage period.

Subtracting cost savings from predicted price, I arrive at the following estimate of DC2 in week t.

$$DC2_{i,t} = \Delta Q_{i,t}(\hat{P}_{i,t} - c), t = 3, ..., m, m+1, ..., m+n_i \ \ \forall n \leq 6, \tag{2.4}$$

for the retail channel, with t indexed from week 2 to $m + n_i$ for the food-service channel. I limited the possible effects in the aftermath of the advisory to a maximum of 6 weeks to reflect an approximately 90-day industry planning horizon. Following week six of the aftermath period, all fields planted prior to the issued advisory should have been harvested or plowed under. Total damages for volumes of romaine product i that could not be harvested and sold due to the outbreak are the summation of the weekly losses:

$$DC2_i = \sum_{t=2(3)}^{m+n_i} DC2_{i,t}. \tag{2.5}$$

DC3 measures damages associated with product already in the pipeline at the time of the Nov. 20, 2018 alert issued. This product had incurred harvesting, processing, and (possibly) shipping expense but could not be sold due to the advisory. As noted, I assume that DC3 applies in the first two weeks (weeks 1 and 2) after the announcement for the retail sector and one week prior to and after the announcement (weeks -1 and 1) for food service. I estimate sales in these two weeks in the but-for world of no outbreak using the same approach used to estimate but-for quantities for DC2. This product would have been sold at the estimated but-for price computed for DC1.

I assume there is no cost savings for DC3 because product has been harvested and was in the distribution pipeline when the outbreak was announced. Estimated damages in each of the two weeks are:

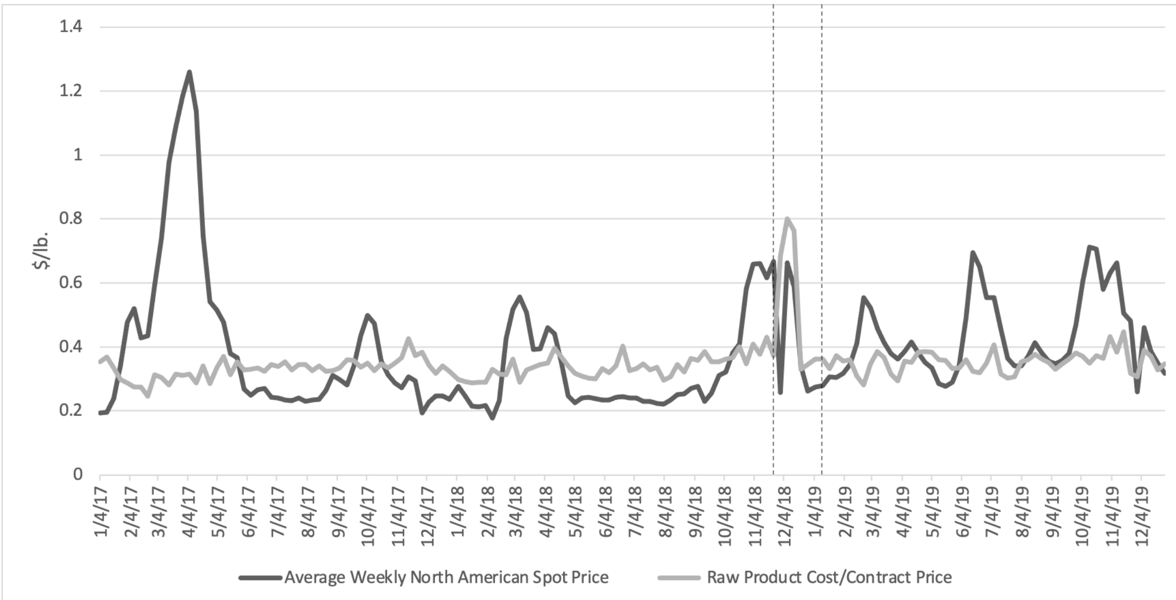
$$DC3_i = \hat{P}_{i,1} * \hat{Q}_{i,1} + \hat{P}_{i,2} * \hat{Q}_{i,2}. \tag{2.6}$$

2.5.3 Apportionment of Losses to Supply-Chain Participants

Figures 2.1 and 2.2 compare AMS spot prices for romaine leaf (romaine harvested as heads is designated as romaine leaf by AMS) with raw product costs provided by the cooperating processor for food-service and retail suppliers, respectively.[3] I assumed that these prices were representative of contract prices paid in the industry overall. The figures aptly illustrate that growers selling under contract are exposed to much less price volatility than sellers in the spot market. Spot prices spiked upward in Nov. 2018 around the time of the E. coli incident. Raw products costs for the food-service channel also spiked, although with delay, reflecting the trigger price provisions contained in the food-service contracts as well as higher processor costs per unit due to plow under or sub-optimal harvest times. In contrast, raw product costs in the retail channel increased only modestly and also with delay relative to the spot price.

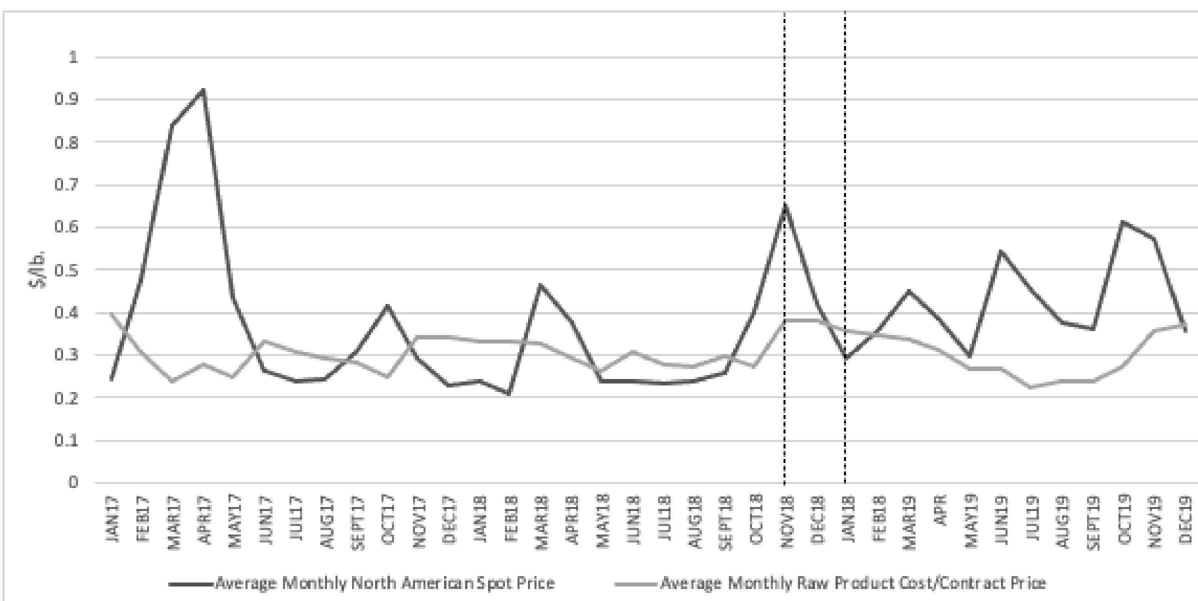
[3]AMS spot prices are plotted on a weekly basis in figure 2.1 and a monthly basis in figure 2.2 for consistency with the reporting provided to us for the corresponding wholesale price. This causes the two spot-price plots to look somewhat different.

Figure 2.1: AMS Spot-Market Price and Food Service Channel Contract Price for Romaine Leaf



†Both raw product costs and spot prices are weekly averages. The vertical lines represent the approximate beginning and end of the advisory.

Figure 2.2: AMS Spot-Market Price and Retail Channel Contract Price for Romaine Leaf



†Both raw product costs and spot prices are monthly averages because I do not have weekly contract prices for the retail sector. The vertical lines represent the approximate beginning and end of the advisory.

Apportionment of DC1 to growers required that I estimate but-for prices for spot-market sales, as well for food service and retail contract sales. Industry sources suggested that spot sales represented about 10% of total sales, but the identities of spot buyers and sellers are not clear. I assumed that spot buyers were either food-service operators or retailers, and that each sector purchased 10% of its supplies through spot purchases. Handlers and growers may each act as sellers on the spot market if they have supply over and above what can be sold via contract. I assumed that half of spot sales were by growers and half by handlers.[4]

For DC2 and DC3 in the retail channel I assumed that all volume reductions were captured in the reduced sales observed in the retail scanner data. I am then able to feed these quantity reductions through the supply chain and compute DC2 and DC3 separately. Whether processors or retailers incurred losses associated with DC3 depends on where in the supply chain the product was at the time of the E. coli advisory and who controlled it at that point. Based on feedback from the industry, I assumed that retailers incurred DC3 in week 1 of the advisory period and processors incurred it in week 2.

I lacked comprehensive consumer market data for the food-service channel comparable to what I had access to for retail, and only observed volume reductions at the processor level. Processor sales dropped immediately upon issuance of the advisory, but the advisory also impacted product that had already left processors' facilities and was in distributors' or food-service operations' facilities or en route to them. Such product also had to be removed and destroyed.

I assumed that the quantity reductions observed during the outbreak week correspond to product that was still in coolers of processors or shippers (wholesale). I further assumed that the product that was sold the week prior to the outbreak advisory in the food service channel was en route or had already arrived at distributors, restaurants or institutions, and constituted a loss to food service operations. I, thus, added romaine that was sold to distributors one week prior to the issued advisory to the observed quantity reductions in

[4]Handlers may sell on spot markets when their contracted acquisitions exceed the total amount demanded by downstream buyers. Processors and shippers could also make purchases on the spot market in situations when their contracted production was less than buyer demands. This seems less likely during the advisory and aftermath periods when demand for romaine was low.

week one of the outbreak. I then used average distributor marketing margins to calculate losses incurred by food service sellers or distributors as a result of removing these products. I was not able to estimate lost sales to restaurants, cafeterias, etc. due to the the advisory. In my view such losses would have been small and limited to cases of consumers who elected not to eat food away from home because of the advisory.

2.5.4 Total Societal Loss Due to the Outbreak

Damage components 1 - 3 are intended to measure losses to participants in the romaine supply chain, but they cannot simply be summed to obtain the total loss from the incident. Price changes, in particular, as measured in DC1, largely net out in calculating social costs and benefits because higher prices represent gains to sellers and losses to buyers and vice versa. Similarly, this analysis to this point has not considered how the welfare of consumers or that of suppliers of inputs to the romaine industry was impacted by the issued advisory overall.

The societal loss from the outbreak is based on the total value of product that was unable to be produced, harvested, and sold due to the incident. Losses to processors, food-service operators and retailers from reduced sales volumes are measured by DC2 and DC3, but these losses need to be expanded to account for losses incurred by consumers who were unable to purchase romaine products and by suppliers of inputs to the romaine industry, e.g., harvest and processing labor, who lost employment or sales to the industry in regions that were unable to harvest and sell romaine due to the outbreak and the issued advisory.

Here, I present a methodology for estimating the total societal loss from the E. coli incident based on production and sales of romaine products that were lost during the outbreak period and extending into its aftermath. I describe the methodology for the retail channel, but a similar approach was also applied to the food-service channel. Let $\hat{Q}_{i,t}\ \forall t = 1, ..., m, m+1, ..., n_i$ represent the predicted weekly retail romaine sales in product category i in week t in the but-for world of no outbreak, where n_i represents the last period where a quantity effect due to the outbreak is detected for product category i based on this econometric analysis. Then let $Q_{i,t}$ be the *actual* retail volume sold in category i and period t. The predicted retail price in the but-for world of no outbreak is $\hat{P}_{i,t}$, as defined previously.

The last piece of information needed for the retail channel is the retail price associated with sales volume $Q_{i,t}$. The actual retail prices that prevailed during the the outbreak and its aftermath are not appropriate because they reflect reduced demand due to consumer avoidance of romaine products. I need the retail price in the but-for world associated with sales volume $Q_{i,t}$ for each romaine category. In this regard, I assume demand for romaine products would have been constant over the period of analysis but-for the outbreak and issued advisory and project the price associated with $Q_{i,t}$ based on estimates of the price elasticity of retail consumer demand for each romaine category i.[5]

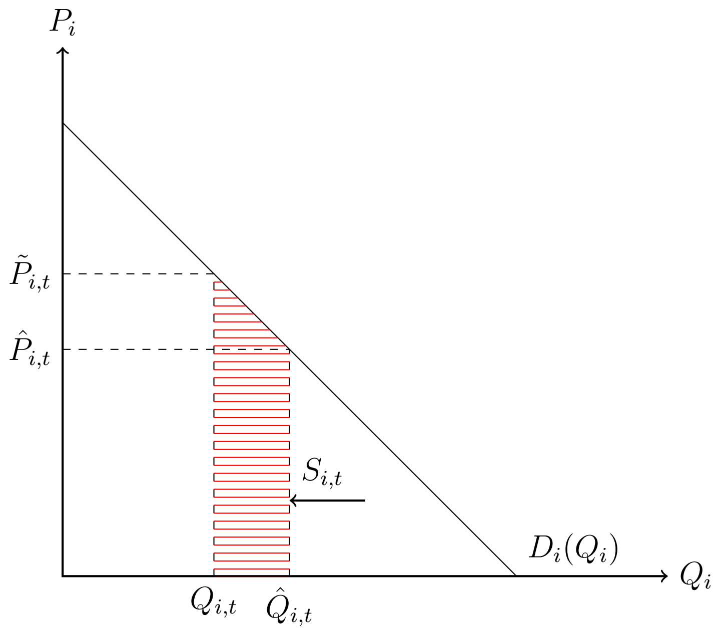
The scientific literature does not provide precise estimates of price elasticity of demand for specific romaine products. Thus, my approach was to estimate the societal loss under a range of plausible values for these price elasticities. The price elasticities play a minor role in the calculations, so the lack of precise information on their values is not a major limitation.

Let the weekly but-for total inverse demand curve for product i be represented by $P_{i,t} = D_i(Q_{i,})$. Then the price associated with a specific sales volume, e.g., $Q_{i,1}$ based on the but-for demand curve for product i is $_{i,1} = D_i(Q_{i,1})$. My estimate of the societal loss from lost sales of romaine product i is illustrated in figure 1. The total shaded area in figure 1 reflects retail consumer willingness to pay for romaine product i for the volumes between $Q_{i,t}$ and $\hat{Q}_{i,t}$. The difference between $\hat{Q}_{i,t}$ and $Q_{i,t}$ represents valuable production and consumption that was lost due to the outbreak. The entire area indicated in figure 1 represents either net benefit to consumers or payments to participants in the supply chain including retailers, handlers, growers, and those who supply inputs to them.

Importantly, these calculations assume that labor that was unemployed in the romaine supply chain due to the E. coli outbreak did not find alternative employment during the

[5]Price elasticity of demand is the percentage change in quantity demanded that results from a one percent change in price.

Figure 2.3: Total Societal Loss for Product i in Week t: $S_{i,t}$



outbreak and the relevant aftermath period. Given the relatively short-term nature of the incident, this seems like a reasonable assumption. To the extent that workers were able to obtain alternative employment and comparable wages, these estimates will overstate the true social loss from the incident.[6]

Now I have everything needed to compute the total surplus loss, S_i, for each romaine commodity i due to the outbreak week by week for the outbreak and aftermath periods (as I define them based on my econometrics). It is simply the sum across weeks of the area or integral under the demand curve:

$$S_i = \sum_{t=1}^{m+n_i} \int_{Q_{i,t}}^{\hat{Q}_{i,t}} D_i(Q_{i,t})\, d\tau\,, \tag{2.7}$$

where the equation mathematically represents the sum across weeks of the shaded area in figure 2.3.

[6]Some workers who lost employment due to the outbreak and accompanying advisory may have received unemployment compensation. The loss of employment still, however, represents a societal loss, with government bearing the burden for unemployment compensation payments.

2.6 Data

Estimating financial impacts from the November 2018 E. coli incident required accessing data from several sources, as well as relying on industry contacts for additional information regarding contract provisions that would impact gains or losses to supply-chain participants. In this section I describe the data utilized to estimate damage components 1 - 3.

2.6.1 Spot-Market Transaction Data

The USDA AMS is the key provider of information on prices and quantities for produce items being transacted through open-market exchange. AMS publishes Market News Reports that contain daily data on shipping-point prices, volumes, quality, and condition for many fruits, vegetables, and specialty crops.[7] The data specify daily high and low prices and identify production method (e.g., organic vs conventional), product size, and city or region of origin. I gathered AMS data for five leafy greens commodities—romaine lettuce, romaine hearts, leaf lettuce, iceberg lettuce, and spinach—to analyze direct and indirect price and quantity effects of the outbreak on spot-market sales.

AMS reports information for a wide range of container types and sizes. I converted all price and quantity information into per pound measures, relying for this purpose on information provided in the AMS Shipping Point and Market Inspections Instructions (2004), as well as other industry sources. To capture movements in spot market prices year round, I used reported prices across all North American growing regions and computed weekly average commodity prices per pound for the three-year period from January 2017- December 2019.

[7] https://marketnews.usda.gov/mnp/fv-report-config-step1?type=termPrice

2.6.2 Contract Production: Processor's Cost per Pound Harvested

Grower prices received under contracts with shippers and processors are not included in the AMS data. Although trends observed in spot prices serve as an important signal to market participants in contract negotiations, contract prices, as noted earlier, are generally less volatile than spot-market prices and may even be fixed over the term of the contract. I used procurement cost data provided by a large leafy-greens processor with significant presence in both the food service and retail channels to estimate contract procurement costs for romaine.

For the food service channel, the data I received included the weekly raw product cost per pound for the processor, pounds shipped, gross product income, and direct labor cost per lb. for romaine, iceberg lettuce, green leaf, spring mix, and spinach from January 2017 through December 2019. The gross product income per lb. corresponds to the wholesale price per lb. received by the processor when contracting with distributors.

For the retail channel, the data received included weekly pounds sold and revenue received for close to 1,000 products identified by stock-keeping unit (SKU) across four categories: romaine, lettuce, spinach, and spring mix. SKUs reported in the romaine category include romaine hearts, romaine heads, as well as salad mixes that contain romaine. For products that include ingredients other than romaine, the pounds reported for each SKU correspond to the weight of romaine only. I aggregated these data to an average weekly price per pound per product category. I also obtained monthly raw product costs (per pound) for the processor for contracts to serve the retail channel.

2.6.3 Grocery Retail Data

For the retail channel, I had access to national scanner data for pre-packaged salads (PPS) collected by the Nielsen Company. This Nielsen data provided weekly sales by Universal Product Code (UPC) in 9 leafy greens product subcategories: romaine hearts, classics, premium classics, kits, blends, bowls, greens, spinach, and cole slaw over the 2017 - 2019 study period. Nielsen reported that 93% of all lettuce were sold as PPS in 2019 while only 7% were sold as random weight, indicating that PPS sales dominate the consumer market. Nielsen collects data from a variety of retailers (e.g., grocery stores, mass-merchandisers, drugstores, convenience stores, specialty markets) with sales above $2 million annually. Not all retailers share their data but Nielsen estimates sales for large non-cooperators such as such as Aldi and Trader Joe's to attain total food sales. Although coverage varies slightly depending on product category, these data capture an estimated 85% of the retail market overall. I adjusted the estimates to represent a 100% coverage for PPS but did not make additional adjustments for random weight sales due to data limitations.[8]

The Nielsen data include over 2,000 distinct products based on UPC codes in the PPS product category. In collaboration with the processor that shared both retail and food service data, I created an identifier for all UPCs that include romaine in the kits, blends, and bowls category. I then matched UPCs that contain romaine to SKUs listed in the romaine category in the wholesale data provided by the processor. I converted retail quantity reductions of kits and blends into wholesale and grower quantity reductions for romaine using product weight in lbs and a conversion factor of 83% romaine for kits and 31% romaine for blends based on consultation with the cooperating processor.[9]

2.6.4 Additional Production-Cost Data

Estimating damages associated with produce that was not harvested and processed as a result of the advisory (damage component 2) required information on average harvest costs and variable processing costs, e.g., labor, since these costs were avoided on product that was plowed under in fields. Harvest costs for romaine hearts were available from a 2019 University of California Cooperative Extension-Agricultural Issues Center study on production costs for

[8] I do not have access to retail prices and quantities or wholesale prices for lettuce sold as random weight.

[9] While the bowls category includes products that contain romaine as well, I was not able to adequately match UPCs and SKUs and derive a conversion factor for this category.

romaine hearts (Tourte et al., 2019). Based on this study, I estimated an average per pound harvest cost saving of 31.2 cents for romaine that was planted but not harvested. Romaine heads are less costly to harvest than hearts because workers do not need to remove the outer leaves for heads and package them differently. I relied on industry feedback to adjust harvest costs downward for romaine heads.

The data provided by the processor allowed us to compute an average processing labor cost saving of 10.3 cents per pound for romaine that was not processed. I applied these average cost savings uniformly across the produce categories included in my damage calculations.

2.7 Estimated Price and Quantity Effects

I utilized econometric analysis to estimate prices and sales volumes that would have prevailed in the leafy-greens supply chain but for the November 2018 advisory issued. The basic methodology involved statistically correlating (regressing) weekly observed prices and quantities over the three-year period from January 2017 - December 2019 on variables to account for month of the year (e.g., to account for seasonality in demand or supply), year (e.g., to account for secular trends in demand across the three years), and {0,1} indicator variables to denote each specific week 1 - 8 associated with the advisory period and then each specific week 1 - 12 associated with the advisory aftermath period.[10] In other words, I seek to explain weekly prices and quantities over this three-year period based on values of the aforementioned explanatory variables. These predicted prices and quantities then are utilized in computing damages components 1 - 3 as described in section 2.5.

As in the prior sections, Q denotes volume or quantity, P denotes price, i subscript denotes a particular commodity, and t subscript denotes time period. I express the dependent

[10] These variables have values of 0 for a week that was not part of the advisory period or aftermath period and a value of 1 for each specific week of the advisory and aftermath. Thus, at most one week as a value of 1 for each indicator variable

variables, $Q_{i,t}$ and $P_{i,t}$, in logarithmic form so that that I can easily convert estimated coefficients on the advisory and post-advisory indicator variables into percent changes in quantity and price. The specific form of the estimating equations are the following:

$$ln(Q_{i,t}) = \beta_0 + \beta_1 * AdvisoryWeek1 + ... + \beta_8 * AdvisoryWeek8+ \tag{2.8}$$

$$\beta_9 * PostAdvisorybreakWeek1 + ... + \beta_{20} * PostAdvisorybreakWeek1+ \tag{2.9}$$

$$\gamma_m + \alpha_y + \eta_{w,i}, \tag{2.10}$$

$$ln(P_{i,t}) = \gamma_0 + \gamma_1 * AdvisoryWeek1 + ... + \gamma_8 * AdvisoryWeek8+ \tag{2.11}$$

$$\gamma_9 * PostAdvisoryWeek1 + ... + \gamma_{20} * PostAdvisoryWeek1+ \tag{2.12}$$

$$\lambda_m + \omega_y + \nu_{w,i}, \tag{2.13}$$

where β_j measures the impact of advisory or post advisory week t on the log of sales in week t, and γ_t represents the estimated effect on price in week t. The monthly fixed effects are indicated by γ_m and λ_m in the two equations, while α_y and ω_y denote the year fixed effects. Finally, $\eta_{w,i}$ and $\nu_{w,i}$ represent mean zero random errors.

I estimated price and quantity effects of the E. coli incident at different stages of the supply chain for a number of different leafy greens using these regression specifications. The key variables for purposes of the analysis are the indicator variables denoting the advisory period and its aftermath. The estimated coefficients for these variables, i.e., the β_t and the γ_t, represent my best estimates as to how the advisory impacted sales or price for weeks when the advisory was in effect or the weeks in the aftermath period for the commodity and stage of supply chain being studied.

The signs of the estimated coefficients on the advisory and post-advisory indicator variables are themselves of interest. For the quantity regressions for romaine, I expect reduced sales (negative signs on the estimated coefficients) both due to the removal of product during the advisory period and also to consumersâ concerns about food safety. These concerns may well have persisted even after the advisory was lifted. The magnitude and statistical significance of indicator variables for the post-advisory weeks provide a mechanism to detect how long such effects persisted. I considered post-advisory impacts up to 12 weeks based upon an initial analysis of USDA-AMS price and movement data.

The expected impact of the advisory and its aftermath on prices of romaine and products containing romaine is not clear ex ante because both supply and demand were impacted adversely, with offsetting consequences for price, as discussed in section 2.5. This price effect (whether positive or negative) on product that is sold during the advisory and during the aftermath period is the key consideration in damage component 1 of my damage estimates for growers and handlers.

Among the outputs from the regression models is a measure for each estimated coefficient of the statistical precision with which it was estimated. Coefficients are said to be "statistically significant" if one can say with a high degree of confidence, usually set at 90% or 95%, that the true effect is not zero. In the majority of the regressions for romaine, I found statistically significant price and quantify effects extending into the aftermath period for between 8 - 12 weeks, depending on commodity.

Although I estimated the effect on prices and quantities for each week of the advisory period and through 12 post-advisory weeks, I adopted the rule that three consecutive weeks of no statistically significant effect of the aftermath week indicator variables marked the end of the advisory's impact on that particular variable. As such, the weeks for which I measure price or quantity effects varies by product or commodity based upon this rule.[11]

[11] This assumption avoids imputing significance to spurious correlations that sometimes occur. Consistent with this cut-off rule, I also include estimated weekly effects in the analysis even if they are not statistically significant if they occur prior to this three-week period or through the entire 12 week post-advisory period if no such three-week period exists.

2.7.1 Grower Prices

To capture the effect of the advisory on grower prices, I estimated three regression models. The first uses the average weekly North American spot price from USDA-AMS as the dependent variable. The second and third models utilize the cost per pound paid by the cooperating processor for produce supplied to it for the retail and food service marketing channels. Combined, the three models capture movements in the spot market and contract prices received by romaine growers in both the food service and retail supply chains during the advisory period and its aftermath.

I report separate estimation results for regression models with AMS data for romaine hearts, romaine leaf, and iceberg lettuce. Leaf lettuce and spinach represent two other possible substitutes for romaine, but regression results for these commodities showed little impact from the advisory on their prices, and results for these commodities are not reported.

Figures 2.4 and 2.5 show point estimates for the coefficients on the indicator variables for romaine hearts and romaine head/leaf for each week of the advisory and post-advisory periods, as well as a 90% confidence interval for each point estimate.[12] If the confidence interval includes zero, the estimate is not statistically significant at the 90% level.

For both romaine hearts and head/leaf, there are positive price effects through the sixth week of the outbreak. The coefficients on the advisory dummy variables during these weeks range from a high of 0.762 (1.058) in week 3 to a low of 0.149 (0.129) in week 6 for hearts (leaf). These coefficients translate into a 114% (188%) increase in prices in week 1 and 16% (14%) increase in week 6 for hearts (leaf) relative to the same week under normal market conditions (i.e., no outbreak).[13]

[12] The width of the bar in the figures represents the 90% confidence interval, i.e., I have 90% confidence that the true impact lies within the range indicated by the bar.

[13] The coefficients in the logarithmic regression models are converted to percentage changes based on the following formula: $\%change = 100 \times (e^{\beta_i} - 1)$, where β_i is the estimated coefficient on the indicator variable. Recall from the previous discussion that the indicator variables change from 0 to 1 for a week during the advisory or aftermath periods. Thus, applying the preceding formula gives us the estimated percentage impact of the advisory or aftermath in that specific week on price. Percentage changes in quantities are derived in a similar manner.

These results show that romaine lettuce that was safe and marketable during the advisory period sold on the spot market at a premium for the first several weeks following the initial alert. Following week six, however, price effects were negative. By this time, the advisory had been confined to a small region, so most production was saleable, but demand for romaine had decreased, likely due to reduced consumer confidence in the safety of the product.

Starting in week 4 of the post-advisory period, there are, as shown in figure 2.5, several consecutive weeks with no significant price effect for romaine leaf, thus marking the end of the advisory's impact on romaine leaf. Conversely, figure 2.4 indicates that significant negative price effects for romaine hearts persisted though the entire 12 weeks of the aftermath period studied.

Figure 2.6 examines the impact of the advisory on the spot price for iceberg lettuce, commonly agreed to be the closest substitute for romaine. Iceberg spot prices were significantly higher than in the comparable non-advisory periods for the first six weeks of the outbreak. This corresponds very closely to the positive price impacts for salable romaine in the first weeks of the advisory. After week 6, the advisory was confined to the immediate region of the source of the outbreak, allowing other romaine production to be sold and largely eliminating the lettuce shortage that was spurring higher prices.

Figure 2.4: Average North American Spot Price Regression Estimates for Romaine Hearts

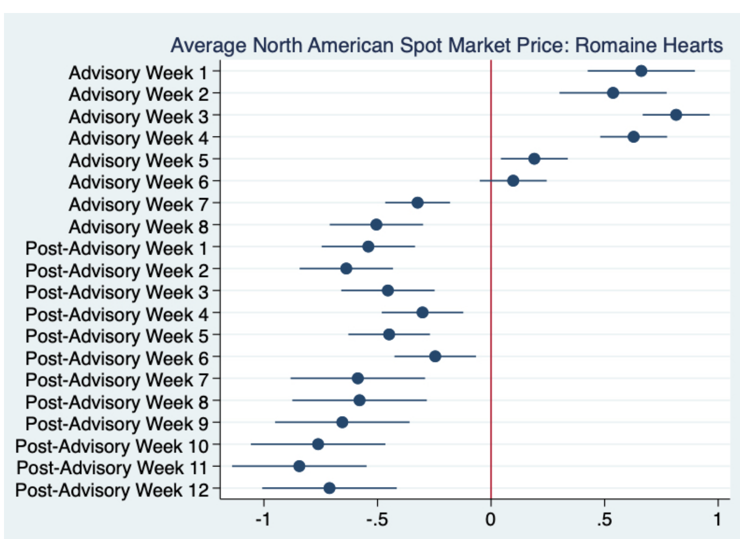


Figure 2.5: Average North American Spot Price Regression Estimates for Romaine Leaf

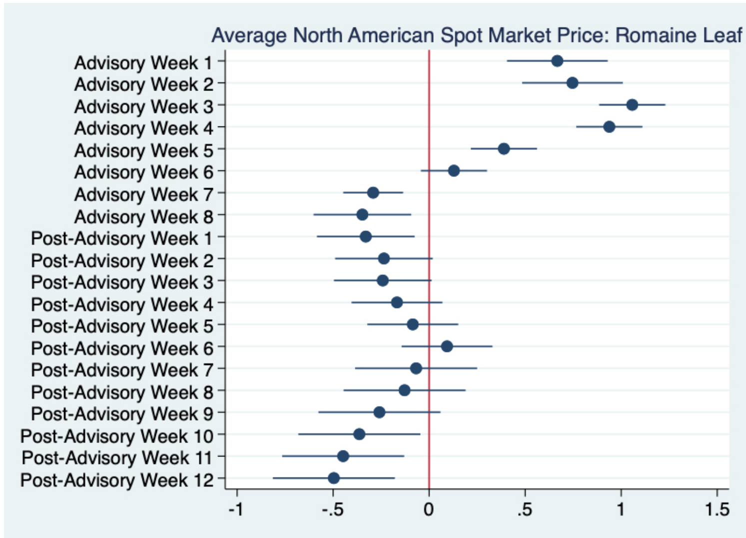
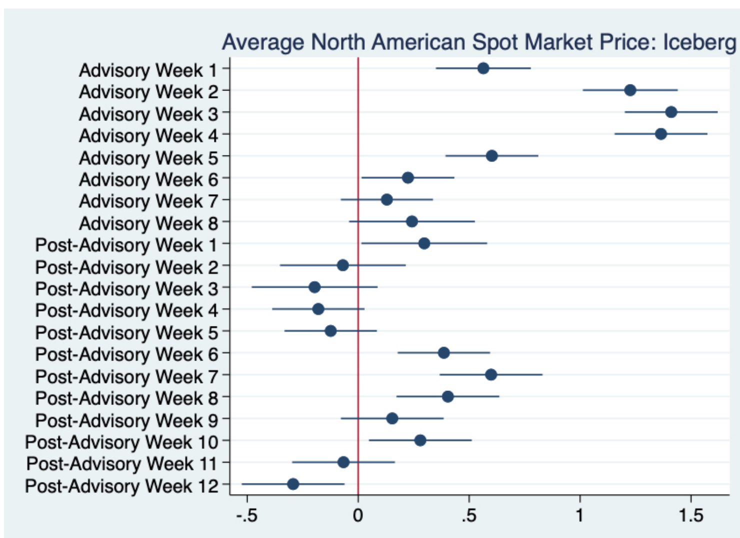


Figure 2.6: Average North American Spot Price Regression Estimates for Iceberg



The second model uses the average monthly cost of romaine for retail sale for the cooperating processor as the dependent variable, while the third model utilized the average weekly cost of romaine for food service incurred by the same processor as the dependent variable. Because the retail data provided by the processor are monthly, I designated November and December 2018 as months 1 and 2 of the advisory period and January, February, and March of 2019 as months 1–3 of the post-advisory period.[14] Tables 2.1 and 2.2 display the regres-

[14]This characterization, though unavoidable given data availability, does not match precisely with the timing

sion output for these two models. All months in the advisory and post-advisory periods were associated with an increase in retail contract costs to acquire romaine. The increases ranged from approximately 30% in November and December 2018 to 11% in March 2019. Based on my understanding that growers for retail operate with fixed-price contracts, these statistically significant cost increases for the cooperating processor represent mostly or entirely costs associated with inability to sell contracted product and costs associated with harvesting contracting product at suboptimal times due to the advisory and its aftermath.

Table 2.1: Estimated Impacts of Advisory and Aftermath on Processorâs Retail Acquisition Cost

	Romaine
advisory_m1	0.267***
advisory_m2	0.268***
post_advisory_m1	0.232***
post_advisory_m2	0.200**
post_advisory_m3	0.111***
N	49
R^2	0.218

The dependent variable is the natural log of average monthly price per pound. Robust Standard Errors. */**/*** denotes significance at the 90/95/99 percent levels. Regressions include year fixed effects.

The processor's procurement costs per pound of romaine for the food service channel were significantly higher for weeks 2 to 4 of the advisory. Thereafter, there were no consistent effects on cost and relatively few of the estimated effects are statistically significant. Cost effects were especially large weeks 2 through 4 of the advisory, with coefficients corresponding to price increases of 78%, 131% and 121% in those weeks, respectively.

Higher input costs for the processor in the food-service channel likely reflect both adjustments in price paid to growers, based on price triggers in the typical food-service contract, and loss of some contracted product that became unsalable due to the advisory. In both the

of the advisory as discussed earlier in this report.

retail and food-service channels, effects of the advisory on procurement costs were generally less than in the spot market, consistent with the earlier discussion regarding relative price stability in produce production contracts.

Table 2.2: Estimated Impacts of Advisory and Aftermath on Processor's Food-Service Acquisition Costs

	Romaine	Iceberg
advisory_w1	-0.030	0.086***
advisory_w2	0.579***	0.432***
advisory_w3	0.837***	0.682***
advisory_w4	0.791***	0.691***
advisory_w5	-0.051	-0.010
advisory_w6	-0.003	0.223***
advisory_w7	0.113*	0.023
advisory_w8	0.109*	-0.122**
post_advisory_w1	0.027	-0.045
post_advisory_w2	0.141**	-0.057
post_advisory_w3	0.173***	-0.059
post_advisory_w4	0.181***	0.055
post_advisory_w5	0.031	-0.078*
post_advisory_w6	-0.064	0.048
post_advisory_w7	0.057	0.141***
post_advisory_w8	0.158***	0.298***
post_advisory_w9	0.108***	0.395***
post_advisory_wk10	-0.042	0.329***
post_advisory_wk11	-0.110***	0.303***
post_advisory_wk12	0.010	-0.166
Constant	-1.174***	-1.483***
N	157	157
R^2	0.770	0.524

The dependent variable is the natural log of average weekly grower contract prices for the food service sector. All regressions have a base of January 2017. Robust Standard Errors. */**/*** denotes significance at the 90/95/99 percent levels. Regressions include month and year fixed effects.

Table 2.2 also contains regression results for food-service contract costs for iceberg lettuce during the advisory period, given iceberg's role as a key substitute for romaine. Results show strongly positive price/cost effects during the first four weeks during the advisory period, peaking at a 100% increase in the procurement cost in week 4 of the advisory. Saleable romaine or iceberg lettuce, sold as a substitute, appear to have earned price premiums through at least the early weeks of the advisory period. Contract procurement costs for romaine did not decline at any time during the advisory or aftermath periods. However, spot-market sellers received consistently lower prices throughout the aftermath period, as lower consumer demand for products containing romaine caused buyers to have little reason to enter the spot market to augment their contract purchases.

2.7.2 Prices Received by Processors

To assess price effects of the advisory and its aftermath for processors and shippers of leafy greens, I utilized data provided by the cooperating processor and presumed that they would be representative of the processing sector and handlers as a whole. For food service sales, I used the average weekly wholesale price per pound received by the processor as the dependent variable. Estimation results are contained in table 2.3 for both romaine and iceberg. Prices received by processors for romaine increased in weeks 2 through 4 of the outbreak period by between 24% and 41%. Thereafter, however, prices received by processors for romaine were, in general, moderately lower throughout the rest of the advisory period and the 12-week aftermath. Iceberg also received higher prices at the start of the advisory period, but prices received by processors returned to near normal after the fifth week, with few significant price effects appearing thereafter.

Table 2.3: Estimated Impacts of Advisory and Aftermath on Processor's Wholesale Price for Sales to Food Service

	Romaine	Iceberg
advisory_w1	-0.020	0.028
advisory_w2	0.214***	0.381***
advisory_w3	0.344***	0.536***
advisory_w4	0.295***	0.568***
advisory_w5	-0.173***	0.160***
advisory_w6	0.001	0.031
advisory_w7	-0.111**	-0.017
advisory_w8	-0.082	-0.007
post_advisory_w1	-0.099*	-0.031
post_advisory_w2	-0.097*	-0.042
post_advisory_w3	-0.100**	-0.061
post_advisory_w4	-0.109**	-0.058
post_advisory_w5	-0.109**	-0.045
post_advisory_w6	-0.103**	-0.051
post_advisory_w7	-0.180***	0.014
post_advisory_w8	-0.165***	0.171***
post_advisory_w9	-0.162***	-0.005
post_advisory_wk10	-0.166***	-0.108**
post_advisory_wk11	-0.165***	-0.064
post_advisory_wk12	-0.212**	-0.188**
Constant	-0.026	-0.720***
N	157	157
R^2	0.574	0.456

The dependent variable is the natural log of average weekly food service wholesale prices. All regressions have a base of January 2017. Robust Standard Errors. */**/*** denotes significance at the 90/95/99 percent levels. Regressions include month and year fixed effects.

I estimated price effects for processors serving the retail channel based on the average weekly wholesale price per pound received for romaine by the cooperating processor for retail sales. I estimated regressions for each of the four main product categories: romaine hearts, kits, blends, and premium classics. For the latter three, I limit the analysis to products that contain romaine. Estimation results are provided in table 2.4. All products experienced a relatively sharp decline in price received in the second week (the first full week of the advisory), with decreases ranging from -25% for kits to -46% for romaine hearts. Small but positive price effects for kits persisted throughout the entire study period. Price effects for blends were generally negative for the remaining weeks of the advisory, but quantitatively small. Similarly, there was little price impact for premium classic salads. With very few exceptions, romaine hearts experienced statistically significantly lower prices throughout the 12-week aftermath period.

To interpret these wholesale price impacts, recall that most contracts between produce processors and retailers have fixed prices for a contract period that is typically one to two years in duration. The sharp decrease in price shown for each product category in week 2 is likely the result of some product not being salable. The rather small but statistically significant price effects for hearts, blends, and kits during the aftermath period likely reflects new contract provisions with some retail buyers that reflect changes in consumer demands for bagged salad products in the aftermath of the romaine advisory. Romaine hearts experienced the most adverse demand reaction to the outbreak, most likely because of consumer avoidance of romaine. The exclusive romaine content of hearts would have been obvious to consumers, whereas its presence in kits and blends would have been less clear to the average shopper. Indeed, results suggest that possibly kits experienced increasing demand as consumers substituted away from romaine-only bagged salads.

Table 2.4: Estimated Impacts of Advisory and Aftermath on Processorâs Wholesale Price for Sales to Retail

	Romaine Hearts	Blends	Kits	Premium Classics
advisory_w1	-0.130	-0.058***	-0.011	0.061**
advisory_w2	-0.625***	-0.313***	-0.294***	-0.501***
advisory_w3	0.052	-0.047*	0.039	0.091***
advisory_w4	0.047	-0.072***	0.049*	0.094***
advisory_w5	-0.012	-0.046*	0.045*	0.093***
advisory_w6	-0.074	-0.031	0.050*	0.093***
advisory_w7	-0.003	-0.000	0.055**	0.004
advisory_w8	-0.210**	-0.055*	0.084***	0.007
post_advisory_w1	-0.212**	-0.034	0.091***	0.007
post_advisory_w2	-0.201**	-0.047	0.083***	0.007
post_advisory_w3	-0.207**	-0.059*	0.086***	0.007
post_advisory_w4	-0.154*	-0.016	0.097***	0.003
post_advisory_w5	-0.139*	-0.061*	0.095***	0.003
post_advisory_w6	-0.092	-0.081**	0.092***	0.003
post_advisory_w7	-0.260***	-0.092***	0.049***	0.003
post_advisory_w8	-0.341***	-0.079**	0.043***	0.003
post_advisory_w9	-0.364***	-0.188***	0.057***	0.003
post_advisory_wk10	-0.324***	-0.171***	0.033***	0.003
post_advisory_wk11	0.071	-0.219***	0.029**	0.003
post_advisory_wk12	-0.376***	-0.223***	0.034***	0.003
Constant	0.765***	0.634***	0.708***	-0.066***
N	145	145	145	145
R^2	0.548	0.576	0.829	0.878

The dependent variable is the natural log of average weekly price per pound. All regressions have a base of January 2017. Robust Standard Errors. */**/*** denotes significance at the 90/95/99 percent levels. Regressions include month and year fixed effects.

2.7.3 Prices Received by Grocery Retailers

I used the average weekly retail price by product category constructed using Nielsen data as the dependent variable to measure price effects for retailers and estimated regression models for premium classics, romaine hearts, kits, and blends. I, again, limit the analysis to only products within those categories that contain romaine. Table 2.5 contains the estimation results.

In general, price effects, if any, at retail from the advisory and its aftermath are very minor. This finding is consistent with the general understanding of how large food retailers set prices. Most retailers prefer to maintain stable prices for their customers, especially for staple products like bagged salads. Indeed, as table 2.4 showed, retailers' costs for bagged salads were themselves little impacted for most weeks of the advisory and aftermath periods, so even retailers that were inclined to pass changes in acquisition costs forward to consumers had little reason to adjust prices.

Table 2.5: Estimated Impacts of Advisory and Aftermath on Retail Prices

	Romaine Hearts	Blends	Kits	Premium Classics
advisory_w1	0.065***	-0.008	0.013**	-0.013
advisory_w2	0.147***	-0.016**	-0.051***	-0.014
advisory_w3	0.123***	-0.002	-0.023***	-0.010
advisory_w4	0.092***	-0.007	-0.017***	-0.032**
advisory_w5	0.070***	-0.009	-0.007	-0.025*
advisory_w6	0.063***	-0.004	-0.003	-0.035**
advisory_w7	0.071*	0.085***	0.030***	0.050**
advisory_w8	0.001	0.081***	0.003	0.045**
post_advisory_w1	0.040	0.078***	0.023***	0.048**
post_advisory_w2	-0.017	0.058***	0.008	0.032
post_advisory_w3	0.013	0.055***	-0.029***	0.045*
post_advisory_w4	0.015	0.061***	-0.004	0.017
post_advisory_w5	-0.021	0.056***	0.003	0.002
post_advisory_w6	-0.048*	0.057***	-0.014*	0.051**
post_advisory_w7	-0.087***	0.046***	-0.027***	0.036*
post_advisory_w8	-0.037	0.040***	-0.002	0.001
post_advisory_w9	-0.017	0.056***	0.003	0.007
post_advisory_wk10	-0.024	0.046***	0.003	0.025
post_advisory_wk11	-0.035	0.038***	-0.003	0.041**
post_advisory_wk12	-0.089*	0.034***	0.002	0.003
Constant	1.593***	1.705***	1.645***	1.311***
N	156	156	156	156
R^2	0.574	0.758	0.679	0.551

The dependent variable is the natural log of average weekly price per pound. All regressions have a base of January 2017. Robust Standard Errors. */**/*** denotes significance at the 90/95/99 percent levels. Regressions include month and year fixed effects.

2.7.4 Impacts of the Advisory on Quantities Sold

Whereas damage component 1 measures price impacts of the advisory and its aftermath and provides critical information on gainers and losers within the supply chain due to the E. coli incident, damage components 2 and 3 are based on quantity impacts, which are the key factors in determining societal loss due to the incident. Although the USDA-AMS data contain shipment volumes, the data are difficult to interpret because relatively little volume moves through spot sales. I was able to get evidence on sales impacts to the food-service channel through information provided by the cooperating processor. I used the average weekly pounds of product sold to food service providers by this processor as the dependent variable in a regression model, with the same explanatory variables as in the models for price effects. Table 2.6 contains results for both romaine and iceberg lettuce. There is a large decrease (72%) in the volume of romaine sold to food service in the first week of the advisory, followed by smaller decreases in most subsequent weeks through week 10 of the post-advisory period. These results suggest that food-service operators reduced orders of products containing romaine not just during the advisory but for several weeks thereafter.

Quantity effects for iceberg due to the advisory were mild. There was a significant decrease in sales in week 1, likely reflecting confusion over the scope of the advisory, and then some small but statistically significant increases in sales in weeks 2 and 3, as some food-service operators switched from romaine to iceberg. In general, however, quantity effects for iceberg are small, inconsistent in sign, and often not statistically significant in the remaining weeks of the advisory and the aftermath period. Given that moderate decreases in romaine sales to food service were experienced through 10 weeks of the aftermath period, results for iceberg suggest that food-service operators did not, except for the initial weeks of the advisory, substitute iceberg in place of romaine and, rather, likely included fewer salad items on their menus during this period.[15]

[15] Ability of downstream operators to acquire additional iceberg product is limited through the advisory and early portions of the aftermath period by the fact that iceberg supplies are largely fixed during this period by planting decisions made prior to the issuance of the advisory.

Table 2.6: Estimated Impacts of Advisory and Aftermath on Processorâs Food-Service Sales

	Romaine	Iceberg
advisory_w1	-1.288***	-0.213***
advisory_w2	-0.418***	0.122***
advisory_w3	0.045	0.180***
advisory_w4	-0.139*	0.078
advisory_w5	-0.253***	-0.048
advisory_w6	-0.318***	-0.127**
advisory_w7	-0.265***	-0.065*
advisory_w8	-0.132***	0.053
post_advisory_w1	-0.117***	0.022
post_advisory_w2	-0.182***	-0.012
post_advisory_w3	-0.231***	-0.079***
post_advisory_w4	-0.170***	-0.073***
post_advisory_w5	-0.154***	-0.057***
post_advisory_w6	-0.158***	-0.061***
post_advisory_w7	-0.175***	-0.043*
post_advisory_w8	-0.148***	0.016
post_advisory_w9	-0.089**	-0.007
post_advisory_wk10	-0.142***	-0.099***
post_advisory_wk11	-0.038	0.000
post_advisory_wk12	0.008	0.039
Constant	14.679***	15.414***
N	157	157
R^2	0.874	0.735

The dependent variable is the natural log of average weekly food service wholesale prices. All regressions have a base of January 2017. Robust Standard Errors. */**/*** denotes significance at the 90/95/99 percent levels. Regressions include month and year fixed effects.

Impacts of the advisory and its aftermath at retail can be assessed with considerable accuracy using the Nielsen data. I estimated volume sales at retail for the same romaine-based product categories (hearts, blends, kits, and premium classics) as studied for price effects. Results are reported in table 2.7. For each product category, there are statistically significant decreases in sales in nearly every week of the study period. The decreases are most pronounced in week 2 of the advisory when product was largely absent from retail shelves, and range from a reduction of 91% for blends to 96% for romaine hearts.

Decreases in sales associated with the early weeks of the advisory are largely attributable to retailers removing romaine products from shelves and shippers and retailers removing product in the supply pipeline. The persistent decreases in sales throughout the post-advisory period, however, indicate that consumers shifted consumption away from products containing romaine for several weeks after the all clear had been issued. In fact, only in the 12^{th} week post advisory do I finally see no sales impact for any of the four romaine-based products. In total, I estimate that retail sales were down 26% for premium classics, 25% for romaine hearts, 18.5% for blends containing romaine, and 16.6% for kits containing romaine, when summing sales across the entire advisory and aftermath periods.

Table 2.7: Estimated Impacts of Advisory and Aftermath on Retail Sales

	Romaine Hearts	Blends	Kits	Premium Classics
advisory_w1	-0.479***	-0.385***	-0.461***	-0.528***
advisory_w2	-3.464***	-2.435***	-2.749***	-3.010***
advisory_w3	-1.152***	-0.647***	-0.734***	-0.764***
advisory_w4	-0.559***	-0.330***	-0.286***	-0.445***
advisory_w5	-0.442***	-0.228**	-0.252***	-0.395***
advisory_w6	-0.439***	-0.250***	-0.350***	-0.323***
advisory_w7	-0.285***	-0.224***	-0.169***	-0.324***
advisory_w8	-0.114***	-0.051*	-0.025	-0.180***
post_advisory_w1	-0.160***	-0.084***	-0.052**	-0.159***
post_advisory_w2	-0.254***	-0.203***	-0.064***	-0.235***
post_advisory_w3	-0.157***	-0.165***	-0.053*	-0.272***
post_advisory_w4	-0.175***	-0.172***	-0.084**	-0.253***
post_advisory_w5	-0.113***	-0.095***	-0.077**	-0.212***
post_advisory_w6	-0.134***	-0.082***	-0.076**	-0.203***
post_advisory_w7	-0.146***	-0.102***	-0.043	-0.221***
post_advisory_w8	-0.122***	-0.088***	-0.075***	-0.207***
post_advisory_w9	-0.148***	-0.097***	-0.085***	-0.220***
post_advisory_wk10	-0.113***	-0.124***	-0.098***	-0.147***
post_advisory_wk11	-0.091***	-0.095***	-0.055*	-0.196***
post_advisory_wk12	0.014	-0.010	0.048	-0.042
Constant	14.864***	15.294***	15.069***	14.513***
N	156	156	156	156
R^2	0.955	0.896	0.916	0.916

The dependent variable is the natural log of average weekly lbs sold. All regressions have a base of January 2017. Robust Standard Errors. */**/*** denotes significance at the 90/95/99 percent levels. Regressions include month and year fixed effects.

2.8 Damages Due to the November 2018 E. coli Incident

I provide separate estimates for each of the three damage components from the November 2018 E. coli incident for growers, processor/shippers, retailers, and food-service operators. Growers at most incurred damages for only components 1 and 2, because they would have been compensated for product that had been harvested and delivered or en route to food service and groceries at the time of the advisory (i.e., DC3). Food retailers and food-service operators incurred losses for non-salable product under their ownership at the time of the advisory (DC3) and also were potentially impacted by price effects due to the advisory and its aftermath (DC1). Processors/shippers were impacted by all three damage components.

2.8.1 Grower Impacts

Although the E. coli problem originated at the grower stage of the supply chain, the nature of contracting in the leafy-greens industry insulated growers from most losses due to the advisory. Contract growers for the retail channel largely operate with fixed-price contracts and, thus, were unaffected by price changes caused by the incident. Conversely, growers selling in the spot market were exposed fully to price changes, while most contract growers for food service were subjected somewhat to price changes based upon trigger price provisions that are commonly placed in these contracts.

Contract growers were also largely protected from losses due to reduced demand and sales during the advisory period and its aftermath. Grower-processor contracts specify production on fixed acreage or for fixed volumes, and represent a commitment by processors to pay for the contracted product. Processors operate under a minimum 60-90 days planning cycle and contracts often cover an entire growing season. If produce is not needed due to unanticipated market conditions, such as the E. coli incident, processors bear the loss—DC2 in my framework. Only growers selling on the spot market would have incurred losses for

DC2.

Table 2.8 contains estimates of grower losses due to the November 2018 advisory assuming that growers represented half of the sales occurring through spot markets (assumed to be 10% of the total trade), while processors comprised the other half. Table 2.8 shows that growers as a group only experienced modest effects from the advisory and its aftermath. Whereas spot sales incurred losses (indicated by parentheses around the dollar values) relative to the but-for world, contract sellers actually fared better due to price effects that were positive on net. Spot sellers incurred an estimated $347,000 in losses from DC2.

Table 2.8: Damages Incurred by Growers

	DC1	DC2	DC3	Total
Spot Sales	$ (299,000)	$ (347,000)	NA	$ (646,000)
Contract Sales	$ 592,000	NA	NA	$ 592,000
Total	$ 293,000	$ (347,000)	NA	$ (54,000)

2.8.2 Damages to Processors and Shippers

Leafy green processors and shippers were the sector most impacted by the November 2018 E. coli advisory and its aftermath. Processors and shippers incurred losses (DC3) for product that had been harvested and was in their possession at the time of the advisory. I estimate that this loss was approximately $20.649 million (table 2.9). Given the nature of contracting for leafy greens, processors/shippers also bore primary responsibility for planted romaine that could not be harvested and sold, either due to the advisory itself or to reduced demand caused by the incident. I estimate that this loss was substantial—$37.3 million over the advisory period and the aftermath.

The E. coli incident roiled the leafy-green markets, but transmission of price effects was muted by the nature of contracting in the industry, as I have discussed. Processors' contracts with both growers and downstream buyers generally involve either fixed prices, or prices that only change when certain triggers are reached. I estimate that processors incurred minor losses to the extent they were selling on the spot market during this period, but actually gained an estimated $5.7 million from improved margins on contract purchases and sales. On net, across the three damage components, I estimate that processors and shippers lost $52.7 million because of the E. coli incident.

Table 2.9: Damages Incurred by Processors and Shippers

	DC1	DC2	DC3	Total
Spot Sales/Purchases	$ (475,000)	$ (216,000)		$ (644,000)
Contract Sales/Purchases	$ 5,716,000	$ (37,122,000)		$ (31,406,000)
Total	$ 5,241,000	$ (37,338,000)	$ (20,649,000)	$ (52,746,000)

2.8.3 Damages to Grocery Retailers

My analysis of damages in the retail channel focuses on romaine hearts, premium classics, kits with romaine, and blends with romaine. As noted, I am able to convert quantity reductions observed at the UPC level at retail into romaine commodity volume reductions for these products. I exclude random weight lettuce sales and romaine sales in other categories such as bowls. Other categories, in general, have significantly lower sales than hearts, classics, kits, and blends. Additionally, I am not able to account for possible spillover effects to products that do not include romaine. To the extent losses incurred in these categories were not offset by possible gains, they cause the damage estimates to be conservative and can be interpreted as a lower bound on retailer damages due to the outbreak.

Estimated damages incurred by retailers are reported in table 2.10. Grocery retailers were impacted by the advisory through effects on prices of products containing romaine and due to inability to sell romaine products under their ownership control at the time of the advisory (DC3). DC3 comprises the lion's share of retailers' losses, an estimated $18.3 million.

Retailers were impacted as both buyers and sellers due to price effects caused by the advisory. I assumed that retailers as a sector obtained 90% of their romaine product via contract purchases and the remaining 10% through spot purchases. Impacts of the advisory and aftermath period on contract prices paid by retailers for hearts, blends, kits, and premium classics were reported in table 2.3, while figures 2.4 and 2.5 indicate impacts on acquisition costs for retailers sourcing romaine from spot markets.

Given that processor-retailer contracts generally feature fixed prices, table 2.3 shows little movement in prices for contract purchases. Indeed, the only statistically significant impacts appear in the aftermath period, and generally show lower prices paid by retailers, perhaps due to renegotiation of some contracts or reformulation of products to reflect changes in consumer demand for romaine-based products due to the E. coli incident. Retailers who used the spot market to source romaine were subject to wider price swings for both romaine hearts and leaf, with prices rising for salable romaine in the early weeks of the advisory. Prices then turned lower as figures 2.4 and 2.5 document. On balance, the analysis indicates that retailers lost $7.3 million on net due to price effects, but this net figure involves a small price benefit on spot purchases that was more than offset by losses on contract purchases and sales.

Table 2.10: Damages Incurred by Grocery Retailers

	DC1	DC2	DC3	Total
Spot Purchases	$ 1,186,000	NA	$ (1,833,000)	$ (647,000)
Contract Purchases	$ (8,521,000)	NA	$ (16,501,000)	$ (25,022,000)
Total	$ (7,335,000)	NA	$ (18,334,000)	$ (25,669,000)

Impacts of the advisory on prices charged by retailers for romaine products (hearts, blends, kits, and premium classics) were generally minor as well, reflecting the tendency of most retailers to prefer to present stable prices to their customers and the fact that retailers' acquisition costs experienced only minor changes. As table 2.5 shows, prices increased in the early weeks of the advisory for romaine hearts and then in the later weeks and aftermath period for blends. Summing across DC1 and DC3, my estimate is that grocery retailers lost approximately $25.7 million due to the incident.

2.8.4 Damages to Food-Service Operations

I also assumed that food-service operations as a sector acquired 90% of their romaine through contract and the remaining 10% through spot purchases. Table 2.11 shows that impacts of the advisory period and aftermath on food-service operators were minor. I estimate that food service incurred losses of $3.6 million on romaine product in its possession at the time of the advisory (DC3). This small loss for DC3 for food service relative to retail reflects the substantial difference in romaine utilization between the two channels. My estimates are representative of distributor losses but do not account for lost restaurant or institutional sales due to data limitations. To the extend that these lost sales were not offset by increased sales for other menu items, the estimates can be interpreted as a lower bound on food-service operations damages due to the outbreak.

The other impact of the advisory on food-service operations based on this analysis is through acquisition costs for romaine, given I assumed no changes in prices to food service from the incident. Table 2.11 shows that food service received a price benefit of about $2.7 million from lower contract acquisition costs on net over the advisory period and aftermath. Acquisition costs in the spot market were slightly higher on net, to the tune of $250 thousand. Across both DC1 and DC3, I estimate that net losses to food service from the incident were only about $1.2 million.

Table 2.11: Damages Incurred by Restaurants and Food Service

	DC1	DC2	DC3	Total
Spot Purchases	$ (250,000)	NA	$ (360,000)	$ (609,000)
Contract Purchases	$ 2,691,000	NA	$ (3,236,000)	$ (545,000)
Total	$ 2,441,000	NA	$ (3,596,000)	$ (1,154,000)

2.8.5 Impacts on Related Commodities

The econometric analysis indicated some significant price effects for iceberg lettuce in the early weeks of the advisory period. Prices for other leafy greens were little impacted, confirming that iceberg is the key substitute for romaine. Due to data limitations, I was only able to examine impacts for iceberg in the food-service sector and not the retail sector.[16] Tables 2.2 and 2.3 show that processors' acquisition costs increased for iceberg lettuce in the early weeks of the advisory, as did the price they received for iceberg from food-service operators. Conversely, estimated impacts on iceberg volumes were small and mostly not statistically significant, an unsurprising result given that iceberg supplies were largely fixed by planting decisions made in advance of the E. coli advisory.

Based on the estimated price impacts for iceberg, I estimate that growers of iceberg lettuce gained $7.3 million due to the romaine advisory, and processors gained $5.0 million because, although they faced higher acquisition costs, they were able to achieve increased prices to food service that more than compensated those costs. I estimate that food-service lost $12.2 million due to higher iceberg acquisition costs caused by the romaine advisory. Notable and interesting is that the spillover impact on iceberg prices resulted in a much larger loss for food service than the direct price impacts, DC1, for romaine itself.

2.8.6 Overall Welfare Losses

I estimated total societal loss for both the retail and food service sectors based on the methodology described in section 2.5. I estimate welfare losses in the retail channel at the consumer level. For the food service channel, the estimates are based on prices paid by food-service operators, instead of by consumers because I have no way to attach consumer valuations to salads consumed through the myriad of food-service operations.

[16] Similarly, as noted, I was not able to include possible spillover effects for other products not containing romaine in the retail sector analysis.

My approach requires imputing an aggregate price elasticity of demand, ϵ_D, for romaine products. I used values of -0.5., -1.0, and -1.5 for this purpose for both market channels.[17] Total societal losses decrease as demand becomes more elastic, ranging from \$280 million when $\epsilon_D = -1.5$ to nearly \$350 million when $\epsilon_D = -0.5$. About 95% of societal losses are associated with the retail sector based on this analysis. This is due to several factors—the retail channel is much larger, the food-service welfare losses are based on prices paid by food-service operators, not consumers, and on balance quantity reductions on a percent basis were larger for retail than for food service.

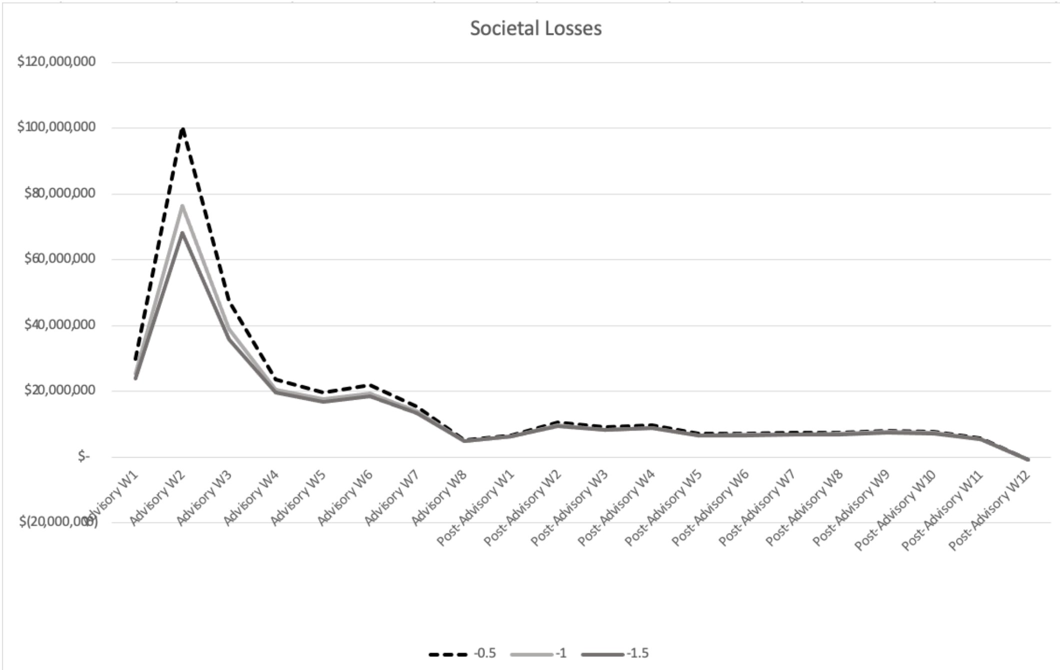
Table 2.12: Total Societal Losses

Total Societal Losses			
	$\epsilon_D = -0.5$	$\epsilon_D = -1$	$\epsilon_D = -1.5$
Retail	\$ (332,082,000)	\$ (282,223,000)	\$ (265,603,000)
Food Service	\$ (17,495,000)	\$ (15,461,000)	\$ (14,783,000)
TOTAL	**\$(349,578,000)**	**\$(297,684,000)**	**\$(280,386,000)**

Figure 2.7 shows the time path of total societal losses for the different demand elasticity values over the advisory period and aftermath. Losses are clearly greatest in the initial weeks when product that had already been harvested and was in various stages of distribution had to be pulled and discarded. In general, losses declined monotonically week by week thereafter, but persisted through 11 weeks after the all clear was issued on January 9, 2019.

[17] For example, an elasticity of -1.0 implies that a 10% increase in price results in a 10% decrease in sales.

Figure 2.7: Societal Losses by Week and Elasticity Value



2.9 Conclusion

I have endeavored to estimate the economic impacts of the Fall 2018 E. coli incident for romaine lettuce. This analysis benefited greatly from extraordinary data access provided by a large leafy-greens processor that, in essence, opened its books to us and whose employees provided great insights into the operations of the industry. I also benefited from the insights of many other leafy-greens industry professionals.

Even with the extraordinary level of access and cooperation I received, estimating the magnitude of damages and especially the distribution of damages across industry participants was challenging, given that most exchange is handled via contracts, with the specific provisions being confidential to the contracting parties. Nonetheless, I was able to show that an incident that was due to the operations of a single farm caused widespread damages to industry participants and society as a whole. Growers tended to be relatively insulated from damages due to the nature of contracts, while processors as a group bore the lion's share of damages within the supply chain. Total societal losses of $280 to $350 million vastly exceeded the losses to any single group of industry participants.

Given that most contracts protect growers from volume losses due to an incident, and price effects may be positive or negative depending upon the interplay of both supply and demand reductions, growers have little direct incentive as a group to improve food-safety practices. The fact that an incident that may eventually be traced to one or a few farms roils the entire industry and imposes widespread losses is a clear prescription for industry-wide measures to address food safety. The LGMA is an industry organization devoted to improving food-safety practices in the leafy greens industries, but participation in LGMA and adherence to its standards is voluntary.

The results also carry important lessons for the CDC and FDA, the public agencies responsible for issuing, refining, and eventually lifting food-safety advisories. Perhaps it is unavoidable that the initial advisories are broad brush until the source of an outbreak can be isolated, but the consequence is significant economic losses for consumers and supply-chain participants who bore no responsibility for the incident. To limit damages, it is imperative that the source of an outbreak be isolated as quickly as possible and then that the advisories be quickly revised, refined, and publicized to reflect new information. Agencies must recognize that their advisories shake consumer confidence in the impacted product and also likely for related products. Romaine is a low-calorie and highly nutritious product, but reduced sales at retail and food service carried forward for many weeks after the all clear was issued, with demand down 25% or more for some romaine salads over the 20-week period studied. In discharging their public responsibilities, it may be reasonable for FDA and CDC to play a more proactive role in reassuring consumers of the fundamental safety of a product like romaine in the aftermath of an incident.

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2.A Damage Formulas

2.A.1 Growers

$$DC_1 = \frac{1}{sr}\sum_{t=1}^{20} .05 * Q_{r,t} * \Delta P_{spot,t} + \frac{1}{sf}\sum_{t=1}^{20} Q_{f,t} * (.05 * \Delta P_{spot,t} + .95 * \Delta P_{contract,t})$$

$$DC_2 = \frac{1}{sr}\sum_{t=1}^{12} .05 * \Delta Q_{r,t} * \hat{P}_{spot,t} + \frac{1}{sf}\sum_{t=1}^{12} \Delta Q_{f,t} * .05 * \hat{P}_{spot,t}$$

2.A.2 Handlers

$$\begin{aligned} DC_1 =& \frac{1}{sr}\sum_{t=1}^{20} .Q_{r,t} * (.9 * \Delta P_{r\_wholesale,t} + .05 * \Delta P_{spot,t}) + \\ & \frac{1}{sf}\sum_{t=1}^{20} .Q_{f,t} * (.05 * \Delta P_{spot,t} + .9 * \Delta P_{f\_wholesale,t} - .95 * \Delta P_{raw\ product,t}) \end{aligned}$$

$$\begin{aligned} DC_2 =& \frac{1}{sr}\sum_{t=1}^{12} \Delta Q_{r,t} * (.05 * (\hat{P}_{spot,t} - c_{harvest,t}) + .9 * (\hat{P}_{r\_wholesale,t} - c_{labor,t} - c_{harvest,t})) + \\ & \frac{1}{sf}\sum_{t=1}^{12} \Delta Q_{f,t} * (.05 * (\hat{P}_{spot,t} - c_{harvest,t}) + .9 * (\hat{P}_{f\_wholesale,t} - c_{labor,t} - c_{harvest,t})) \end{aligned}$$

$$DC3 = \frac{1}{sr}\Delta Q_{r,2} * \hat{P}_{r\_wholesale,2} + \frac{1}{sf}\Delta Q_{f,1} * \hat{P}_{f\_wholesale,1}$$

2.A.3 Retail

$$DC_1 = \frac{1}{sr}\sum_{t=1}^{20} Q_{r,t} * (\Delta P_{retail,t} - .1 * \Delta P_{spot,t} - .9 * \Delta P_{r\_wholesale,t})$$

$$DC3 = \frac{1}{sr}\Delta Q_{r,1} * \hat{P}_{retail,1}$$

2.A.4 Food Service 6/1

$$DC_1 = \frac{1}{sr}\sum_{t=1}^{20} Q_{f,t} * (-.1 * \Delta P_{spot,t} - .9 * \Delta P_{r\_wholesale,t})$$

$$DC3 = \frac{1}{sr} Q_{r,-1} * P_{restaurant,-1}$$

2.B Additional Regression Figures

Grower

Figure 2.B.1: Raw Product Cost for Processors: Retail Romaine

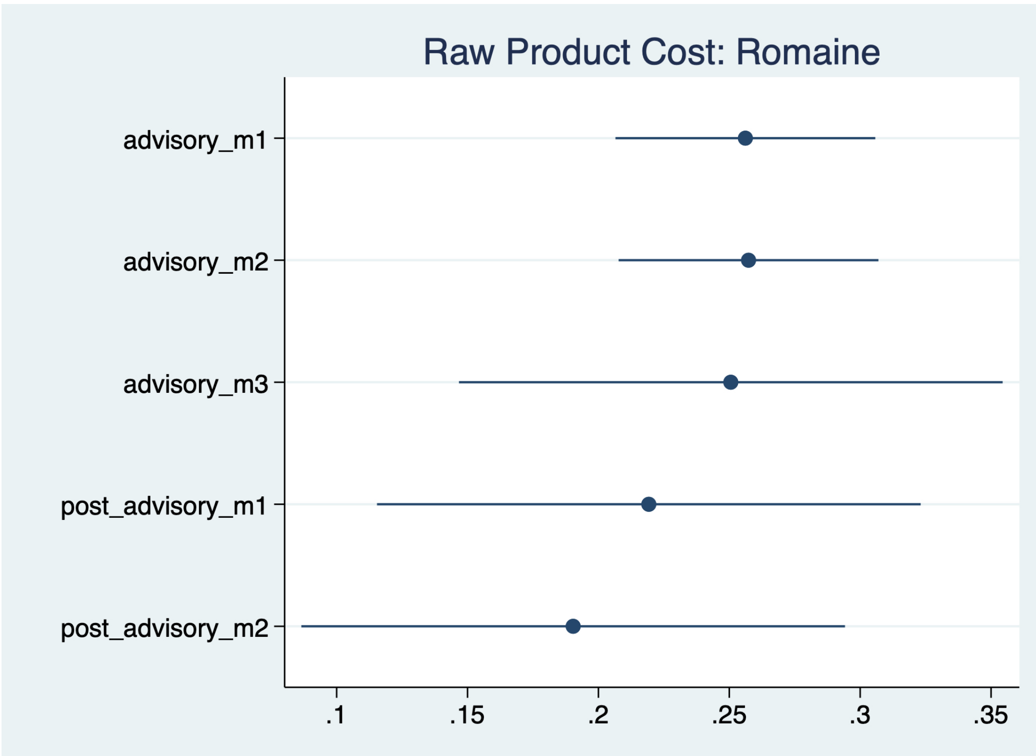


Figure 2.B.2: Raw Product Cost for Processors: Food Service Romaine

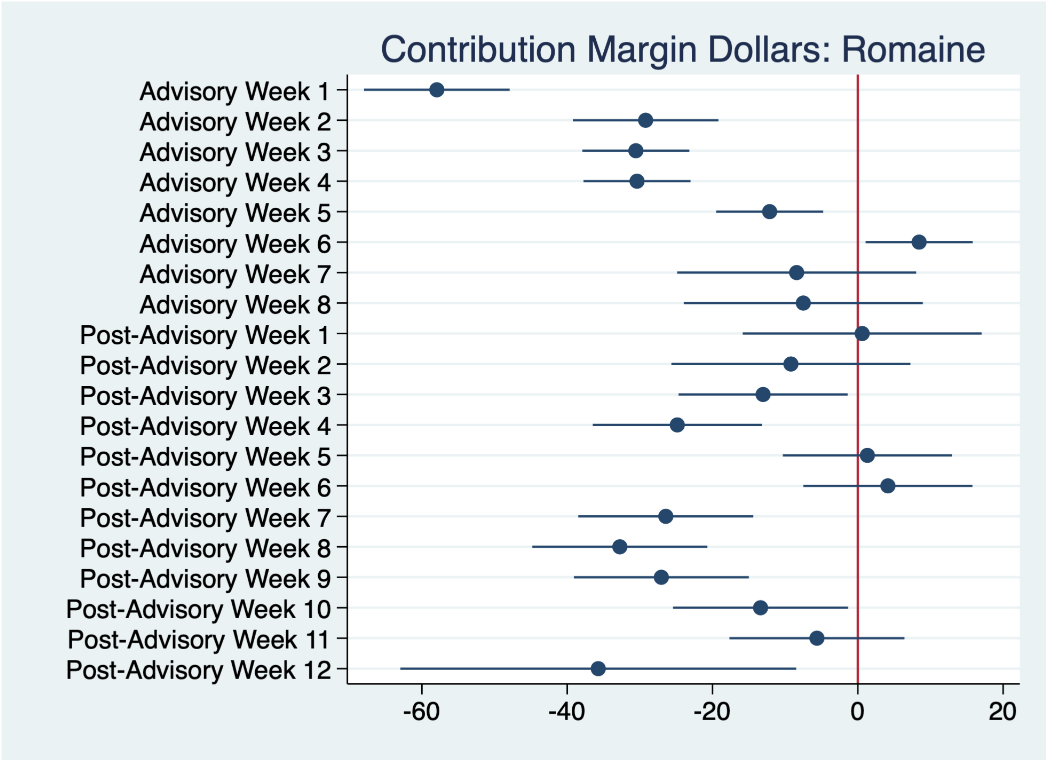
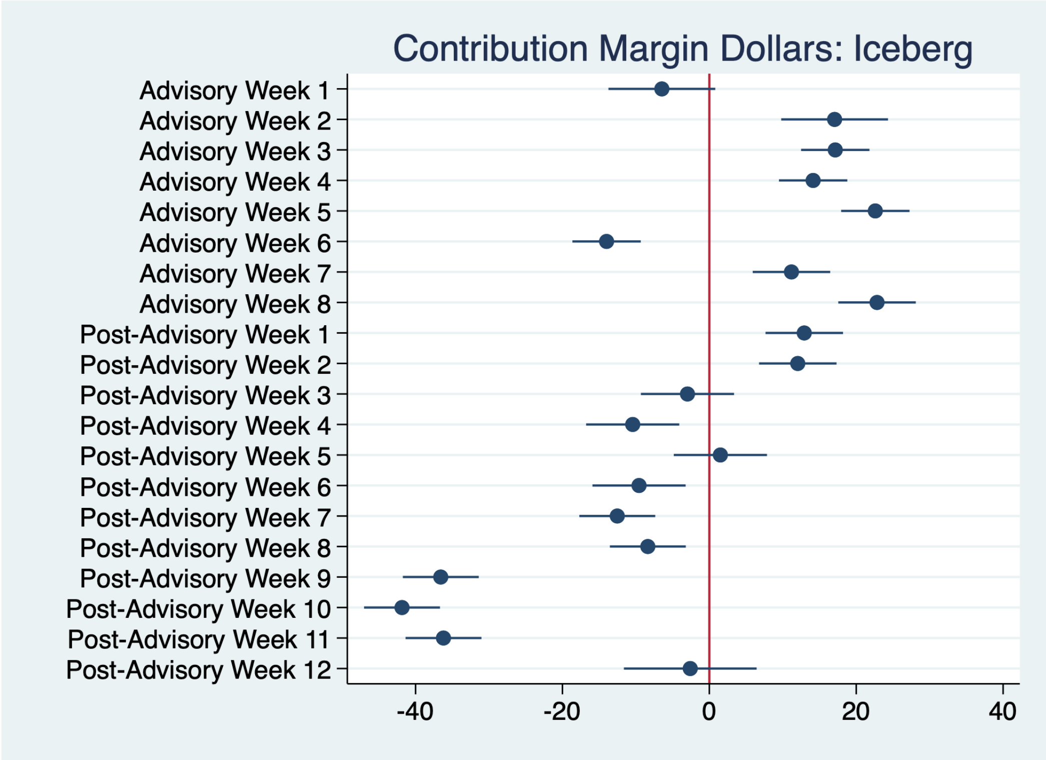


Figure 2.B.3: Raw Product Cost for Processors: Food Service Iceberg



Retail

Figure 2.B.4: Wholesale Price Regression Estimates for Romaine Hearts

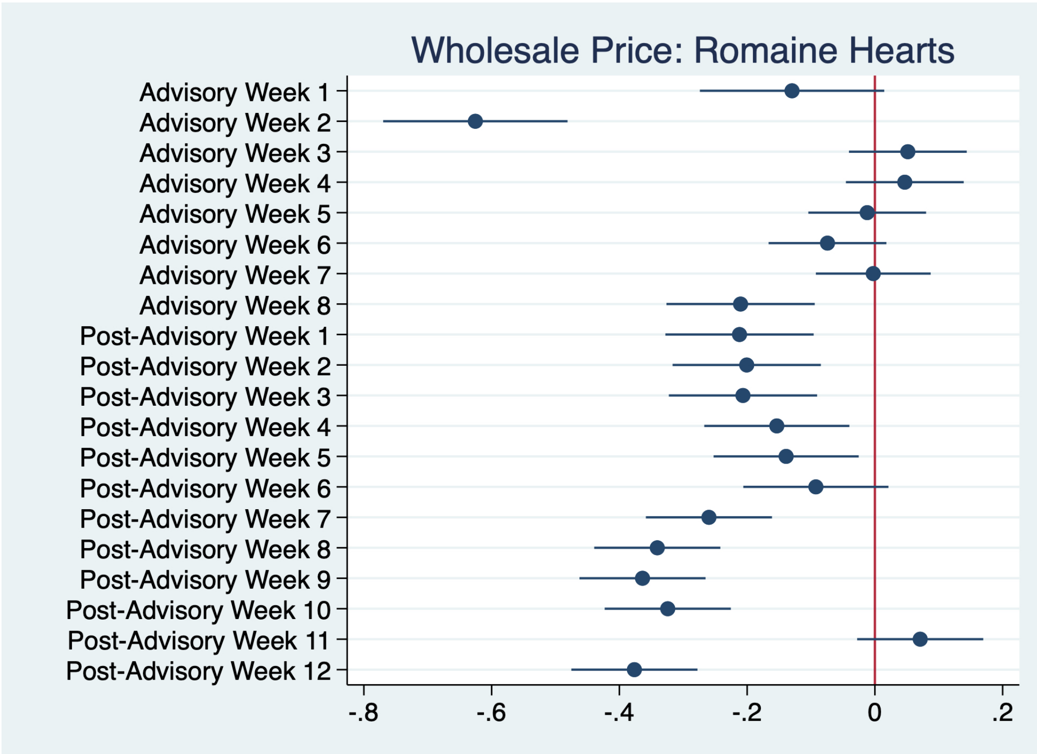


Figure 2.B.5: Wholesale Price Regression Estimates for Blends

Figure 2.B.6: Wholesale Price Regression Estimates for Kits

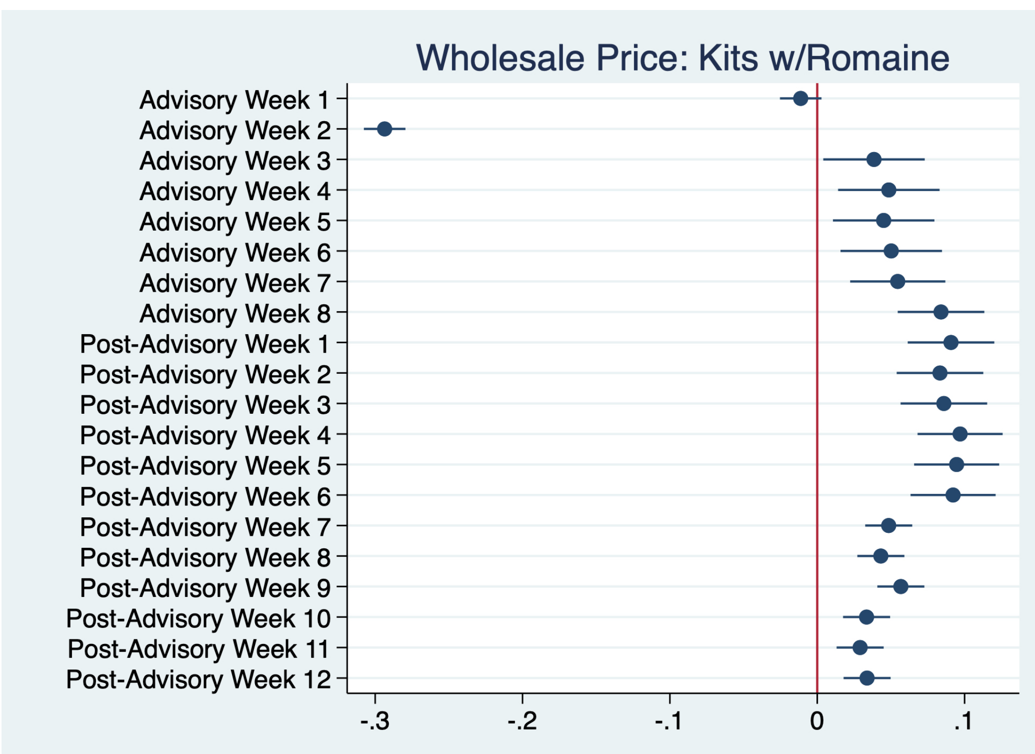


Figure 2.B.7: Wholesale Price Regression Estimates for Premium Classics

Retail

Figure 2.B.8: Retail Quantity Regression Estimates for Romaine Hearts

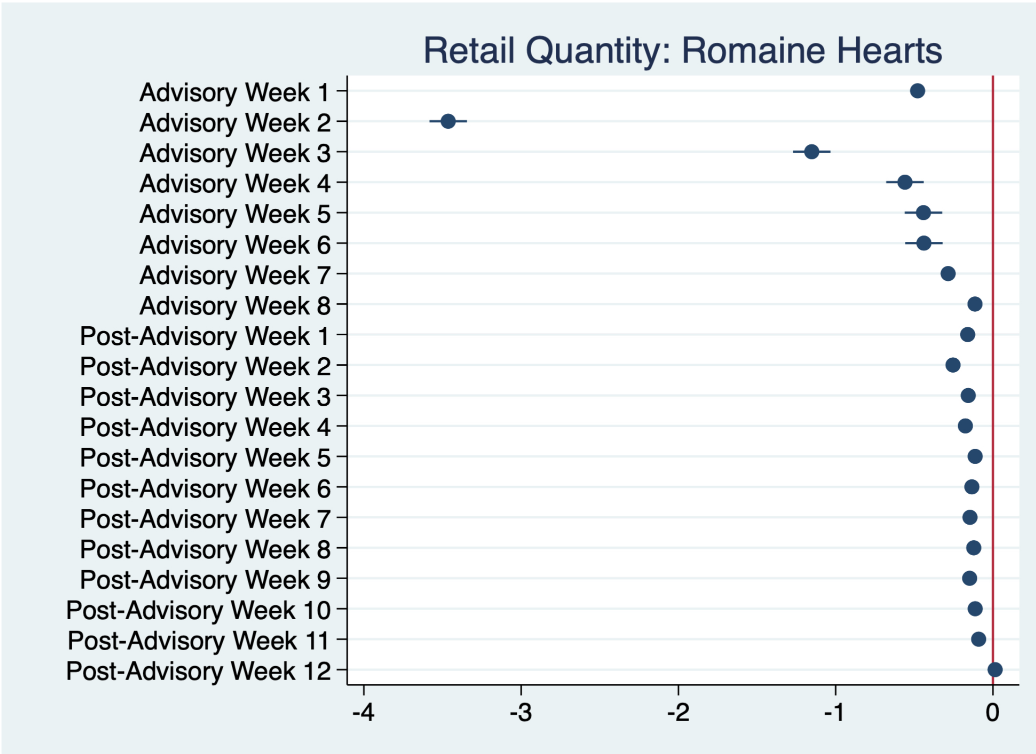


Figure 2.B.9: Retail Quantity Regression Estimates for Blends

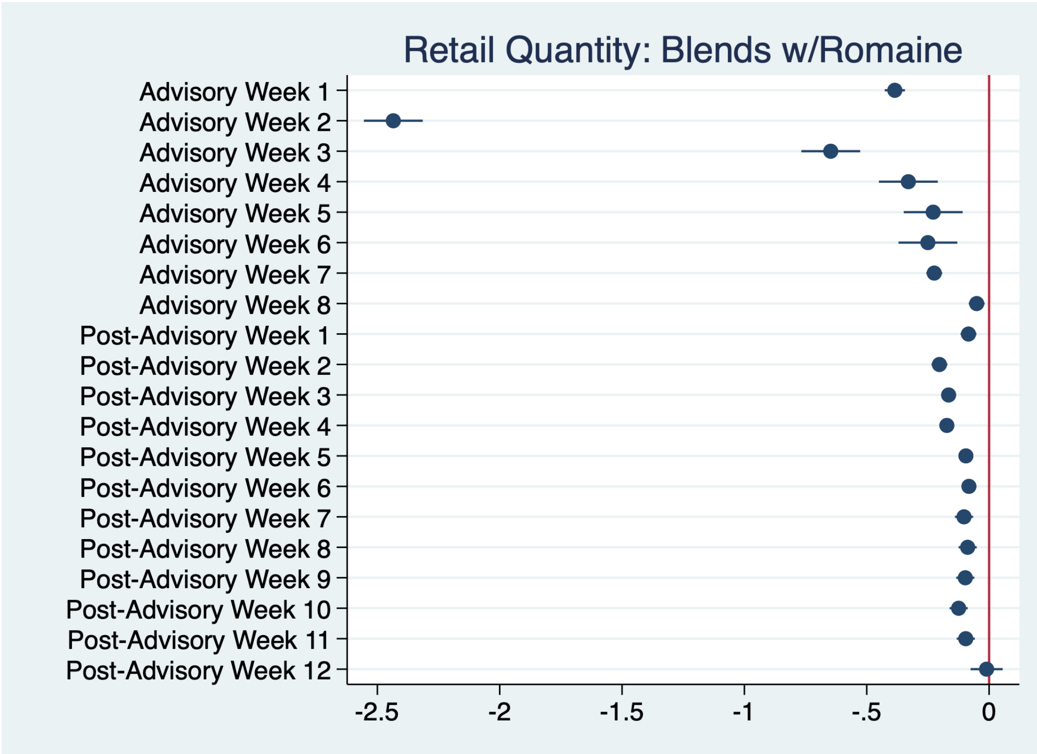


Figure 2.B.10: Retail Quantity Regression Estimates for Kits

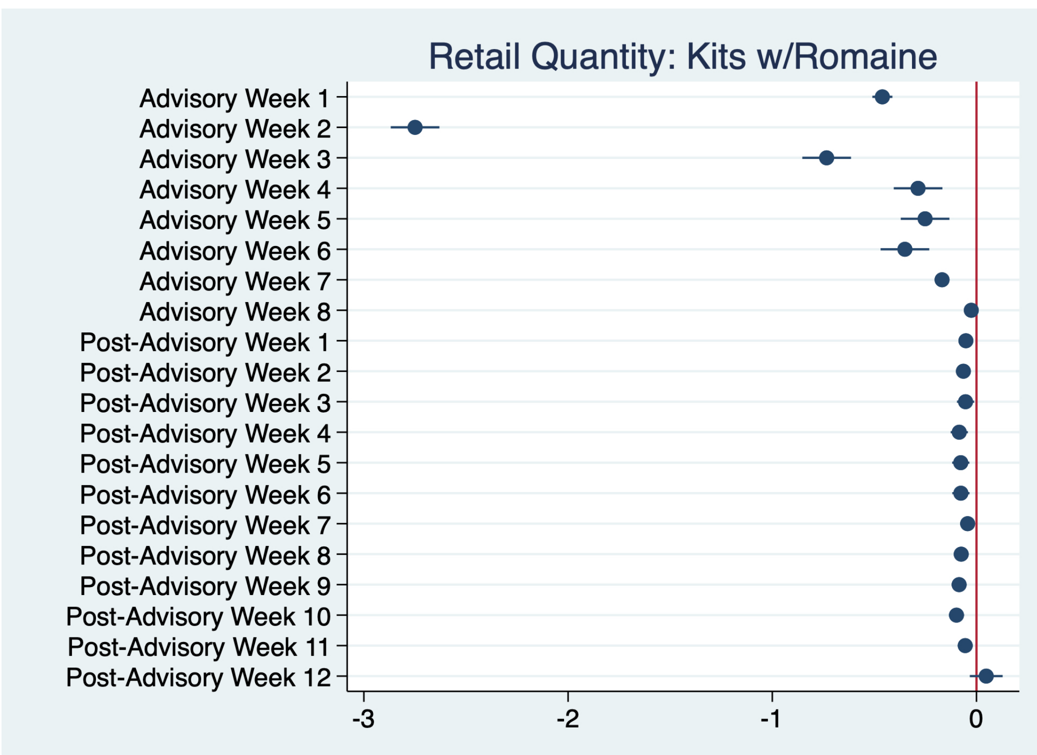
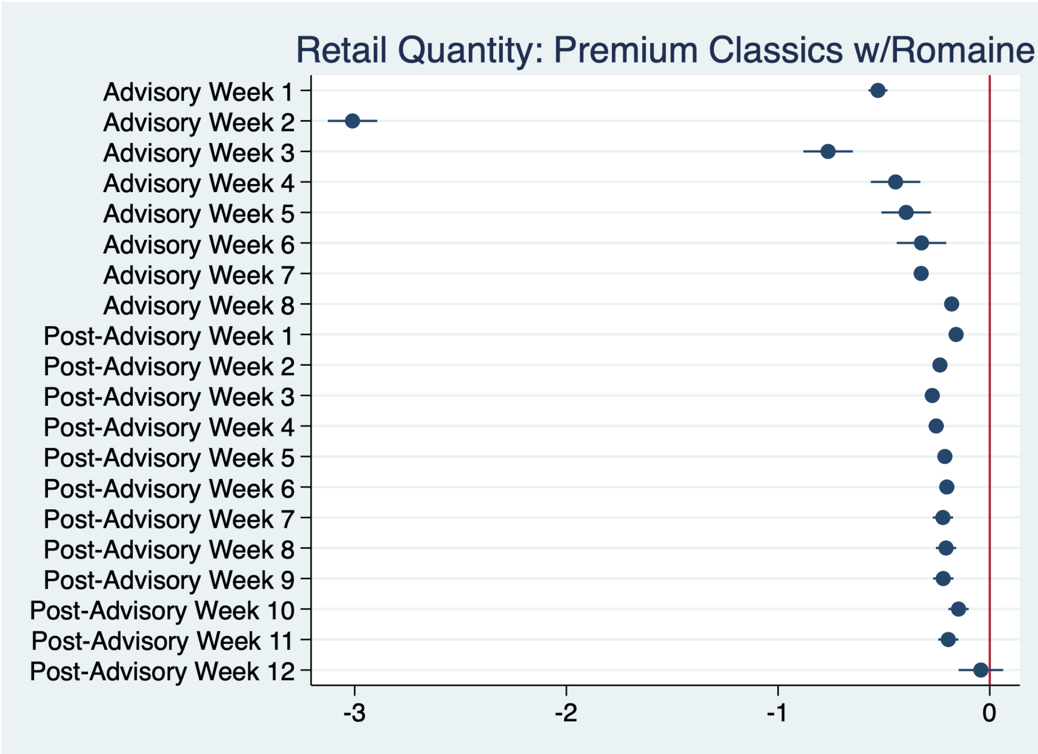


Figure 2.B.11: Retail Quantity Regression Estimates for Premium Classics



Food Service

Figure 2.B.12: Food Service Wholesale Price Regression Estimates for Romaine

Figure 2.B.13: Food Service Wholesale Price Regression Estimates for Iceberg

Figure 2.B.14: Quantity Sold to Food Service Regression Estimates for Romaine

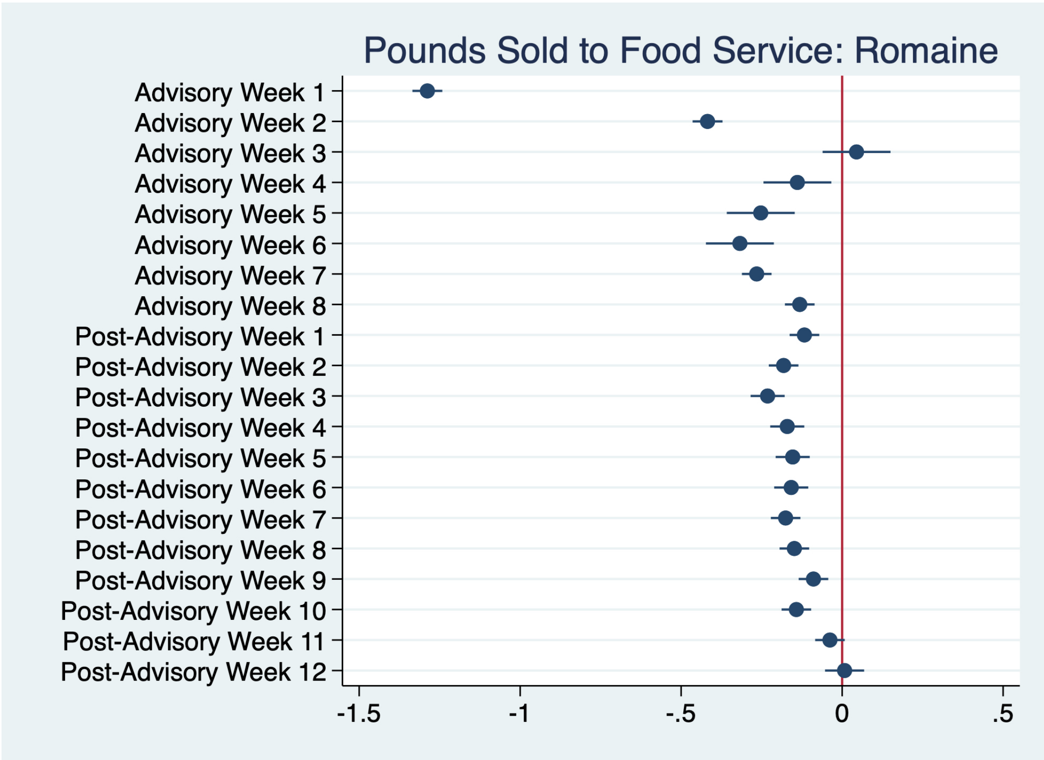
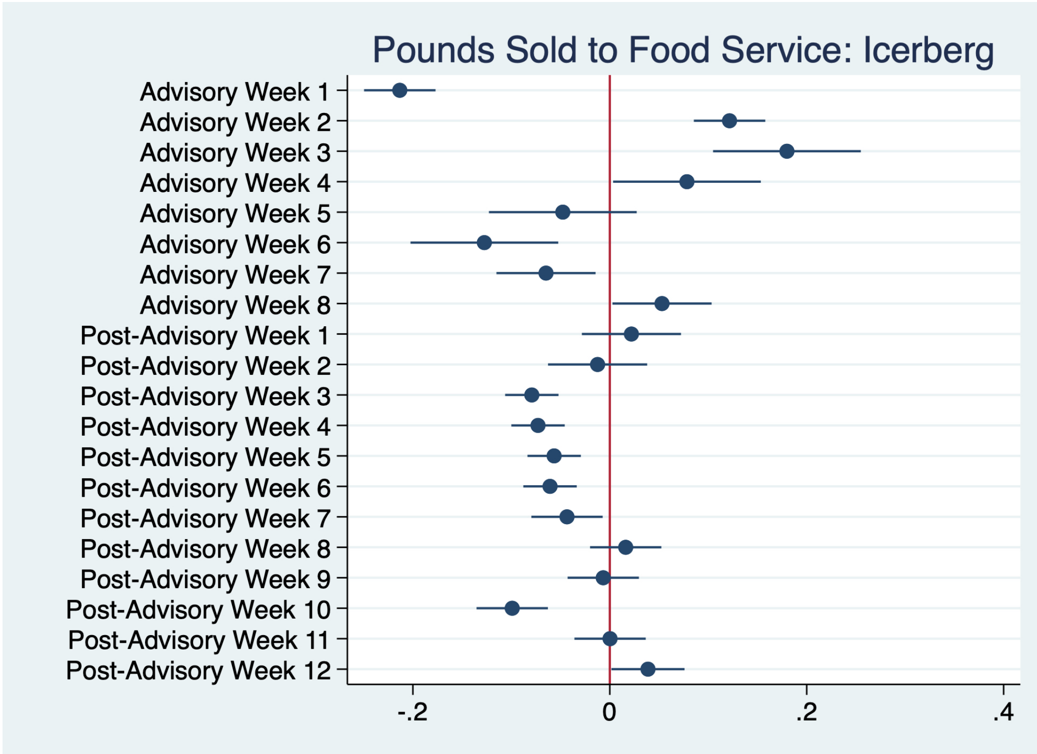


Figure 2.B.15: Quantity Sold to Food Service Regression Estimates for Iceberg



Essay 3

Consumer Preferences and Marketing Strategies for Locally Produced Foods: A Retail Labeling Experiment

3.1 Introduction

The U.S. government has shown strong support for local food systems as a means of economic development. Between 2009 and 2015, the U.S. Department of Agriculture (USDA) invested over $800 million in local and regional food businesses and infrastructure projects, and in 2015, it named local and regional food systems as one of the four pillars of agriculture and rural economic development (Vilsack, 2016).[1] In doing so, the agency reaffirmed its commitment to creating local markets, growing regional businesses through strong regional supply chains (e.g., food hubs), making resources more accessible to help regional food systems grow, and pursuing expanding markets (e.g., schools, hospitals, retailers, and institutional and wholesale buyers).

The extent to which the local food movement can support policy goals will depend largely

[1]The other three pillars are bio-based manufacturing, conservation markets, and agricultural production.

on how consumers respond to marketing strategies available to local producers. Increased participation in local food markets and new marketing opportunities for local foods are likely driven by consumer preferences rather than a full suite of policy priorities. A pre-pandemic Nielsen study comparing awareness of 16 different food-related causes ranked local production higher than any other quality dimension, including avoidance of genetically modified ingredients and organic production (Nielsen, 2019). Further, a number of academic studies have indicated that consumers have a preference for local foods and are willing to pay an additional premium for them (see Martinez et al. (2010) for an overview). Despite this, local food markets continue to account for a small share of U.S. agricultural production and food sales, indicating there may be a disconnect between consumers stated preferences and their purchasing behavior.

The primary purpose of this study is twofold: 1) to develop a better understanding of consumer preferences for locally produced foods and their interdependence with other value-added attributes and 2) to explore whether consumers' stated and revealed preferences for local foods align. I focus largely on value-added food products because foods are increasingly marketed as such due to advancements in production practices and post-harvest technologies. Generally defined as products that have been altered or packaged in a way that is not required for transportation before being sold, these goods typically command a higher price than unprocessed commodities and can provide agricultural producers with means to increase revenue while making use of excess output.[2] Being able to successfully market food products as locally produced, like many new quality dimensions, critically depends on identity-preserving marketing systems and compelling disclosure of information to consumers. How consumers react to local labels in today's complex retail environment, and what implications can be drawn regarding the effectiveness of local marketing strategies, especially for small and medium-sized regional producers, is ultimately an empirical

[2]The USDA defines value-added products based on a change in the physical state or form of the product, the production of a product in a manner that enhances its value, or the physical segregation in a manner that results in the enhancement of the value of the product (Agricultural Marketing Resource Center, 2021).

question.

In collaboration with two local food co-ops, I designed and distributed a survey that assesses differences in willingness-to-pay (WTP) and intensity of preference for local produce and processed foods and examines consumer perceptions of what a "Local" label communicates. Both stores clearly define local foods based on a specific distance these goods traveled from production to consumption and carry a variety of goods that meet these definitions. At the time of the survey, both stores already promoted local produce via in-store displays and were planning to implement "Local" labels in other product categories. I subsequently conducted a market-level experiment that introduced "Local" shelf labels to products in five categories in one of these stores and collected detailed information on product claims, product placement, and promotions for products in each store. By jointly analyzing stated and revealed consumer preferences, this analysis provides insights on the extent to which the two are aligned and explores how and why consumers react to "Local" labels in today's complex retail environment.

Much of the research on willingness to pay (WTP) for local foods uses stated preference methodologies, such as surveys (Carpio and Isengildina-Massa, 2009), hypothetical field and laboratory experiments, or auctions (Willis et al., 2013). These studies fail to connect stated preferences to consumers' retail behavior with regard to local foods. Furthermore, this research has focused primarily on agricultural commodities, largely ignoring additional branding opportunities and current consumer trends toward value-added products. Even without consideration of increased product differentiation in today's agricultural markets, consumers' stated purchase intentions do not always correspond to their stated purchase behavior (Morrison, 1979; Morwitz, 1997).

The empirical strategy in this analysis draws on insight developed in the advertising literature over the last 50 years. This literature distinguishes between local production as a one-dimensional searchable product attribute or a perceived multi-dimensional quality that consumers cannot easily verify even after purchasing a product. The growing behavioral economics literature that relies on models of explanatory preferences and motivated beliefs to better understand decision-making under uncertainty allows me to offer a tentative explanation for why consumers might not become better informed and systematically adjust their preferences.

The vast majority of shoppers at both stores expressed a preference for locally produced produce and processed foods. Respondents valued both local ingredients and local production for processed foods but placed a larger emphasis on local ingredients. Over half of the respondents were able to name specific local brands and were aware of existing promotional efforts to highlight local foods at their store. Their knowledge and perceptions of what local means differed greatly, however. Few (10%) could correctly state their store's definition of local production, and when asked to pick the statement most likely to be associated with a "Local" label displayed by either store, the storeâs definition of local was not ranked as the most likely association. Rather, respondents ranked a conjunction of traits such as organic production, small or artisan production, and an overall higher quality as more likely to be associated with the "Local" label. This suggests consumers' preferences for local foods are driven by a complex array of perceived quality attributes.

The preferences expressed in the survey do not carry forward to increased sales for products affixed with a "Local" label in the retail experiment. An analysis of the sales data in a triple-triple difference framework fails to detect significant average treatment effects. I do, however, detect significant heterogeneous treatment effects for select products. For instance, across all products and relative to products with no manufacturer claims, "Local" labels have a smaller effect on sales of organic products. Similarly "Local" shelf labels have a smaller effect on sales for products with packaging that highlights their geographic origin relative to products without a specified geographic origin. The results are consistent with the idea that the experimental labels primarily draw attention to or highlight products at the point of purchase, and might be more effective for products that do not already capture consumers' attention through manufacturer's claims, retailer discounts, or prime shelf-positioning.

Together, these results indicate that consumers likely overstated their preferences for local foods. Local labels, even if based on specific, proximity-based definitions of local production, may not provide consumers with information that causes them to change their purchasing behavior. Selective inattention and present bias might prevent them from updating their beliefs of which products are indeed locally produced and seeking those products out repeatedly. While consumers might respond to these labels for select products when they are present on shelves and this information is easily accessible, they might revert to their perceptions of which foods are local in the long term and only remember and repeatedly seek out products for which their experience supports their previously held beliefs. As such, local labels might be more effective when combined with other marketing strategies that capture consumer attention at the point of purchase. This interdependence suggests that marketing value-added goods with local labels implemented at the retail level may do little to strengthen local and regional food systems. To the contrary, they might limit rather than strengthen marketing opportunities for small and medium-sized farmers and food producers and put them at a disadvantage in today's increasingly concentrated retail and media environments.

3.2 Definitions, Policy Priorities, and Market Trends for Local Foods

The 2008 Farm Act defined local foods as those sold fewer than 400 miles from the productâs origin or within the state in which the product is produced. This definition has been used for funding purposesâbetween 2009 and 2015, the USDA invested more than $1 billion in local food businesses and regional food systemsâbut definitions of "local" used for marketing purposes continue to vary (Low et al., 2015; Martinez et al., 2010; Plakias, Demko, and Katchova, 2020). While buying foods grown and produced closer to where you live is commonly viewed as a means to improve the environmental footprint of food systems, federal, state, and local governments link increasing consumer demand for local foods to a wider range of policy goals. They extend beyond enhancing the environmental sustainability of food production and consumption and include support for rural economies, strengthening of agricultural producers and markets, increasing nutrition intake and access to healthier foods, or simply wanting to better inform consumers about where, how, and by whom their food was produced (Vilsack, 2016).

Policymakers increasingly rely on transparency approaches or compelling disclosures of information as a means of ameliorating externalities and improving the provision of public services, especially when polarized political environments limit the ability to implement more restrictive policy tools such as bans, taxes, or subsidies. However, a focus on better informing consumers and relying on their purchasing power to nudge markets towards more sustainable food systems defined by desirable environmental, social, and economic outcomes has its own unique challenges. A careful consideration of market settings and strategic firm responses coupled with new insights from behavioral research will be crucial in determining how effectively targeted transparency approaches can achieve specific policy goals (Weil, Grahman, and Fung, 2013).

Defining the role marketing strategies for local foods play in advancing overall sustainability goals might require a narrower focus on specific policy goals. It is generally accepted that many factors unrelated to local production and transport miles, such as efficiencies and dietary choices, matter when analyzing the environmental sustainability of food systems. In terms of social sustainability, local food systems can contribute to a sense of community but are not necessarily more resilient. Few communities can achieve self-sufficiency in food production. Further, local foods, especially local foods produced by small and medium-size enterprises, can be less affordable for consumers. Effectively marketing local foods, however, could contribute to rural development, increase employment opportunities, and strengthen local economies overall (Stein and Santini, 2021). A key aspect in that regard might be a reliance on shorter supply chains and more direct marketing channels that keep the value added in these communities. While no uniform standard in terms of distance traveled has emerged, the promotion of local food systems is often understood as support of local ownership and short supply chains. (Low et al., 2015; Plakias, Demko, and Katchova, 2020).

The USDAâs Local Food Marketing Practices Survey collects information directly from farmers participating in local and regional food systems.[3] In 2015, about 167,000 farms (or 7.8% of all U.S. farms) participated in local and regional markets and sold $8.7 billion worth of local foods.[4] They sold through direct-to-consumer (DTC) channels (e.g., via farmers markets, farm stores or stands, and community-supported agriculture arrangements), reached local consumers through institutions or intermediary marketing channels (e.g., local distributors such as food hubs), or sold directly to retailers. Sixty-nine percent used direct-to-consumer sales, 36 % sold to institutions or through intermediary channels, and 14% sold directly to retailers in their local communities (U.S. Department of Agriculture, National Agricultural Statistics Service, 2016).[5] Small farms were more likely to sell DTC, medium-sized farms more often sold to local intermediaries, and both were less likely to sell to retailers (grocery stores and restaurants) than large farms (Plakias, Demko, and Katchova, 2020).[6]

Participation in DTC channels only amounted to 35% of all dollar sales reported in the survey (Low et al., 2015). The Census of Agriculture further indicates that though the number of farms selling directly to consumers has steadily increased, between 2007 and 2012, overall DTC dollar sales did not. Furthermore, while the number of farmers markets in the U.S. increased by roughly 3,500 in the past decade to a total of 8,771 in 2019, growth has slowed to less than one percent annually since 2016 (U.S. Department of Agriculture, Agricultural Marketing Service, 2021). Opportunities to market local foods through DTC channels might have plateaued long before the pandemic, and small and medium-sized en-

[3]"Local and regional food systems" are defined as place-specific clusters of agricultural producers (e.g., all kindsâfarmers, ranchers, fishers), along with businesses, institutions, and consumers engaged in processing, distributing, selling and buying foods (Low et al., 2015)

[4]Numbers for 2020 have been collected but are not yet available.

[5]Some farmers sell via more than one marketing channel.

[6]The current USDA cutoff defining small farms is $350,000 in gross annual income generated, but this study defined small farms as those with $1-249,999 in gross value of sales and large farms as those with more than $1 million based on the data collected in the survey.

trepreneurs using these channels are competing with each other for a relatively small overall share of food sales.

Sales directly to institutions, retailers, and other local intermediaries accounted for the remaining share of local and regional sales (64%), though total added value generated through retail channels is neither accurately captured by this data, nor is it easily measured via other sources. Added value associated with proximity of production is only relevant to consumers in specific geographic regions, making it more likely that local products are promoted directly at retail locations rather than via package claims.

Nielsen, the leading industry source for consumer purchase data, tracked $239 million in sales of local foods based on package claims in 2019 (Nielsen, 2019). Large retail chains source between 25 and 40% of their produce locally, and Walmart might be the largest buyer of local foods.[7] These retailers have begun to market local foods more aggressively via shelf labels. Industry experts have estimated that sales of local foods more than doubled from $5 billion in 2008 to $12 billion in 2014, and anticipated that sales would reach $20 billion by 2019. Some argued that sales of local foods could eclipse organic food sales (Tarkan, 2015). [8]

Retailers will likely continue to promote local foods strategically, and especially since consumers state that one of the main barriers to buying more local foods is that they are not clearly advertised (Burt, Silvermann, and Goldblatt, 2015).

[7] Walmart does not share their store-level scanner with Nielsen.

[8] These numbers are based on a proprietary study conducted by Packaged Facts, a marketing research firm that is referenced in the source cited here.

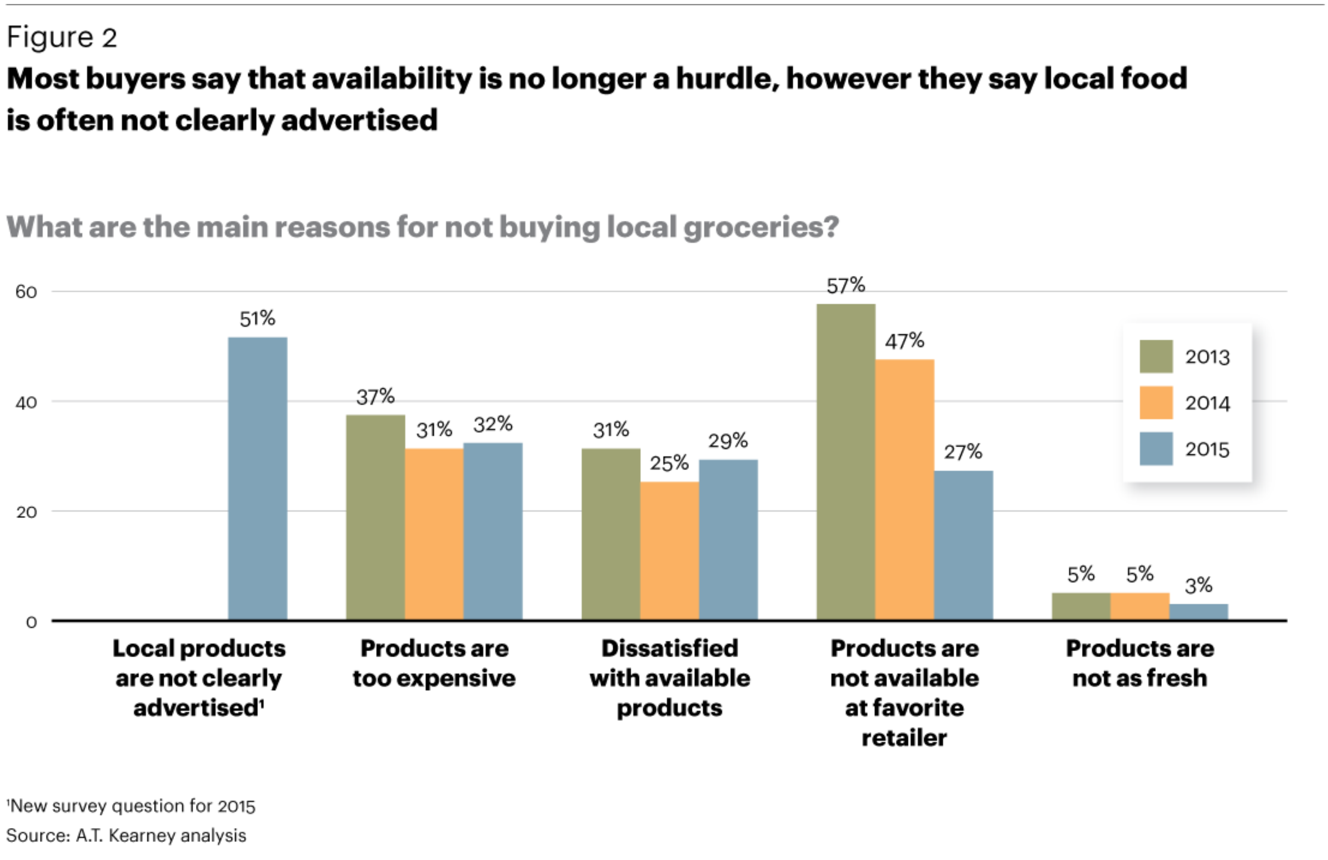


Figure 3.1: Reasons for Not Buying Local Foods

Why consumers value local foods might be more complex, however. Their perceptions range from the belief that baked goods, eggs, and produce are local only if they originate in the same city/town as where they are sold, to the beliefs that milk and dairy are local if they are produced in state, and frozen and shelf-stable goods are local as long as they are made in the U.S. (Nielsen, 2019). The environmental impact of transport miles might be part of their considerations. Foods that travel fewer miles or are marketed via direct marketing channels might taste fresher or retain more nutrients, and smaller regional producers might use more authentic recipes. Some consumers associate "localness" primarily with adherence to organic and/or sustainable production practices, and are focused on community impacts of production (where community impacts include a desire to support small, independently owned enterprises and access to healthier foods for all community members).

Consumers might not always be getting what they think when they buy local foods in grocery stores, and local labels might be used as marketing hype in these settings rather than as a way to better inform consumers about production practices. Whether unregulated marketing strategies for local foods successfully support economic viability of small and medium-sized enterprises in local and regional markets despite increased product differentiation and concentration in manufacturing, distribution and retail (Sexton, 2013) will depend on how they react to local labels in these settings.

3.3 Empirical Strategy and Data Collected

The empirical strategy aims at jointly analyzing consumer perceptions of local foods and reactions to “Local" shelf labels implemented in a real market setting. I collect new and unique data allowing me to better understand stated and revealed consumer preferences for local foods and discuss the effectiveness of unregulated marketing strategies. Importantly, I make a clear distinction between marketing strategies that can turn local production into an easily accessible search attribute (e.g., defined by proximity of production and clearly specified mile radii) and potentially more complex quality dimensions that might be the basis of strong consumer preferences for local foods.

As first argued by Nelson (1974, 1970), advertising and marketing strategies pursued by firms are primarily a result of consumer decision-making under uncertainty about product quality. Nelson argues that while all advertising is beneficial to consumers when making decisions under uncertainty resulting from incomplete information, how useful the information provided by advertising is to the consumer when trying to resolve information asymmetries varies. The marginal benefit of informative advertising that allows consumers to form accurate expectations and choose products most closely aligned with their preferences is higher than that of persuasive advertising that only provides indirect information merely signaling the product's existence. Consumer purchasing power can nudge firms towards providing more direct information. The regulatory effect of this purchasing power is greater, however, when products can be differentiated by (one-dimensional) searchable attributes rather than by (multi-dimensional) experience qualities. Products differentiated by experience qualities can be defined as products for which consumers can determine quality differences in a less costly manner via personal experience post purchase, even if they might be able to form accurate expectations about these differences by engaging in a more costly information search prior to purchasing a product.

Darby and Karni (1973) introduced credence qualities as an additional quality dimension often used to describe production attributes such as local or organic. Information search is even more costly, and accuracy can not be verified even after purchase. While it is plausible to assume that clearly specified definitions, and in some cases, regulation or certification of advertising claims can turn these quality dimensions into searchable attributes, consumers might not properly update their perceptions and assumptions. As an example, the National Organic Program regulates and certifies organic claims to mean that producers employ an ecological management system that focuses on the use of renewable resources and the conservation of soil and water to enhance overall environmental quality of production inputs, yet a large share of consumers believe that organic foods are better tasting and healthier than conventionally produced but otherwise equivalent products (Funk and Kennedy, 2016).

More recent advertising models that distinguish between the persuasive, the informative, and the complementary nature of advertising provide additional insights. Advertising and product claims that simply draw attention to a product can persuade or remind consumers of its existence and aim at creating a uniform perception that the product is high quality. In contrast, advertising and claims that are directly informative to at least some consumers might trigger a re-evaluation of purchasing choices. Of course, providing such information does not necessarily increase demand for all products, and adding these claims could reduce sales of some (Johnson and Myatt, 2006). Ackerberg (2003, 2001) argued that one could empirically distinguish between persuasive (indirectly informative) and informative advertising by observing behavior of inexperienced and experienced consumers. Both groups can be persuaded by advertising, but only less experienced consumers should be affected by informative advertising.

In collaboration with these two local consumer co-ops (henceforth, Store 1 and Store 2), I surveyed consumers to obtain information about their preferences and perceptions about local foods. I then implemented shelf labels promoting locally produced, value-added food products in several product categories in one store these consumers frequent. These unique data allow me to jointly analyze stated and revealed preferences for local foods and discuss the effectiveness of unregulated marketing strategies.

I chose the two stores for this study because they are cooperatively owned by their members who regularly shop at these stores and operated within the same local or regional food system. These stores prioritize sourcing their products whenever possible from the same agricultural production region and are more likely to use shorter and more direct marketing channels when buying processed products than large national chains. Both stores also clearly define what they mean by local foods based on a mile radius (200-mile radius for Store 1 and a 100-mile radius for Store 2) in which these products need to be produced, and they communicate these definitions to their consumers via newsletters and social media. The promotion of local foods in these stores (as compared to Walmart or other national chains) is more closely aligned with the above summarized policy approaches, and customers shopping at these stores hold values that match with complex policy goals as well. The fact that stores are independently owned and operated makes it slightly more challenging to define one as a treatment and the other as a control store than if the stores were part of a chain. That they are a similar type of store, serve customers in the same geographic region, and carry similar products, makes this approach feasible, nevertheless.

The experimental "Local" shelf labels implemented do not explicitly reference the store definition. If consumers are familiar with this definition and updated their perceptions about local foods accordingly, the labels directly inform them which products are produced locally. They can better identify these products and choose to purchase them. I would expect these labels to significantly increase sales of local foods on average. Having learned that these products meet the store's definition of "local", they could repeatedly seek them out even after the labels are removed. If despite having received feedback from their stores about what "local" means, consumers are not updating their beliefs and perceptions, these labels might at best highlight products at point of purchase they have not already noticed, or reinforce their choice or already established preference for products that captured their attention at point of sale prior to the posting of "Local" shelf labels.

3.3.1 Soliciting Data on Stated Consumer Preferences

I created an online survey which was distributed by both Stores 1 and 2 to their customers via a mailing list in March of 2019. The survey, included in full in Appendix A, assessed consumers' sense of their preferences for locally produced foods, the differences in WTP and intensity of preference for local produce and local value-added products, and which traits consumers associate with local production. Eight hundred and sixty-two customers, 475 from Store 1 and 387 from Store 2, responded to the survey.

The survey begins by eliciting the strength of respondents' preferences for local produce and, separately, local, value-added food products. Using a seven-point Likert scale, I asked respondents to indicate the degree to which they agree or disagree that they have a preference for locally grown produce. The survey then poses a similar question but in reference to locally produced, value-added goods. It may be that consumers value local, value-added goods because they are produced locally or because they could contain local ingredients. To disentangle this, I followed up the prior question by asking respondents the degree to which they agree or disagree with the statement, "For locally produced, value-added food products (e.g., jams, olive oil, salsa, etc.), it is important to me that the good also contains locally grown ingredients." These three questions serve to immediately and directly establish consumers' preferences for different types of local foods.

The survey then asked customers how much more they would be willing to pay for a food product (e.g., a jam) that carries a "Local" label if a similar but unlabeled food item costs $3.00 at a supermarket. Organic production is the most prominent value-added food attribute and previous studies indicate that consumers might assign independent and complementary values to locally and organically grown foods (Onuzaka and McFadden Thilmany, 2011). I, therefore, also asked customers specifically how much more they would be willing to pay for an organic product that carries a "Local" label if a similar organic food item (not labeled as local) costs $3.00 at the supermarket.

In addition to measuring stated preferences and willingness to pay for local foods, I sought to better understand what underlies these preferences. I examined what associations consumers make when they see a "Local" label and if these associations might be influenced by motivated reasoning or subjective beliefs. In particular, I focus on testing for the availability heuristic and confirmation biases as an indication of whether consumers treat local production as a search attribute or experience quality. I did so by asking customers to rank a series of statements, shown in question 8 of Appendix A, based on the perceived likelihood that they are associated with a store's "Local" label or promotion. I include organic production, support of smaller farms or food businesses, and the general notion that these production attributes translate into a higher overall product quality.

Additionally, I tested for the presence of the conjunction fallacy, defined as the perception that multiple conditions combined are more probable than a single condition (Twersky and Kahneman, 1983) by including statements with two or more conditions (e.g., "The food item was produced according to the co-opâs definition of local and uses only organic ingredients."). To be specific, the accurate choice, given the information at hand (i.e., they only know that the product is labeled or otherwise marketed as local) is to rank "the food item was produced according to the co-op's definition of local" as the most likely, while the rank order of the latter seven statements is trivial.

Ranking statements with two or more conditions as more likely indicates the presence of conjunction fallacy. Individuals who rank any of these as most probable are not computing probabilities correctly, as a single event (e.g. the good is produced according to the co-opâs definition of local) is always at least as probable as a combination of multiple events (e.g. the good is produced according to the co-opâs definition of local and is organic). Detecting the presence of conjunction fallacies would further suggest that consumer perceptions are based on a range of associations they make and values they hold rather than easily accessible information.

3.3.2 Collecting Data to Analyze Revealed Preferences

To analyze the impact of local labels on consumers' actual purchasing decisions, I also conducted an in-store labeling experiment, affixing "Local" shelf labels to products in five product categories in one of the stores (treatment store or store 1) from April 11, 2019 through May 8, 2019. I included all products in the following five categories: preserves, honeys, oils and vinegars, salad dressings, and salsas/snack dips (fresh and shelf stable). Importantly, Store 2 did not affix "Local" labels on the shelves to highlight local products, which allows me to define this store as the control unit in the experiment.

Figure 3.2: “Local” Shelf Label Implemented in Store 1

I chose these categories based on the ex ante belief that they would have a high proportion of local goods. I also wanted to include categories that can be defined as minimally processed, such as salsas, as well as shelf-stable categories such as vinegar. Finally, I included categories of relevance for California production (e.g., olive oils) and small-batch or artisan production (e.g., honey).

Each store provided weekly UPC-level scanner data for all products in the five categories for each of the four weeks before, during, and after the implementation of our experimental labels (12 weeks total). The data include the brand name, item size in ounces, retail price, cost, quantity sold, dollar sales at the retail price, and dollar sales net of member discounts for each product. Both stores further provided a list of the local brands they carry. Data from Store 2 designated each product as local or not local, whereas Store 1 provided the miles traveled for each product, which I used to create a local indicator based on this store’s definition of local. Both retailers define the sales week as Thursday through Wednesday. The pre-treatment period is March 14, 2019 through April 10, 2019, and the post-treatment period spans May 9, 2019 through June 5, 2019. The 12 weeks comprising the pre-treatment, treatment, and post-treatment periods are collectively referred to as the study period.

Table 3.1 shows the number of unique products each store sold during the study period by category, as well as the number of unique treatment products sold in each category, where treatment products are defined as those that meet Store 1's definition of local. The number of unique treatment items sold ranges from zero preserves in Store 2 to 62 oils and vinegars in Store 1.[9] Due to the limited overlap for preserves, I am not able to estimate effects separately for preserves.

	Store 1		Store 2	
	# of Products	#Treatment Products	# of Products	#Treatment Products
Honey	32	26	31	3
Oils and Vinegars	144	62	134	26
Preserves	63	5	64	0
Salad Dressing	88	57	106	32
Salsa	71	38	104	12
Total	366	188	439	73

Table 3.1: Number of Unique Treatment Products by Category and Store

The sales data are combined with a unique and comprehensive data set of product claims already included on packages for 547 of the 645 unique products in the sales data.[10] This includes attributes with certified labels (e.g., the USDA organic seal) and text-based regulated claims (e.g., âno trans fatâ), and unregulated claims. The data do not capture or include any attributes that are not highlighted by a claim or not present (e.g., olive oils do not have dairy-free labels despite not containing dairy ingredients, so they are not marked as dairy-free in these data). This will enable control for a large number of product claims in the analysis and explore interdependence among existing claims and the experimental shelf label. The number of labels on a product's packaging range from 0 to 10 with a mean and median number of claims of 3.8 and 4, respectively. The products included in the data

[9]This does not mean that there was no overlap in the unique treatment preserves carried by each store, but rather that those overlapping products were not sold in Store 2 during the study period.

[10]This data was collected manually during visits to the stores.

contain a total of 83 unique labels or claims.

Information provided on these claims is aggregated into content and credibility/accuracy categories. The initial content groupings are as follows with the number of claims in each category specified in parenthesis: dietary restrictions and preferences (20), nutrition claims (14), production and processing (23), production and processing - animal welfare (3), production and processing - environmental (10), production and processing - ethical (6), production and processing - quality standards (3), and artisan (4). Claims are further aggregated into just production/processing (49) and dietary/nutrition (34) categories. In another content-based grouping, the analysis explores how the potentially related attributes presented in the survey affect consumers' purchasing behavior by focusing on claims related to organic production, artisan production (e.g., small-farm production or handmade), and quality grades and certifications. To further control for the possibility that manufacturers already marketed their products as local, the data include a variable indicating whether or not geographic origin is specified on a product's packaging. Finally, claims are aggregated based on credibility or accuracy of the information provided. This characterization distinguishes between third-party certified (e.g., GMO free), government regulated (e.g., low fat), both certified and regulated (e.g., organic), and neither certified nor regulated (e.g. lactose free) groups.

The sales data identify which products were highlighted by sales promotions, as such promotions may affect sales independently of "Local" shelf labels. In store visits, I further noted the location of each product on the shelf to control for the effects of shelf location on sales. Product location is measured as the product's shelf number, beginning at one for the bottom shelf, divided by the total number of shelves in that aisle location and is used to generate two sets of location category variables. The first classifies goods as being in a low, medium, or high position, where low, medium, and high correspond to $location < 0.33$, $0.33 \leq location < 0.66$, and $0.66 \leq location \leq 1$, respectively. The second measures whether a product is approximately at, below, or above eye level. Here, a product is considered to be at eye level if it's location is between 0.6 and 0.8. A greater share of local products in Store 1 are at eye level than in Store 2.

Table 3.2 shows the share of unique treatment products at, above, and below eye level by store. Nearly a quarter of unique treatment products in Store 1 are located at eye level compared to 11% in Store 2. It is possible that products above or below eye level will benefit more from the added attention brought about by labels than those already in prime shelf positions.

	Store 1	Store 2
Above Eye Level	38%	38%
At Eye Level	24%	11%
Below Eye Level	38%	51%

Table 3.2: Share of Unique Treatment Products by Shelf Position

3.4 Econometric Specifications

In addition to comparisons of means and a graphical analysis of the collected survey responses, I analyze the collected categorical survey data in an ordered logit regression model. The store-level data provided by both stores is analyzed using a triple-difference framework commonly used in policy evaluation literature and market-level experiments (Kiesel and Ji, 2021; Kiesel and Villas-Boas, 2013; Villas-Boas et al., 2020).

3.4.1 Stated Preferences Regressions

I specify a pair of econometric models to examine how the beliefs indicated in question 8 affect consumer preferences for local produce and value-added food products. Questions 1 through 3 of the survey elicit preferences for these items using a seven-point Likert scale. These responses serve as the dependent variables in the model specifications. Likert scale data are characterized as ordinal as opposed to nominal.[11] To account for this, this analysis uses an ordinal regression, specifically the proportional odds model, a type of ordered logit. The ordered logit class of models is designed to work with ordered categorical data and is commonly used in the social sciences to analyze Likert scale survey data (Bürkner and Vuorre, 2019). As such, it is more appropriate for these purposes than other classes of models, such as the Poisson model, which uses count data (e.g. the number of car accidents in a given location), and the multinomial logit model, which uses nominal dependent variables.

Let Y be an ordinal variable containing $J = 7$ Likert scale responses to the statement "I have a preference for locally grown produce." and $\mathbf{X}$ a vector of explanatory variables. Here, Y contains categories strongly agree, agree, somewhat agree, neither agree nor disagree, somewhat disagree, disagree, and strongly disagree with corresponding probabilities $\pi_1, ..., \pi_7$. The proportional-odds ordered logit relies on the parallel lines assumption, which stipulates that the distances between response levels are equal. For instance, the distance between "strongly agree" and "agree" is equal to the distance between "neither agree nor disagree" and "more or less agree" for a given survey respondent. The Brant test confirms that explanatory variables in the models specified here do not violate the parallel lines assumption.

Let $P(Y \leq j|\mathbf{X}) = \pi_1 + ... + \pi_j$ be the cumulative probability that Y is less than or equal to category j. Thus, the odds, ℓ_j, of being less than or equal to category j are

$$\frac{P(Y \leq j|\mathbf{X})}{P(Y > j|\mathbf{X})} \ \forall j = 1, ..., J-1. \tag{3.1}$$

The log of the odds function is equivalent to $\alpha_j + \beta\mathbf{X}$. It is common to express output of ordered logit models in the odds-ratio form, where the odds ratios are derived by exponentiating the coefficients. In this form, the change in the odds of $Y > j$ as opposed to $Y \leq j$ associated with a one-unit increase in explanatory variable n, all else equal, is equal to $exp(\beta_n)$, and the percentage change in odds is equal to $100 * (1 - exp(\beta_n)$.

[11] Ordinal variables have an intrinsic ordering. Nominal variables have two or more values but no intrinsic ordering (e.g. hair color).

The analysis uses the following two proportional odds models:

$$\begin{aligned}\ell_j = logitP(Y \leq j|\mathbf{X}) = \alpha_j - \beta_1 ConjunctionBias + \gamma\mathbf{X} + \epsilon \text{ and} \\ \ell_j = logitP(Y \leq j|\mathbf{X}) = \alpha_j - \beta_1 * Fallacy1 + ...\beta_7 * Fallacy7 + \gamma\mathbf{X} + \epsilon.\end{aligned} \tag{3.2}$$

The set of explanatory variables, $\mathbf{X}$, control for respondents' co-op membership status, ability to define the store's definition of local, and awareness of local brands and promotions for local products. In the first specification, the variable $ConjunctionBias$ is a dummy variable equal to one if the respondent rated anything but the correct statement as being most likely associated with a "Local" label in Question 8 of the survey. The second specification replaces this with indicator variables for each fallacy presented in Question 8 that are equal to one if the given fallacy is ranked as the most likely to be associated with a "Local" label. The pair of models use both preferences for local produce and preferences for local, value-added goods as the dependent variable.

The following log-linear specifications estimate the relationship between WTP, percentage price premiums or intensity of preference for local goods and conjunction fallacy:

$$\begin{aligned} ln(P_i) &= \alpha + \beta_1 ConjunctionBias_i + \gamma\mathbf{X}_i + \epsilon_i \text{ and} \\ ln(P_i) &= \alpha + \beta_1 Fallacy1_i + ... + \beta_7 Fallacy7_i + \gamma\mathbf{X}_i + \epsilon_i. \end{aligned} \tag{3.3}$$

Here, P_i is the percentage price premium for value-added food products with a "Local" label relative to otherwise identical food products without a label for respondent i, and $\mathbf{X}_i$ is a vector of indicator variables denoting a preference for local produce (equal to one if respondents answered "somewhat agree" or above), co-op membership, and so on. As in the ordered logit models, the first specification is primarily concerned with the presence of conjunction fallacy, whereas the second breaks out the individual fallacies. The percentage price premium for organic, value-added food products with a "Local" label relative to otherwise identical organic products without a label serves as the dependent variable in the final set of survey regressions.

3.4.2 Revealed Preferences Regressions

I analyze consumers' revealed preferences by estimating the effect of the experimental "Local" shelf labels on product sales within a DDD framework using the following basic specification:

$$
\begin{aligned}
ln(S_{ijt}) &= \alpha + \beta_1(TreatPeriod_t * TreatStore_j * TreatLabel_i) + \\
&+\beta_2(TreatPeriod_t * TreatStore_j) + \beta_3(TreatPeriod_t * TreatLabel_i) \\
&+\beta_4(TreatStore_j * TreatLabel_i) + \beta_5 TreatPeriod_t + \\
&+\beta_6 TreatStore_j + \beta_7 TreatLabel_i + \gamma \mathbf{X_{ijt}} + \epsilon_{ijt}
\end{aligned}
\tag{3.4}
$$

The dependent variable is the log of weekly unit sales (S) for product i identified by Universal Product Code (UPC) in store j and in week t. The specification includes indicators for the treatment period (weeks during which the experimental labels were posted on shelves), treatment store (store 1), and products that were or would have been highlighted with the experimental shelf labels, as well as all pairwise and three-way interactions of those terms. The three-way interaction term serves as the average treatment effect (ATE) variable. The vector X_{ijt} denotes additional control variables added to the regression, including varying additional quality dimensions already highlighted by package claims, product size, product price and an indicator for advertised discounts, both of which might vary by store and week, and an identifier that captures differences in strategic placement of products at each store.

The validity of estimated ATE in this framework depends on the exogeneity of the defined treatment. Shelf labels were implemented as a research experiment and both stores were planning to implement "Local" labels in the future according to similar time lines. Comparisons of sales for labeled as well as non-labeled products in each store, and the inclusion of a variety of product and store-specific controls can further control for store-specific differences that might be correlated with the treatment assignment and placement of shelf labels in store 1. The chosen log-linear specification accounts for significant differences in sales volumes across products and means that the regressions are comparing differences in percentage sales for each product rather than unit sales. The regressions do not including product-fixed effects or category-fixed effects, as these would absorb all additional product characteristics, potential differences in consumer perception, and already implemented marketing strategies that are of interest and used in this analysis to better understand how “Local” shelf labels affect product sales.

I first estimate ATEs jointly and separately for each product category, and then test for additional heterogeneous treatment effects based on synergies or crowding out effects when trying to capture consumer attention at point of sale with retail-level marketing strategies (e.g., price promotions and shelf placement), as well as manufacturer-level marketing strategies (e.g., product claims already made). Specification 1, heretofore referred to as the "base" specification, examines only ATEs. The second heterogeneous treatment effects uses indicators for.[12] Following specifications test whether specific claims could be complementary to the “Local” labels or make the “Local” labels redundant based on consumer perceptions. These include claims that already indicate where a product was produced (”origin“), how a product was produced e.g., ”organic“ and ”artisan“), and claims that turn quality differences consumers can experience after purchase into searchable attributes (”quality grades“).

The primary analysis defines the pre-treatment period as the control period and the treatment period as the four weeks in which the experimental labels were displayed. Secondary analysis uses the same pre-treatment period but defines the treatment period as the four weeks after the experiment to estimate pseudo-treatment effects. As labels were removed after the four-week treatment period, this specification examines if and to what extent consumers’ recollection of the “Local” labels affects their purchasing decisions. A final analysis defines the experiment and post-experiment periods as the treatment period.

[12] The data include products that do not make any marketing claims on their packages, which allows me to include all of these categories.

3.5 Customer Survey and Market-level Experiment Results

Sections 5.1 and 5.2 summarize the results from the collected survey responses and then present results from an analysis of store-level scanner data provided by both stores for the entire study period. Section 5.3 presents a tentative explanation of these findings.

3.5.1 Analysis of Stated Consumer Preferences

Of the respondents for Store 1 and Store 2, respectively, 87% and 92.5% are co-op members. The majority of respondents from both stores expressed a preference for locally grown produce, as shown in Figure 3.3. From Store 1 and Store 2, respectively, 69% and 64% strongly agreed with the statement "I have a preference for locally grown produce". Another 25% and 27% agreed. In total and across both stores, 98% expressed a preference for local produce.[13]

[13] Having a preference is defined as providing a response of either agree, somewhat agree, or strongly agree.

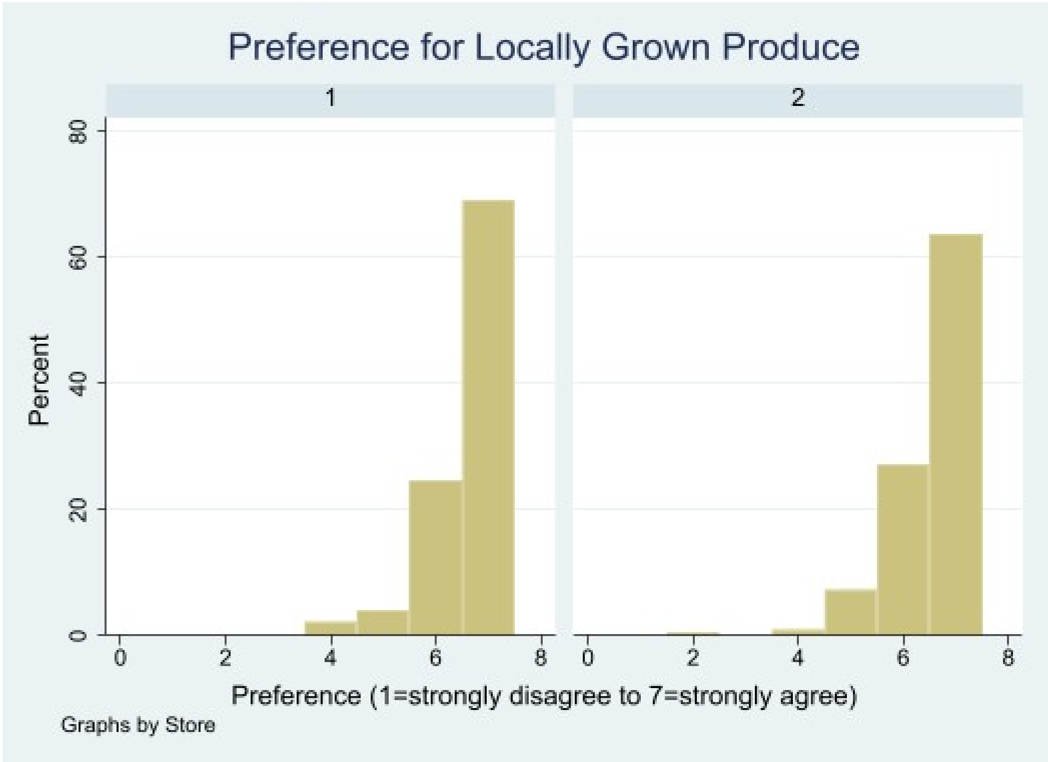


Figure 3.3: Response to "I have a preference for locally grown produce" by Store

The majority of customers in Store 1 (93%) and Store 2 (89%) also expressed a preference for locally produced, value-added food products, though their preferences were not as strong. Across both stores, 39% said they strongly agreed that they have a preference for local, value-added foods, and an additional 39% agreed with that sentiment. They further agree that it is important that locally produced, value-added food products contain locally grown ingredients. While nearly all customers have a preference for local value-added foods, only 58% can also name brands that they believe promote their products as locally grown or produced off the top of their heads.

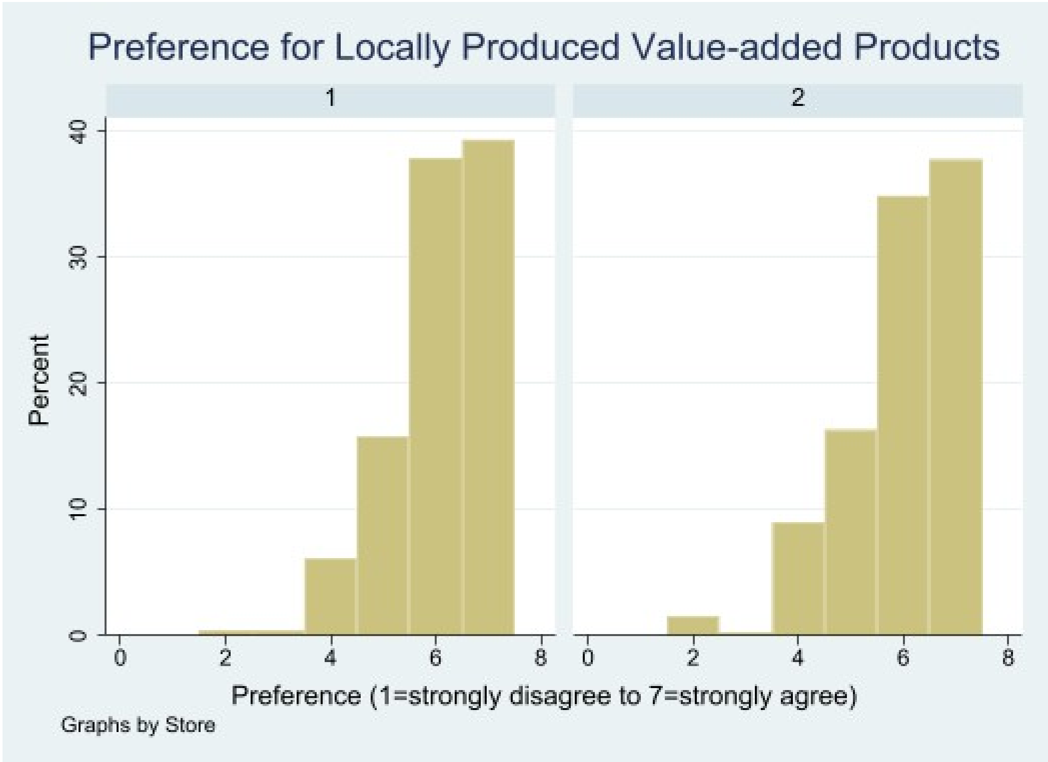


Figure 3.4: Response to "I have a preference for locally produced, value-added food products" by Store

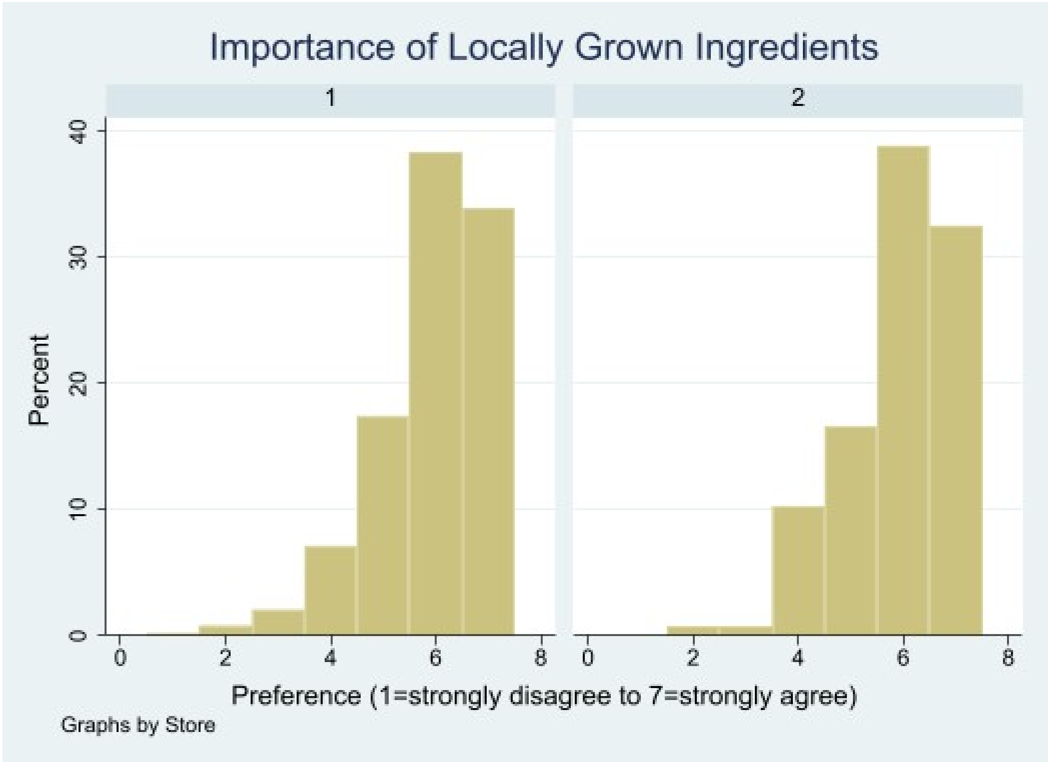


Figure 3.5: Response to "For locally produced, value-added food products (e.g. jams, olive oils, salsas, etc.), it is important to me that the good also contains locally grown ingredients" by Store

Survey results indicate respondents, on average, are willing to pay a premium for locally produced, value-added food products relative to their conventional counterparts. The mean and median responses for how much additional money they are willing to pay are \$0.93 and \$0.90, respectively, for Store 1 and \$0.87 and \$0.75, respectively, for Store 2. Figure 3.6 shows the distribution of responses.[14] Overall respondents also indicated they would be willing to pay a premium for an organic, value-added food product that carries a "Local" label relative to an identical organic food product without such a label. The mean and median premiums for Store 1 are \$1.09 and \$1.00, respectively, and are \$1.02 and \$1.00, respectively, for Store 2.[15] For both stores, this premium is greater than the mean premium for non-organic local products, and two-tailed T tests indicate the means are statistically significantly different at

[14] Across both stores, there are 245 responses above \$3.00. I drop all responses above \$3.00 to avoid possible ambiguities about whether these responses represent the total price respondents are willing to pay for the item rather than the premium. All results reported for WTP do not include the dropped responses.

[15] I once again drop responses above \$3.00.

the 5% level.

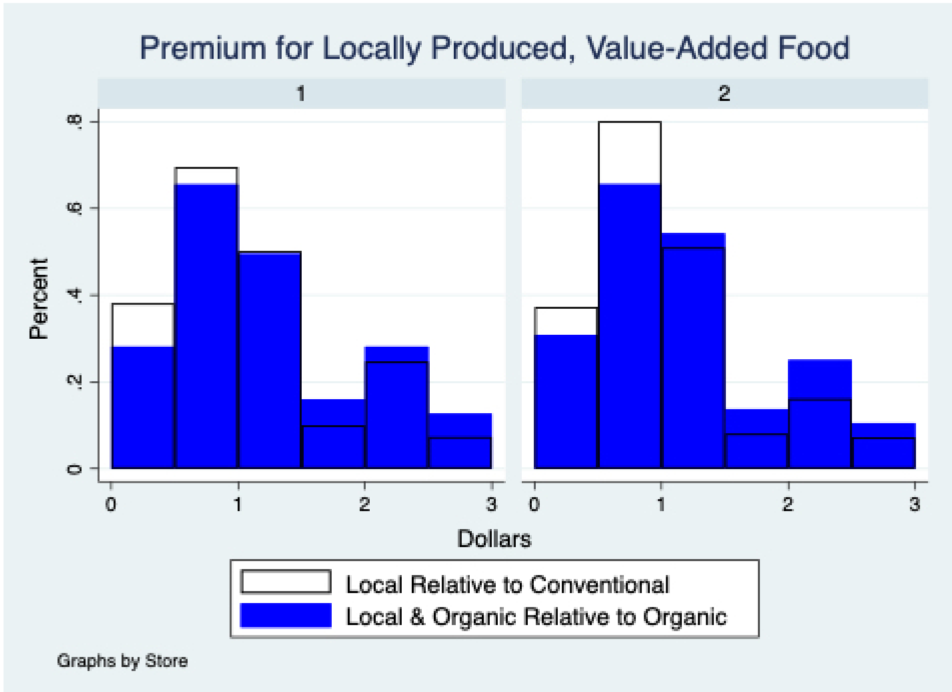


Figure 3.6: Premium (Stated Additional WTP) for Locally Produced, Value-added Food Products

In testing which statements respondents rate as most likely to be associated with a “Local” label, only 20% of respondents ranked “the food item was produced according to the co-op’s definition of local" as most likely. The remaining customers perceived other statements to be at least as likely, with 49% believing a “Local” label most likely indicates a food item is produced by a small farm or business using only organic ingredients, and is of higher product quality.

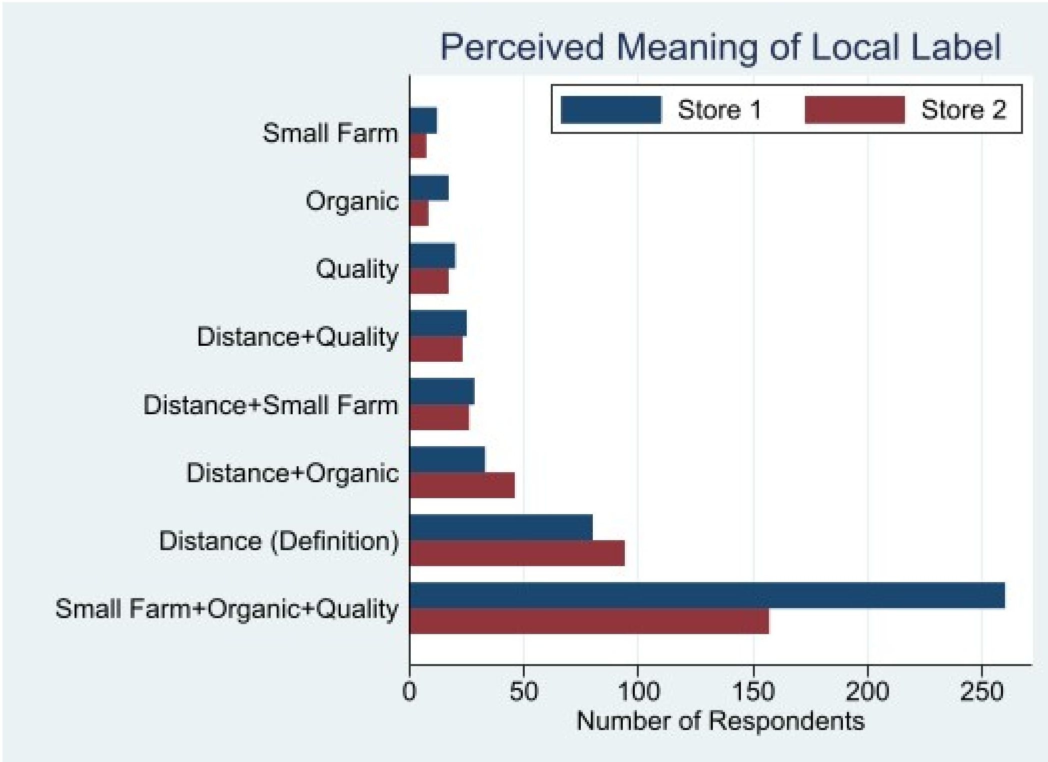


Figure 3.7: Consumers' Perceived (Most Likely) Meaning of a "Local" Label or Promotion

Despite the respondentsâ strong preference for local foods overall, only 27% of respondents across both stores indicate that they know their store's definition of local foods. Among those, only 38% were able to accurately state the definition for their store. Some believed the definition meant a product was produced within the store's city limits while others believed it indicates products produced within different mile radii of the store than the store uses as its criterion. While many do not know their respective store's definition of local, 56% across Store 1 and Store 2 are aware of promotional efforts at the each store to highlight local produce. Forty-six percent state that they are also aware of promotional efforts to highlight local, value-added food products. Neither store currently promotes local, value-added goods at the store level, and respondents may be referring to brand promotions here.

Table 3.3 shows the exponentiated coefficients or odds ratios (OR) for the first pair of ordered logit regressions. Model A, shown above, is concerned only with the presence of conjunction bias, while Model B removes the conjunction bias indicator and instead includes indicator variables for the specific statements respondents ranked as most likely associated with a "Local" label. Recall that, all else being equal, the percentage change in odds of $Y > j$, where j represents one of the seven Likert-scale responses, as opposed to $Y \leq j$ associated with a one unit increase in explanatory variable n is equal to $100 * (1 - OR_n)$. For example, Model A indicates that for respondents displaying conjunction bias, the odds of at least somewhat agreeing with the preference statement are approximately 57% more than the odds of being neutral or disagreeing to any degree. Because of the parallel lines assumption, the same odds ratio applies to other breaks in the response variable. For instance, it is also true that respondents displaying conjunction bias are 57% more likely to agree or strongly agree than they are to at most somewhat agree.

Model B shows that not all fallacies impact preferences for local produce. For instance, believing a "Local" label most likely indicates a good is organic does not have a statistically significant effect on how strongly one agrees or disagrees with the preference statement. On the other hand, the odds of at least somewhat agreeing with the statement, relative to being at most neutral, are 99% higher if one believes that a "Local" label most likely indicates the product meets the store's definition of local and is produced by a small farm or business and are 76% higher if one thinks a "Local" label most likely indicates the item is produced by a small farm or business using only organic ingredients, and is of higher product quality.

Table 3.3: Impact of Conjunction Bias on Preference for Local Produce

	Model A	Model B
Correctly defined local	1.260	1.236
	(0.335)	(0.330)
Believes They Can Name Local Brands	1.730***	1.755***
	(0.255)	(0.261)
Aware of Promotions for Local Produce	1.351*	1.382*
	(0.200)	(0.206)
Co-op Member	1.128	1.044
	(0.258)	(0.243)
Conjunction Bias	1.569**	
	(0.274)	
Distance+Organic		1.411
		(0.397)
Distance+Quality		1.449
		(0.491)
Distance+Small Farm		1.986*
		(0.689)
Organic		0.915
		(0.370)
Quality		0.951
		(0.356)
Small Farm		0.905
		(0.443)
Small Farm+Organic+Quality		1.759**
		(0.332)
N	851	851

Exponentiated coefficients; Standard errors in parentheses;
Ordered Logit Regression; $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I run the same ordered logistic specifications with Likert-scale responses for preference for local, value-added food items as the dependent variable. The odds ratios are presented in Table 3.4. Here, the general presence of conjunction bias does not affect the scale to which one agrees with the preference statement. However, odds of at least somewhat agreeing with the statement relative to being at most neutral are 53% higher if one believes that a "Local" label or promotion most likely indicates the item is produced by a small farm or business using only organic ingredients, and is of higher product quality.

Table 3.4: Impact of Conjunction Bias on Preference for Local, Value-Added Food Products

	Model A	Model B
Correctly defined local	0.739	0.735
	(0.174)	(0.173)
Believes They Can Name Local Brands	1.373*	1.409*
	(0.192)	(0.199)
Preference for Local Ingredients	4.549***	4.526***
	(0.384)	(0.384)
Aware of Promotions for Local VA Goods	1.075	1.075
	(0.151)	(0.152)
Co-op Member	1.135	1.083
	(0.246)	(0.238)
Conjunction Bias	1.364	
	(0.227)	
Distance+Organic		1.165
		(0.311)
Distance+Quality		1.188
		(0.382)
Distance+Small Farm		1.475
		(0.444)
Organic		1.215
		(0.484)
Quality		0.829
		(0.281)
Small Farm		0.953
		(0.437)
Small Farm+Organic+Quality		1.533*
		(0.274)
N	851	851

Exponentiated coefficients; Standard errors in parentheses;
Ordered Logit Regression; $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Tables 3.5 and 3.6 display results for the price premium analysis. The first uses the percentage price premium for local relative to non-local VA food products. For respondents of store 1, the general presence of conjunction bias does not affect the percentage price premium, nor do any of the individual fallacies. Across both stores, the presence of conjunction bias is associated with a 6.9 percentage point increase in the local premium, and fallacies 1 and 7 are associated with premium increases of 9.7 to 27.4 percentage points.

Table 3.5: Premiums (Stated Additional WTP) for Local Relative to Non-Local Food Products Calculated in Percentages

	Model A			Model B		
	All Stores	Store 1	Store 2	All Stores	Store 1	Store 2
Preference for Local Produce	15.725***	18.668***	11.341*	15.453***	17.452***	11.937*
	(3.622)	(4.838)	(5.274)	(3.733)	(4.919)	(5.492)
Preference for Local VA Food	3.895	9.518*	-2.245	3.886	10.216**	-2.622
	(2.828)	(3.791)	(3.990)	(2.839)	(3.847)	(4.058)
Preference for Local Ingredients in Locally-Produced VA Food	-0.527	-6.265	6.531	-0.231	-5.788	6.465
	(2.786)	(3.767)	(3.808)	(2.855)	(3.859)	(3.925)
Correctly defined local	3.470	5.341	4.238	3.682	6.400	4.300
	(3.300)	(20.207)	(3.513)	(3.326)	(20.346)	(3.570)
Believes They Can Name Local Brands	6.268**	4.975	7.360**	6.183**	4.535	7.244*
	(1.983)	(2.830)	(2.736)	(2.019)	(2.855)	(2.806)
Aware of Promotions for Local Produce	1.613	2.505	-0.424	1.504	2.587	-0.308
	(2.356)	(3.225)	(3.168)	(2.359)	(3.191)	(3.253)
Aware of Promotions for Local VA Food	0.420	-1.306	3.522	0.278	-1.923	3.563
	(2.301)	(3.147)	(3.134)	(2.275)	(3.047)	(3.179)
Co-op Member	1.971	3.273	1.227	2.208	4.265	0.887
	(2.690)	(3.411)	(3.985)	(2.707)	(3.349)	(4.133)
Conjunction Bias	6.948**	4.530	8.890***			
	(2.217)	(3.629)	(2.645)			
Distance+Organic				6.882*	1.822	9.780*
				(3.432)	(4.685)	(4.579)
Distance+Quality				7.746*	6.118	11.104*
				(3.838)	(6.155)	(5.010)
Distance+Small Farm				7.654	2.814	10.167
				(4.373)	(6.183)	(6.544)
Organic				8.232	9.505	1.041
				(6.804)	(8.764)	(6.527)
Quality				6.405	5.361	4.755
				(4.174)	(6.320)	(5.586)
Small Farm				13.611	16.012	12.569
				(8.325)	(12.219)	(10.336)
Small Farm+Organic+Quality				6.441*	3.821	8.836**
				(2.506)	(3.892)	(3.354)
N	546	299	247	546	299	247
F	116.955	68.057	52.809	70.746	41.764	31.866
R^2	0.649	0.660	0.657	0.650	0.663	0.659

The dependent variable is the percentage premium; Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6 replaces the dependent variable with the percentage premium for local and organic food products relative to otherwise identical organic food products. While conjunction bias in general and specific individual fallacies have no statistically significant effect on the percentage premium for Store 1, the regression jointly analyzing responses from both stores indicates that the presence of conjunction bias is associated with a 6.2 percentage point increase in the stated price premium. Further, three of the individual fallacies are associated with increases in the premium ranging between 5.7 to 16.6 percentage points.

Table 3.6: Premiums (Stated Additional WTP) for Local + Organic Relative to Organic Food Products Calculated in Percentages

	Model A			Model B		
	All Stores	Store 1	Store 2	All Stores	Store 1	Store 2
Preference for Local Produce	19.561***	23.639***	14.069*	19.316***	22.612***	15.047*
	(3.943)	(5.481)	(5.579)	(4.035)	(5.533)	(5.872)
Preference for Local VA Food	3.417	6.879	0.095	3.526	7.569	-0.233
	(3.092)	(4.533)	(4.084)	(3.090)	(4.574)	(4.203)
Preference for Local Ingredients in Locally-Produced VA Food	0.623	-3.768	6.228	0.813	-3.505	6.020
	(2.968)	(3.991)	(4.307)	(3.045)	(4.076)	(4.477)
Correctly defined local	1.718	1.601	2.338	1.873	2.463	2.479
	(3.301)	(19.552)	(3.510)	(3.357)	(19.535)	(3.592)
Believes They Can Name Local Brands	8.326***	7.530*	8.813**	8.228***	7.374*	8.477**
	(2.149)	(3.103)	(3.059)	(2.178)	(3.160)	(3.144)
Aware of Promotions for Local Produce	3.009	3.159	2.553	2.867	3.449	2.214
	(2.508)	(3.471)	(3.462)	(2.514)	(3.451)	(3.517)
Aware of Promotions for Local VA Food	-2.128	-3.785	0.870	-2.340	-4.543	1.140
	(2.417)	(3.275)	(3.401)	(2.383)	(3.178)	(3.429)
Co-op Member	3.217	5.103	1.057	3.465	5.757	0.775
	(2.943)	(3.704)	(4.646)	(2.978)	(3.686)	(4.814)
Conjunction Bias	6.193**	2.486	9.706***			
	(2.328)	(3.849)	(2.768)			
Distance+Organic				6.612	0.687	10.845*
				(3.564)	(4.897)	(4.966)
Distance+Quality				4.459	-1.381	11.715
				(4.632)	(6.523)	(7.104)
Distance+Small Farm				6.876	1.033	11.392
				(4.805)	(6.465)	(7.810)
Organic				6.247	6.029	1.181
				(5.071)	(6.530)	(6.744)
Quality				6.909	2.039	9.780
				(4.209)	(6.023)	(6.275)
Small Farm				16.608*	15.866	18.386
				(7.549)	(11.620)	(9.350)
Small Farm+Organic+Quality				5.743*	2.439	8.768*
				(2.663)	(4.170)	(3.515)
N	546	299	247	546	299	247
F	140.703	79.277	68.256	87.577	51.028	42.471
R^2	0.689	0.694	0.696	0.690	0.696	0.698

Standard errors in parentheses

The dependent variable is the percentage premium; Robust standard errors in parentheses;

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Overall, this analysis suggests that consumers do not treat local production as a one-dimensional searchable quality attribute. Instead, their preferences are based on a range assumptions and associations they make between the quality of local food and values they hold. Despite the existence of a clearly specified and easily accessible store definitions based on transport miles, customers of both stores continue to perceive local production as a multi-dimensional experience attribute.

3.5.2 Analysis of Revealed Preferences

An analysis of the store-level scanner data for the study period of the in-store experiment provide little evidence that stated strong preferences and high premiums for local foods result in significantly increased sales of value-added food products that received a "Local" shelf label. Table 3.7 summarizes results aggregated across all product categories. Column 1 reports the base specification that estimates an ATE. The results reported in columns 2 and 3 explore heterogeneous treatment effects based on existing retail-level marketing strategies that may capture consumer attention at point of sale. Specifically, column 2 adds an indicator for when a product was on sale or a discounted price was advertised, as well as interactions of the discount variable with the treatment store identifier and ATE variable.[16] The next specification includes an indicator variable equal to one if the product is positioned at eye level at either store, as well as an interaction of the eye-level and ATE variables. It tests for a differential effect of "Local" shelf labels on products placed at eye level relative to labels on products above or below eye level. Finally, column 4 includes linear and non-linear variables indicating the number of unique product claims already included on packages, as well as interactions between each of those variables with the ATE variable.[17]

[16] Price reductions and in-store advertising of these discounts vary by store. *Price* is included in all regressions and captures the average net price paid per ounce. This discount indicator tracks whether discounts were a marketing strategy to capture consumer attention at point of purchase.
[17] These marketing strategies vary only by product but not by store.

Table 3.7: Triple Difference Regressions with Heterogeneous Treatment Effects for Price Promotions, Shelf Placement, and Number of Package Claims - All Products

	Base	Discount	Shelf Position	# of Claims
Average treatment effect (ATE)	-0.104	-0.115	-0.075	0.015
	(0.084)	(0.085)	(0.086)	(0.093)
Treatment product	0.131	0.103	0.128	0.138
	(0.090)	(0.083)	(0.090)	(0.090)
Treatment store	0.594***	0.747***	0.571***	0.596***
	(0.065)	(0.064)	(0.068)	(0.065)
Treatment period	0.098***	0.043	0.098***	0.098***
	(0.025)	(0.023)	(0.025)	(0.025)
Treatment period & store	-0.164***	-0.066	-0.164***	-0.164***
	(0.042)	(0.040)	(0.042)	(0.042)
Treatment period & product	0.131	0.150*	0.131	0.130
	(0.071)	(0.070)	(0.071)	(0.071)
Treatment store & product	0.053	0.053	0.077	0.076
	(0.116)	(0.107)	(0.120)	(0.118)
Product size (ounces)	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Price per ounce	-0.780***	-0.652***	-0.793***	-0.791***
	(0.175)	(0.143)	(0.195)	(0.193)
Discount*ATE		-0.057		
		(0.059)		
Discount*treatment store		0.005		
		(0.044)		
Discount		0.506***		
		(0.031)		
Eye level*ATE			-0.175*	
			(0.073)	
Eye level*treatment store			0.170	
			(0.128)	
Eye level			-0.060	
			(0.087)	
# of claims*ATE				-0.081**
				(0.030)
# of claims^2*ATE				0.007*
				(0.004)
# of claims				-0.011
				(0.030)
# of claims^2				0.000
				(0.003)
Constant	1.282***	0.857***	1.301***	1.331***

	(0.107)	(0.092)	(0.119)	(0.132)
N	6018	6018	5877	5877

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Across all specifications in the table, I detect no significant ATEs.[18] On average, I observe higher product sales at the treatment store and during the treatment period. Although lower on average, sales might increase faster over time for the control store, resulting in a negative and significant coefficient for the treatment period and store interaction term. Products that receive a shelf label do not sell at higher volumes both on average or just at the treatment store. Advertising products at discounted prices does significantly increase sales by 65.8% at both stores, a first indication that price promotions successfully capture consumers' attention.[19] Discounts or promotions, however, do not have a differential effect on products affixed with a "Local" label at the treatment store relative to those without a label.

The "Local" label has a smaller effect on sales for products placed at eye level relative to products both above and below eye level. Unlike for price promotions, the data do not capture changes in strategic placement over time. The observed difference indicates that the "Local" labels might better highlight products not already highlighted by prime shelf location.

Similarly, manufacturers' strategies as to which labels and claims to put on a product's package do not change over the study period, whereas the experimental labels do change over time. I find that for products with one or more manufacturing claims that received a "Local" label relative to products with no manufacturing claims that received a "Local" label, average

[18] Although not reported here, I also ran specifications that include the indicator and count variables described above but not the interactions between these variables and the ATE and also do not detect significant average treatment effects.

[19] The coefficients in the log-linear regression models are converted to percentage changes based on the following formula: $\%change = 100 \times (e^{\beta_i})$, where β_i is the estimated coefficient. For small values of β_i this approximates to $\%change = 100 \times (\beta_i$.

sales decreased by 7.4 % based on the combined effect estimated. The effect decreases in absolute value if I instead compare products that both already make product claims and differ by one or more claims. The direction of the combined effect is consistent with an assumption that information becomes less salient as the number of claims posted increases. Products with more existing claims might have been less likely to attract consumer attention prior to the posting of shelf labels, and would therefore experience less of a reduction in sales in the first place.[20] Again, I interpret this as an indication that the "Local" shelf labels might have highlighted products that had not yet captured consumers' attention with existing product and possibly led them to substitute away from products that had previously captured their attention.

Table 3.8 reports results when analyzing possible interactions between manufacturer-level marketing strategies more closely. Column 1 examines differences in the information content or accuracy of such claims (e.g., certified, regulated). The remaining two columns focus on specific claims that might make the "Local" shelf label redundant based on consumers' already held beliefs. First, I distinguish between products that already make claims about where a product was produced. I then include separate variables that indicate whether a product is certified organic, has an "artisan" claim, or a claim that denotes a higher quality (e.g. a quality grade certification).

Table 3.8: Triple Difference Regressions with Heterogeneous Treatment Effects for Specific Package Claims - All Products

	Credibility	Origin	Survey
Average treatment effect (ATE)	-0.031	-0.139	-0.055
	(0.097)	(0.089)	(0.086)
Treatment product	0.213*	0.132	0.142
	(0.091)	(0.090)	(0.090)
Treatment store	0.577***	0.594***	0.577***

[20] As a reminder, the number of claims made on a product in the data ranges from 0 to 10, with median number of 3.8 product claims. While the estimated combined coefficients indicate that the effect of already posted claims would switch signs for comparisons of products with six or more claims, it has little practical relevance.

	(0.064)	(0.065)	(0.065)
Treatment period	0.098***	0.098***	0.098***
	(0.025)	(0.025)	(0.025)
Treatment period & store	-0.164***	-0.164***	-0.164***
	(0.042)	(0.042)	(0.042)
Treatment period & product	0.130	0.130	0.131
	(0.071)	(0.071)	(0.071)
Treatment store & product	0.087	0.090	0.097
	(0.115)	(0.118)	(0.120)
Certified*ATE	0.143		
	(0.079)		
Gov. regulated*ATE	-0.099		
	(0.075)		
Certified & gov. reg*ATE	-0.183*		
	(0.076)		
Neither cert nor reg*ATE	0.012		
	(0.083)		
Price per ounce	-0.824***	-0.796***	-0.764***
	(0.211)	(0.195)	(0.194)
Product size (ounces)	-0.005	-0.002	-0.002
	(0.003)	(0.003)	(0.003)
Certified claims	0.233***		
	(0.059)		
Gov. regulated claims	-0.182***		
	(0.055)		
Certified & gov. regulated claims	0.074		
	(0.062)		
Neither reg. nor certified claims	-0.188**		
	(0.065)		
Origin*ATE		0.042	
		(0.061)	
Origin		0.014	
		(0.054)	
Organic*ATE			-0.242**
			(0.081)
Artisan*ATE			0.156*
			(0.076)
Quality*ATE			-0.197**
			(0.070)
Organic			0.092
			(0.051)
Artisan			-0.131*
			(0.062)

Quality Grades and Certifications			0.110
			(0.106)
Constant	1.401***	1.291***	1.257***
	(0.140)	(0.117)	(0.118)
N	5877	5877	5877

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I detect significant heterogeneous treatment effects associated with the type of information portrayed on product claims. The effect of the "Local" label on sales for products that are already highlighted by certified and government-regulated claims is 20.1% lower compared to products without manufacturer claims. This suggests certified and government-regulated claims may capture consumer attention better than other claims prior, and benefit less from the attention drawn to these products by "Local" labels than products without manufacturer claims. I do not find significant differences in sales for products that are already highlighted by claims classified in the remaining categories, indicating the "Local" labels do not affect products with these claims differently than products with no claims.

With the exception of the indicator for the certified and regulated category, however, the category indicators themselves are significant. These are harder to interpret, however, given the specifications and data used. These product claims stay constant for each product and do not vary over time or by store. They might indicate that different consumers shopping at different weeks pay attention to different claims or even that the same consumers pay attention to different claims during different shopping trips.

Compared to products with no manufacturer claims, "Local" labels have a smaller effect on organic products. I do not find significant differences in the effect of "Local" shelf labels for products that already shared information about where a product was produced relative to products that do not indicate their geographic origin. I do, however, detect heterogeneous treatment effects for related quality dimensions consumers associate with a local food promotion according to the survey analysis. Contrary to the results from the survey analysis, I find that “Local” shelf labels have a smaller effect on sales for products with packaging that highlights their geographic origin relative to products without claims (by 27.3 %). Local shelf labels increase average sales for products depicting an artisan or small batch production claim by 16.8 % relative to products without manufacturer claims. I do not, however, find significant increases or decreases for products that signal higher quality via product claims (e.g., extra virgin olive oils).

These results seems to suggest that “Local” shelf labels might be more effective for products that are not already highlighted by organic claims than for products that do. In contrast, they reinforce artisan claims, and consumers might not have paid close attention to products making these claims on packages prior. In terms of overall quality differences, consumers might respond less to package claims and rely more on their experiences post purchase. “Local” shelf labels neither draw additional attention to these labels, nor do they crowd them out.

When analyzing labeling effects separately for each product category, I once more detect no significant ATEs.[21] For all but the salsa product category, I also detect no significant heterogeneous treatment effects. When estimating regressions separately for each product category, the ability to estimate heterogeneous treatment effects for each category is limited, as the number of observations for each category is relatively small and few or none of the identified products might have sold during the study period in both stores. Salsas are minimally processed and less shelf-stable than products in the other categories. As a result, they might be purchased more frequently. Detected strong consumer preferences for local produce and use of local ingredients might further be more closely aligned preferences for local foods in this category and allow me to detect differences in which products consumers pay attention to and choose after labels are posted in this category. I report average and heterogeneous treatment effects for the salsa category in Table 3.9 and 3.10 but omit results for the other categories.

[21] As I stated earlier, I was not able to estimate the ATE for the preserve category separately as none of the products that received a label were purchased at both stores during the study period.

Table 3.9: Triple Difference Regressions with Heterogeneous Treatment Effects for Price Promotions, Shelf Placement, and Number of Package Claims - Salsa

	Base	Discount	Shelf Position	# of Claims
Average treatment effect (ATE)	0.099	0.023	0.111	0.048
	(0.140)	(0.173)	(0.140)	(0.146)
Treatment product	1.016***	1.007***	1.004***	1.099***
	(0.260)	(0.232)	(0.252)	(0.280)
Treatment store	0.415*	0.838***	0.298	0.409*
	(0.184)	(0.186)	(0.197)	(0.190)
Treatment period	0.096	0.052	0.095	0.096
	(0.052)	(0.044)	(0.052)	(0.052)
Treatment period & store	-0.240*	-0.152	-0.237*	-0.240*
	(0.094)	(0.092)	(0.094)	(0.095)
Treatment period & product	0.126	0.085	0.125	0.124
	(0.108)	(0.100)	(0.108)	(0.108)
Treatment store & product	0.186	0.093	0.267	0.204
	(0.344)	(0.312)	(0.345)	(0.354)
Product size (ounces)	-0.205***	-0.190***	-0.201***	-0.209***
	(0.040)	(0.040)	(0.039)	(0.039)
Price per ounce	-4.314***	-3.888***	-4.518***	-4.309***
	(0.825)	(0.811)	(0.825)	(0.802)
Discount*ATE		0.098		
		(0.130)		
Discount*treatment store		-0.373***		
		(0.092)		
Discount		0.690***		
		(0.065)		
Eye level*ATE			-0.075	
			(0.118)	
Eye level*treatment store			0.118	
			(0.450)	
Eye level			-0.345	
			(0.188)	
# of claims*ATE				0.241*
				(0.112)
# of claims^2*ATE				-0.093**
				(0.036)
# of claims				0.053
				(0.089)
# of claims^2				-0.003
				(0.011)
Constant	5.383***	4.495***	5.501***	5.297***

	(0.815)	(0.804)	(0.790)	(0.810)
N	1282	1282	1282	1282

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.10: Triple Difference Regressions with Heterogeneous Treatment Effects for Specific Package Claims - Salsa

	Credibility	Origin	Survey
Average treatment effect (ATE)	0.016	0.007	0.092
	(0.147)	(0.143)	(0.140)
Treatment product	1.544***	1.136***	0.969***
	(0.283)	(0.270)	(0.256)
Treatment store	0.398*	0.383*	0.287
	(0.155)	(0.171)	(0.185)
Treatment period	0.095	0.095	0.096
	(0.052)	(0.052)	(0.052)
Treatment period & store	-0.238*	-0.239*	-0.241*
	(0.095)	(0.095)	(0.095)
Treatment period & product	0.122	0.126	0.126
	(0.108)	(0.108)	(0.107)
Treatment store & product	0.087	0.098	0.328
	(0.344)	(0.342)	(0.338)
Gov. regulated*ATE	-0.288**		
	(0.102)		
Neither cert nor reg*ATE	0.260**		
	(0.082)		
Price per ounce	-4.465***	-4.364***	-4.291***
	(0.690)	(0.793)	(0.815)
Product size (ounces)	-0.188***	-0.198***	-0.197***
	(0.034)	(0.039)	(0.037)
Certified claims	0.406**		
	(0.152)		
Gov. regulated claims	0.286		
	(0.148)		
Certified & gov. regulated claims	0.309		
	(0.167)		
Neither reg. nor certified claims	-0.533***		
	(0.153)		
Origin*ATE		0.262***	

		(0.071)	
Origin		-0.384**	
		(0.144)	
Organic*ATE			0.215***
			(0.048)
Artisan*ATE			-0.186***
			(0.020)
Organic			0.261
			(0.147)
Artisan			-0.550***
			(0.167)
Quality Grades and Certifications			
Constant	5.022***	5.440***	5.300***
	(0.676)	(0.780)	(0.807)
N	1282	1282	1282

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

I do not detect heterogeneous treatment effects for products highlighted by price promotions. However, for this specification, the coefficient for the treatment store interaction is significant and negative. In this category, customers at the treatment store might react less to price promotions, price promotions might have been used less or been less effectively posted at the treatment store. I also do not detect differences based on whether salsas were placed at eye level on the shelf. This might be due to the fact that salsas are primarily displayed in cooling shelves that are designed differently than retail shelves for shelf-stable foods. They have fewer rows and often also stack products horizontally in deeper shelves at lower levels.

Differences based on the number of product claims already included on packages are significant once more, although they are not consistent with the differences detected across all product categories combined. "Local" shelf labels are associated with an increase in sales for products displaying manufacturer-level claims on the package relative to those that do not display any labels or claims. These effects decrease in magnitude once more as the number of claims increases.

I do not estimate heterogeneous treatment effects for salsas that already included certified and regulated claims on their packages due the limited number of these products that sold in both stores, but I now detect heterogeneous treatment for salsas that carry one or more regulated claim. These are larger in magnitude (33.3%) but go in the same direction as the previously reported effects. Salsas with unregulated product claims that now receive a "Local" shelf label also increase in sales by 29.6% relative to salsas with no claims that received a "Local" label. In contrast, salsas with government-regulated claims and a "Local" label experienced a 25% lower increase in sales due to the "Local" label than salsas with no claims.

The results also suggest a heterogeneous treatment effect for salsas with packaging that already make claims about the geographic origin of the product. "Local" shelf labels increase sales for salsas that already highlight their geographic origin by 30% relative to salsas without geographic origin claims. This suggests the "Local" labels further draw consumers' attention to these products. "Local" shelf labels also highlight organic salsas further and increase sales of these products. They do decrease sales for salsas with artisan claims, however. Finally, I was once more not able to estimate a significant heterogeneous treatment effect with quality claims for salsas.

Some of the differences in the estimated heterogeneous treatment effects for all product categories and this category might primarily be due to data limitations. Analysis of this category includes 1,282 observations compared 6,018 observations for all product categories combined. Some might be a result of differing consumer perceptions and preferences reinforced by their experiences that result in "Local" labels attracting their attention at the point of sale differently. In either case, once consumers have noticed select products highlighted by these labels and purchased them, they might repeatedly seek out these products even after experimental labels were removed.

In alternative specifications that consider the pre-experiment period as a control period and the four weeks after the labeling experiment as a pseudo treatment period, heterogeneous effects become mostly insignificant or switch direction when significant. For the salsa category, I now even detect a significant negative average treatment effect in the specification that considers price promotions. These results are an indication that consumers did not update their beliefs and continued seeking out products that were previously labeled. "Local" shelf labels might have been able to capture consumer attention at point of purchase, especially for products consumers paid relatively less attention to prior to the experiment, but these effects were short-lived. Once these labels were removed, other marketing strategies might have more effectively captured their attention at point of purchase. Overall, these results suggest the implemented labels did not allow consumers to become better informed about which products were locally produced and did not result in consumers adjusting their purchases in alignment with their stated preferences.

Because the analysis suggests no lasting effects, I also estimate specifications that define the pre- and post-treatment periods as the control period. These reproduce the heterogeneous treatment effects already reported above, with one exception. The heterogeneous treatment effect for salsas with artisan claims is now positive and significant. Increasing the number of observations might have led to more accurately capturing these effects than in specifications that only use pre-treatment weeks. It indicates that these salsas increase in sales by 17.2% during the treatment period as compared to the pre- and post-treatment period, and it supports that the labels might have successfully highlighted products produced in small batches overall, and in the salsa category specifically.

Overall, the effects detected in these specifications further strengthen the notion that at best, these labels can capture consumer attention at the point of purchase. Results for pseudo-treatment effects and treatment effects using all data available are included in the appendix for all products and the salsa category only.

3.5.3 Discussion of Results

The regression results for the in-store experiment suggest that local shelf labels did not cause consumers to adjust their purchases in alignment with their stated strong preferences for local foods. Recent advancements in behavioral economics allow me to expand on why this might be the case. A detailed discussion of the rapidly growing literature on how consumers use motivated reasoning when additional feedback or new information is available (Zimmermann, 2020) is beyond the scope of this essay. The more general insight that this literature provides is that revealed and even stated preferences will be affected by how consumers employ useful but sometimes misleading cognitive heuristics to form and update their beliefs based on explanatory preferences (Lombrozo, 2016). Selective inattention and present bias result in consumers under-investing in direct information search (Benabou and Tirole, 2002; Carillo and Mariotti, 2000), especially the type of costly search required for credence qualities. Consumers heavily rely on their personal experiences and pay attention to information that is already familiar to them, while ignoring or downplaying information that contradicts their existing beliefs (Sharot et al., 2012). This notion is especially important when receiving noisy feedback. While consumers will at least partially incorporate new information directly after receiving feedback, they might revert to more preferable explanations longer term and only remember more easily accessible facts that support previously held beliefs (Zimmermann, 2020).

In summary, whether unregulated marketing of credence qualities provides direct or indirect information to consumers and results in consumers more accurately updating their beliefs might depend on whether they perceive them as search or experience qualities. If consumers primarily perceive them as (potentially multi-dimensional) experience qualities, marketing strategies would at best capture consumer attention and inform them of the existence of a product. The decision of whether to repeatedly purchase a product will be made primarily based on consumers' reinforced beliefs about their already formed associations made between the quality of local food and the values they hold.

Clearly stated and one-dimensional definitions, like in the definitions both stores adopted, could turn credence qualities into search attributes and allow consumers to rank or re-rank products using the direct information advertising now provides. It becomes more complicated when consumers consider various quality dimensions simultaneously, and remain imperfectly informed about some of them. The survey results indicate that consumer preferences for local foods are at least partially based on quality dimensions that can be reinforced by their subjective experiences after consuming purchased foods. These findings alone made it less likely that "Local" shelf labels consistently affected consumer purchases.

Consumers' selective inattention and present bias combinedâconsideration of additional experience qualities, and the immediately felt benefit of applied discountsâlikely result in streamlined paths of decision-making that move consumer choices further away from their stated preferences regarding this single-quality dimension for which they don't become fully informed. Nelson already predicted greater advertising expenditures for products perceived to have experience qualities and greater product differentiation but also greater market power for producers that create a hype rather than provide direct information to consumers via advertising. The literature documents that manufacturers continue to shift part of their resources from traditional media advertising to product claims and in-store marketing and retailers employ sophisticated shelf-management strategies (Chandon et al., 2009).

It suggests that marketing strategies for local foods will likely provide little information to consumers in general and will be most effective when combined with other marketing strategies. This limits the opportunities to market local foods for small and medium-sized farms and businesses. Even at the retail level, they might be more successfully used by large retailers rather than local independent retailers that have smaller marketing budgets and are less sophisticated in their use of price promotions and store-management practices, including strategic placement of products to capture consumer attention.

3.6 Conclusion

I analyzed consumers' stated and revealed preference for locally produced food products using both a survey and a market-level labeling experiment. The vast majority of shoppers at both stores expressed a preference for locally produced produce and processed foods and indicated they would be willing to pay a premium for them, though only 10% could correctly state their store's definition of local production. Most associated a "Local" label with organic production practices, small farms, and higher quality, suggesting consumers' preferences for local foods are driven by a complex array of perceived quality attributes. The preferences for local indicated in the survey, however, did not carry forward to increased sales for products affixed with a "Local" label in the retail experiment. An analysis of the sales data in a triple-triple difference framework failed to detect significant average treatment effects. Significant heterogeneous treatment effects suggest that the experimental labels primarily draw attention to or highlight products at the point of purchase, and might be more effective for products that do not already capture consumers' attention through manufacturer's claims, retailer discounts, or prime shelf-positioning.

This study contributes to a better understanding of consumer preferences for locally produced foods and their interdependence with other value-added attributes. By jointly analyzing stated and revealed consumer preferences, this analysis suggests that consumers do not treat local production as a one-dimensional and easily accessible or searchable quality dimension based on proximity of production. Their valuation of local foods is likely based on more complex multi-dimensional quality considerations for which they rely at least partially on their experiences.

When marketing local foods, an emphasis on transport miles will likely not capture consumer attention or result in consumers updating their beliefs properly. In fact, it might lead to outcomes that are contrary to multifaceted policy goals. Prioritizing a standardization of local labels based on proximity of production would likely limit marketing opportunities for regional producers in general, especially those with limited advertising budgets that cannot engage with consumers and capture their attention via the use of sophisticated marketing strategies. The ability to use shorter or more direct supply chains and collaborative marketing efforts that create stronger and more recognizable region-specific brands could instead allow small and medium-sized entrepreneurs to form authentic relationships with consumers even in retail environments. As such, the European use and regulation of geographic indicators might be an alternative approach to mileage definitions, especially for agricultural commodities and minimally processed foods, for which consumers have stronger preferences and perceive them to be of higher quality when produced locally.

This is especially true since claims of local production are just one example of value-added claims increasingly being used to differentiate food products by information provision. Local labels are both competing with other marketing strategies used to capture consumer attention and reinforce other related claims. As significant information asymmetries will likely continue to exist, whether manufacturers and retailers can successfully market their products in this environment will depend on how well they can reinforce consumers' perceptions of higher quality.

In addition to providing experiences that reinforce the notion of higher quality in the short term or directly (e.g., minimally processed foods with unique flavors), if farmers, producers, and retailers want to use local production as an effective marketing strategy, they might need to more clearly link their products to broader concepts that consumers value (e.g., health and sustainability). Shelf labels will not be able to provide this more complex information effectively.

A flexible, results-based policy approach that funds research and disseminates scientific information regarding health and sustainability impacts of select regionally grown and produced foods might further help even small producers to tell their stories in inspiring and relatable ways, and ultimately allow consumers to become more informed about today's complex agricultural supply chains in general.

In this context, it is worth mentioning a major limitation of this study. While the collaboration with local and cooperatively owned retailers gave me access to a unique data set, preferences for local foods might be more important in determining store choice than actual product choice. The results regarding stated and revealed consumer preferences presented here might not be representative of consumer behavior in national and larger retail chains, as this research primarily analyzes behavior of experienced consumers with strong preferences for and subjective beliefs about locally produced foods. Quality perceptions of local production might also vary significantly across regions and states, even in similar retail settings.

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3.A Consumer Survey

1. Please evaluate the following statement: “I have a preference for locally grown produce.”
   - Strongly Agree

- Agree
- More or less agree
- Neither agree nor disagree
- More or less disagree
- Disagree
- Strongly disagree

2. Please evaluate the following statement: "I have a preference for locally produced, value-added food products (e.g. jams, olive oils, salsa, etc.)."

- Strongly Agree
- Agree
- More or less agree
- Neither agree nor disagree
- More or less disagree
- Disagree
- Strongly disagree

3. Please evaluate the following statement: "For locally produced, value-added food products (e.g.jams, olive oil, salsa, etc.), it is important to me that the good also contains locally grown ingredients."

- Strongly Agree
- Agree
- More or less agree
- Neither agree nor disagree
- More or less disagree
- Disagree
- Strongly disagree

4. Off the top of your head, can you think of brands that promote their products as locally grown or produced?

- Yes
- No

5. Please list local brands that come to mind. 6. How much more would you be willing to spend on a food product that carries a “Local” label (e.g. a jam) if a similar food item (not labeled) costs $3.00 at a supermarket? (Please enter an amount in cents)

7. How much more would you be willing to spend on an organic food product that carries a “Local’â label (e.g. a jam) if a similar organic food item (not labeled) costs $3.00 at a supermarket? (Please enter an amount in cents)

8. If you saw a “Localâ’ label or promotion at your Food Co-op, how would you rank order the following statements according to your perceived likelihood, using 1 for the most likely and 8 for the least likely.

(a) The food item was produced according to the Co-opâs definition of local
(b) The food item uses only organic ingredients
(c) The food item was produced according to the Co-opâs definition of local and uses only organic ingredients
(d) The food item was produced by a small farm or business
(e) The food item was produced according to the Co-opâs definition of local and by a small farm or business
(f) The food item is of higher product quality
(g) The food item was produced according to the Co-opâs definition of local and is of higher product quality
(h) The food item was produced by a small farm or business using only organic ingredients, and is of higher product quality

9. Do you know how your Food Co-op defines local foods?

- Yes
- No

10. What is your Food Co-op’s definition of local foods?

11. How do you define local foods?

12. Are you aware of current promotional efforts to highlight local produce at your Food Co-op?

- Yes
- No

13. Are you aware of current promotional efforts to highlight local, value-added food products (i.e. jam, olive oil, etc.) with shelf labels that indicate a product was locally produced at your Food Co-op?

- Yes
- No

14. Are you a member of this Food Co-op?

3.B Regression Results: Pre- and Post-Treatment Periods

In these regressions, I define the treatment period as the four weeks post-treatment and drop the treatment period. That is, I am comparing the pre- and post-treatment periods to determine the extent recall affects sales in the post-label period.

Table 3.B.1: Triple Difference Regressions with Heterogeneous Treatment Effects for Price Promotions, Shelf Placement, and Number of Package Claims - All Products

	Base	Discount	Shelf Position	# of Claims
Average treatment effect (ATE)	0.040	0.060	0.014	0.056
	(0.088)	(0.085)	(0.092)	(0.101)
Treatment product	0.136	0.110	0.134	0.142
	(0.089)	(0.082)	(0.090)	(0.089)
Treatment store	0.583***	0.726***	0.562***	0.587***
	(0.065)	(0.063)	(0.068)	(0.065)
Treatment period	-0.003	0.014	-0.003	-0.002
	(0.031)	(0.028)	(0.031)	(0.031)
Treatment period & store	-0.048	-0.068	-0.048	-0.048
	(0.053)	(0.049)	(0.053)	(0.053)
Treatment period & product	0.054	-0.006	0.054	0.054
	(0.067)	(0.063)	(0.067)	(0.067)
Treatment store & product	0.036	0.037	0.053	0.055
	(0.115)	(0.106)	(0.120)	(0.118)
Product size (ounces)	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Price per ounce	-0.742***	-0.636***	-0.738***	-0.746***
	(0.159)	(0.131)	(0.176)	(0.176)
Discount*ATE		0.022		
		(0.058)		
Discount*treatment store		0.017		
		(0.043)		
Discount		0.481***		
		(0.031)		
Eye level*ATE			0.078	
			(0.094)	
Eye level*treatment store			0.178	
			(0.128)	
Eye level			-0.025	
			(0.089)	
# of claims*ATE				0.009
				(0.038)

# of claims^2*ATE				-0.002
				(0.004)
# of claims				-0.019
				(0.030)
# of claims^2				0.001
				(0.003)
Constant	1.296***	0.906***	1.301***	1.353***
	(0.101)	(0.087)	(0.111)	(0.125)
N	5304	5304	5162	5169

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B.2: Triple Difference Regressions with Heterogeneous Treatment Effects for Specific Package Claims - All Products

	Credibility	Origin	Survey
Average treatment effect (ATE)	0.110	0.086	0.077
	(0.104)	(0.095)	(0.097)
Treatment product	0.210*	0.136	0.149
	(0.089)	(0.090)	(0.090)
Treatment store	0.571***	0.584***	0.565***
	(0.064)	(0.065)	(0.065)
Treatment period	-0.003	-0.003	-0.003
	(0.031)	(0.031)	(0.031)
Treatment period & store	-0.047	-0.048	-0.047
	(0.053)	(0.053)	(0.053)
Treatment period & product	0.055	0.054	0.054
	(0.067)	(0.067)	(0.067)
Treatment store & product	0.069	0.071	0.081
	(0.116)	(0.118)	(0.120)
Certified*ATE	-0.400***		
	(0.106)		
Gov. regulated*ATE	0.279**		
	(0.089)		
Certified & gov. reg*ATE	-0.048		
	(0.098)		
Neither cert nor reg*ATE	-0.066		
	(0.102)		
Price per ounce	-0.747***	-0.736***	-0.706***
	(0.187)	(0.175)	(0.173)

Product size (ounces)	-0.006	-0.004	-0.004
	(0.003)	(0.003)	(0.003)
Certified claims	0.221***		
	(0.058)		
Gov. regulated claims	-0.142**		
	(0.055)		
Certified & gov. regulated claims	0.048		
	(0.063)		
Neither reg. nor certified claims	-0.160*		
	(0.066)		
Origin*ATE		-0.140	
		(0.083)	
Origin		-0.015	
		(0.054)	
Organic*ATE			0.117
			(0.086)
Artisan*ATE			-0.164
			(0.095)
Quality*ATE			-0.201*
			(0.098)
Organic			0.090
			(0.051)
Artisan			-0.160**
			(0.060)
Quality Grades and Certifications			0.096
			(0.102)
Constant	1.360***	1.297***	1.262***
	(0.130)	(0.108)	(0.109)
N	5169	5169	5169

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B.3: Triple Difference Regressions with Heterogeneous Treatment Effects for Price Promotions, Shelf Placement, and Number of Package Claims - Salsa

	Base	Discount	Shelf Position	# of Claims
Average treatment effect (ATE)	-0.304	-0.359*	-0.222	-0.261
	(0.176)	(0.164)	(0.176)	(0.190)
Treatment product	1.148***	1.110***	1.134***	1.299***
	(0.231)	(0.197)	(0.219)	(0.254)

Treatment store	0.447*	0.744***	0.327	0.438*
	(0.186)	(0.182)	(0.201)	(0.195)
Treatment period	0.133*	0.115*	0.133*	0.133*
	(0.060)	(0.053)	(0.060)	(0.060)
Treatment period & store	0.002	0.019	0.003	0.002
	(0.114)	(0.107)	(0.113)	(0.114)
Treatment period & product	0.193	0.172	0.193	0.194
	(0.136)	(0.101)	(0.137)	(0.136)
Treatment store & product	-0.087	-0.170	0.034	-0.054
	(0.323)	(0.285)	(0.326)	(0.337)
Product size (ounces)	-0.207***	-0.186***	-0.201***	-0.215***
	(0.042)	(0.039)	(0.041)	(0.042)
Price per ounce	-4.107***	-3.500***	-4.280***	-4.093***
	(0.873)	(0.804)	(0.885)	(0.860)
Discount*ATE		0.094		
		(0.106)		
Discount*treatment store		-0.190*		
		(0.084)		
Discount		0.529***		
		(0.060)		
Eye level*ATE			-0.389***	
			(0.100)	
Eye level*treatment store			0.204	
			(0.450)	
At eye level			-0.362	
			(0.187)	
# of claims*ATE				-0.034
				(0.215)
# of claims^2*ATE				-0.006
				(0.100)
# of claims				0.099
				(0.089)
# of claims^2				-0.007
				(0.011)
Constant	5.327***	4.421***	5.414***	5.189***
	(0.857)	(0.801)	(0.849)	(0.866)
N	1114	1114	1107	1113

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.B.4: Triple Difference Regressions with Heterogeneous Treatment Effects for Specific Package Claims - Salsa

	Credibility	Origin	Survey
Average treatment effect (ATE)	-0.296	-0.335	-0.295
	(0.192)	(0.185)	(0.176)
Treatment product	1.653***	1.242***	1.073***
	(0.258)	(0.252)	(0.234)
Treatment store	0.417*	0.422*	0.310
	(0.165)	(0.174)	(0.188)
Treatment period	0.135*	0.134*	0.135*
	(0.060)	(0.060)	(0.060)
Treatment period & store	0.001	0.001	0.001
	(0.115)	(0.114)	(0.114)
Treatment period & product	0.192	0.193	0.192
	(0.136)	(0.136)	(0.136)
Treatment store & product	-0.132	-0.155	0.100
	(0.326)	(0.328)	(0.328)
Certified*ATE			
Gov. regulated*ATE	-0.182		
	(0.158)		
Certified & gov. reg*ATE			
Neither cert nor reg*ATE	0.051		
	(0.125)		
Price per ounce	-4.080***	-4.087***	-4.126***
	(0.754)	(0.849)	(0.861)
Product size (ounces)	-0.189***	-0.198***	-0.200***
	(0.037)	(0.042)	(0.039)
Certified claims	0.461**		
	(0.151)		
Gov. regulated claims	0.224		
	(0.156)		
Certified & gov. regulated claims	0.335*		
	(0.165)		
Neither reg. nor certified claims	-0.400*		
	(0.156)		
Origin*ATE		0.089	
		(0.111)	
Origin		-0.352*	
		(0.145)	
Organic*ATE			0.322***
			(0.059)

Artisan*ATE			-1.036***
			(0.016)
Quality*ATE			
Organic			0.267
			(0.146)
Artisan			-0.580***
			(0.157)
Quality Grades and Certifications			
Constant	4.799***	5.325***	5.277***
	(0.747)	(0.834)	(0.849)
N	1113	1113	1113

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

3.C Regression Results: All Periods

In these regressions, I use both the pre- and post-treatment periods as the control period to determine how consumers adjusted their purchases when the "Local" shelf labels were posted.

Table 3.C.1: Triple Difference Regressions with Heterogeneous Treatment Effects for Price Promotions, Shelf Placement, and Number of Package Claims - All Products

	Base	Discount	Shelf Position	# of Claims
Average treatment effect (ATE)	-0.105	-0.125	-0.069	0.006
	(0.083)	(0.081)	(0.084)	(0.092)
Treatment product	0.168*	0.111	0.166	0.177*
	(0.086)	(0.081)	(0.087)	(0.086)
Treatment store	0.584***	0.730***	0.557***	0.587***
	(0.063)	(0.059)	(0.066)	(0.063)
Treatment period	0.100***	0.041	0.100***	0.100***
	(0.023)	(0.022)	(0.023)	(0.023)
Treatment period & store	-0.148***	-0.045	-0.148***	-0.148***
	(0.039)	(0.036)	(0.039)	(0.039)
Treatment period & product	0.103	0.147*	0.103	0.102
	(0.070)	(0.067)	(0.070)	(0.070)
Treatment store & product	0.057	0.070	0.067	0.062
	(0.110)	(0.103)	(0.115)	(0.113)

Product size (ounces)	-0.004	-0.003	-0.004	-0.004
	(0.003)	(0.002)	(0.003)	(0.002)
Price per ounce	-0.891***	-0.730***	-0.914***	-0.916***
	(0.192)	(0.155)	(0.220)	(0.218)
Discount*ATE		-0.066		
		(0.057)		
Discount*treatment store		-0.001		
		(0.037)		
Discount		0.503***		
		(0.027)		
Eye level*ATE			-0.193*	
			(0.080)	
Eye level*treatment store			0.199	
			(0.125)	
At eye level			-0.062	
			(0.085)	
# of claims*ATE				-0.083**
				(0.029)
# of claims^2*ATE				0.008**
				(0.003)
# of claims				-0.019
				(0.030)
# of claims^2				0.001
				(0.003)
Constant	1.362***	0.925***	1.386***	1.435***
	(0.115)	(0.096)	(0.131)	(0.140)
N	8013	8013	7807	7814

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.C.2: Triple Difference Regressions with Heterogeneous Treatment Effects for Specific Package Claims - All Products

	Credibility	Origin	Survey
Average treatment effect (ATE)	-0.052	-0.160	-0.072
	(0.097)	(0.089)	(0.086)
Treatment product	0.246**	0.170	0.181*
	(0.089)	(0.087)	(0.086)
Treatment store	0.570***	0.584***	0.566***
	(0.062)	(0.063)	(0.063)

Treatment period	0.100***	0.100***	0.100***
	(0.023)	(0.023)	(0.023)
Treatment period & store	-0.148***	-0.148***	-0.148***
	(0.039)	(0.039)	(0.039)
Treatment period & product	0.102	0.103	0.103
	(0.070)	(0.070)	(0.070)
Treatment store & product	0.073	0.081	0.088
	(0.111)	(0.113)	(0.115)
Certified*ATE	0.289***		
	(0.087)		
Gov. regulated*ATE	-0.203**		
	(0.077)		
Certified & gov. reg*ATE	-0.158*		
	(0.079)		
Neither cert nor reg*ATE	0.026		
	(0.086)		
Price per ounce	-0.929***	-0.916***	-0.876***
	(0.232)	(0.220)	(0.217)
Product size (ounces)	-0.007*	-0.004	-0.004
	(0.003)	(0.003)	(0.003)
Certified claims	0.218***		
	(0.060)		
Gov. regulated claims	-0.166**		
	(0.055)		
Certified & gov. regulated claims	0.057		
	(0.061)		
Neither reg. nor certified claims	-0.175**		
	(0.065)		
Origin*ATE		0.101	
		(0.065)	
Origin		-0.006	
		(0.054)	
Organic*ATE			-0.278**
			(0.085)
Artisan*ATE			0.215**
			(0.077)
Quality*ATE			-0.117
			(0.073)
Organic			0.089
			(0.050)
Artisan			-0.147*
			(0.063)
Quality Grades and Certifications			0.101

			(0.105)
Constant	1.475***	1.380***	1.340***
	(0.147)	(0.127)	(0.128)
N	7814	7814	7814

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.C.3: Triple Difference Regressions with Heterogeneous Treatment Effects for Price Promotions, Shelf Placement, and Number of Package Claims - Salsa

	Base	Discount	Shelf Position	# of Claims
Average treatment effect (ATE)	0.220	0.187	0.200	0.144
	(0.120)	(0.157)	(0.121)	(0.129)
Treatment product	1.139***	1.080***	1.126***	1.240***
	(0.240)	(0.223)	(0.236)	(0.261)
Treatment store	0.390*	0.793***	0.267	0.385
	(0.190)	(0.180)	(0.205)	(0.198)
Treatment period	0.048	0.016	0.048	0.048
	(0.053)	(0.044)	(0.053)	(0.053)
Treatment period & store	-0.233**	-0.152*	-0.231**	-0.233**
	(0.082)	(0.076)	(0.082)	(0.082)
Treatment period & product	0.041	0.024	0.041	0.039
	(0.092)	(0.089)	(0.093)	(0.093)
Treatment store & product	-0.034	-0.110	0.116	-0.001
	(0.336)	(0.308)	(0.346)	(0.347)
Product size (ounces)	-0.215***	-0.193***	-0.210***	-0.221***
	(0.040)	(0.038)	(0.040)	(0.040)
Price per ounce	-4.735***	-4.081***	-4.948***	-4.720***
	(0.793)	(0.759)	(0.795)	(0.777)
Discount*ATE		-0.004		
		(0.122)		
Discount*treatment store		-0.304***		
		(0.074)		
Discount		0.663***		
		(0.056)		
Eye level*ATE			0.074	
			(0.117)	
Eye level*treatment store			0.064	
			(0.474)	
At eye level			-0.365*	

			(0.184)	
# of claims*ATE				0.261*
				(0.126)
# of claims²*ATE				-0.090
				(0.053)
# of claims				0.070
				(0.091)
# of claims²				-0.005
				(0.011)
Constant	5.713***	4.661***	5.831***	5.622***
	(0.797)	(0.762)	(0.783)	(0.802)
N	1693	1693	1686	1692

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.C.4: Triple Difference Regressions with Heterogeneous Treatment Effects for Specific Package Claims - Salsa

	Credibility	Origin	Survey
Average treatment effect (ATE)	0.127	0.136	0.205
	(0.130)	(0.125)	(0.119)
Treatment product	1.644***	1.254***	1.066***
	(0.264)	(0.248)	(0.230)
Treatment store	0.371*	0.365*	0.259
	(0.167)	(0.175)	(0.191)
Treatment period	0.047	0.047	0.048
	(0.053)	(0.053)	(0.053)
Treatment period & store	-0.232**	-0.233**	-0.234**
	(0.083)	(0.082)	(0.082)
Treatment period & product	0.039	0.042	0.045
	(0.093)	(0.092)	(0.092)
Treatment store & product	-0.112	-0.124	0.115
	(0.338)	(0.331)	(0.327)
Certified*ATE			
Gov. regulated*ATE	-0.209		
	(0.108)		
Certified & gov. reg*ATE			
Neither cert nor reg*ATE	0.252**		

	(0.080)		
Price per ounce	-4.767***	-4.719***	-4.733***
	(0.698)	(0.768)	(0.785)
Product size (ounces)	-0.199***	-0.207***	-0.206***
	(0.036)	(0.040)	(0.038)
Certified claims	0.421**		
	(0.152)		
Gov. regulated claims	0.274		
	(0.152)		
Certified & gov. regulated claims	0.301		
	(0.168)		
Neither reg. nor certified claims	-0.460**		
	(0.161)		
Origin*ATE		0.239***	
		(0.069)	
Origin		-0.380*	
		(0.148)	
Organic*ATE			0.113*
			(0.046)
Artisan*ATE			0.159***
			(0.014)
Quality*ATE			
Organic			0.209
			(0.148)
Artisan			-0.640***
			(0.163)
Quality Grades and Certifications			
Constant	5.283***	5.723***	5.667***
	(0.705)	(0.775)	(0.797)
N	1692	1692	1692

The dependent variables is the log of number of units sold per week;
Robust standard errors in parentheses;
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$