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Contextualizing Farmers' Market Needs: Assessing the Impact of Community Type on Market Management

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Abstract

While the number of farmers' markets has exponentially increased in the United States, many of these markets are at risk of failure without adequate support and technical assistance. Based on 17 interviews with Wisconsin farmers' market managers, this paper reflects on the differences in infrastructure issues, data collection activities, and stakeholder relationships of markets situated in varying community types (metropolitan, micropolitan, suburban, and rural). Findings suggest that technical assistance should be better tailored to meet the needs of markets based in these distinct community settings. Peer-to-peer learning networks are suggested to better cross-pollinate ideas between markets of similar size and geography.

Keywords: farmers' markets, geographic location, market management, rural community development, urban community development

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Introduction

In search of higher-quality food and connections to farms, U.S. consumers have become more interested in purchasing locally grown products. Between 1992 and 2015, direct-to-consumer food purchases increased over 300% to reach $3 billion in sales (Low and Vogel, 2011; USDA, 2016a). One of the key avenues for accessing local food are farmers' markets, which accounted for 23% of all direct-to-consumer sales in 2015, totaling $711 million (USDA, 2016a). From 2006 to 2016, the number of farmers' markets voluntarily self-reporting to the USDA's National Farmers Market Directory doubled from 4,385 to more than 8,669 (USDA, 2016c).[1]

Consumer demand does not appear to be the sole reason that communities start or sustain farmers' markets. Kloppenburg et al. (2000) found that efforts to implement farmers' markets are grounded in a variety of social, economic, and ecological goals. Farmers' markets have the ability to foster community engagement and develop new social ties for farmers and customers alike (Hinrichs, 2000; Lyson, 2007; Bubinas, 2011). Farmers' markets can also have a positive impact on food access and health by facilitating increased consumption of less-processed foods and fresh fruits and vegetables (Larsen and Gilliland, 2009; Landis, LaBarre, and Day, 2011; Jilcott Pitts et al., 2014). Selling products at farmers' markets has supported better financial returns for producers (O'Neill, 1997; Conner et al., 2010; Feenstra et al., 2003; Hinrichs, Gulespie, and Feenstra, 2004; Morales, 2009) in addition to generating a ripple effect on the local economy. In fact, both Lev and Stephenson (2002) and Bubinas (2009, 2011) found that farmers' markets spur spending at downtown centers, which increases sales at nearby establishments like retail stores, restaurants, and museums. Hunt (2007) also found that the social relationships developed between farmers and customers at farmers' markets can encourage more environmentally sustainable farming practices, such as reduced application of chemicals to crops.

With the influx of new farmers' markets, however, it is critical to understand the kinds of challenges that farmers' market managers experience. Even while the country has seen a net increase in new farmers' markets, many new markets fail after only 1–4 years in operation (Stephenson, Lev, and Brewer, 2008). While farmers' markets may support more sustainable communities, more research and resources are needed to build farmers' markets that are themselves more sustainable. In particular, our research explores whether farmers' markets that exist in areas of different population densities (metropolitan, micropolitan, suburban, and rural, referred to hereafter as "community type") face different challenges regarding infrastructure and relationships with key stakeholders.

Little research has focused specifically on the role that community type plays in the viability of farmers' markets, though recent studies have cited the role that geographic location plays in the effectiveness of marketing strategies and the overall longevity of farmers' markets (Oberholtzer and Grow, 2003; Stephenson, Lev, and Brewer, 2008; Barham and Coleman, 2011; Witzling, Shaw, and Trechter, 2016). This line of inquiry is particularly important because—if markets in different community types face different challenges—current markets may not be receiving adequate technical assistance without more appropriately tailored resources and training.

[1] Market managers voluntarily submit market information to the USDA's National Farmers Market Directory, which should not be taken as a true census of market growth over time.

There are many valuable resources for farmers' market managers, including comprehensive guides (Farmers' Market Federation of New York, 2010; Idaho State Department of Agriculture, 2014) and marketing support (Krowkowski and Gaouette, 2009; Cowee, Curtis, and Gatzke, 2010; Fagin, 2010; Newvine, 2013; Alvarez, Knights, and Newvine, 2014). Recently, researchers have also developed resources to guide data collection strategies at farmers' markets, since the extent to which markets collect and analyze data can also impact their relationships with market stakeholders and overall market sustainability (Lev, Stephenson, and Brewer, 2007; Market Umbrella, 2010; Vancity Community Foundation and British Columbia Association of Farmers Markets, 2013; University of Wisconsin-Madison, 2017). However, the recommendations in such resources are not specifically geared toward markets in different geographical or community contexts. By comparing the perceptions and experiences of market managers across the rural–urban spectrum, this research explores whether farmers' market supporters need to more appropriately address the challenges in market management, promotion, and evaluation that present themselves in different community types.

Research on Market Management, Location, and Customers

Several studies on farmers' markets, while not specifically focusing on the impact of community type, have suggested that a market's setting impacts its viability. Through a survey of Oregon farmers' markets and a series of focus groups with market managers, Stephenson, Lev, and Brewer (2008) found that the major reasons that markets fail are attributable to high management turnover, low resources, small size, and inexperienced management. While their study did not explicity explore community type, they did find that four of the nine failed markets studied were in rural settings, with just one located in a major urban center.

In another study, Lohr et al. (2011) used responses to the USDA's 2006 *National Farmers Market Managers Survey* (Ragland and Tropp, 2006) to visually map the average distance that vendors and customers travel to markets across the country. The mapped competition zones illustrate increased competition for vendors among markets in major metropolitan areas like Boston, Chicago, Los Angeles, and New York. Because customers will generally not travel far to attend a farmers' market, the authors theorized that competition is especially high for customers in locations where markets have proliferated. While this study helped inform where markets are situated on a macro level, it did not dive into the specifics of the challenges and advantages of running a market in each type of community.

Far more research related to farmers' markets has examined customer preferences and behavior (Ruelas, 2012; Dodds et al., 2013; Rice, 2015), or has involved random sampling of respondents at the county, state, or national level (Wolf, Spittler, and Ahern, 2005; Zepeda, 2009; Conner et al., 2010). While these studies have built a foundation for understanding who generally frequents farmers' markets and why they attend, results rarely differentiate markets by community type. However, recent market research studies have suggested that community demographics impact the effectiveness of certain a farmers' market marketing approaches (Barham and Coleman, 2011; Witzling, Shaw, and Trechter, 2016).

Study Methods and Procedures

This research focused on farmers' markets in Wisconsin, which has an estimated 265 markets in operation across the state (K. Krowkowski, personal communication, July 19, 2017). In the past 2 decades, new markets have opened all around Wisconsin, not just in populous city centers. While many markets operate in urban metropolitan cores, small cities, suburbs, and rural towns host many as well (USDA, 2016b).

Our study aimed to better understand the varying needs of markets in different community types through a series of qualitative interviews with market managers around Wisconsin. Recent farmers' market research has used a similar approach of interviews or focus groups to better explore underlying issues that are often difficult to decipher by quantitative survey data alone (Oberholtzer and Grow, 2003; Stephenson, Lev, and Brewer, 2008). Approved by the UW-Madison Institutional Review Board, the research team conducted 17 semi-structured phone interviews with Wisconsin farmers' market managers or market directors, each lasting 30–120 minutes. An interview script was collaboratively developed by the research team and then refined after the initial interviews to address the key research questions. All interviews were recorded while interviewers concurrently took notes.

Table 1. Definition of Community Types

Community Type	**Population Description**[a]
Metropolitan	>50,000
Micropolitan	10,000 to 50,000
Suburban	<10,000; within a core based statistical area[b]
Rural	<10,000; outside a core based statistical area

[a] Population Descriptions derive from the U.S. Office of Management and Budget's definitions for metropolitan and micropolitan areas (U.S. Census Bureau, 2016).
[b] We use a core-based statistical area (CBSA) to describe areas within both metropolitan and micropolitan statistical areas.

The 17 market managers interviewed were intentionally selected to reflect a range of market types. Researchers interviewed five managers from larger, metropolitan markets (over 50,000 people), four managers from smaller, micropolitan cities (10,000 to 50,000 people), four suburban managers (less than 10,000 people in a metropolitan statistical area), and four market managers in rural towns (less than 10,000 people outside a metropolitan area) (Table 1). Interviewees were also chosen to include different types of market-governance structures: market managers working for non-incorporated organizations, vendor associations, nonprofit organizations, municipalities, chambers of commerce, Main Street Program participants,[2] and downtown business improvement districts were all intentionally included in the study.

Researchers employed the grounded theory method for their qualitative data analysis, which develops theory based on systematic review of data rather than constructing a theoretical

[2] Main Street Program participants are organizations that receive technical assistance from the Wisconsin Economic Development Corporation to plan, manage, and implement strategic development projects in downtowns and urban neighborhoods (Wisconsin Economic Development Corporation, 2017).

framework prior to research (Corbin and Strauss, 2008; Saldana, 2013). Market managers were asked a series of standard interview questions on their community partnerships and business sponsorships, promotional efforts and marketing strategy, and data collection and analysis activities. In addition, questions were formulated to better understand the kinds of marketing and communications assistance or resources that market managers would find useful. While all managers were asked the same set of questions, the semi-structured interview format allowed interviewers to build rapport with the interviewees and capture a richer dataset.

Once the interview phase was complete, members of the research team transcribed the audio and subsequently uploaded it into NVivo (2012) for systematic coding. In grounded theory methodology, the analysis process requires an iterative coding scheme in order to fully capture respondents' thinking and understanding of the activity. In the first cycle of coding, the researchers applied initial coding, identifying trends, patterns, and differences among the interviewee's transcripts, categorizing comments based on the key topics of conversation (descriptive coding) and actions or emotions taken in response to situations (process coding) (Saldana, 2013). A series of analytical memos was developed to describe these patterns, which were then shared and reviewed by other members of the research team prior to a second coding of the transcripts.

During the second cycle of coding, the researchers applied axial coding, in which trends and patterns are reconfigured and connected to determine the data's dominant themes. The researchers then employed theoretical coding, in which they ultimately identified the core contexts, conditions, and interactions that help to explain farmers' market managers' experiences (Richards, 2009; Saldana, 2013).

Study Results

Each market manager interviewed provided their unique experiences, innovative promotional ideas, and ongoing obstacles associated with maintaining a farmers' market in their community. While their successes and challenges varied, patterns emerged that aligned markets according to community type. The experiences of suburban and rural markets were markedly different from those shared by urban farmers' markets located in downtown micropolitan or metropolitan areas. The most distinct patterns stemmed from market characteristics, issues with physical infrastructure, data collection practices, vendor and customer relationships, and community partnerships.

Market Size, Age, and Leadership

Depending on the market's location in a metropolitan urban, micropolitan, suburban, or rural community, patterns emerged regarding the market's age, size, and organizational structure (Table 2). Although the sample size for the interviews does not allow for statistical comparisons, these patterns suggest that there may be future quantitative research opportunities to explore how geographic location influences market traits.

Researchers categorized markets into five age brackets: new (1–3 years old), young (4–6 years old), established (7–10 years), institutional (11–25 years), and historical (26+ years old).

Table 2. Characteristics by Market Community Type

	Metropolitan	Micropolitan	Suburban	Rural
Market Age				
New (1–3 years)	–	–	1	–
Young (4–6 years)	–	–	2	2
Established (7–10 years)	1	–	–	1
Institutional (11–25 years)	2	2	–	1
Historical (>26 years)	2	2	1	–
Market Size				
Micro (5–8 vendors)	–	–	–	2
Small (9–30 vendors)	–	–	2	1
Medium (31–55 vendors)	3	3	2	1
Large (>56 vendors)	2	1	–	–
Organizational structure				
501(c)3 nonprofit	3	1	1	–
Municipally run	–	–	3	–
Economic development organization[a]	1	2	–	2
Vendor association[b]	1	1	–	1
Unincorporated	–	–	–	1

[a] Economic development organizations include Main Street Programs, chambers of commerce, and downtown business associations.
[b] Vendor associations refer to markets where vendors had direct control of decision making in the market.

Suburban markets were predominantly new or young, aside from one outlier, a market in an inner-ring suburb that was over 100 years old. Rural markets were also predominantly younger, while micropolitan and metropolitan markets were predominantly older.

A market's size also appeared to be correlated with community type, with smaller markets found in rural and suburban communities and larger markets found primarily in more urban settings. Using the market size categories defined by Stephenson, Lev, and Brewer (2008), two rural markets were defined as micro-sized (5–8 vendors), while two suburban and one rural market fell into the small size category (9–30 vendors). Medium-sized markets (31–55 vendors) were the most common in the study, which included two suburban, one rural, three micropolitan, and three metropolitan markets. There were three large markets (56+ vendors), one micropolitan and two metropolitan.

Our study's patterns of market age and size categorized by community type suggest that rural and suburban markets may be more susceptible to instability. Stephenson, Lev, and Brewer (2008) found that younger, smaller markets are more likely to fail. Many rural and suburban market managers also mentioned manager turnover as a significant concern, which Stephenson, Lev, and Brewer (2008) found to be another indicator of instability. Two suburban markets were in the process of hiring a new market manager, while another had hired a new manager within the last year. Of the rural markets, three of the four market managers were in the process of retiring from their positions. "It's not like there's a large group of people who have been farmers' market managers," said a southeastern Wisconsin manager of a suburban market, who had just left her position. "It's hard to say that the person that they find to replace me will even have a background in market management. I'll be around to help train them with some of it, but still, they're going to have to start all over."

Manager turnover was also mentioned as an issue in micropolitan and metropolitan markets. One micropolitan market director interviewed was in the process of hiring a new manager, while another manager at a metropolitan market left her position in the months after being interviewed for this research. Two of the metropolitan managers had less than two seasons of experience working at their market organization, but both had prior farmers' market management experience before transitioning to their current roles. Rather than suggesting that market management turnover is not a problem in more urban locations, there is a stronger suggestion that all markets are susceptible to manager turnover, with rural and suburban markets being potentially more prone to such disruptions.

In addition to market size and age, comparing market organizational structure across community types also yielded interesting patterns. In metropolitan markets, three out of five interviewed were 501(c)3 nonprofit organizations whose main missions were to organize farmers' markets. Only one of the four suburban markets was incorporated as a 501(c)3 nonprofit organization. Likewise, just one micropolitan market in the study was managed by a nonprofit, but that organization ran a series of other community initiatives in addition to the farmers' market. Similarly, two of the rural markets were run by nonprofit organizations that focused more broadly on community economic development. The specialization of urban farmers' market organizations in market management may imply a difference in capacity and capability among those in metropolitan communities compared to other community types.

In suburban communities, three of the four markets in the study were organized by municipalities (two under the Parks and Recreation Department, and one under the Public Health Department), whereas none of the other markets in other community types was managed directly by a government entity. Due to weaker nonprofit support in suburban communities (Kneebone and Berube, 2013), local government may currently play a more important role in managing markets in this type of community.

Infrastructure

The type of community in which a market is organized also factored into the kinds of issues market managers experienced regarding physical infrastructure. Overall, parking was the greatest infrastructure concern shared by urban markets. A metropolitan market manager in south-central Wisconsin noted that

> Parking is the big challenge with the downtown market because it's expensive and often far away to park. So then, we have this message that we want you to come grocery shop, and fill up your canvas bags, and maybe buy a pumpkin that weighs 25 pounds—but, oh yeah, you get to schlep it five blocks to your car, for $8.00 in a ramp!

Not surprisingly, concerns about parking were largely absent from interviews with rural and suburban market managers. However, at least one suburban market voiced transportation concerns as a barrier to customer attendance. “The infrastructure is more difficult. We’re not on a bus line,” she explained. “We’re kind of isolated by some farms.” So, even while parking was not an issue for this suburban market, the manager believed the lack of public transit posed a challenge for encouraging more customers to shop.

Data Collection Practices

Another area in which market managers differed by community type was in their data collection practices. In rural and suburban communities, farmers’ market managers did not tend to see the need for data collection or the potential role it could play in sustaining their operations. The rationale used by market managers for not collecting data was a belief that this practice was more suitable for markets trying to generate some financial gain or profit. The manager of a rural market in southwestern Wisconsin explained, “It’s not a money maker. It’s simply to provide fresh vegetables and produce and to bring people to town.” This sentiment was echoed by a suburban market manager in southeastern Wisconsin.

Even suburban markets operated by government entities did not see the need to collect data or track information. “We have not done any data collection, at all, through the years,” noted the manager of a municipally run suburban market in southeastern Wisconsin. “Any staff time I put in, we really do not track that, nor do we track the registration time of our staff. We haven’t been doing that. We kind of felt it was a service to the community.”

In addition, market managers actively questioned the purpose of collecting this data for their markets. The potential return on their investment of time and money for data collection activities was unclear to many rural and suburban market managers. A rural market manager in north-central Wisconsin remarked, “I don’t know if it’s better to use [money] for advertisements to let more people know that we’re there or to pay somebody to track how many people *don’t* show up [laughing].” Rural and suburban market managers perceived that the scale of their communities did not necessarily warrant systematic, quantitative analysis. Rather, managers believed that the feedback they could gather informally from vendors and community members was sufficient to provide them with insights for market decision making.

In contrast to their rural and suburban counterparts, urban markets were more likely to collect data on market activities. The manager of a large, urban market in south-central Wisconsin said, “I would say that we have pretty robust data collection in terms of how the market itself is performing… Looking at how many vendors we have, how close we are to capacity, and tracking both annual and seasonal variation of that.” More than one urban manager contextualized their data collection activities by noting the need to fulfill requirements by market funders, especially those supporting farmers’ market access for low-income families. While not all micropolitan and metropolitan markets equally believed in the utility of collecting data, there was a general acceptance among more urban markets that data collection was a necessary part of their work.

Relationship Dynamics with Vendors

Depending on the market's geographical location, market managers also experienced different issues and opportunities regarding vendor recruitment, selection, and retention. In rural and suburban markets, managers generally struggled to recruit and retain vendors. Meanwhile, managers in urban areas had to consider procedures for managing vendor waitlists.

All rural market managers interviewed expressed concerns about aging vendors at their markets and what would happen to their market operations as more and more vendors retired. A market manager in northern Wisconsin said,

> A lot of our farmers are in their 60s and 70s. We had a couple who retired last year—we lost one of our great farmers who just decided to hang it up. We live in a different world than Madison, Central, or even Wausau. We have to work with those situations as best as we can.

While the reality of aging farmers was mentioned by urban market managers as a general societal issue, rural managers expressed a more immediate challenge in terms of losing these vendors and having few choices for replacing them. Finding new vendors, of any age, to fill booth slots was a substantial challenge for rural and suburban market managers.

Indeed, a major aspect of the role of market managers in small towns and suburbs is on vendor recruitment. To that end, rural and suburban market managers expressed how marketing efforts needed to serve a dual purpose in both attracting new customers as well as attracting new vendors. The shortage of vendors also affected the ways in which rural and suburban market policies were implemented or the kinds of requests managers felt comfortable making of their vendors. "I mean, we're very much at the mercy of keeping vendors interested in participating because it's not exactly a market they're going to get rich at," said a market manager in north-central Wisconsin. "You know, there's no waiting list for vendors to participate."

In urban markets, by contrast, market managers appeared to maintain more power in their relationships with vendors. One of the urban market managers interviewed was in the unique position of having run a suburban market before moving into her current management role. "[The urban market] does a pretty good job of filling up itself," she said. "It was *very* interesting coming into this market because the acceptance was just so different from my experience at [a nearby suburban market] where, at the beginning of the season, anyone who applied we found a spot for." When there are more vendors vying to sell at the market, managers have the ability to set restrictions on what can be sold and make more deliberate, consumer-centric choices for new vendors based on the market's needs.

Maintaining a vendor waitlist, however, brings its own unique challenges for urban market managers. When farmers' markets can afford to be more selective with regard to vendors, they often develop more formal rules and procedures to enforce policies like requiring that all vendors produce what they sell. Many of the urban managers were struggling to ensure that all farmers complied. "It would be wonderful to have more time and resources to do more vendor vetting and farm inspections," confided a metropolitan farmers' market manager in western Wisconsin.

"It's something that comes up so often, and I don't know how anybody does it given the time we usually have as managers. But, you know, just to kind of improve the integrity of the market."

Relationship Dynamics with Customers

Just as the relationships with vendors differ depending on community type, so too do the ways in which markets relate to their customers. For rural and suburban markets, the majority of managers interviewed explained their desire to grow their customer base. When asked what they wanted the market to look like in 5 years, market managers shared a similar vision: more vendors and more customers. One director of a suburban market in south-central Wisconsin said, "Well I'd *love* to see a booming market, 20 vendors with a waiting list, and 500 people there every day. That's a big dream of mine."

Rural and suburban markets felt caught in a perpetual cycle of not having the appropriate vendor mix to attract more customers, while simultaneously not being able to attract a diverse set of vendors due to low customer attendance. Several market managers described this as the "chicken-and-egg" dilemma. "That was certainly the challenge the first couple of years, the chicken and the egg of you've got to have the farmers to get the customers, but you've got to get the customers to keep the vendors," a rural market manager in north-central Wisconsin explained.

Downtown urban markets were less likely to express the same desire to grow in size and customer base. "Physically, we're where we'd like to be. We always say bigger isn't always better," one urban market manager in northeast Wisconsin said.

Rather than seeking a larger customer base, micropolitan and metropolitan market managers were more often looking for strategies to encourage existing customers to spend more per visit on market products. One downtown metropolitan market manager in south-central Wisconsin explained, "We are really in the position where we don't want to attract more people to the market—it's like wall-to-wall bodies. We want the people that come to the market to buy more." Urban managers who felt satisfied with the number of customers they had were looking to focus their marketing plans more strategically on certain demographics who they believed would spend more money. They were generally more wary of attracting out-of-town tourists and, instead, looked to target people who would use the market to engage in more substantial grocery shopping.

This does not mean that managers were only looking for patrons with higher incomes. Rather, many market managers noted that food access was an underlying goal for their market. In particular, managers recognized the power that food assistance programs have in both supporting farmers and in getting fresh, healthy products to people who are most in need. However, markets in all geographies cited having trouble attracting more people to use their Food Share program vouchers; Women, Infants and Children (WIC) vouchers; or electronic benefits transfer (EBT) cards at the market.

Managers were even struggling to increase participation in "double dollars" programs, which double the face value of food assistance vouchers for purchases made at farmers' markets. Depending on the community type, however, managers attributed the problem to different reasons. Urban market managers felt that they needed to develop stronger marketing and outreach campaigns to inform community members about how shoppers could use these benefits at farmers' markets. One urban market manager in northeast Wisconsin noted,

> Our [EBT] sales are down 50% from what they were last year. So, I don't know if there's a perception there that the farmers' market is too overpriced, or if they're just unaware that it's available at the farmers' market. We're working on different ways with our local community organizations and churches to see about getting that word out.

But in a small-town market setting, the manager of a rural market that offered foodshare and EBT use to customers believed it was the lack of anonymity, as opposed to a lack of awareness, that was predominantly keeping users away. He said,

> I've been struggling trying to find another small-town market that's had success with [EBT]… I don't know if setting up another SNAP/EBT machine where they can buy tokens somewhere else off-site, so they're not standing at a big sign, being identified at the market—it's one of the things that larger cities, or larger towns don't have to worry quite as much about—you know, being identified.

More research is needed on how farmers' markets, especially within rural or small-town settings, can overcome the perceived social stigma that EBT users experience when purchasing items.

Partnerships with Community

The challenges and opportunities for partnerships with community organizations, neighborhood associations, businesses, and government were even more fragmented by community type.

In suburban communities, market managers brought up feelings of being isolated from community activity in ways that made it more difficult to establish partnerships. "[Our town] is a really nice area, but we don't necessarily have the same strong sense of community that some of the inner city markets might, that they can pull upon," said a suburban market manager in southeastern Wisconsin. Without as many community groups working on food security or economic development, farmers' market managers in suburban settings can lack the network necessary to support market programming and promotional efforts.

Unlike those in suburban locations, managers in urban locations cited community partnerships as one of their biggest strengths. The ecology of businesses, food-related nonprofit organizations, and civic groups nurture urban farmers' markets in ways that suburban markets may not be able to achieve.

Farmers' markets in small, rural communities shared sentiments that had more in common with urban than suburban markets. The strong social fabric and intimacy of their towns helped support and sustain their market operations. One rural market manager in north-central Wisconsin, for example, had served in the chamber of commerce and played in the same basketball league as some of the farmers who vend at the market. He attributed much of the farmers' market success to personal relationships cultivated through other local institutions and organizations.

Whether collaborating with the chamber of commerce or a local business, rural markets strongly valued these partnership opportunities and welcomed ways to cross-promote with coinciding events. For example, a farmers' market manager in rural northern Wisconsin found success in advertising the market alongside special events like the town's Pow Wow Days and annual Frog Jumping Contest.

Larger communities did not always view these cross-promotional opportunities so positively. Rather, market managers voiced concerns that concurrent events could interfere with the market and clog downtown areas, making it more difficult for regular market attendees to purchase their groceries. "The biggest concern that we have is people seeing the 2,000 to 3,000 people coming to our farmers' market and saying, 'How do I get a piece of that action?'" said a micropolitan market manager in central Wisconsin. More-rural markets welcomed cobranding, but those in larger city centers felt threatened by cross-promotion, or at least did not perceive significant benefits.

Discussion

Researchers set out to understand whether a farmers' market's community type influences its needs and challenges with respect to market management, promotion, and evaluation. From market managers' interview responses, it is clear that community type plays a significant role in perceived barriers to market success and long-term sustainability. Depending on a market's location, market managers experienced varying challenges with parking and public transit connectivity; had different attitudes about data collection; and related to their vendors, consumers, and community partnerships in distinct ways. The results of the study have implications for how academic institutions, nonprofit organizations, Extension educators, state agencies, municipalities, and other local food supporters can better support farmers' markets.

Where appropriate, resources and technical assistance should be tailored to community types in ways that adequately address local contexts. For rural and suburban markets, supporters should provide assistance for market managers looking to overcome the "chicken-and-egg" dilemma of attracting more vendors and customers, especially in fostering the young and beginning farmers that are so necessary to keeping small-town markets in existence. Extension offices and other technical assistance providers can support the viability of markets in their communities by facilitating beginning farmer apprenticeships, for example, and connecting new farmers with specific local markets. To better deal with high turnover between market managers, assistance providers can also share guidance on developing successful transition processes for market management.

Resources and support to help market managers overcome feelings of isolation might also improve market sustainability, particularly for suburban markets. Extension offices serving suburban areas can play a critical role by more closely partnering with those markets and introducing them to regional food system partners. Municipalities or metropolitan planning organizations proposing new public transit routes can also play a more supportive role by considering how bus lines can improve access to farmers' markets.

For both micropolitan and metropolitan markets, technical assistance and support should focus on helping markets manage vendor policies and monitor activities, something that many of the urban market managers struggled to accomplish. Technical assistance providers can specifically help disseminate model vendor application and agreement forms, farm inspection documents, and manageable enforcement and auditing procedures. The focus of assistance can also be redirected from growing the number of customers to helping increase customer expenditures.

In terms of community partnerships, urban market managers need support to build more strategic relationships to nearby community groups, conduct outreach about food assistance programs, and determine the effect of cobranded events on market sales. Data collection and visualization can help establish, build, and analyze the effectiveness of these relationships. Measuring the economic impact of the farmers' market on surrounding businesses can also be useful in making the case for their financial support. With reliable data and powerful infographics, farmers' markets may also be able to more successfully partner with city governments to address parking and public transit issues. For example, demonstrating a market's positive impact on other downtown businesses may convince a local government to provide free access to municipal parking lots during farmers' market hours.

For markets in every community context, peer-to-peer learning networks between markets of similar geography and size would provide a more appropriate community of practice for market managers to cross-pollinate ideas and glean best practices. Of the 17 market managers interviewed, 12 voiced interest in more opportunities to network, learn, and collaborate with other market managers. While there are already efforts to connect farmers' markets across the state, trainings or gatherings for markets of a certain geographic type may prove more beneficial.

The emerging themes found among markets of similar community types included in this study may not necessarily hold true for markets in other regions. Furthermore, the market managers of each category who agreed to participate in the interview process may not necessarily be representative of other market managers in similar geographic contexts. In particular, more variation may exist among metropolitan markets, as the study predominantly included representatives of centrally located downtown markets over markets located in more residential urban neighborhoods. While four markets located in residential urban neighborhoods were contacted for an interview, their lack of response to an interview inquiry may speak to their more limited capacity compared to downtown market organizations.

To that end, further research into how community type affects a market's operation would provide market managers and their technical assistance providers with more appropriate promotional and organizational strategies for success. The field of farmers' market research would especially benefit from deeper inquiries into the interplay between community type and market size, market age, and organizational structure—all factors that have been shown to have an impact on farmers' market viability (Stephenson, Lev, and Brewer, 2008). The patterns that emerged in this study regarding market characteristics and geographical context also warrant more quantitative review across a broader geographic scope, as this work focused solely on

Wisconsin communities. In addition, future research might specifically assess the efficacy of community-specific, peer-to-peer learning initiatives and their ability to help markets reach goals or resolve problems.

Conclusion

Farmers' markets are valuable community assets with the potential to strengthen economic, social, and ecological sustainability in communities of all sizes. As the number of markets increases around the country, supporters of local food systems and farmers' markets play a critical role in helping these operations thrive in their different geographical contexts and community types. While prior research into promoting and supporting farmers' markets has yielded insights into general customer preferences and management best practices, little attention has been paid to how the type of the community affects markets' opportunities for and barriers to success.

The results of our qualitative interviews with farmers' market managers in different geographies around Wisconsin allow us to start the conversation about how community context plays a role in farmers' market management. Depending on whether a market was rural, suburban, micropolitan, or metropolitan, the markets studied had varying descriptive characteristics, infrastructure issues, data collection practices, and community partnerships.

Based on the nuances of market management shared among markets of similar geographic context, there is a need for resources, programming, and technical assistance tailored to markets in each community type. In addition, peer-to-peer networks that create a community of practice for markets in similar geographic settings are highly recommended to provide more effective technical assistance. Indeed, markets across all geographic types have demonstrated that they can be sustainable operations that support farmers, community members, and local economies. With more customized technical assistance, farmers' market advocates can better help rural, suburban, micropolitan, and metropolitan markets thrive and continue to benefit farmers and their communities.

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Do Farmers' Markets Boost Main Street? Direct-to-Consumer Agricultural Production Impacts on the Food Retail Sector

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Abstract

We estimate the county-level impacts of direct-to-consumer (DTC) agricultural production on two food and beverage retail subsectors in Arkansas, Louisiana, Oklahoma, and Texas using a first-difference model. We test for the endogeneity of DTC agricultural production by using a drought index and the lagged value of DTC production as instruments. We find that DTC agricultural production impacts the food services and drinking places subsector (which includes restaurants). This effect on food retail sales is positive in metropolitan counties and negative in nonmetropolitan counties. Our results inform planners about the complementarity between local agricultural production and food retail sectors.

Keywords: food retail, local foods, regional economic development

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Introduction

Given consumer interest in locally sourced foods, investigating whether local agricultural production can stimulate the downstream local "food economy" is a research priority. Vibrant food retail establishments can be an important source of revenue for communities, but previous research estimating the economic impacts of local agricultural production has focused on upstream effects, such as how local food markets provide jobs for farm laborers and/or revenue for input suppliers (e.g., Jablonski and Schmit, 2015). The impact of local agricultural production on the food retail sector has not been rigorously investigated in the literature.

In this study, we estimate the county-level impacts of direct-to-consumer (DTC) agricultural sales (defined as sales at on-farm stores, farmers' markets, and other direct marketing venues) on the economic performance of the food and beverage retail subsectors. Using data from 2007–2012 (the most recent time period for which county-level data on DTC production is available as of this writing), we focus on the U.S. Census Bureau West South Central (WSC) division—comprising Arkansas, Louisiana, Oklahoma, and Texas—a region in which sales to local retailers are a relatively important marketing opportunity for farmers. We examine the two most prominent food retail subsectors: food and beverage stores, which include grocery stores, and food services and drinking places, such as restaurants and cafeterias. In the WSC region, direct sales by farmers to retailers like supermarkets and restaurants accounted for 55% of local food sales in 2015, the highest percentage in the country (U.S. Department of Agriculture, 2016a).

Estimating a causal relationship between DTC production and food retail sales can be confounded by the potential for endogeneity from unobservable county-level attributes. This region and time period have attributes that make it possible to establish a causal link between DTC production and the food retail sector. Our identification strategy exploits the severe drought that impacted the WSC region between 2007 and 2012 as a natural experiment. The drought index that we create is a compelling instrument for our purposes for three reasons: i) there was variation in the severity of the drought within the WSC region; ii) the drought had a pronounced negative effect on agricultural production; and iii) we consider the drought to be exogenous with regard to unobserved factors that might influence food retail sales. We also use the lagged value of DTC agricultural production as an instrument. Lagged changes in the values of DTC production are correlated with current changes in the WSC division.

Enhancing local food systems has emerged as an economic development priority across the United States. For example, food policy councils have been formed across the country, in part to support this objective (Johns Hopkins Center for a Livable Future, 2018). Despite this interest, policy makers have little evidence to guide them in understanding the economic linkages between local agricultural production and food retail sectors. DTC production could support the food retail sector by increasing consumer interest, and subsequent expenditures, at food retail outlets. However, DTC markets could also compete with grocery stores and restaurants for consumer expenditures. A central contribution of our study is to provide greater insight into how incorporating local food production into food systems planning efforts would impact food retail businesses.

Background

DTC Production and Food Retail Linkages

Farmers sell agricultural products locally through various supply chains. DTC agricultural sales occur at farmers' markets, roadside stands, pick-your-own operations, community-supported agriculture (CSA) programs, and at other direct marketing outlets. DTC agricultural sales occur predominantly among small and medium-sized farms (Detre et al., 2011; Low and Vogel, 2011; Ahearn and Sterns, 2013). Local food sales can also occur when farmers sell products directly to anchor institutions, supermarkets, restaurants, or other intermediaries such as food hubs, which are distributors that aggregate and market locally branded food products. In 2015, local food sales from farms totaled $9 billion nationally (U.S. Department of Agriculture, 2016a).

Consumer interest in buying local foods can present a market opportunity for farmers and an economic development strategy for communities. Jablonski and Schmit (2015) found that local food farms have a greater dependence on labor and other local inputs relative to conventional farms. Other research studies (Hughes et al., 2008; Hughes and Isengildina-Massa, 2015; Jablonski, Schmit, and Kay, 2016; Rossi, Johnson, and Hendrickson, 2017; Watson et al., 2017) found that the localized economic impacts of local food sales can be higher than traditional food retail sales due to import substitution. Swenson (2010) estimated that fruit and vegetable agricultural production marketed locally would have a positive economic impact in the Upper Midwest if it displaced corn and soybean production.

Other studies have estimated linkages between local food production and other sectors in the economy. Brown et al. (2014) used U.S Census of Agriculture data to estimate the impacts of DTC agricultural production on aggregate agricultural production and, in turn, how agricultural production impacted aggregate economic activity. O'Hara and Benson (2018) found that dairy and DTC agricultural production had a positive impact on both local milk and local nonmilk purchases by school districts. Lev, Brewer, and Stephenson (2003) studied ten farmers' markets in Oregon and Idaho between 1998 and 2003. They found that, in some cases, the presence of a downtown farmers' market led to increased expenditures at neighboring businesses. There is, however, a dearth of studies that have empirically and systematically estimated whether DTC market outlets can influence food retail activity over a larger geographic region.

DTC agricultural production can increase food retail sales through supply-side mechanisms: DTC markets can provide a critical way for vendors to develop entrepreneurial skills and market their businesses (e.g., Feenstra et al., 2003; Morales, 2011; Lawson, Drake, and Fitzgerald, 2016; Horst, McClintock, and Hoey, 2017). Moreover, some farmers' markets serve as business incubators for new agricultural enterprises by providing shared facilities like kitchens or storage, retail space, or other forms of technical assistance (O'Hara and Coleman, 2017). This service enables some food retail businesses (e.g., a local baker) to coexist at farmers' markets alongside DTC farmers. Therefore, the existence of a farmers' market anchored by DTC farmers can help food retail vendors and businesses earn additional revenue and increase their visibility among community residents.

DTC markets can be amenable for beginning farmers since they have relatively low entry costs. Thus, marketing activity at DTC markets could provide a gateway for farmers and vendors to subsequently market products to local intermediaries in larger volumes. Examples include marketing higher-valued agricultural products (like vegetables) to restaurants or value-added products (like tomato sauce) to grocery stores or specialty food stores and selling directly to distributors that subsequently sell locally branded products to food retail establishments. Some farmers with local food sales use a variety of marketing channels, including both DTC and non-DTC outlets (Park, Mishra, and Wozniak, 2014; Low et al., 2015; U.S. Department of Agriculture, 2016a). In South Carolina, Hughes and Isengildina-Massa (2015) found that, among farmers with farmers' markets sales, 44% of their revenue came from farmers' markets, while the rest came from other market venues like restaurants and grocery stores.

On the demand side, DTC market venues can increase consumer awareness for local foods and contribute to increased demand for farm-to-table initiatives among restaurants and other retailers. For instance, product freshness and quality are important factors that influence local purchases by consumers (Low et al., 2015). Therefore, if a consumer becomes sensitized to these factors at a DTC market, the presence of local agricultural products on restaurant menus or on grocery store shelves might induce them to shop at food retail outlets that they might not otherwise patronize. In addition, they might spend more at food retail establishments. Increased expenditures may not come entirely from local residents; rather, some DTC markets could attract tourist expenditures from nonlocal residents at restaurants and other venues if local agricultural products are of high quality.

While the discussion thus far has emphasized the complementarity between DTC production and the food retail sector, these two market segments could also be substitutes. On the supply side, local producers may be reluctant to sell through non-DTC market channels if, for instance, higher prices at DTC markets crowd out the development of non-DTC local food market channels. On the demand side, more purchases at DTC agricultural markets could reduce expenditures at restaurants as consumers increase at-home food consumption at the expense of away-from-home consumption. Also, increased food purchases at DTC agricultural markets could result in consumers shopping for fewer products at grocery stores.

Trends in WSC Food Retail Subsectors

The WSC division experienced a 6% increase in real per capita income between 2007 and 2012, the largest among all U.S. Census Bureau divisions. We convert all monetary values into 2014 U.S. dollars using the Consumer Price Index (U.S. Department of Labor, 2015). Certain sectors that are exogenous to the food services sector contributed considerably to the region's growth. For instance, personal income from the mining, quarrying, and oil and gas extraction ($35 billion, or 52%); professional, scientific, and technical services ($9 billion, or 11%); finance and insurance ($8 billion, or 14%); and pipeline transportation sectors ($7 billion, or 114%) increased in the WSC division between 2007 and 2012 (U.S. Department of Commerce, 2015).

Two 3-digit North American Industry Classification System (NAICS) subsectors encompass food retail sales. The food and beverage stores (FBS) subsector (NAICS code 445) represents sales from retail merchandise industries at fixed point-of-sale locations, including grocery stores;

specialty food stores; and beer, wine, and liquor stores. The food services and drinking places (FSDP) subsector (NAICS code 722) represents industries that prepare food and beverages for consumption and may also offer other service and entertainment options. Businesses in the FSDP subsector include full-service restaurants; limited-service eating places where customers pay before eating (e.g., cafeterias); special food services (e.g., food service contractors, caterers, and mobile food services); and drinking places where alcoholic beverages are served. We focus on the NAICS classifications at the 3-digit level because county-level data are reported less frequently for more granular classifications. Of the 470 counties in the WSC division, 260 reported sales in the FSDP and FBS subsectors in 2007, and 220 reported sales in these two subsectors in 2012.

While the value of sales in 2012 was similar in magnitude for the two subsectors in the WSC division, annual payroll in the FSDP subsector was 3.1 times larger than in the FBS in 2012, with 4.4 times as many employees (Table 1). The FSDP sector experienced greater growth than the FBS sector between 2007 and 2012, both in absolute and relative terms, across all four reported metrics. This is consistent with longer-term national trends, since away-from-home food expenditures in the United States increased from 26% of total food expenditures in 1970 to 44% in 2014 (U.S. Department of Agriculture, 2016b). Average pay in the two subsectors is fairly low, perhaps because not all jobs are full-time (Table 1). In 2012, the average annual salary was $20,343 in the FBS subsector and $14,359 in the FSDP subsector.

Table 1. Food Retail Sector Trends in the West South Central Division

	Value of Sales/Receipts (2014 $thousands)	**Establishments**	**Annual Payroll (2014 $thousands)**	**Employees**
Food and beverage stores subsector				
2007	$58,670,138	13,181	$5,421,942	268,256
2012	$66,765,019	13,258	$5,761,711	283,225
Absolute change	$8,094,881	77	$339,769	14,969
Percentage change	14%	1%	6%	6%
Food services and drinking places subsector				
2007	$54,141,129	56,837	$15,271,494	1,108,760
2012	$63,143,562	62,812	$17,756,025	1,236,563
Absolute change	$9,002,433	5,975	$2,484,531	127,803
Percentage change	17%	11%	16%	12%
Aggregated food retail subsectors				
2007	$112,811,267	70,018	$20,693,436	1,377,016
2012	$129,908,580	76,070	$23,517,736	1,519,788
Absolute change	$17,097,314	6,052	$2,824,300	142,772
Percentage change	15%	9%	14%	10%

Methods

First-Difference Model

We test the hypothesis that DTC agricultural production impacts food retail businesses. A challenge with estimating a causal impact of DTC production on the food retail sector is that factors that are unobserved or challenging to measure could be correlated with both variables. Also, the economic linkages between these two sectors could flow in the opposite direction if food retail businesses stimulate DTC production. Under these circumstances, the coefficient on DTC production would be biased.

We use two techniques in our empirical strategy to mitigate the possibility of a biased coefficient. First, we estimate first-difference regressions in which the variables represent the change in their values over time rather than their levels at a particular point in time. We do this because first-difference regressions eliminate the possibility of correlation between time-invariant unobserved effects and the regression's error term. Second, we test and control for time-varying sources of endogeneity through the use of two instruments that, we argue, are correlated with DTC production but are uncorrelated with the food retail sectors that we examine via other mechanisms.

We estimate a first-difference equation:

(1) $$y_{it} - y_{it-1} = (x_{it} - x_{it-1})\alpha + \varepsilon_{it} - \varepsilon_{it-1}.$$

The dependent variable in equation (1) is represented by y_{it}, where subscripts i and t reflect the observation for a particular county in the WSC division and time period (t = 2012; t−1 = 2007), respectively. The independent variables are represented by x_{it}. We estimate parameter α in equation (1) using pooled ordinary least squares.

We use the value of sales, shipments, receipts, revenue, or business done[1] to represent the economic performance of the sectors we examine as the dependent variable. These data are reported in the Economic Census (U.S. Census Bureau, 2017). We estimate separate regressions for the FSDP and FBS subsectors since there could be differences in the magnitudes of the impacts that they experience from DTC agricultural production.

Our main independent variable of interest is DTC agricultural sales. County-level DTC agricultural sales data are publically reported in the Census of Agriculture every 5 years. Data from 2012, the most recent year for which Census of Agriculture data are available and

[1] The U.S. Census Bureau specifies that this category includes "sales of merchandise for cash or credit at retail and wholesale by establishments primarily engaged in retail trade; amounts received from customers for layaway purchases; receipts from rental of vehicles, equipment, instruments, tools, etc.; receipts for delivery, installation, maintenance, repair, alteration, storage, and other services; the total value of service contracts; gasoline, liquor, tobacco, and other excise taxes that are paid by the manufacturer or wholesaler and passed on to the retailer; and shipping and handling receipts."

applicable to this study, represent unprocessed agricultural products sold directly by producers to individuals for human consumption at DTC market outlets (U.S. Department of Agriculture, 2014). Products can include fresh fruit, fresh vegetables, eggs, chickens, turkey, cattle, or lamb. Sales of nonedible products, commodities that are not produced on the vendor's farm, and processed products like cheese, sausage, and cider are excluded from the definition.[2]

We include control variables to account for changes in county-level socioeconomic characteristics. We control for changes in total population since greater population density will increase the level of economic activity at food retail establishments. We also test whether our results are sensitive to changes in the age profile of the population. This is important since the proportion of food expenditures for at-home consumption (relative to away-from-home consumption) increases as people age (Foster, 2015). We control for these changes by including variables that represent the percentage of residents between the ages of 25 and 44, the percentage of residents between the ages of 45 and 64, and the percentage of residents aged 65 or older (U.S. Census Bureau, 2017). The omitted variable corresponds to the percentage of residents under the age of 25.

We control for changes in aggregate per capita income (U.S. Department of Commerce, 2015) since households can reduce away-from-home food expenditures during macroeconomic contractions (e.g., Todd and Morrison, 2014). Income can also be correlated with the consumption of DTC agricultural products (O'Hara and Low, 2016). We use aggregate per capita income as a control variable because food retail is ubiquitous relative to more geographically concentrated sectors (e.g., manufacturing or natural resource production). This implies that income changes from more delineated subsectors would result in having fewer observations. It is possible that there are feedback mechanisms between the food retail subsectors and aggregate income levels, which could imply that income is endogenous. However, we assume per capita income is exogenous since the increase in income in the WSC division during the 2007–2012 period was attributable, to a considerable extent, to factors exogenous to the food services sector, such as increased oil and gas production. Simultaneity is not plausible with regard to this sector since, for example, oil wells are not developed in areas with bustling food retail sectors.

We control for the state in which the county is located and use rural–urban continuum codes (U.S. Department of Agriculture, 2013) to control for its metropolitan designation. These indicator variables capture whether there are changes over time that are specific to a particular state or attributable to the metropolitan status of a county. We control for metropolitan and nonmetropolitan counties because consumer preferences may have changed differently between 2007 and 2012 in metropolitan areas relative to nonmetropolitan areas. If so, such shifts could impact the relationship between DTC production and food retail sales. We also estimate separate specifications in which we include the interaction between DTC sales and metropolitan counties

[2] Other local food data sources exist, including a recent USDA survey that solicits information about various local food distribution channels used by farmers (U.S. Department of Agriculture, 2016a). However, we use the Agricultural Census data since these represent a cross-sectional sample of farms and cannot be used for panel data applications. There are also insufficient observations in the sample to link to food retail subsector data for a county-level study.

as a control variable. DTC markets can be more feasible to establish in areas with larger populations, since vendors prefer selling at a smaller number of larger markets (e.g., Schmit and Gomez, 2011). Thus, it might be easier for a farmer selling at a farmers' market to identify food retailers who will then market their products in more densely populated regions.

County-level DTC sales data represent the county where the agricultural operation is located. The production county may not always correspond to the county where a direct marketing transaction occurs, although in many cases it does, since U.S. Department of Agriculture (2016a) data show that 61% of agricultural operations selling at farmers' markets traveled less than 20 miles to reach their highest grossing market and 82% traveled less than 40 miles. Regardless, we also estimate a regression in which we include DTC agricultural sales in neighboring counties as an independent variable as a sensitivity test to evaluate whether there are spatial implications to the relationship between DTC production in nearby counties and the food retail sector.

We report elasticities for the statistically significant variables to facilitate interpreting the results. We calculate the percentage increase in the independent variables as a 1-unit increase in their average county-level values in 2007. We calculate the percentage change in food retail subsector sales for a particular independent variable using the corresponding parameter estimate from the regression and the average county-level sales value in 2007 for the food retail subsector of interest.

Endogeneity Test

Even though we control for both unobserved time-invariant factors and exogenous socioeconomic changes, there could be other unobserved factors correlated with changes in DTC sales and food retail sales. For example, residents in some counties may have developed a "foodie" culture over time that resulted in increased expenditures at both DTC agricultural markets and food retail establishments. Alternatively, some counties may have undertaken economic development initiatives to revitalize both sectors simultaneously. For example, planners or economic development officials may seek to draw shoppers to a business district by promoting both a farmers' market and local restaurants.

We use the severe drought that impacted the WSC division between 2007 and 2012 as an instrument to test for endogeneity. Since measuring drought conditions is inherently challenging, we represent drought conditions by using the U.S. Drought Monitor index (U.S. Drought Monitor, 2015). These county-level data are reported weekly and show the percentage of a county that is in various stages of drought. There are six classifications: "nothing" (i.e., neither in a drought nor considered a drought watch area), "abnormally dry," and four drought categories that range from "moderate drought" to "exceptional drought." We classify these categories on a sequential scale of 1 for "nothing" to 6 for "exceptional drought." We subsequently create a single index number for each week of 2007 and 2012 in each county by multiplying these index values by the corresponding percentage of the county in that stage of drought. We then average the weekly conditions to obtain an annual composite index for each county. This variable's resulting parameter estimate in our first-stage regression is an estimate of how changes in drought conditions affected DTC sales between 2007 and 2012.

The drought index is a useful instrument for several reasons. First, there is exogenous variation in drought severity across the WSC. Second, the drought had a negative impact on conventional agriculture in the region (Ziolkowska, 2016). While the adverse drought impacts on agricultural commodity sectors received considerable attention, given their prominence in the region, we also hypothesize that the drought would have had similarly negative impacts on DTC agricultural production.

A third reason we use the drought index is that we assume it to be exogenous with regard to unobserved factors that may influence expenditures at food and beverage retail establishments. This exclusion restriction implies that the only impact drought would have on food retail establishments would be its impact on DTC agricultural production. A possible way by which the exclusion restriction could be violated is if non-DTC farmers were unable to supply products to restaurants and grocery stores within their county. However, we do not view this as a concern because the prominent crops produced in the WSC division (like cotton and grains) are not directly consumed by humans.[3] Also, since non-DTC livestock production is marketed at the regional or national scale, we assume that such impacts would not be specific to the county in which the livestock production occurred.

We also use the 5-year lag of changes in DTC agricultural sales as an instrument. These changes are not a source of simultaneity with the dependent variable, by construction, since the changes in their values occurred in previous time periods. Although lags of longer duration are preferable relative to lags of shorter duration, we utilize a 5-year lag based on feedback about recent regional trends that we received at a listening session with 40 county-based agricultural educators (OCES, 2016).[4] The agricultural educators emphasized that some experienced local food farmers had retired in recent years and not been replaced. This implies that, at markets with fewer farmers selling locally, this could have a proportionally large negative impact on market activity. They also indicated that, while there has been an influx of prospective farmers undertaking local food marketing, particularly among retirees or those pursuing a second career, after several years these new farmers discontinued and ended up renting out their land.

We perform Hausman tests to estimate whether DTC agricultural sales are endogenous. Specifically, we first regress DTC agricultural sales on the instruments and the other explanatory variables. We then use the residuals from this regression as an independent variable in a second-stage regression in which the sales level of the respective food retail subsector is regressed on this residual term and the other independent variables. DTC agricultural sales is an endogenous

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[3] We do not report results when including control variables for field crops like grains/oilseeds, hay, or cotton production because these data are not reported for all counties. Thus, including these controls restricts the number of observations used in the regressions even further.

[4] Agricultural educators in the region are tasked with providing technical assistance and resources to farmers and ranchers. This implies awareness of agricultural trends in their counties, including the emergence (or lack thereof) of small farms and ranches selling DTC. Additionally, agricultural educators in some instances manage their local farmers' market, so they know which farmers were selling at the market as well as the market's overall activity.

variable if the residuals coefficient in the second-stage regression is statistically significant (Wooldridge, 2002).

Descriptive Statistics

Table 2 presents descriptive statistics. DTC sales and FBS and FSDP sales are reported for 195 and 221 counties in the WSC division for 2007 and 2012. The descriptive statistics are highly similar between the two observations that are included in the two regressions. County-level sales in the two subsectors increased, on average, by similar levels—approximately $33 million.

County-level DTC agricultural sales decreased by approximately $70,000 on average between 2007 and 2012. The U.S. Drought Monitor index increased by 1.4 and 1.6, on average, in the FBS and FSDP subsectors. Texas counties accounted for between 50% and 57% of the sample, while the rest of the sample was nearly equally distributed across the remaining three states. On average, 40%–42% of counties were metropolitan. Population increased on average by approximately 11,000 residents per county. There were modest increases in the average percentage of residents in older age cohorts.

Table 2. Descriptive Statistics (difference between 2007 and 2012)

	Food and Beverage Stores (N = 195)		**Food Services and Drinking Places (N = 221)**	
Variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Total sales/receipts ($thousands)	$32,655	$137,858	$33,305	$114,768
DTC sales 2007–2012 ($thousands)	−$69	$163	−$73	$178
Metropolitan county	0.42	0.49	0.40	0.49
Oklahoma	0.18	0.38	0.15	0.36
Arkansas	0.17	0.38	0.16	0.37
Louisiana	0.15	0.36	0.12	0.33
Population	11,177	39,685	10,662	36,968
Per capita income	$3,036	$3,384	$3,846	$4,869
% residents age 25–44	−0.01	0.02	−0.01	0.02
% residents age 45–64	0.02	0.01	0.02	0.01
% residents age ≥ 65	0.01	0.01	0.01	0.01
DTC neighboring counties ($thousands)	−$61	$55	−$60	$53
DTC × metro ($thousands)	−$25	$142	−$25	$143
Drought index	1.43	0.85	1.60	0.87
DTC sales 2002–2007 ($thousands)[a]	$75	$244	$83	$254

Notes: [a] There were 188 observations for 2002 DTC sales and 210 observations for 2007 DTC sales.

Results

Endogeneity Tests

We present the first-stage regression results in Table 3. The FBS specifications use fewer observations than the corresponding regressions for the FSDP subsector since the FBS subsector data are not reported in as many counties. The 5-year lag of DTC agricultural sales is negative and statistically significant ($p < 0.01$). The negative coefficient suggests that greater decreases in DTC agricultural production occurred between 2007 and 2012 in counties that experienced greater increases in DTC agricultural production between 2002 and 2007 after controlling for the drought and other socioeconomic changes. As we elaborate later, this negative coefficient is consistent with the declining trends in DTC production perceived by agricultural educators (OCES, 2016).

Table 3. Instrumental Variable Diagnostic Checks

	Food and Beverage Stores Sales ($thousands)	**Food Services and Drinking Places Sales ($thousands)**
First-stage regression results		
Drought index coefficient	−9.01	0.02
DTC sales 02–07 coefficient ($thousands)	−0.55***	−0.58***
N	188	210
F-statistic	32.64***	40.41***
Instrumental variable test statistics		
Hausman exogeneity test first-stage residual *p*-value	0.64	0.02
Second-stage observations	188	210
Overidentifying restrictions χ^2 test statistic	0.02	0.08

Notes: Coefficients for other independent variables not reported for brevity. Triple asterisks (***) indicate significance at the 1% level.

The drought index has a negative and statistically significant impact on DTC agricultural sales when it is the only instrument included in the regression. However, we do not report these regression results in Table 3 because the *F*-statistics from the first-stage regressions are less than 10 in magnitude. The drought index is not statistically significant in the first-stage regression when we also include the 5-year lag of DTC agricultural sales as an instrument. The magnitudes of the *F*-statistic in the first-stage regression are 32.6 and 40.4 for the FBS and FSDP subsector, respectively, when both the 5-year lag of DTC agricultural sales and the drought index are included as instruments.

The Hausman tests indicate that DTC agricultural sales are exogenous when FBS sales is the independent variable but endogenous with regard to FSDP subsector sales. We further see that the overidentification test statistic is statistically insignificant in both FSDP and FBS specifications. This latter result provides justification for the use of both instruments.

First-Difference Regression Results

We present first-difference (FD) regression results in Table 4.[5] Sales from the FBS and FSDP subsectors are the dependent variables in specifications 1–3 and 4–6, respectively.

Population has a positive and statistically significant impact ($p < 0.01$) on both food retail subsectors in each of the specifications that we estimate. The coefficient magnitudes imply that a 1-person increase in population leads to an approximately $3,400 increase in county-level FBS sales and an approximately $3,000 increase in county-level FSDP sales. These parameter estimates imply that both food retail subsectors are elastic with respect to population changes. The elasticity values for population in specifications 1 and 4 are 1.91 and 1.89, respectively.

Per capita income does not impact sales in the FBS subsector; however, per capita income has a positive impact on sales at FSDP establishments ($p < 0.05$). The coefficient's magnitude implies that a $1 increase in county-level per capita income increases county-level sales at FSDP establishments between $560 and $730. Although the per capita income coefficients in specifications 4 through 6 are statistically significant, they are inelastic. For instance, the coefficient magnitude in specification 4 corresponds to an elasticity of 0.13.

The percentage of residents between the ages of 25 and 44 has a positive effect on both food retail subsectors. However, the impact that this percentage has on FBS subsector sales is more pronounced than in the FSDP subsector. The parameter coefficients imply that the FBS and FSDP subsectors have elasticities of 0.83 (specification 1) and 0.28 (specification 4), respectively. The other two age cohort percentage parameter estimates are statistically insignificant in all of the reported specifications.

DTC agricultural sales does not have a statistically significant impact on the FBS subsector. In specification 4, we find that a county-level $1,000 increase in DTC agricultural sales increases the county-level FSDP sales by $31,870 ($p < 0.05$). However, this corresponds to a modest elasticity value of 0.04. A $1,000 increase in DTC sales is a relatively large change compared to the implied change in FSDP sales.

The impact of DTC sales on the FSDP subsector varies depending on the metropolitan status of the county. In specification 5, the interaction term of DTC sales and metropolitan counties is positive and statistically significant ($p < 0.01$). The impact of a $1,000 increase in DTC sales

[5] We also estimate a Seemingly Unrelated Regression (SUR) as a robustness check. There are only 136 observations in the SUR since the greater number of variables decreases the number of counties that do not have missing values for at least one variable. The SUR results are similar to the FD regression results. Specifically, population has a positive and statistically significant impact on both subsectors, with similar coefficient magnitudes to the FD regressions. DTC sales are statistically insignificant with regard to the FBS subsector, while positive and significant with regard to the FSDP subsector.

Table 4. First-Difference Regression Results

Dependent Variable	**Food and Beverage Stores Sales ($thousands)**			**Food Services and Drinking Places Sales ($thousands)**		
Specification No.	**1**	**2**	**3**	**4**	**5**	**6**
DTC sales 2007–2012	24.38	−2.25	27.16	31.87**	−9.67**	33.61**
	(22.81)	(9.29)	(23.41)	(14.87)	(4.55)	(15.48)
Metropolitan county	−5,998	−3,430	−6,683	−406	5,256	−601
	(6,599)	(6,591)	(6,829)	(5,294)	(4,942)	(5,303)
Oklahoma	−837	−1,775	−2,305	3,848	3,233	2,786
	(3,915)	(3,899)	(3,600)	(3,007)	(3,078)	(3,008)
Arkansas	12,159**	11,797*	12,563**	5,683**	7,016**	5,564**
	(6,092)	(6,092)	(6,241)	(2,781)	(2,891)	(2,815)
Louisiana	1,507	456	2,399	9,871	7,825	10,285
	(5,849)	(5,803)	(6,271)	(6,071)	(5,831)	(6,245)
Population	3.37***	3.36***	3.35***	3.01***	3.00***	3.00***
	(0.35)	(0.34)	(0.34)	(0.27)	(0.26)	(0.27)
Per capita income	−0.03	−0.20	−0.19	0.73***	0.56**	0.69***
	(0.51)	(0.51)	(0.52)	(0.26)	(0.24)	(0.25)
% residents age 25–44	432,024*	445,459**	405,785**	209,850*	242,089**	189,305*
	(182,702)	(181,214)	(167,343)	(114,240)	(121,348)	(104,553)
% residents age 45–64	19,349	153	−37,041	57,683	−11,161	−1,959
	(152,001)	(151,306)	(172,792)	(80,439)	(79,732)	(126,500)
% residents age ≥ 65	227,361	211,450	134,896	−25,364	−72,081	−71,280
	(160,080)	(161,682)	(166,215)	(101,621)	(97,741)	(94,289)
DTC × metro		38.11			69.68***	
		(31.76)			(21.97)	
DTC neighboring counties			−53.81			−36.52
			(52.84)			(43.18)
R^2	0.92	0.92	0.92	0.94	0.94	0.94
F-statistic	225.38***	204.93***	204.93***	328.22***	310.31***	298.26***
N	195	195	195	221	221	221

Notes: Numbers in parentheses are robust standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively.

results in a FSDP subsector increase of approximately $70,000, more than twice the size of the coefficient magnitude on DTC sales in specification 4. Thus, the impact of DTC agricultural production on the FSDP subsector is more pronounced in metropolitan counties. When the interaction term is included in specification 5, the coefficient on DTC sales is negative and statistically significant ($p < 0.05$). DTC agricultural sales in neighboring counties do not impact either of the food retail subsectors (specifications 3 and 6).

Instrumental Variable Regression Results

The instrumental variable (IV) regression results in Table 5 are similar to the FD regression results in Table 4. In particular, population has the same coefficient magnitudes in Table 5 as in specifications 1 and 4 in Table 4. Likewise, per capita income has a positive impact on the FSDP subsector but a statistically insignificant impact on FBS subsector sales. The percentage of residents between the ages of 25 and 44 is statistically insignificant in the IV regression with regard to the FSDP subsector. While this contrasts with the FD regression results, the parameter estimate in the FSDP IV regression is close in magnitude to the FD regression coefficient reported in specification 4.

Table 5. Instrumental Variable Regression Results

Dependent Variable	Food and Beverage Store Sales ($thousands)	Food Services and Drinking Places Sales ($thousands)
DTC sales	18.87	48.60***
	(28.38)	(18.38)
Metropolitan county	−9,267	−791
	(6,311)	(5,361)
Oklahoma	−936	4,129
	(3,964)	(3,249)
Arkansas	6,302	4,818*
	(4,010)	(2,927)
Louisiana	2,549	9,971
	(6,248)	(6,421)
Population	3.37***	3.01***
	(0.35)	(0.26)
Per capita income	0.02	0.82***
	(0.50)	(0.28)
% residents age 25–44	396,900**	208,885
	(181,796)	(137,274)
% residents age 45–64	15,998	87,625
	(165,539)	(90,468)
% residents age ≥ 65	252,898	−10,567
	(163,110)	(115,910)
F-statistic	325.76***	412.34***
N	188	210

Notes: Numbers in parentheses are robust standard errors. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level, respectively. *F*-statistics are calculated for the joint significance of the socioeconomic variables.

DTC sales has a positive and statistically significant impact on the FSDP subsector. The IV coefficient's magnitude implies that a $1,000 increase in county-level DTC agricultural sales increases FSDP sales by approximately $48,600. Thus, the magnitude of the DTC sales parameter estimate in the IV regression is greater than the corresponding coefficient in the FD regression.

Discussion

We find that the drought had a detrimental impact on DTC agricultural production, which is consistent with the adverse impacts that conventional agricultural sectors similarly experienced. We attribute the negative coefficient on the 5-year lag of DTC agricultural sales in the first-stage regression to supply-side constraints that adversely impacted DTC market performance in the region, as reported by agricultural educators (OCES, 2016).

The positive coefficient on population with respect to both dependent variables is consistent with the expected sign. While both food retail subsectors are highly elastic with regard to population changes, they experience different outcomes from changes in other socioeconomic variables. For example, if an expenditure at an FSDP establishment represents more of a luxury purchase than one at an FBS establishment, then per capita income impacts sales in the FSDP subsector but not necessarily the FBS subsector. The positive impact that the percentage of the population between the ages of 25 and 44 has on both food retail subsectors could be due to people in this age cohort consuming food in greater quantities than do other age cohorts. However, the relatively smaller impact that this percentage has on the FSDP subsector could be because other socioeconomic factors, such as income changes, have a relatively greater influence on these expenditures.

Our finding that DTC production is exogenous with regard to the FBS subsector but endogenous with regard to the FSDP subsector could be due to the different ways in which people shop at the stores. A demand-side explanation for this finding is if FBS expenditures at grocery stores are more for staple foods and less influenced by whether such products are local. In contrast, expenditures at restaurants may be more influenced by quality attributes of the food product. A supply-side explanation for this finding is that grocery store supply chains may be more consolidated and challenging for DTC farmers to access, whereas selling products directly to a restaurant may be more straightforward. Regardless, so as to not overstate this finding, we emphasize that the magnitude of the impact on restaurant sales from changes in DTC sales is modest, corresponding to an elasticity of 0.04.

We find that DTC production and the FSDP subsector were complements in metropolitan areas and substitutes in nonmetropolitan areas. It may be more efficient for food retail businesses to sell at direct markets in metropolitan areas if the greater population density reduces their per unit direct marketing transaction costs by a relatively greater amount (e.g., Schmit and Gomez, 2011). Also, direct marketing farmers may be able to more easily connect with food retail businesses that will market their products where population density is greater. If such opportunities are not as easy to establish in nonmetropolitan areas, then DTC markets could compete with food retail businesses for customer purchases. Alternatively, residents of nonmetropolitan areas may patronize food businesses in metropolitan areas, where it could be easier to promote locally sourced products.

Conclusion

In the United States, two food consumption trends have emerged in recent decades: i) an increasing proportion of away-from-home food expenditures and ii) greater consumer awareness and interest in buying source-identified local foods. While numerous mechanisms provide plausible explanations as to why DTC agricultural production could bolster food retail sectors, the complementarity of these sectors has not been extensively researched. Such research is valuable given the headwinds confronting the retail sector in general and the food retail sector in particular. For instance, traditional food retailers have confronted challenges from the increasing consolidation of the sector, such as an increasing market share of supercenters, as well as from an increased share of sales occurring online (Daniels, 2017; U.S. Department of Agriculture, 2018).

Our results suggest that policy makers and economic development officials can view supporting DTC production as reinforcing the FSDP subsector in metropolitan counties. Practically, our results suggest that planners should engage local agricultural producers and food retail enterprises collectively in planning efforts in such areas. We also found that DTC markets can be a substitute for restaurants in nonmetropolitan counties. Thus, planners in nonmetropolitan counties should be aware of the trade-offs between these sectors when developing long-term economic development programs. We did not find that DTC production impacts the performance of the FBS subsector, which similarly informs planners that enhancing DTC markets has neither positive nor negative impacts on grocery stores and supermarkets.

In recent years, researchers have surveyed farmers (U.S. Department of Agriculture, 2016a), distributors/food hubs (Hardy et al., 2016), and institutional sectors such as schools (O'Hara and Benson, 2018) in an effort to understand opportunities, supply chain logistics, and market size in buying local foods. While our findings provide evidence of a relationship between DTC production and food retail businesses at the county level, there have been few studies examining food retail business practices pertaining to local food sourcing. Future research could involve surveying food retail enterprises to identify trends and patterns in both sourcing local food products and marketing at DTC outlets.

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College Students' Preferences and Willingness to Pay for Fresh Apple Varieties in Peru

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Abstract

We investigate Peruvian college students' preferences for fresh apple quality attributes. We conducted a sensory taste test and incentive-compatible experimental auction to elicit preferences for three apple varieties available in the Peruvian market: 'Delicia', 'Royal Gala', and 'Fuji'. We found that college students participating in our sensory taste test preferred apples with the 'Royal Gala' quality profile over 'Delicia' and 'Fuji'. Revealing the name of the apple variety and its associated country of origin did not affect willingness to pay. In general, panelists were willing to pay a price premium for larger fruit sizes and higher crispness. Our findings underscore the importance of appearance and eating quality apple attributes on overall preference and willingness to pay. This information, although not representative of the general Peruvian population, could serve as an indication of the factors deemed most important to individuals when choosing to consume a fruit product.

Keywords: apple varieties, experimental auctions**,** Peru, sensory taste test, willingness to pay

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Introduction

Food choice is, in general, a complex process. The literature suggests that including the perspectives of different disciplines when studying food choice enables more reliable modeling compared to what would be achieved using a single discipline (Köster, 2003). A common belief held by economists studying food (and non-food) decisions is that individuals are rational, their choices are guided by conscious motives, and explanations for their behavior can be explicitly reported (Köster, 2003). However, disciplines such as psychology postulate that consumers do not necessarily process information systematically but rather use simple heuristics to select or eliminate products from their choice set on the basis of a few salient quality characteristics (Combris et al., 2009). Hence, when studying food choice, it is important to understand how consumers perceive and value a food product based on the available intrinsic and/or extrinsic information.

The objective of this study is twofold: First, we elicit the value that individuals posit on inherent apple quality attributes or whether attribute bundles are valued equally across different apple varieties. Second, we investigate whether disclosing the name of the apple variety and its associated country of origin influenced consumers' willingness to pay (WTP).

We choose fresh apples because, unlike from other fresh food products, they exhibit external characteristics that enable consumers to visually differentiate across varieties. In this context, apple varieties act like brand categories, in which members of one category share common characteristics that distinguish them from other categories (Richards and Patterson, 2000). The salient differences in external appearance for fresh apples—that is, how the fruit looks, its color, shape, and size—are believed to drive consumers' first impulses to buy the apple (Shapiro, 1983). However, subsequent purchasing decisions are influenced by consumers' previous experiences with the eating quality of similar products or varieties (Shapiro, 1983).

We focus on college students, the millennial generation, because their preferences will shape future demand for products and services (Fromm and Garton, 2013). Changing lifestyles, changing eating habits, and the possibility of expanding food choices are believed to influence consumer expectations for food, in general, but especially among younger generations (Szczepanski, 2016). Such expectations are fueled by the desire for fresh, exciting flavors; the need for convenience; the pursuit of health and wellness; and demand for transparency and authenticity (Szczepanski, 2016).

While scholars have conducted abundant market research on the general characteristics of millennials (Fromm and Garton, 2013; Howe and Strauss, 2009; Greenberg and Weber, 2008), scant research addresses Latin American millennials, especially in those Latin American countries classified as emerging, such as Peru. Peru's population grew at an average rate of 6.1% between 2005 and 2014 (World Bank, 2015), and 35% of the total population are millennials (Perú Instituto Nacional de Estadistica e Informatica, 2015). Peru's millennials are also educated: approximately 80% of Peruvian millennials have completed higher education (De la Cruz, 2016), implying that this group will have more disposable income to fuel the demands of the future middle class and influence lifestyle trends for the decades to come. Peru's growing middle class, with their increasing purchasing power, appears to be more open than previously to new and high-quality food products. This is reflected in an emerging trend: Goods with high nutritional and health value are becoming more popular among Peruvian consumers (Foreign Affairs and International Trade Canada, 2011). Despite using a sample of millennials, we do not aim to make generalizations about Peruvian millennials' preferences for fresh fruits; rather, we hope to understand how a segment of this group (represented by college students) perceptions of the intensity of quality attributes impact WTP and whether knowing the country of origin of the food product affects this valuation.

Fresh Apple Consumption in Peru

In many countries—including Peru—there is concern that low rates of fruit and vegetable consumption among some population sectors will lead to future public health problems (El Peruano, 2015). In 2016, Peru produced a total of 158 thousand metric tons of apples on 9.7 thousand hectares, with a productivity rate of 16 t/ha (Perú Ministerio de Agricultura y Riego, 2018). In 2013, consumption of fresh apples was 5.6 kg/person/year (FAOSTAT 2018b). Average apple consumption in Peru is lower than in other countries with similar gross domestic products ($5,500–$6,500 per capita, in 2010 U.S. dollars) such as China (21.2 kg/person/year), Iran (18.6 kg/person/year), Turkmenistan (8.6 kg/person/year), and Azerbaijan (14.1 kg/person/year) (FAOSTAT, 2018b, World Bank, 2017).

Peru has traditionally imported apples from Chile, but the United States has recently increased its market share in the Peruvian apple market. Chile is a major—by volume—producer of apples in the Southern Hemisphere. In 2016, 36,063 ha were dedicated to apple production, yielding 1.76 million tons of apples (FAOSTAT, 2018a). In 2016, Chile exported 764 thousand tons of apples (United Nations, 2018). The United States is the second-largest producer—by volume—of apples in the world, after only China, producing 4.65 million tons in 2016 (FAOSTAT, 2018a). In 2016, the United States exported 1,069.67 thousand tons of apples (United Nations, 2018). In 2016, Chile exported 47.9 thousand tons of apples to Peru, while the United States exported 4.8 thousand tons (United Nations, 2018).

This international transit of food has been fostered by the emergence and expansion of trade agreements, in which Peru, Chile, and the United States have been involved. In 1991, the United States enacted the Andean Trade Preference Act, eliminating tariffs on a number of products from Bolivia, Ecuador, Colombia, and Peru. In 2006, the United States and Peru signed a bilateral Trade Promotion Agreement, effective in 2009, which eliminated most tariffs on exports in both countries (Perú Ministerio de Comercio Exterior y Turismo, 2016). Peru also has a history of trade agreements with Chile. In 1998, the two countries signed an Economic Complementation Agreement developed as part of the Latin American Integration Association. In 2009, a Free Trade Agreement was put into effect between the two countries, with a scheme of progressive trade tariff elimination to be completed in July 2016 (Perú Ministerio de Comercio Exterior y Turismo, 2016).

Literature Review

A large body of literature in the sensory science discipline has analyzed consumer preferences for apple quality attributes (see, e.g.,, Daillant-Spinnler et al. 1996; Jaeger et al., 1998; Cliff, Sanford, and Johnston, 1999; Hampson et al., 2000; Hampson and Kemp, 2003; Harker, Gunson, and Jaeger, 2003; Jesionkowska and Konopacka, 2006; Harker et al., 2008; Dinis, Simoes, and Moreira, 2011; and Cliff, Stanich, and Hampson, 2014). A common finding across these studies is that textural (e.g., firmness and crispness) and flavor (e.g., sweetness, acidity, balance between sweetness and acidity) quality characteristics impact consumers' preferences for fresh apples.

A branch of literature in the applied economics discipline centers on estimating the value that consumers place on or their WTP for different fresh apple quality characteristics. Studies vary in the empirical approaches used, ranging from hedonic price models (Kajikawa, 1998; Carew, 2000), conjoint analyses (Manalo, 1990; Choi et al., 2017) and contingent valuation (McCluskey et al., 2007 and McCluskey et al., 2013) to experimental auctions (Lund et al., 2006; Yue et al., 2007; Yue and Tong, 2011; Costanigro et al., 2014; Zhang and Vickers, 2014; Seppa et al., 2015; Gallardo et al., 2017). These studies concur with the sensory science literature, finding that perceived superior textural (e.g., firmness and crispness) and flavor (e.g., sweetness, acidity, balance between sweetness and acidity) quality characteristics positively impact consumers' WTP.

In this study, our goal is to elicit the value that individuals posit on inherent apple quality attributes and investigate whether disclosing the name of the apple variety and its associated country of origin influenced WTP. We used three apple varieties, typically sold in the Peruvian marketplace: U.S. imported 'Fuji', Chilean imported 'Royal Gala', and locally grown 'Delicia'. Locally grown 'Delicia' represented 60% of all apples sold in the main wholesale fruit market in Lima in 2014 (Perú Ministerio de Agricultura y Riego, 2018). The most-demanded imported apple varieties in Peru are 'Fuji', 'Royal Gala', 'Granny Smith', and 'Red Delicious' (Fresh Plaza, 2016).

Fresh food eating quality is often examined at a conceptual level, given that product tasting is not often incorporated into protocols (Harker, Gunson, and Jaeger. 2003). A limitation is that fresh foods are perishable (i.e., quality attributes change throughout the marketing season), and consumer perceptions could therefore change throughout the year. This is evident when comparing different varieties, which are often harvested at different times. Other difficulties include procuring a representative sample of individuals to participate in the taste test and the fact that the facilities where tastings take place are likely to be different from the typical contextual associated with fruit purchase (Harker, Gunson, and Jaeger, 2003).

We attempted to mitigate these potential difficulties by mimicking as closely as possible a routine grocery shopping experience. Participants were presented with three apple varieties with which they were familiar and that were being sold at most grocery stores at the time the study took place. Moreover, we used incentive-compatible experimental actions to elicit values. In experimental auctions, participants are involved in an active market environment, exposed to market feedback, and face real economic consequences to their responses (Lusk and Shogren 2007). Due to the significant advantages over other value elicitation methods, experimental auctions have become increasingly popular for valuing quality and information attributes of agricultural products (e.g., Alfnes and Rickertsen, 2003; Groote et al., 2011; Melton et al., 1996; Rozan, Stenger, and Willinger, 2004; Yue and Tong, 2011; Groote et al., 2016). In addition, the fact that the study took place in a laboratory setting enabled us to control for potential external factors that could influence preference.

We used a second-price auction format in which each participant submits a sealed bid; the individual submitting the highest bid wins the auction and must pay the second-highest bid for the product. We chose this mechanism because it is demand revealing, is relatively simple to explain to participants, and exhibits an endogenous market-clearing price. Detractors of the second-price auction argue that there is a risk that individuals will overbid and lose interest in multiple bidding rounds, especially for low-value bidding individuals (Colson, Huffman, and Rousu, 2011). The random *n*th-price auction offers an alternative, but the literature does not provide any conclusive evidence indicating which auction mechanism is superior. Lusk and Shogren (2007) claimed that second-price auctions are better for individuals whose valuations are close to the market value and that random *n*th-price auctions are better for individuals whose valuations are far below the market price. We underscore the ease of implementation of the second-price auction and the evidence that participants without prior training and without a thorough understanding of the auction mechanism could systematically bias auction results (Corrigan and Rousu, 2008).

Methods

Data Collection

We conducted the experimental auctions and sensory taste tests in June 2015 at the facilities of the Universidad Nacional Agraria la Molina in Lima, Peru. One hundred college students were recruited 2 weeks in advance by flyers posted around campus. We used the standard sample size of 100 individuals for a sensory evaluation in a central location (Meilgaard, Civille, and Carr, 1999). Sensory science practitioners concur that the correct number of consumers to be enrolled in a sensory test depends on the complexity of the sensory task to be performed (Mammasse and Schlich, 2010). We justify our choice of 100 individuals using claims made by Mammasse and Schlich (2010) and Chambers and Baker Wolf (2005) stating that the number of panelists to be enrolled in a hedonic sensory evaluation should range from 50 to at least 100, if no preference segmentation is sought.

To participate in the study, individuals had to have eaten apples in the last 3 months. We acknowledge that using student pools is often questioned. In principle, the goal of this paper is not to generalize about Peruvian consumers' preferences for fresh apple varieties but to investigate whether attribute bundles are valued equally across different apple varieties and whether disclosing the name of the apple variety and its associated country of origin influence WTP. Logistically, recruiting college students was more convenient and less costly than recruiting a nationally representative sample of individuals. Nalley, Hudson, and Parkhurst (2006) argue that students perform similarly to other groups in economic experiments. Moreover, Smith, Suchanek, and Williams (1988) conclude that experienced and inexperienced subjects exhibit similar forecasting behaviors.

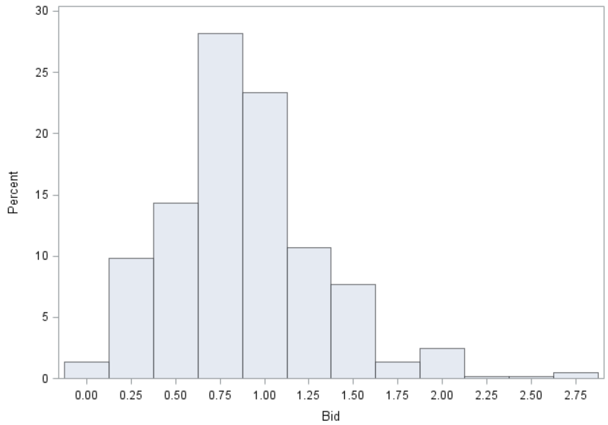
The experiment was conducted in two different sessions, each hosting 50 individuals. Each participant was given S/. 20 (nuevos soles, the Peruvian currency) (the equivalent of $6.3 U.S. dollars) as compensation for their time and as an initial endowment for the experimental auctions. As of June 18, 2015, $1 was equivalent to S/. 3.16 (Banco Central de Reserva del Perú, 2015). At the beginning of each session, the moderator explained the study goals. Then, the moderator explained the sensory taste test and the experimental auction. A practice auction using pencils was performed to familiarize participants with the experimental auction procedure. The moderator emphasized that an actual payment would be required from the winner of the auction. Next, the moderator explained each sensory quality attribute included in the questionnaire (e.g., crispness or acidity).

The experiment consisted of two rounds. The first round included the sensory evaluation of each apple sample and bid elicitation without any information about the name of the variety or its country of origin. The second round was the same as the first, but the name of the variety and associated country of origin were disclosed.

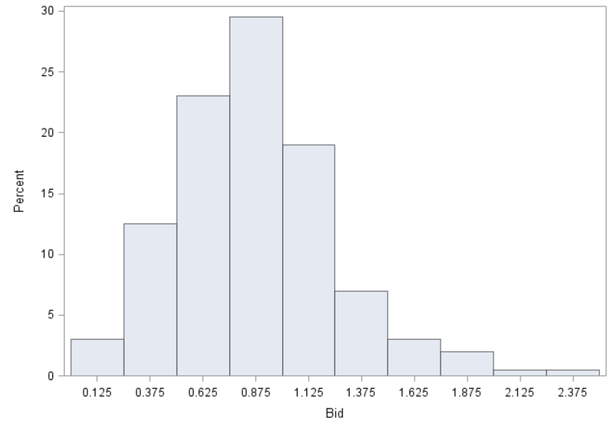
During the first round, each participant was presented with three apple samples, each from a different variety, identified with letters D, N, and S. First, participants evaluated the samples visually. Appearance attributes included the perceived presence of external defects, color, shape, and size. Next, participants rated each sample on a 9-point scale (where 1 = dislike extremely, …, 9 = like extremely) to indicate how much they liked the appearance, size, color and shape of each sample. Next, researchers cut each participant's apple sample in half and asked participants to measure the transverse diameter of each apple sample with a ruler and record its size in the questionnaire. They were also asked to assess the presence of defects using a 9-point scale (1 = no defects, …, 9 = abundant defects). Next, participants were asked to smell the apple, bite, and taste, rinsing their mouths with water between tasting each sample. Then they rated several attributes—aroma, crispness, firmness, juiciness, flavor, sweetness, and acidity—using a 9-point scale (1 = dislike extremely, …, 9 = like extremely). They were also asked to rate the perceived intensity of each attribute on a 9-point scale (1 = not intense, …, 9 = extremely intense). Once most participants had signaled that they had finished responding to the questionnaire, they submitted a bid in nuevos soles per kilo for each of the apple samples evaluated. The bids were organized in ascending order, and the first- and second-highest bids were identified along with the panelists submitting those bids. Researchers recorded the winning bids; that is, bids were not revealed to participants after the first round of bids, in order to avoid the possibility of influencing subsequent bids.

During the second round of the experiment, researchers revealed the name of the apple sample variety and associated country of origin, and participants subsequently submitted a second round of bids. The same procedure was repeated: Bids were organized in ascending order, and the first- and second-highest bids were identified along with the panelists submitting those bids. After the second round of bids, the moderator randomly chose a binding apple sample and a binding bid round, identifying a single winner for the session. Finally, participants responded to a questionnaire about apple fruit consumption, purchasing habits, and sociodemographic information.

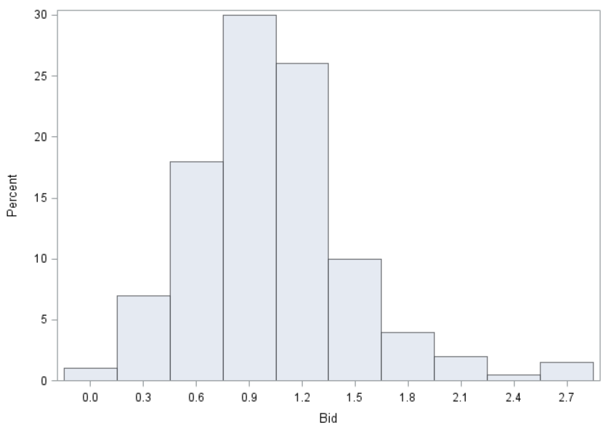
Empirical Model



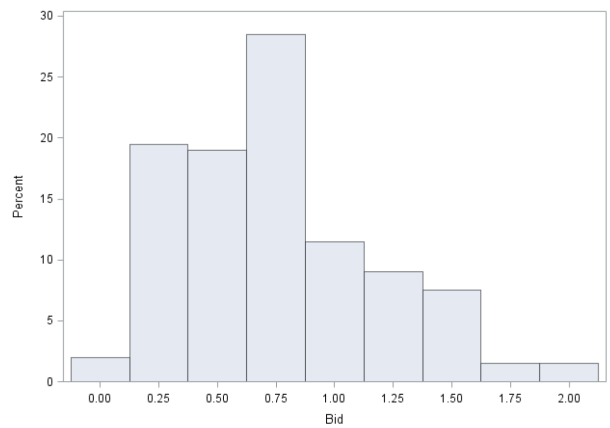
Distribution of Bids for all Apple Varieties



Distribution of Bids for 'Delicia'



Distribution of Bids for 'Royal Gala'



Distribution of Bids for 'Fuji'

Figure 1. Histogram of Bid Distributions

Given that participants often bid zero values, we use censored models to analyze the experimental auction bid data. In our sample, 1% of bids (6 out of 600) were zeroes. Figure 1 showed that the bid distribution leans to the left, or positive skewness. Results from a skewness test show a positive non-zero value.[1] Skewness values for all bids are 0.83, for 'Delicia' apple bids 0.81, for 'Royal Gala' 0.87, and for 'Fuji' 0.72. We use a Tobit model to explain the variation in bids for the different apple samples. In censored models, the latent unobserved variable bids, y^*, are represented by y, the bid actually observed. We consider our bids to be left censored, following Greene (2008):

[1] The formula to estimate skewness is $\frac{n}{(n-1)(n-2)}\sum_{i=1}^{n} w_i^{3/2}\left(\frac{x_i-\bar{x}_w}{s_w}\right)^3$, where n is the number of non-missing values for a variable, x_i is the ith value of the variable, $\bar{x}_w$ is the sample average, s is the standard deviation, and w_i is the weight associated with the ith value of the variable.

$$(1) \quad \begin{aligned} y_1^* &= \mathbf{X}_i\beta + \varepsilon_{ij} \\ y^* &= 0 \text{ if } y_i^* \leq 0 \\ y^* &= y_i^* \text{ if } y_i^* > 0 \end{aligned}$$

where $\mathbf{X}_i$ is the vector of explanatory variables for individual i's preference ratings for apple quality attributes (including appearance, taste, and texture) and ε_{ij} is the error term assumed with mean 0 and variance σ^2. The parameter estimates are obtained by maximizing the likelihood function, L, which is represented by

$$(2) \quad L = \prod_{i=1}^{N} \left(\frac{1}{\sigma} \phi \left(\frac{y_i - \mathbf{X}_i\beta}{\sigma} \right)^{UC_i} \right) \Phi \left(\frac{-\mathbf{X}_i\beta}{\sigma} \right)^{LC_i},$$

where UC_i and LC_i are indicator variables representing uncensored and left-censored bids and Φ represents the cumulative standard normal distribution (Lusk and Shogren, 2007).

Recall that we elicited ratings for how much individuals liked the quality attributes of each apple sample and for the intensity perceived for the same quality attributes. A Pearson correlation test (Table 4) demonstrates that all preference ratings and perceived-intensity ratings are correlated. Therefore, we conduct separate regressions using either preference or intensity ratings as explanatory variables. We use different measures of goodness of fit to investigate which regression—that using preference ratings or that using perceived intensity ratings—offered better explanatory power. We used the Akaike Information Criterion (AIC), which evaluates the likelihood function relative to the number of parameters in the empirical formulations. We also used the Bayesian Information Criterion (BIC), which includes different prior probabilities according to the number of the candidate model (Greene, 2008). Further, we compared the adjusted R^2 and the log-likelihood functions. All measures of goodness of fit indicated that using preference ratings as explanatory variables offered better explanatory power than using intensity ratings (Table 1). Therefore, we only present the results of the parameter estimates in equation (2) using preference ratings as explanatory variables.

Table 1. Measures of Goodness of Fit Comparing Models Having Preference Ratings versus Perceived Intensity Ratings

	'Delicia'		**'Royal Gala'**		**'Fuji'**	
Goodness of Fit	**Preference**	**Intensity**	**Preference**	**Intensity**	**Preference**	**Intensity**
Adjusted R^2	0.082	0.115	0.108	0.049	0.146	0.064
AIC[a]	210.800	201.300	290.100	307.400	243.700	259.900
BIC[a]	214.000	204.500	293.300	310.600	246.900	263.100
Log-likelihood	−99.650	−104.400	−144.050	−152.700	−120.850	−128.950

[a] Akaike Information Criterion.
[b] Bayesian Information Criterion.

We elicited bids for samples of three apple varieties. We conduct an F-test to infer whether conducting separate regressions for each apple sample offers superior explanatory power compared to conducting a single regression using pooled data. Results from the F-test (F statistic

= 2.31, F critical value (22, 559) = 1.56) suggest that separate regressions for each sample offer better explanatory power than a single regression using pooled data. Data were analyzed using SAS® v. 9.2.

Results

Summary Statistics

Compared to the 2014 population estimates from the Peruvian Instituto Nacional de Estadistica e Informatica, our sample had fewer household members (3 vs. 5) and was younger (21 vs. 25) than the general Peruvian population. There were more females than males in our sample (61% vs. 50%), and more of our sample had achieved higher education than the general population (90% vs. 31% with more than high school). A much larger portion of our panelists (74%) were born in Lima, compared to 31% of the total Peruvian population. Our sample also overrepresented the upper-tier neighborhoods of Lima, with 31% of panelists living in upper-tier neighborhoods, compared to 3% of the total population in Lima; the middle tier was closely represented (17% vs. 15%), and the lower tier was underrepresented (51% vs. 82%). The median income of our sample panelists was higher than for the general Peruvian population (S/. 3,000 /month vs. S/. 1,555 /month) (Table 2).

Table 2. Summary Statistics of Survey Respondent and Census Demographics

	Panelists	Peru General Population
Size of household	3	5.4
Average age	21.26	25.5
Gender (% female)	61	49.9
Education (% with more than high school)	90	31.3
Born in Lima (%)	74	31.3
District of Lima		
Upper tier (%)	31	3.4
Medium (%)	17	14.6
Low tier (%)	51	82
Median income (nuevo sol/month)	S/. 3,000	S/. 1,555
($US/month)	($949)	($492)

Source: Peru, Institute of Statistics and Informatics (2015).

With respect to purchasing habits, panelists considered price to be an important factor when buying apples (average of 5, “important,” on a 7-point scale, where 1 = extremely unimportant, …, 7 = extremely important). In general, panelist bought apples once a month and bought 5 apples at each purchasing opportunity. If we consider that the average household size of our panelists is 3 and assume that each apple weighs 0.26 kg, then the per capita consumption of apples of our sample of panelists is 5.10 kg/person/year, relatively close to the 5.6 kg/person/year reported by FAOSTAT (2018). Most panelists in our study (40%) buy apples at traditional/artisan markets in the district (Table 3).

Table 3. Summary Statistics of Purchasing Habits

Purchase Habit	**Average/Percentage Responses per Category**
Importance of price when purchasing apples	5
(1= extremely unimportant to 7=extremely important)	
Frequency of apple purchase	Once a month
Number of apples bought when purchasing	5
Where do you most often buy apples?	% Responses
Wholesale producers market	24
Supermarket	11
District market	40
Private market	3
Small store	13
Kiosk	7
Other	2

Considering preference ratings for each apple sample variety presented, participants assigned higher preference scores for appearance attributes, such as external appearance and fruit size, to ‘Royal Gala’, followed by ‘Fuji’ and ‘Delicia’. Lack of state-of-the-art postharvest handling is reflected in the poor external appearance of Peruvian-grown ‘Delicia’ apples (M. Silva, personal communication, 2015). Considering textural quality attributes (crispness, firmness, and juiciness), participants assigned consistently higher preference scores to ‘Royal Gala’, followed by ‘Fuji’ and ‘Delicia’. When considering flavor quality attributes, participants’ preference ratings were mixed. For apple-like flavor and sweetness, participants assigned higher scores to ‘Royal Gala’ followed by ‘Delicia’ and ‘Fuji’. For aroma, higher scores were observed for ‘Delicia’, followed by ‘Fuji’ and ‘Royal Gala’; for acidity, higher scores were assigned to ‘Delicia’, followed by ‘Royal Gala’ and ‘Fuji’. Table 4 reports these ratings as well as perceived intensity ratings. Across the three varieties, perceived defects and preference for external appearance are negatively correlated. Preference ratings for fruit size, aroma, crispness, juiciness, apple flavor, sweetness, and acidity are positively and statistically significant correlated with perceived intensity; that is, higher perceived intensity correlates with higher preference ratings. The exception is firmness, for which the correlation between preference and perceived intensity was negative for ‘Delicia’ and ‘Royal Gala’, with no evidence of statistically significant correlation for ‘Fuji’.

Table 5 lists bids for each variety in rounds 1 and 2, and a pairwise comparison of bids across varieties and across rounds within each variety. In general, bids for ‘Royal Gala’ were statistically significantly higher compared to ‘Delicia’ and ‘Fuji’. Within the same variety, there were no statistically significant differences between bid 1 and bid 2, implying that knowing the apple variety and the location where it was grown did not significantly affect the amount bid.

Table 4. Summary Statistics of Preference and Perceived Intensity Ratings for Quality Characteristics for 'Delicia', 'Royal Gala' and 'Fuji' Apples

	Preference Rating		Intensity Rating			
Quality Attributes	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Pearson Correlation**	***p*-value**
'Delicia'						
Ext. app./defects	5.340	1.655	4.630	1.983	−0.341	0.001
Size	6.000	1.598	7.928	0.329	0.120	0.092
Aroma	6.530	1.588	5.830	1.411	0.462	0.001
Crispness	6.380	1.712	5.690	1.676	0.770	0.001
Firmness	6.030	1.972	5.570	1.749	−0.439	0.001
Juiciness	5.630	1.916	4.940	1.775	0.711	0.001
Apple flavor	6.290	1.697	6.030	1.470	0.818	0.001
Sweetness	6.250	1.562	5.210	1.377	0.705	0.001
Acidity	5.860	1.737	4.540	1.834	0.371	0.001
'Royal Gala'						
Ext. app./defects	6.680	1.610	2.890	1.677	−0.214	0.002
Size	7.242	1.193	7.355	0.281	0.169	0.017
Aroma	4.590	1.794	3.150	1.686	0.615	0.001
Crispness	7.250	1.594	6.870	1.884	0.767	0.001
Firmness	6.879	1.700	5.320	2.034	−0.104	0.146
Juiciness	7.384	1.472	7.100	1.607	0.807	0.001
Apple flavor	6.680	1.979	6.350	1.779	0.820	0.001
Sweetness	6.600	1.684	6.400	1.672	0.661	0.001
Acidity	5.800	1.854	3.960	2.010	0.397	0.001
'Fuji'						
Ext. app./defects	6.380	1.927	2.590	1.876	−0.157	0.027
Size	6.710	1.516	6.999	0.286	0.136	0.056
Aroma	5.430	2.142	4.850	2.445	0.847	0.001
Crispness	6.690	1.825	7.000	1.653	0.673	0.001
Firmness	6.545	1.758	4.828	2.311	0.092	0.197
Juiciness	6.687	1.942	6.810	1.769	0.697	0.001
Apple flavor	4.080	2.204	4.370	2.199	0.840	0.001
Sweetness	4.170	2.103	4.000	2.312	0.765	0.001
Acidity	4.350	1.946	3.400	2.055	0.327	0.001

Table 5. Summary Statistics and Pairwise Comparison of Bids for 'Delicia', 'Royal Gala' and 'Fuji' Apples

	'Delicia'		'Royal Gala'		'Fuji'	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Bid – round 1						
Peruvian nuevo sol	2.68[a]	1.24	3.28[b]	1.47	2.36[c]	1.35
U.S. dollar	0.85	0.39	1.04	0.47	0.75	0.43
Bid – round 2						
Peruvian nuevo sol	2.79[a]	1.69	3.22[b]	1.55	2.34[c]	1.33
U.S. dollar	0.88	0.53	1.02	0.49	0.74	0.42

Notes: Bids across apple sample varieties were statistically significantly different after a pairwise comparison test, while bids for the same variety in rounds 1 and 2 were not.

Willingness to Pay

In relation to external appearance quality attributes, parameter estimates are positive and statistically significant for size preference for 'Royal Gala' and 'Fuji' but not statistically significant for 'Delicia'. Parameter estimates for external appearance preference were not statistically significant for any of the three varieties. This finding supports Cliff, Sanford, and Johnston (1999), who reported that consumers value large fruit size. That study did not include preference for external appearance.

In relation to textural quality attributes across all varieties, parameter estimates for crispness were positive and statistically significant, signalling that participants were homogeneous in their preferences and valuation for crisper apples. However, preferences for firmness and juiciness were mixed across varieties. The parameter estimate for firmness was negative and statistically significant for 'Royal Gala' but not statistically significant for the other two varieties. Juiciness was negative and statistically significant for 'Delicia', positive for 'Royal Gala', and not statistically significant for 'Fuji'.

Results for flavor quality attributes were different across varieties. Parameter estimates for aroma preference were positive and statistically significant for 'Delicia' but not statistically significant for the other two varieties. Parameter estimates for apple flavor preference were positive and statistically significant for 'Fuji' but not statistically significant for the other two varieties. Parameter estimates for sweetness and acidity were not statistically significant for any variety. In sum, we found no conclusive indication of what flavor attributes impact WTP (Table 6).

Daillant-Spinnler et al. (1996) and Cliff, Stanich, and Hampson (2014) found that apple consumers can be divided into two groups: one that likes a sweet, hard apple, and a second that prefers a juicy, less sweet, more acidic apple. Harker, Gunson, and Jaeger (2003) concluded that the target for textural and flavor attributes differs across individuals, suggesting that a cultivar must be considered in relation to a specific market niche. In other words, a specific group of consumers would positively respond to a particular bundle of sensory attributes. In this study, we faced the challenge of conducting a study in a country where apple varieties offered in the marketplace at any given time have not necessarily been harvested in the same season or under

Table 6. Parameter Estimates for the Tobit Model Explaining Variations in Bids Across Three Apple Sample Varieties 'Delicia', 'Royal Gala', and 'Fuji' ($N = 200$)

	'Delicia'			'Royal Gala'			'Fuji'		
Variable	Parameter Est.	Std. Err.	*p*-Value	Parameter Est.	Std. Err.	*p*-Value	Parameter Est.	Std. Err.	*p*-Value
Intercept	0.321	0.164	0.051	−0.019	0.265	0.943	−0.072	0.183	0.696
Ext. app.	0.016	0.017	0.325	0.028	0.026	0.278	−0.008	0.017	0.649
Size	−0.009	0.018	0.592	0.086	0.032	0.007	0.048	0.021	0.022
Aroma	0.038	0.018	0.036	−0.023	0.020	0.259	0.004	0.014	0.767
Crispness	0.030	0.018	0.097	0.070	0.035	0.042	0.039	0.020	0.055
Firmness	−0.024	0.017	0.159	−0.071	0.031	0.021	0.007	0.021	0.719
Juiciness	−0.055	0.018	0.003	0.071	0.035	0.046	−0.005	0.019	0.808
Flavor	0.028	0.023	0.227	−0.018	0.029	0.548	0.055	0.022	0.011
Sweetness	0.025	0.023	0.282	−0.004	0.033	0.901	0.014	0.022	0.529
Acidity	0.030	0.018	0.108	−0.009	0.021	0.692	−0.009	0.017	0.592
Information	0.031	0.049	0.529	−0.021	0.063	0.743	−0.006	0.055	0.911
Sigma	0.346	0.017	0.001	0.439	0.022	0.001	0.385	0.020	0.001
Log-likelihood		−71.290			−118.155			−93.689	
AIC[a]		166.580			260.309			211.379	
BIC[b]		206.160			299.647			250.716	

[a] Akaike Information Criterion.
[b] Bayesian Information Criterion.

similar conditions. We acknowledge that the varieties evaluated in this study might have differed in their ripeness. Harker, Gunson, and Jaeger (2003) warned that "care needs to be taken to ensure consumer preferences attributed to different cultivars are not actually driven by preferences in the ripeness of each cultivar" (p. 340). Nonetheless, we argue that this study reflects the reality faced by Peruvian consumers in the marketplace, hence the challenge to identify a cluster of preferred attributes or attribute levels. Moreover, our findings support those of Combris et al. (2009), who claim that consumers use simple heuristics to select or eliminate products from their choice set based on a few salient quality characteristics. It is evident that crispnesss was salient among our sample of participants, but flavor attributes were not.

Furthermore, we acknowledge that the external appearance cues of each variety could potentially influence how panelists perceived external and internal characteristics. We designed the experiment this way for two reasons: First, because we were interested in inferring the preferred external appearance of apples, presence of external defects, and size. Second, because we assumed that the general Peruvian consumer is not familiar with the country of origin of the food products they consume (Spillan Antúnez de Mayolo, and Kucukemiroglu, 2007), especially fresh apples. Hence, they might not have a solid idea of the name of the variety or the country of origin of the apples presented to them before this information was disclosed.

In relation to the effect of information on the WTP, we found no evidence that disclosing information about the name of the variety and its associated country of origin affected bids, as the parameter estimate for this information was not statistically significant.

Summary and Conclusions

Investigating the drivers of food choice is a complex task. Literature suggests that using elements from various disciplines could help improve the understanding of food choice. In this study, we combine sensory evaluation techniques with experimental auctions to elicit the preferences and values that individuals posit on inherent apple quality attributes and determine whether attribute bundles are valued equally across apple varieties. In addition, we investigate whether disclosing the name of the apple variety and its associated country of origin influenced WTP. We conducted the experiment in two rounds. In the first, panelists evaluated the fruit, filled out a questionnaire on their perceptions, and submitted bids for each variety. In the second round, researchers revealed the name of the cultivar and its associated country of origin and panelists submitted bids again.

Participants in our study signaled a positive WTP for larger fruit sizes, an appearance attribute, and higher crispness, a textural attribute. However, no conclusive evidence was found with respect to flavor attributes. Also, revealing the name of the apple variety and its associated country of origin did not impact the WTP for each variety.

Determining key external and internal quality attributes that drive preferences and WTP for fresh fruits such as apples remains challenging. The tendency persists to consider consumers as a homogeneous group from a physiological standpoint or to characterize them by their sociodemographic information. However, as research has shown, consumer preferences are based on many factors, including familiarity with the product, socioeconomic status, age, gender, culture, and social norms (Lyman, 1989).

We acknowledge this study's pitfalls: limited control over the time of harvest and postharvest handling and the relatively small participant sample. Our findings underscore the importance of appearance and eating quality for the sample of participants, as the name of the variety and its associated country of origin did not change overall preferences or WTP for the apple samples. This information, although not representative of the general Peruvian population, could indicate the factors deemed most important to individuals when choosing to consume a fruit product. Fruit quality expectations—expressed in terms of external appearance and internal quality, taste, and texture—surpass credence expectations such as variety name and associated country of origin.

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The Use of Time-Series Analysis in Examining Food Safety Issues: The Case of the Peanut Butter Recall

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Abstract

This study presents a time-series analysis of the demand for peanut butter in the wake of the product recall involving Peter Pan and Great Value brands. A 2-lag directed acyclic graphs/Bernanke vector error correction model was estimated using weekly time-series data. The outbreak variable was negatively related to the demand for peanut butter, supporting the hypothesis that foodborne illness reduces consumer demand for a food product category. Hence, time-series models should be complementary to structural/econometric models in examining the impacts of food safety incidents as a check on the robustness of the results.

Keywords: directed acyclic graphs, peanut butter, recall, vector error correction model

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Introduction

In 2006–2007, the U.S. Centers for Disease Control and Prevention (CDC) and state departments of health investigated a multistate outbreak of salmonellosis. Subsequent investigation concluded that the foodborne illnesses had been caused by the consumption of two brands of peanut butter: Peter Pan and Great Value (a Wal-Mart store brand), both manufactured by ConAgra Foods, Inc., at its Sylvester, Georgia, processing plant (CDC, 2007). As a result, ConAgra ceased the production of peanut butter at this plant, destroyed all affected products in their possession, and voluntarily issued a nationwide recall of Peter Pan and Great Value peanut butter products produced since May 2006 through a news release distributed on February 14, 2007 (CDC, 2007). Following the recall, ConAgra not only redesigned this processing plant but also initiated an unprecedented marketing campaign concerning their Peter Pan brand (Bakhtavoryan, Capps, and Salin, 2014b).

A large body of literature has been dedicated to providing empirical evidence for the impacts of food safety issues on demand for various products (Swartz and Strand, 1981; Smith, van Ravenswaay, and Thompson, 1988; van Ravenswaay and Hoehn, 1991; Burton and Young, 1996; Verbeke and Ward, 2001; Marsh, Schroeder, and Mintert, 2004; Piggott and Marsh, 2004; Pritchett et al., 2007). All of these studies found a statistically significant negative relationship between the food safety incident and demand for the product in question.

Using Nielsen Homescan panels for household purchases from 2006 through 2008, Bakhtavoryan, Capps, and Salin (2012, 2014a,b,c) analyzed the influence of the Peter Pan and Great Value recall on various aspects of demand for peanut butter. In particular, these investigations used structural/econometric models to analyze spillover effects, competition among brands, and structural change in demand for peanut butter brands in the wake of the Peter Pan and Great Value recall. Both a single-equation model and a demand systems model were employed.

The objective of this study is to furnish findings on the impact of the Peter Pan and Great Value product recall on the demand for the peanut butter category using a time-series approach, in contrast to the structural/econometric approach previously employed by Bakhtavoryan, Capps, and Salin (2014b). In this way, a check of the robustness of the results between the two alternative approaches can be made, contributing to the extant literature dealing with examining impacts of food safety incidents. Specifically, our aim is to compare empirical results from the structural/econometric model employed by Bakhtavoryan, Capps, and Salin (2014b) to those generated by the use of a vector error correction (VEC) model. The set of variables considered and the data used in this comparison are the same as in the previous study.

Another contribution of this study is that, to the best of our knowledge, most studies dealing with food safety incidents have employed structural models as opposed to time-series models. This work then adds to the extant literature in this capacity. Further, except for the structural/econometric models employed by Bakhtavoryan, Capps, and Salin (2014a,b), previous research on food safety issues has not used the number of confirmed cases of *Salmonella* reported by the CDC as a measure of the outbreak. Instead, previous research has commonly used various types of media variables to account for the impacts of food safety incidents. Finally, this study contributes by utilizing a modified approach in its application of directed acyclic graphs while dealing with casual relationships among variables when addressing the issue of contemporaneous correlations for generating representative impulse-response functions and forecast error variance decompositions.

Literature Review

Prior studies have paid much attention to the problem of consumer response to food safety issues by employing various econometric approaches, including single-equation structural models and demand system models. In particular, Swartz and Strand (1981) investigated the impact of information concerning oyster contamination due to kepone (an insecticide) on the demand for shucked oysters in Baltimore, Maryland. They estimated a single-equation structural model with second-order and 4-lag polynomial distributed lag (PDL) structure, using biweekly data from 1973–1976. The variable reflecting the negative information was constructed based on articles from the four major Baltimore and Washington newspapers. The estimation results showed that the lags of the media variable were statistically significant, negatively impacting the consumption of oysters.

In their study, Smith, van Ravenswaay, and Thompson (1988) analyzed the response of fluid milk sales to negative newspaper coverage related to the heptachlor (an insecticide) contamination of fresh fluid milk in Oahu, Hawaii, by applying a single-equation structural model with second-degree PDL specification and 3 lags. Their study used monthly time-series data from January 1977 to June 1983. A negative media variable was developed using newspaper articles regarding the food contamination incident from two major Honolulu newspapers during the period that contained negative information on milk quality, the level of government protection, and the integrity of milk processors in handling the incident problem. The estimation results suggested a statistically significant negative relationship between the current and lagged negative media variables and fluid milk sales.

Van Ravenswaay and Hoehn (1991) studied the influence of Alar (a carcinogenic chemical sprayed on fruit) on the demand for apples by estimating a single-equation PDL model with 3 lags and employing monthly data from January 1980 to July 1989. The risk information variable concerning Alar was constructed based on the monthly number of articles in *The New York Times*. The empirical findings of the study indicated that the current and the third lag of the risk information variable were significant and negatively impacted the demand for apples.

Burton and Young (1996) investigated the effects of bovine spongiform encephalopathy (BSE) on the demand for beef and other meat products in Great Britain by applying a dynamic Almost Ideal Demand System (AIDS) model and using quarterly data from January 1961 to March 1993. They developed a variable capturing consumer awareness of BSE based on the number of published newspaper articles that contained information on BSE. Their empirical results showed that consumer awareness of BSE resulted in a loss in market shares of beef producers both in the short run and in the long run.

Verbeke and Ward (2001) analyzed consumer response to the negative public media coverage regarding food safety issues associated with fresh meat in Belgium. Their study estimated a linear approximation of the AIDS model for beef and veal, pork and meat mixtures, and poultry, employing panel data on monthly observations from January 1995 to December 1998. The mass media index, which was anticipated to capture consumer awareness of meat-related health issues, was developed by subtracting the number of positive TV reports from the number of negative TV reports associated with the effects of meat consumption on human health. The empirical findings showed that the impact of adverse publicity, primarily concerning BSE, was statistically significant and had a negative influence on the consumption of beef and veal and a positive influence on the consumption of pork and meat mixtures.

Marsh, Schroeder, and Mintert (2004) studied the effects of meat product recall events on the demand for beef, pork, poultry, and other products in the United States by estimating the absolute price version of the Rotterdam model using quarterly data on beef, pork, chicken, and turkey from 1982–1998. Two measures of meat product recalls were constructed using Food Safety Inspection Service (FSIS) reports and media reports from the popular press. The empirical results revealed that, unlike newspaper reports, FSIS reports on recall events negatively influenced the demand for beef and pork and positively influenced the demand for poultry and other products.

Piggott and Marsh (2004) estimated a Generalized Almost Ideal Demand System model to evaluate the effects of public information concerning food safety issues related to beef, pork, and poultry reported in the media on meat demand. The study employed quarterly meat data from the first quarter of 1982 through the third quarter of 1999. They developed food safety indices for each meat type by aggregating the number of newspaper articles regarding food safety issues. The estimation results established a statistically significant relationship between consumer demand and contemporaneous media coverage of health hazards.

Pritchett et al. (2007) evaluated consumer demand for meat cuts of beef, pork, and chicken in light of the announcements associated with BSE in Canada and the United States by estimating the AIDS model and using a dataset derived from monthly retail scanner data for 191 meat products sold in U.S. retail grocery stores from January 2001 through February 2005. They constructed an information variable accounting for the influence of media coverage based on the reported articles. The estimation results indicated that the BSE events negatively affected the demand for ground beef and chuck roasts and positively affected the demand for center-cut pork chops.

The 2007 Peter Pan and Great Value peanut butter recall has been analyzed by prior studies using single-equation structural model and demand systems. In particular, Bakhtavoryan, Capps, and Salin (2012) used the Barten synthetic model to estimate the pre- and post-recall demand elasticities for a statistical comparison using weekly observations from Nielsen Homescan panel data on household purchases of major peanut butter brands from January 2006 through December 2008. The estimation results revealed that demand elasticities statistically increased across the two recall periods, thus contributing to a structural change in the demand for peanut butter brands.

Using the same dataset, Bakhtavoryan, Capps and Salin (2014a) estimated the Barten synthetic model with a PDL specification applied to the variable measuring the impact of the recall to ascertain possible spillover effects among major peanut butter brands in the wake of the Peter Pan and Great Value peanut butter recall. They constructed the recall variable based on the number of confirmed cases of *Salmonella* due to the consumption of contaminated peanut butter reported by the CDC. The empirical findings revealed that the demand for Peter Pan was negatively impacted by the recall, while the demand for Jif enjoyed positive spillover effects as a result of the recall.

In another study by Bakhtavoryan, Capps, and Salin (2014b), a single-equation structural demand model was estimated to study the influence of the 2007 Peter Pan and Great Value peanut butter recall on the demand for peanut butter at the product-category level. A second-degree and a 3-lag PDL structure were imposed on the variable capturing the recall effects and constructed using the number of confirmed cases of *Salmonella* from the consumption of contaminated peanut butter. Contrary to expectations, the impact of the recall variable on the demand for peanut butter was found to be positive, suggesting that the recall had demand-enhancing effects for peanut butter at the product-category level. This unexpected finding was explained by households' restocking behavior, in which jars of tainted peanut butter were substituted with other brands, leading to an overall increase in the consumption of peanut butter.

Finally, Bakhtavoryan, Capps, and Salin (2014c) estimated a multinomial logit models to identify household socioeconomic factors that influenced three consumption patterns associated with the Peter Pan peanut butter. The three consumption patterns were buying Peter Pan in the pre-recall period only, buying Peter Pan in the post-recall period only, and buying Peter Pan in both the pre- and post-recall periods. The estimation results revealed that characteristics such as employment status of the household head, region of residence, race, ethnicity, age and presence of children in the household were statistically significant drivers associated with the actions taken by households in light of the Peter Pan recall. In the same study, findings from the Heckman sample selection model indicated that the change in price, region of residence, race, age and presence of children in the household, and household size were key drivers impacting the change in quantity of Peter Pan purchased across the pre- and the post-recall periods.

The present analysis is similar to prior studies reviewed in that it also attempts to evaluate the impact of a food safety issue on the demand for a product. However, the distinct feature of the present analysis is reflected in its use of a time-series approach complemented with the analysis of the directed acyclic graphs and its inclusion of the number of confirmed cases of *Salmonella* reported by the CDC as a measure of the outbreak.

Methodology

In a single-equation model, constructed based on economic theory, it is implicitly assumed that there is a unidirectional cause-and-effect relationship between the dependent variable and the set of independent or explanatory variables, with the causal flow implying that the set of independent variables is the cause and the dependent variable is the effect. But sometimes there are cases when a unidirectional relationship is not viable. An advantage of estimating the equations as a system rather than individually is the resulting improvement in efficiency, which is obtained because error terms are typically correlated among equations. In the present study, as an initial step, a system of equations in the form of the vector autoregression (VAR) model was estimated, in contrast to the single-equation structural model in Bakhtavoryan, Capps, and Salin (2014b).

Sims (1980) developed and introduced the VAR model, which—along with its variants—has become popular in applied time-series analysis (Brandt and Bessler, 1984; Bessler, 1984a; Awokuse and Bessler, 2003; Capps, Bessler, and Williams, 2016). One reason for the acceptance of the VAR approach is that the identification conditions of structural-equation modeling are relaxed. In a single equation or system of structural equations, the analyst must specify variables as exogenous or endogenous. To estimate the parameters of the system, either exact identification or over-identification conditions have to be fulfilled. The identification conditions are often fulfilled by specifying particular exogenous variables to appear in some equations, while they are omitted from other equations (Gujarati, 2004). This approach was not deemed appropriate by Sims, who maintained that there should not be any postulated distinction between endogenous and exogenous variables and that all variables should be treated equally (Sims, 1980).

Subsequent extensions of time-series methods took into account that, in some situations, variables share common stochastic trends; when they do, they are said to be cointegrated (Granger, 1981; Engle and Granger, 1987). Once a system of variables is determined to have cointegrating relationships, Lütkepohl and Kratzig (2004) suggested considering a specific parameterization supporting the analysis of the cointegration structure, leading to VEC models. The VEC model is sensitive to autocorrelation of the residuals, which may arise during the optimal lag selection procedure (Phoong, Ismail, and Sek, 2014). The residual autocorrelation problem applies to VAR models too. However, the VEC model has the additional imposed restriction that the variances and covariances of the error-correction terms are assumed to be constant (Phoong, Ismail, and Sek, 2014). Just as in a structural single-equation model, VAR models are developed by including variables that are suggested by the economic theory.

In our model, the variables included in the VAR (and subsequently the VEC model) are based on economic theory, as are the variables incorporated in the corresponding structural single-equation model. In particular, consumer theory hypothesizes that quantity demanded of a product is influenced by its own price, price of a substitute or a complement good, and consumer income. Hence, in the final VEC model, the quantity demanded of peanut butter was hypothesized to be affected by the price of peanut butter, the price of jelly as a complement good, and consumer income. Coupons are price reductions and, as such, impact quantity demanded of a product. Hence, in the final VEC model, a variable associated with coupon values for peanut butter was incorporated. Per theory, negative information is expected to decrease quantity demanded of a product. In our case, the outbreak variable was incorporated in the VEC model to capture the effects associated with the recall on the quantity demanded of peanut butter. A dummy variable was included in the VEC model to capture the possible structural change in the demand for peanut butter in the wake of the recall. While the theory does not say anything about the seasonality in the consumption of a product, quarterly dummy variables were incorporated in the VEC model to account for potential seasonality in the demand for peanut butter.

The initial step in accomplishing the objective of this study is to specify a VAR model:

$$\mathbf{X_t} = \boldsymbol{\beta} + \sum_{i=1}^{k} \mathbf{A_i} X_{t-i} + \boldsymbol{\varepsilon_t}, \quad (1)$$

where $\mathbf{X_t}$ is a vector of series corresponding to quantity of peanut butter purchased, real price of peanut butter, real price of jelly, coupon redemption for peanut butter, real income, and the number of confirmed cases of *Salmonella* reported by the CDC (i.e., the outbreak variable). Additionally, $\boldsymbol{\beta}$ is a drift vector, $\mathbf{A_i}$ is a coefficient matrix, $\boldsymbol{\varepsilon_t}$ is a vector of stochastic white noise error terms, *i* represents lags, and *k* is the maximum length of lag. The model was augmented by including seasonal dummies and a dummy variable to control for a structural shift in the demand for peanut butter. In this analysis, a natural logarithm transformation was applied to all the variables except for the number of confirmed cases of *Salmonella* reported by the CDC. For the outbreak variable, a square root transformation was applied to capture diminishing marginal returns associated with the possible nonlinear relationship between the quantity of peanut butter purchased and the outbreak variable (Capps, Bessler, and Williams, 2016).

Per the law of demand, a negative relationship was anticipated between the quantity purchased of peanut butter and own price (Rimal, Fletcher, and Deodhar, 2001). According to economic theory, a negative relationship was anticipated between the quantity purchased of peanut butter and the price of jelly because of the complementary relationship associated with these products (He et al., 2004; Smith, Rossi, and Allenby, 2016; Caine-Bish and Scheule, 2007). A positive relationship was expected between coupon values and the quantity purchased of peanut butter. Peanut butter was hypothesized to be a normal good (Rimal, Fletcher, and Deodhar, 2001). As such, a positive relationship was expected between the quantity purchased of peanut butter and income. Finally, in keeping with economic theory and empirical studies of food safety incidents (Duan, 2014), a negative relationship between the quantity purchased of peanut butter and the outbreak variable was expected.

Before estimating the model, a few practical issues need to be addressed. Augmented Dickey–Fuller (ADF) tests have to be carried out to test for stationarity in the series. If the respective variables are not stationary, then it is necessary to construct a first or second difference to render them stationary. Also, the optimal lag length must be determined based on statistical criteria, such as the Akaike Information Criterion (AIC) or the Schwarz Information Criterion (SIC). Finally, Johansen's cointegrating rank test must be carried out to identify possible cointegrating equations (Johansen, 1988; Juselius, 2006). If there is at least one cointegrating equation, a VEC model is appropriate. A VEC model in first differences with order of $k - 1$ can be written as

$$\Delta X_t = \boldsymbol{\alpha} + \sum_{i=1}^{k} \Gamma_{\boldsymbol{i}} \Delta X_{t-i} + \boldsymbol{\Pi} X_{t-1} + u_t, \quad (2)$$

where $\boldsymbol{\alpha}$ is a drift vector, $\boldsymbol{\Gamma_i}$ is a short-run coefficient matrix, $\boldsymbol{\Pi}$ is a long-run coefficient matrix, $\boldsymbol{\Pi} X_{t-1}$ is the error-correction term, and u_t is the error term.

Directed Acyclic Graphs

In general, VAR and VEC models say little about contemporaneous time correlation among variables. However, ignoring causal orderings among the respective variables in the VEC model in contemporaneous time may not produce representative impulse-response simulations and forecast error variance (FEV) decompositions (Bessler, 1984b; Sims, 1980).

The econometric literature dealing with the use of VAR and VEC models has traditionally accounted for contemporaneous correlations in three ways. The first is the use of Choleski factorization, in which contemporaneous correlations are established by imposing theory-based and recursive causal ordering on the variance/covariance matrix of the error terms (Bessler, 1984b; Sims, 1980; Bessler and Akleman, 1998). The problem with this approach is that situations usually are not recursive and, in general, results from impulse responses and FEV decompositions vary noticeably with the ordering chosen by Choleski factorization. The second approach rests on the use of the structural VAR method (Bernanke, 1986), in which prior notions of evidentially based and/or theoretically grounded, contemporaneously causal orderings may be imposed on the variables that make up the VAR (Bessler and Akleman, 1998). The problem here is that the true contemporaneous orderings that analysts claim to know may not be correct. The third approach developed by Pesaran and Shin (1998), a generalized impulse-response analysis for VAR models (and for cointegration or VEC models as well), avoids orthogonalization of shocks and therefore generates order-invariant results (Babula, Bessler, and Payne, 2004). The use of the third approach requires caution (Doan, 2002) because of difficulty in interpreting impulses from highly correlated shocks within a nonorthogonalized setting.

In this study, the Bessler and Akleman (1998) procedure was used to optimally choose a set of causal relations among six variables and then impose the evidentially supported causal relations on a Bernanke-type structural VAR. In following this procedure, an attempt is made to avoid choosing arbitrarily among competing but otherwise theoretically consistent sets of contemporaneous orderings inherent in Choleski-ordered or Bernanke structural VARs. This is accomplished with the help of directed acyclic graphs and the PC algorithm.[1] Pioneers in applying a graph-theoretical approach to the problem of determining the order of structural VAR were Swanson and Granger (1997), Bessler and Loper (2001), Bessler and Lee (2002), Demiralp and Hoover (2003), and Hoover, Demiralp, and Perez (2009). To address the issues associated with the VAR and VEC models in assessing the contemporaneous time correlation among variables, the present analysis is complemented with directed acyclic graphs and the PC algorithm, explained in the next section.

Directed Graphs and the PC Algorithm

A graph is a data structure, $\mathcal{G}$, consisting of a set of nodes and a set of edges. A pair of nodes $\mathrm{X_i}, \mathrm{X_j}$ can be connected by a directed edge, $\mathrm{X_i} \rightarrow \mathrm{X_j}$, or an undirected edge, $\mathrm{X_i} - \mathrm{X_j}$. Thus, the set of edges, ξ, is a set of pairs in which each pair is one of $\mathrm{X_i} \rightarrow \mathrm{X_j}, \mathrm{X_i} \leftarrow \mathrm{X_j}$, or $\mathrm{X_i} - \mathrm{X_j}$. Whenever $\mathrm{X_i} \rightarrow \mathrm{X_j} \epsilon\, \xi$, we call $\mathrm{X_j}$ child of $\mathrm{X_i}$ and $\mathrm{X_i}$ parent of $\mathrm{X_j}$. We say that $\mathrm{X_1}, \cdots \mathrm{X_k}$ form a path in graph $\mathcal{G}$ if, for every $i = 1, \ldots, k-1$, we have that either $\mathrm{X_i} \rightarrow \mathrm{X_{i+1}}$, or $\mathrm{X_i} - \mathrm{X_j}$. A path is directed, if, for at least one i, we have $\mathrm{X_i} \rightarrow \mathrm{X}_{i+1}$. X is an ancestor of Y in $\mathcal{G}$ and Y is a descendant of X if there exists a directed path $\mathrm{X_1} \cdots \mathrm{X_k}$ with $\mathrm{X_1} = \mathrm{X}$ and $\mathrm{X_k} = \mathrm{Y}$. A cycle in $\mathcal{G}$ is a directed path $\mathrm{X_1} \ldots \mathrm{X_k}$, where $\mathrm{X_1} = \mathrm{X_k}$. A graph is acyclic if it contains no cycles. We call these graphs directed acyclic graphs (DAGs). DAGs are the fundamental graphical representation that underlies Bayesian Networks. A Bayesian Network structure $\mathcal{G}$ is a DAG whose nodes represent random variables $\mathrm{X_1} \ldots \mathrm{X_n}$. Denote $\mathrm{Pa}^{\mathcal{G}}_{\mathrm{X_i}}$ the parents of $\mathrm{X_i}$ in $\mathcal{G}$, and $\mathrm{NonDescendants}_{\mathrm{X_i}}$ the

[1] PC stands for the initials of its inventors: Peter Spirtes and Clark Glymour.

variables in the graph that are not descendants of $\mathrm{X_i}$. Then, $\mathcal{G}$ encodes the following set of conditional independence assumptions, called the local independencies:

$$(\mathrm{X_i} \perp \mathrm{NonDescendants}_{\mathrm{X_i}} | \mathrm{Pa}^{\mathcal{G}}_{\mathrm{X_i}}) \tag{3}$$

or

$$\mathrm{P}(\mathrm{X_1}, \ldots, \mathrm{X_n}) = \prod_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{P}\,(\mathrm{X_i}||\mathrm{Pa}^{\mathcal{G}}_{\mathrm{X_i}}). \tag{4}$$

Basically, equation (3) says that each node $\mathrm{X_i}$ is conditionally independent of its nondescendant given its parents. That is, the other information is irrelevant as long as we can identify the parents of the node.

Equation (4) is a direct consequence of an assumption about equation (3). In other words, since the joint distribution can always be written as a product of conditional probabilities, $\mathrm{P}(\mathrm{X_1}, \ldots, \mathrm{X_n}) = \mathrm{P}(\mathrm{X_1})P(X_2|X_1) \ldots .P(X_n|X_1 \ldots X_{n-1})$, then using the independence assumption on equation (3) and that the graph is acyclic (i.e., there exists at least one node which does not have parents), equation (4) holds true. Equations (3) and (4) are the fundamental ideas behind constructing the DAGs and d-separation (Pearl 1986). Geiger, Verma, and Pearl (1990) show the soundness and completeness of d-separation. By soundness they mean that any independence reported by d-separation is satisfied by the underlying distribution. The completeness of d-separation requires the notion of faithfulness. A distribution is faithful to $\mathcal{G}$ if any independence in distribution is reflected in the d-separation properties of the graph. It can be shown that faithfulness holds for almost all distributions that satisfy equation (4) over $\mathcal{G}$. In other words, for almost all possible choices of conditional probability distributions for the variables, d-separation precisely characterizes the independencies of the underlying distribution (Koller and Friedman, 2010).

Having these tools available, Spirtes, Glymour, and Scheines (2000) incorporated the notion of d-separation into an algorithm (PC algorithm) for building DAGs. The PC algorithm is an ordered set of commands that begins with a set of relationships among variables (in our case innovations [i.e., error terms] from each VAR equation) and proceeds stepwise to remove edges between variables so as to direct causal flow in contemporaneous time (Spirtes, Glymour, and Scheines, 2000; Bessler and Akleman, 1998). The goal is to impose a directed edge among sets of variables $\{\mathrm{X_1}, \mathrm{X_2}, \mathrm{X_3}\}$ in a vertex set (variable set) $\mathcal{X}$: $\mathrm{X_1} \rightarrow \mathrm{X_2} \rightarrow \mathrm{X_3}$, $\mathrm{X_1} \leftarrow \mathrm{X_2} \leftarrow \mathrm{X_3}$, $\mathrm{X_1} \rightarrow \mathrm{X_2} \leftarrow \mathrm{X_3}$.

The algorithm begins with a complete, undirected graph that places an undirected edge between every variable in the system (every variable in graph $\mathcal{G}$ vertex set $\mathcal{X}$). Edges between variables are removed sequentially on the basis of zero correlations or zero partial (conditional) correlations. These conditioning variables on removed edges between variables comprise Bessler and Akleman's (1998) "sepset" of the variables whose edge has been removed.

Data

This study employs weekly time-series data from the Nielsen Homescan Panel on quantities purchased, prices, and coupons from July 26, 2006, through December 30, 2018, for a total of 127 weekly observations.[2] In addition, the dataset included a variable measuring income and a variable measuring the impact of the recall. Table 1 reports descriptive statistics on the variables used in the analysis.

Table 1. Descriptive Statistics ($N = 127$)

Variable	Description	Units	Mean	Std. Dev.
Quantity_PB	Quantity of peanut butter	oz	33.54	1.15
Price_PB	Real unit value of peanut butter	cents/oz	5.01	0.25
Price_Jelly	Real unit value of jelly	cents/oz	3.21	0.24
Coupon_PB	Real coupon of peanut butter	cents	5.42	2.91
Income	Weekly real income	dollars	614.18	8.46
CDC_cases	No. of CDC-confirmed cases	cases	3.79	7.92

Notes: Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

The quantity of peanut butter purchased was calculated by first summing the weekly total ounces of peanut butter brands across households and then by dividing that sum by the number of unique households that actually purchased peanut butter in any given week. Unit values were used as proxies for prices, which were not directly observed. The unit values for peanut butter and jelly were computed by dividing total expenditures by total ounces for each week. The coupon variable for peanut butter was constructed by first summing weekly values of coupons used and then dividing this sum by the number of unique households to express the variable on a per household basis. Weekly interpolations of real disposable personal income reported by the U.S. Department of Commerce (2011) were used as a proxy for household income.

To adjust for inflation, all unit values, coupon values, and income were deflated using the consumer price index (CPI) available from the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor. The base-year CPI corresponded to the period 1982–1984. The variable accounting for the influence of the recall (hereafter referred to as the outbreak variable) was constructed based on the weekly number of CDC-confirmed cases of *Salmonella* Tennessee infection due to the consumption of tainted peanut butter (CDC, 2007). Consistent with previous research, quarterly dummy variables were included in the model to capture potential seasonality in the demand for peanut butter (Rimal, Fletcher, and Deodhar, 2001), utilizing the fourth quarter as the base or reference category. Finally, a potential permanent structural change in the demand for peanut butter was captured by a dummy variable that assumed a value of 0 before the issuance of the recall and a value of 1 afterward.

[2] The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Empirical Results

The presence of stationarity in the historical series was tested with the ADF test. Table 2 presents the results from the ADF tests at the 5% significance level.[3] The null hypothesis of nonstationarity was rejected for the quantity purchased of peanut butter and the coupon value of peanut butter. However, the remaining variables were nonstationary.

Table 2. Augmented Dickey–Fuller Tests for Stationarity Regarding the Natural Logarithms of the Respective Variables in the Time-Series Model

Variable	Test Statistic	Decision (at 5% significance level)
Quantity_PB	−6.405	Reject nonstationarity
Price_PB	−3.179	Fail to reject nonstationarity
Price_Jelly	−3.113	Fail to reject nonstationarity
Coupon_PB	−3.803	Reject nonstationarity
Income	−1.638	Fail to reject nonstationarity
sqrt_CDC_cases	−1.840	Fail to reject nonstationarity

Notes: Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

Table 3 reports the results from the ADF tests for the first differences of all the series at the 5% significance level. As shown in Table 3, all the variables were stationary in first differences except for the income variable, which was stationary using second differences.

Table 3. Augmented Dickey–Fuller Test for the First Differences of the Natural Logarithms of the Series

Variable	Test Statistic	Decision (at 5% significance level)
d_Quantity_PB	−10.558	Reject nonstationarity
d_Price_PB	−8.757	Reject nonstationarity
d_Price_Jelly	−9.585	Reject nonstationarity
d_Coupon_PB	−9.987	Reject nonstationarity
d_Income	−1.473	Fail to reject nonstationarity
d_sqrt_CDC_cases	−10.505	Reject nonstationarity

Notes: d_ indicates first differences. Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

The appropriate number of lags to be included in the model was determined based on AIC and SIC metrics (Table 4). Based on the AIC and SIC, the appropriate lag length was 2 lags because the AIC and SIC values were minimized at lag two.

Johansen's (1995) cointegrating rank tests were performed: A sequence of trace tests and maximum eigenvalue tests were carried out, producing the optimal number of cointegrating

[3] Results from the ADF tests and ADF tests for the first differences were also supported by results from the KPSS tests.

Table 4. Akaike and Schwarz Information Criteria for the Appropriate Number of Lags Selection

Lag	AIC	SIC
0	−11.2969	−11.159
1	−21.6462	−20.6809
2	−23.5858*	−21.7931*
3	−23.5076	−20.8875
4	−23.2668	−19.8193
5	−23.2341	−18.9592

Notes: Single asterisk (*) indicates the appropriate lag length. Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

equations. Table 5 presents the results of the trace tests and the maximum eigenvalue tests at the 5% significance level. The null hypothesis of zero cointegrating vectors was rejected. However, the null hypothesis of two cointegrating vectors was not rejected.

Table 5. Johansen's Cointegrating Rank Tests

Maximum Rank, r	Trace Statistic	5% Critical Value	Eigenvalue	Maximum Eigenvalue	5% Critical Value
= 0	122.4639	94.15	.	52.9442	39.37
≤ 1	69.5197	68.52	0.34528	37.4055	33.46
≤ 2	32.1142*	47.21	0.25862	14.4832*	27.07
≤ 3	17.6310	29.68	0.10940	9.5950	20.97
≤ 4	8.0360	15.41	0.07389	6.3566	14.07
≤ 5	1.6794	3.76	0.04958	1.6794	3.76

Notes: Single asterisk (*) indicates the cointegrating rank. Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

Next, the VEC model parameters were estimated. Basically, the main interest lies in the equation with the dependent variable related to first differences of the quantity purchased of peanut butter. The STATA 12 software package was used to perform the estimation. Table 6 presents the results from the VEC estimation for the equation pertaining to the quantity purchased of peanut butter at the 5% significance level.

The R^2 was 0.5149, indicative of a reasonably good fit. Several coefficients were significantly different from zero. In particular, the estimated coefficient of the price of peanut butter lagged two periods was negative, as anticipated, and was statistically different from zero. This result was consistent with Bakhtavoryan, Capps, and Salin (2014b). The estimated coefficients associated with the first and the second lags of the price of jelly were negative and statistically different from zero, as expected. However, Bakhtavoryan, Capps, and Salin (2014b) did not find this variable to be statistically significant. In addition, the estimated coefficient of the second lag of income was positive and statistically significant, as expected. This finding compared favorably with that of Bakhtavoryan, Capps, and Salin (2014b). Additionally, the estimated

Table 6. Estimation Results for the Quantity Purchased of Peanut Butter Equation from the Vector Error Correction Model, $N = 123$

	Coefficient	***p* Value**
_ce1		
L1	−0.737*	0.000
_ce2		
L1	0.050*	0.000
ln_Quantity_PB		
LD	−0.010	0.934
L2D	−0.065	0.523
ln_Price_PB		
LD	−0.051	0.724
L2D	−0.282*	0.049
ln_Price_Jelly		
LD	−0.225*	0.001
L2D	−0.131*	0.033
ln_Coupon_PB		
LD	−0.001	0.909
L2D	−0.005	0.554
ln_Income		
LD2	−0.897	0.919
L2D2	19.128*	0.030
sqrt_CDC_cases		
LD	−0.009	0.089
L2D	−0.009	0.077
Q1	−0.002	0.807
Q2	−0.019*	0.019
Q3	−0.012	0.160
DUMMY	−0.024*	0.005
Constant	0.024*	0.004

Notes: Single asterisk (*) indicates statistical significance at the 5% level. Log-likelihood = 1,573.709. L1 indicates that the variable is lagged one period, LD indicates lagged first differences, and _ce corresponds to the respective error-correction terms. Q1–Q3 are seasonal dummies and DUMMY is a dummy variable controlling for the structural shift in the demand for peanut butter. The estimation results of the remaining equations are available from authors upon request. Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

coefficient of the second-quarter seasonal dummy variable was negative and significantly different from zero, in accordance with the estimation results by Bakhtavoryan, Capps, and Salin (2014b), who also found seasonality to be a statistically significant factor. Consistent with the previous study, the estimated coefficient associated with the dummy variable was negative and statistically significant, indicating a structural change in the demand for peanut butter. Moreover, as in the previous study, the estimated coefficients associated with the coupon variable were statistically insignificant.

Based on one-tailed tests, the estimated coefficients of the first and second lags of the outbreak variable were negative and statistically significant, supporting the hypothesis of negative impacts associated with food safety incidents. However, this result was at odds with the finding by Bakhtavoryan, Capps, and Salin (2014b) that the parameter estimates associated with the outbreak variable were positive, implying that the outbreak positively influenced the quantity purchased of peanut butter. Differences between the time-series VEC model and the structural/econometric model likely account for the difference in the estimation results in regard to the outbreak variable. This discrepancy provides empirical evidence that alternative model specifications may generate nonrobust results. As such, the use of time-series models as well as conventional structural/econometric models is recommended when analyzing food safety issues.

DAG Application

Before estimating and discussing impulse-response functions and FEV decompositions, it is necessary to illustrate the application of the DAGs to find how the six variables were ordered in contemporaneous time using the R package pcalg (Kalisch et al., 2012). The starting point is Figure 1, the complete undirected graph of all possible edges among the six variables. Figure 2 provides the edges that the algorithm suggested as statistically significant at the 10% level.

Contemporaneous causal ordering was discovered in several steps. First, the algorithm based on unconditional correlations eliminated all statistically zero edges and retained those that were statistically nonzero (Spirtes, Glymour, and Scheines, 2000). Then, the algorithm checked all the remaining conditional correlations and retained the ones that were statistically nonzero. If the edges were fully one-side directed,[4] a unique set of correlations could have been imposed on Bessler and Akleman's DAG/Bernanke VAR model. However, per Figure 2, one edge is bi-directional, which indicated that there existed systems of observationally equivalent contemporaneous causality relationships. In that case, there was a need to find "the best" Bayesian Network that represented the data.

Although finding the best Bayesian Network structures is NP-hard (Chickering, Meek, and Heckerman, 2003),[5] feasible techniques exist for small networks (e.g., Singh and Moore, 2005;

[4] That is, it is not true that $X_i \rightarrow X_j \in \xi$ and $X_i \leftarrow X_j \in \xi$.

[5] In computational complexity theory NP-hardness (nondeterministic polynomial-time hardness) is the property that defines a class of problems. Formally, a decision problem H is NP-hard when for every problem L in NP, there is a polynomial-time reduction from L to H. NP (non-deterministic polynomial time) is a complexity class used to describe certain types of decision problems. For more information, see the work by Cormen et al. (2009).

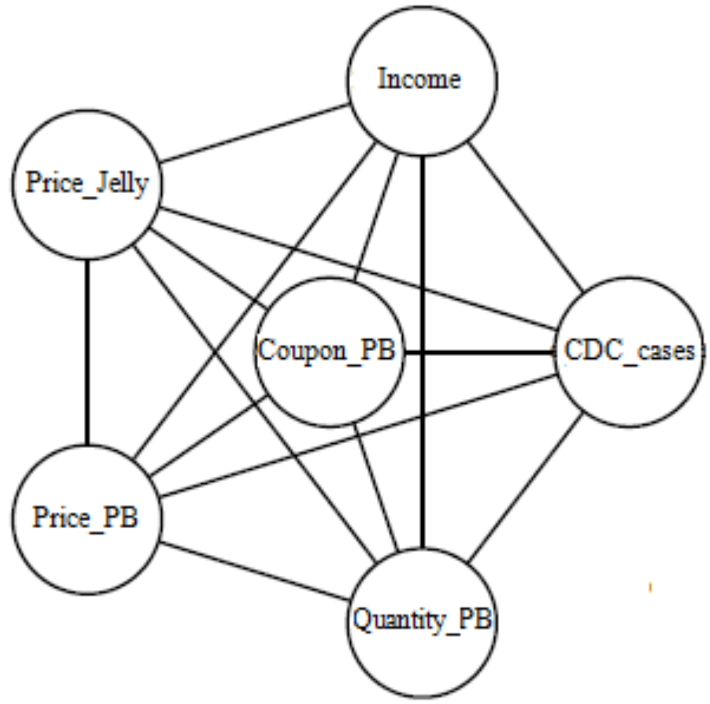

Figure 1. Complete Undirected Graph on Innovations from the VEC Model
Notes: Natural logarithmic transformation was used on all variables, with the square root transformation applied to the CDC_cases variable.

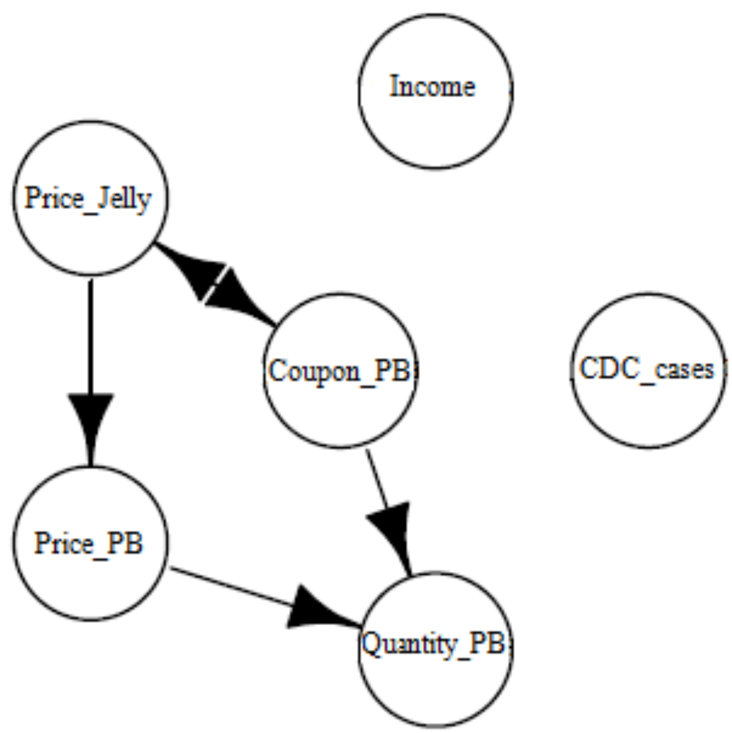

Figure 2. Generated DAG on Innovations from the VEC Model
Notes: Natural logarithmic transformation was used on all variables, with the square root transformation applied to the CDC_cases variable. Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

Silander and Myllymaki, 2006; Haigh and Bessler, 2004). Haigh and Bessler (2004) modified and applied Schwarz's loss metric to the alternative systems of causality and then chose the system of causality that minimizes the Schwartz metric. This study followed the method suggested by Silander and Myllymäki (2006), rather than the Haigh and Bessler approach, to find the best Bayesian Network structure. To use the Silander and Myllymäki method, the scoring functions have to be modular (i.e., given the data, the score of a Bayesian Network structure G = (G_1, …, G_n) for variables X = (1, …, n) must be decomposable to local scores:

(5) $$\text{score}(G) = \sum_{i=1}^{n} \text{score}_i(G_i).$$

The score of the network was the sum of the local scores that depend only on the conditional probability for one variable and its parents. Most of the known scores, such as SIC and AIC, are decomposable (Chickering, 1995). By measuring the local scoring function, the goodness of the parents of X_i is found. This idea naturally leads to finding the best parents for a variable X_i in any given parent candidate set C:

(6) $$g_i^*(C) = \arg_{g \subseteq C} \max \text{score}_i(g).$$

The Bayesian Information criterion (BIC) is used in this study as a scoring rule, following Silander and Myllymäki (2006) and using the method discussed above. Based on Figure 2, there existed two possible relationships in the Bernanke structural VAR to form the DAG/Bernanke VAR model. Therefore, two local scores had to be estimated:

1. ln(Price_Jelly) → ln(Coupon_PB) (i.e., the ln(Price_Jelly) variable is the parent for the ln(Coupon_PB) variable);
2. ln(Coupon_PB) → ln(Price_Jelly) (i.e., the ln(Coupon_PB) variable is the parent for the ln(Price_Jelly) variable).

A choice had to be made between these two possible and competing systems of causal relations based on the provided maximum value. The highest score was provided by the option in which ln(Coupon_PB) was the parent for ln(Price_Jelly) (Table 7). Imposing these relationships, resolved the problem of contemporaneous correlation. Figure 3 shows the final DAG after this imposition.

Table 7. Two Alternative (Observationally Equivalent) Systems of Contemporaneous Causal Relations

Type	**System 1**	**System 2**
Parent	ln(Price_Jelly)	ln(Coupon_PB)
Child	ln(Coupon_PB)	ln(Price_Jelly)
Score Value	80.60	300.61

Notes: Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

Having addressed the issue of contemporaneous correlation, dynamic interrelationships among the variables in the VEC model can be analyzed using methods of innovation accounting such as FEV decompositions and impulse-response functions. FEV decompositions assist in quantifying the importance of each shock in explaining the variation in each variable in the model. This

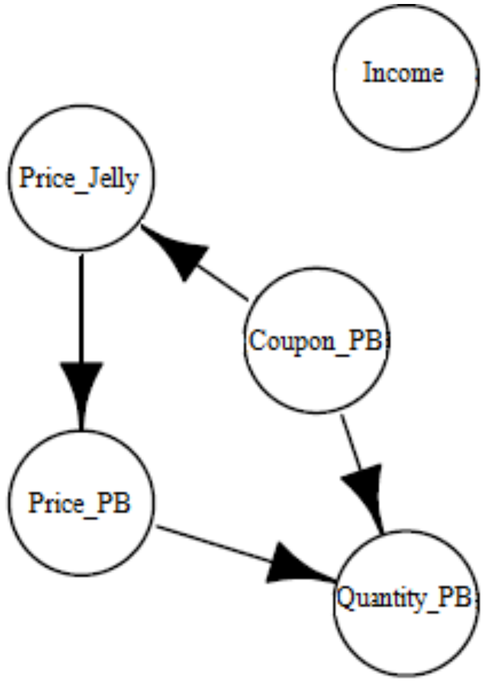

Figure 3. Final DAG Based on Innovations from the VEC Model
Notes: Natural logarithmic transformation was used on all variables, with the square root transformation applied to the CDC_cases variable. Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

metric was calculated as a fraction of the FEV of each variable at different forecast horizons. Impulse-response functions showed the impacts of unit innovations in a particular variable on all variables in the model over time.

Table 8 gives the FEV decomposition from the 2-lag VEC model for the quantity of the peanut butter purchased for 1-, 8-, 16-, 26-, and 52-week forecast horizons. If an innovation of a particular variable accounted for a high percentage of the FEV, then it was considered to be a determinant of the quantity purchased of peanut butter.

Table 8. Forecast Error Variance Decomposition for the Quantity of Peanut Butter Purchased in Percentages

Horizon in Weeks	Quantity_PB	Price_PB	Price_Jelly	Coupon_PB	Income	CDC_cases
1	72.95	24.08	1.58	1.39	0.00	0.00
8	59.46	21.32	7.79	6.65	0.79	3.98
16	57.87	20.85	7.77	6.77	1.87	4.87
26	57.16	20.61	7.77	6.70	2.65	5.09
52	56.64	20.38	7.84	6.63	3.41	5.09

Notes: Rows do not add up to 100% due to rounding errors. Natural logarithmic transformation was used on all variables, with the square root transformation applied to the CDC_cases variable. Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

About 73% and 24% of the 1-week FEV of the quantity purchased of peanut butter were accounted for by innovations in the quantity of peanut butter purchased and the real price of peanut butter, respectively. For longer-term horizons, approximately 57% and 20% of the error variance was accounted for by innovations in the quantity purchased of peanut butter and the real price of peanut butter, respectively. For the 1-week horizon, innovations in the real price of jelly and real coupon values contributed less than 2% to the FEV of the quantity purchased of peanut butter. At the same time, innovations in the real price of jelly and real coupon values contributed about 8% and 7%, respectively, to the FEV of the quantity purchased of peanut butter for longer-term horizons. Innovations in real income and the number of confirmed cases of illnesses began impacting the quantity purchased of peanut butter at a horizon of 8 weeks. In particular, innovations in real income and number of confirmed cases of illnesses accounted for about 3% and 5% of the FEV, respectively, for longer-term horizons.

Figure 4 presents DAG/Bernanke impulse-response functions in graphic format in an attempt to quantify the impact of a 1-standard-deviation shock in the error term or innovation of the variables on the quantity purchased of peanut butter. By applying this one-time exogenous shock to each variable, it was possible to trace out a dynamic picture of how the variables responded over a period of 52 weeks. In Figure 4, the impulse responses for all variables were normalized by dividing them by the historical standard deviation of the corresponding error term (innovation) in the VEC model to make the graphs comparable with each other irrespective of measurement units. In Figure 4, the responses are listed at the top of each column, given a one-time-only shock in the variables listed at the beginning of each row.

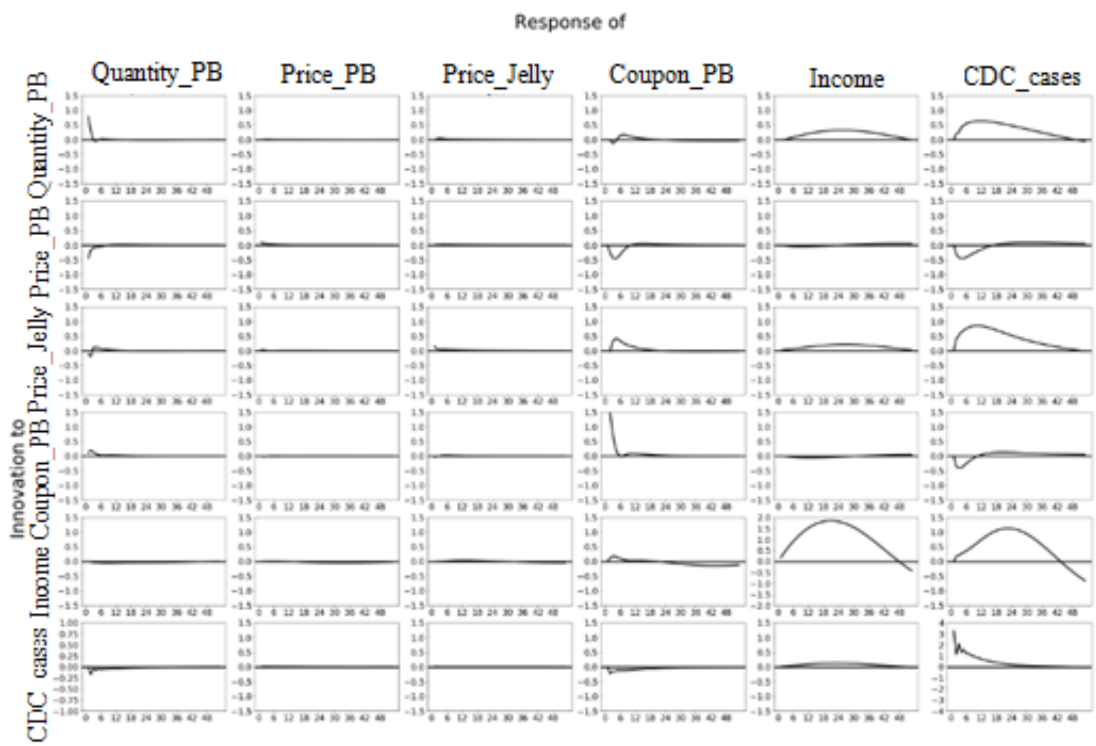

Figure 4. Impulse-Response Functions Generated by the Vector Error Correction Model
Notes: Natural logarithmic transformation was used on all variables, with the square root transformation applied to the CDC_cases variable. Calculated based on data from The Nielsen Company (U.S.), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.

Our primary interest lies in the response of the quantity of peanut butter purchased (the first column of Figure 4) following an initial one-time-shock only in the respective variables. According to Figure 4, the impacts dampened out over the 52-week period. The response of the quantity of peanut butter purchased to its own shock was positive and peaked in week 1. As expected, the response of the quantity of peanut butter purchased to the shock in the real price of peanut butter was negative with the peak taking place in week 1 as well. The response of the quantity of peanut butter purchased to the shock in the real price of jelly started out negative, as anticipated, for the first 2 weeks following the shock, but subsequently turned positive from weeks 3 through 14. The peak of the impact of the real price of jelly took place in week 2. The response of the quantity of peanut butter purchased to the shock in the real income was positive, peaking at week 2. The response of the quantity of peanut butter purchased to the shock of coupon values was negligible. Finally, the response of the quantity of peanut butter purchased to the shock in the number of confirmed cases of illnesses due to peanut butter consumption was negative throughout the 52-week period, with the peak occurring in week 2.

Concluding Remarks

This study presented an alternative methodological approach of time-series analysis, in contrast to a structural analysis by Bakhtavoryan, Capps, and Salin (2014b), to investigate the demand for peanut butter in the wake of a product recall. This study estimated a 2-lag DAG/Bernanke VEC model using weekly time-series data from July 26, 2006, through December 30, 2008, and using the number of confirmed cases of illnesses due to peanut butter consumption to account for the effects of the recall. The estimation results identified the real price of peanut butter, real price of jelly, real income, the outbreak variable, a structural dummy variable, and seasonality as statistically significant determinants of the quantity purchased of peanut butter. In particular, consistent with previous research, the real price of peanut butter negatively influenced the quantity purchased of peanut butter (Rimal, Fletcher, and Deodhar, 2001), the real price of jelly negatively impacted the quantity purchased of peanut butter (He et al., 2004; Smith, Rossi, and Allenby, 2016; Caine-Bish and Scheule, 2007), real income positively affected the quantity purchased of peanut butter (Rimal, Fletcher, and Deodhar, 2001), and the recall negatively impacted the quantity purchased of peanut butter (Swartz and Strand, 1981; Smith, van Ravenswaay, and Thompson, 1988; van Ravenswaay and Hoehn, 1991; Burton and Young, 1996; Verbeke and Ward, 2001; Marsh, Schroeder, and Mintert, 2004; Piggott and Marsh, 2004; Pritchett et al., 2007, Duan, 2014), with the last empirical finding being consistent with the results from the prior studies reviewed. Also, in accordance with previous research, a structural change in the demand for peanut butter was found in the wake of the recall (Bakhtavoryan, Capps, and Salin, 2012), and seasonality emerged as a statistically significant driver of the quantity purchased of peanut butter (Rimal, Fletcher, and Deodhar, 2001).

In addition, all findings compare favorably with those by Bakhtavoryan, Capps, and Salin (2014b), with two exceptions. First, the previous study found the real price of jelly to be a statistically insignificant driver of the quantity purchased of peanut butter. Second, and more importantly, the two studies are at odds concerning the impact of the outbreak variable on the quantity purchased of peanut butter. In particular, while Bakhtavoryan, Capps, and Salin (2014b) found that the outbreak variable positively affected the quantity purchased of peanut butter, the present study found that the outbreak variable had a negative impact on the quantity purchased of peanut butter. The discrepancy can likely be attributed to differences in the methodological approach (i.e., the use of a VEC model as opposed to a structural/econometric model). The use of time-series models in analyzing the impacts of food safety incidents has been sparse in the extant literature. Hence, using time-series models as well as structural/econometric models is recommended when examining impacts of food safety incidents as a check on the robustness of the results.

Foodborne illnesses remain a topical issue, and the empirical finding showing the negative impact of the recall on the peanut butter category has implications for public regulatory institutions responsible for assuring the safety of the nation's food supply. Moreover, food manufacturers' strategic decisions about quality control programs are informed by this research. Given the cost associated with food recalls, the empirical findings from this study provide further incentive for government regulatory bodies to design and implement recall-preventing policies as well as commit more effort and resources to enhancing their capacity to identify and prevent food safety issues. For peanut butter manufacturers, the extent of spillover from an implicated brand to the entire category constitutes an important and interesting element. As such, the empirical results are essential in that they provide manufacturers with an incentive to adopt and invest in safe production practices as well as closely follow food safety standards to avoid experiencing potential losses in sales in the wake of recalls. In any case, the success of these efforts is inextricably linked with a proper understanding of the economic consequences resulting from food safety issues and the welfare benefits stemming from food safety measures. Finally, the causal relationships that emerge from the study of the peanut butter product market are generalizable to the management of food safety events, and similar case studies can also be replicated for other products implicated in food safety issues.

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